nsa National Seed Association of India

Seed Times

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AI AND DIGITAL TECHNOLOGIES FOR SEEDS

ABOUT US

National Seed Association of India (NSAI) is the apex organization representing the Indian seed industry. The vision of NSAI is to create a dynamic, innovative and internationally competitive, research based industry producing high performance, high quality seeds and planting materials which benefit farmers and significantly contribute to the sustainable growth of Indian Agriculture.

The mission of NSAI is to encourage investment in state of the art R&D to bring to the Indian farmer superior genetics and technologies, which are high performing and adapted to a wide range of agro-climatic zones. It actively contributes to the seed industry policy development, with the concerned governments, to ensure that policies and regulations create an enabling environment, including public acceptance, so that the industry is globally competitive.

NSAI promotes harmonization and adoption of best commercial practices in production, processing, quality control and distribution of seeds.

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Message
FROM THE DESK OF PRESIDENT

We all know that seed is universally recognized as one of the most vital inputs for enhancing agricultural production and productivity. High-quality seeds not only play a key role in ensuring food security for a growing population but also contribute significantly to nutritional security. To encourage farmers to adopt quality seeds, it is essential to ensure the availability of adequate quantities of seeds that meet established quality standards, are suitable for diverse agro-ecological conditions, and are accessible at affordable prices.

Artificial Intelligence (AI) and digital technologies are bringing big changes to the seed industry. They are enhancing the processes of seed development, testing, production, and distribution. With the help of tools like machine learning, big data, GPS-based mapping (GIS), satellite images, and Internet-connected devices (IoT), the seed sector is becoming more efficient, accurate, and environment-friendly. AI is helping scientists quickly study large amounts of data to find the best traits in plants such as resistance to drought or disease, or faster growth. This helps in developing new, better seed varieties that grow well in different climates and regions.

In addition, modern agriculture tools like drones, sensors, and satellite images help monitor crop growth, soil condition, and weather in real time. This information is used by AI to plan field trials and manage seed production more effectively. Digital systems also make it easier to track seed movement and quality from research labs to farmers, ensuring that the seeds meet standards and are delivered on time. Farmers also benefit from mobile apps and advisory tools that suggest which seeds to use, when to plant, and how to manage their crops based on local conditions.

Overall, these technologies make the work of seed companies and researchers faster and smarter, while helping farmers grow better crops with lower costs and less harm to the environment. AI and digital tools are key to building a strong and smart farming system that can help feed the growing global population in a sustainable way.

I am happy to see that this edition of "Seed Times" has been brought out on the theme **"AI and Digital Technologies for Seeds"**, which is need of the hour. I am sure, the readers will have opportunity to go through quality articles on AI and Digital Technologies.

M Prabhakar Rao

Message
FROM THE DESK OF EXECUTIVE DIRECTOR

Dear Readers,

The most reputed NSAI quarterly magazine of the seed industry, the **Seed Times** covers scientific research papers/articles/review articles/information on various aspects related to seed industry. It is widely circulated to all the stakeholders of seed industries *viz*., ICAR, SAUs, Central Govt. Agriculture Departments, State Agriculture Departments, NSC, SSC, Private Seed Companies etc.

The theme of January-April, 2025 issue of the Seed Times is **"AI and Digital Technologies for Seeds"** with the aim to disseminate the knowledge about the Artificial Intelligence and Digital Technologies for Seeds by eminent scientists and professionals.

AI and digital technologies are revolutionizing the seed industry by enhancing the efficiency, precision, and sustainability of agricultural practices. With advanced data analytics, machine learning, and remote sensing tools, seed companies can now develop high-yielding, climate-resilient varieties faster than ever before. AI models help analyze genetic traits, predict crop performance, and optimize breeding processes. Digital platforms also facilitate better supply chain management, enabling real-time tracking of seed quality, inventory, and distribution. These innovations empower farmers with data-driven insights, leading to improved productivity, reduced environmental impact, and a more secure food future.

I compliment NSAI team for focusing on AI and Digital Technologies in this edition of Seed Times which is need of the hour for the growth of seed industry.

I hope the readers would greatly be benefited from the magazine.

Happy Reading!

Y R Meena


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TABLE OF CONTENTS

Artificial intelligence in Seed Testing: Replacing Traditional Methods with Smart Solutions

M. KOKILA, T. EEVERA AND R. UMARANI
Department of Seed Science and Technology, Directorate of Seed Centre,
Tamil Nadu Agricultural University, Coimbatore – 641 003
Email: eeverat@tnau.ac.in

Lead Author

DR. T. EVERA

Associate Professor
Department of Seed Technology
Tamil Nadu Agricultural University (TNAU), Coimbatore

Dr. T. Evera is an Associate Professor in the Department of Seed Technology at Tamil Nadu Agricultural University (TNAU), Coimbatore. He holds a B.Sc. (Agriculture), M.Sc. (Agriculture), and Ph.D. in Seed Science and Technology, all from TNAU. With over 20 years of experience in the field, Dr. Evera has made significant contributions to seed science and technology.

He played a key role in the development and release of two salt-tolerant paddy varieties—**TRY 4** and **TRY 5**, released in 2021 and 2022, respectively. He is also the developer of **seed cube technology**, an innovative advancement in seed germination and establishment. Under a National Research Development Corporation (NRDC)-funded project, Dr. Evera has designed and fabricated a **semi-automatic seed cube making machine**, currently undergoing validation.

His research portfolio includes, Completion of **five externally funded projects** (from both public and private agencies),**Ten university research sub-projects**, **Two action plan projects**, and Ongoing leadership as Principal Investigator (PI) or Co-PI in **five private agency-funded projects** and **one ICAR-MSP-RF scheme** focused on the production and supply of **seed cubes** and **Vidhai Amirtham**.

Dr. Evera has an extensive publication record, **78 research articles**: 32 in journals with a NAAS rating above 6, 30 rated between 4 and 6, and 16 below 4, **24 book chapters**, and **4 books** published between 2022 and 2024 by Narendra Publishing House and TNAU, all with ISBNs.

In recognition of his academic excellence, he was selected for the **ICAR-NAHEP-IDP international exposure program (2022–23)**, through which he visited **Nanyang Technological University, Singapore**, and published **two review papers** in journals with NAAS ratings above 6.

Dr. Evera also facilitated the signing of an MoU between **TNAU and Temasek Polytechnic, Singapore**, strengthening international academic collaboration.

Additionally, he has submitted **two major research proposals**—one to the **Tamil Nadu Chief Minister's Research Grant** and another to the **Science and Engineering Research Board (SERB), Department of Science and Technology (DST), Government of India**.

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1. Introduction

As per the section number 6 of the Seeds Act, 1966 seed sold in the market should fulfill quality criteria. In order to evaluate the quality parameters of the certified seeds produced in India, as per the section number 4 of the Seeds Act, 1966 seed testing laboratories were established (Ujjainkar, 2022). During seed testing, the quality parameters like germination, physical purity, genetic purity and moisture content of the seed need to be assessed and it is mandatory for seed certification purpose. Among the listed four parameters except genetic purity, can be quickly assessed by seed analyst in the laboratory (McDonald, 1998). But for assessing the genetic purity, the seed analyst need to follow Grow Out Test (GOT) or molecular marker based genetic purity testing.

Various traditional seed testing methods like physical, physiological, biochemical and pathological tests have been used for decades to evaluate the seed standards (Matthews *et al.,* 2012) and they are assessed manually based on the shape, size and colour or biochemically based on the chemical composition of seeds by following the standardized protocols given by ISTA (Prasad, 2023). Though these methods are scientifically validated, have several limitations that affect the efficiency and accuracy of the seed quality evaluation. One of the major drawback is labor intensive and time consuming (Singh *et al.,* 2025). Genetic purity, germination and vigour assessment usually take several days to week to get the results and requires complete monitoring under controlled conditions to make results reliable and invariable (Sarma, 2024). In addition, tests like physical purity and grow out test (GOT) rely on the manual observation and judgment and it leads to bias in the results. GOT is a time consuming process, the producers need to wait one crop season to know the result and also it require well protected and isolated lands for conducting the test (Nandakumar *et al.,* 2004). Even though the seed testing laboratories are well equipped, it can only process a finite number of samples in a given time. But, recently more number of sample is received by the seed certification department, it demands huge area for conducting the analysis. Moreover, all these tests are destructive in nature which means that some portion of the seed sample is lost in the evaluation process. Another major concern is that only experienced personal can detect many forms of damage, disease, internal infections and infestation without any external symptoms, deterioration and minor genetic variations in the seed lot (Xia *et al.,* 2019).

To address the pitfalls in the traditional seed quality evaluation methods, there is an increasing demand for quick, non-destructive and non-invasive methodologies in the present day requirements. In order to do the seed testing analysis in a systematic way, automation is the need of the hour. For better segregation of the off-type seed from the true to type seed, it is necessary to capture, document and use all those possible variations between the seed crop seed and off-type in the analysis. This led to the development and adoption of Artificial intelligence based seed quality testing methods. AI when integrated with computer vision, machine learning, hyperspectral imaging offers a transformative alternative that addresses the core weakness of the existing methods. This article presents a comprehensive overview of application of AI in seed quality testing and how these advancements establishing a connection between traditional approach and the changing demands of seed quality evaluation.

2. AI technologies for next generation seed quality control

Advanced machine learning methods of seed quality evaluation helps to increase the reliability and reproducibility, accurate and faster quality assessment methods with minimum human intervention are basically required to provide the best levels of seed quality for production and trade purposes. Therefore, the potential of using non-destructive methods such as imaging techniques, NIR, spectroscopy or precise remote sensors to overcome the limitations of conventional methods is gaining increasing attention (Dhiman & Singh, 2025). However, most documented algorithms only use color-based thresholds and estimate parameters to describe the seed including area, perimeter, length, width, roundness and color.

2.1 Imaging techniques

The imaging techniques such as spectral imaging, thermal imaging, fluorescence imaging, X-ray imaging and magnetic resonance imaging offer reliable alternatives to the traditional destructive methods, The X-ray imaging and magnetic resonance imaging are able to provide anatomical details and the spectral imaging, thermal imaging and fluorescence imaging are usually utilized to deliver functional and nutritional information about the seeds being examined (Patel *et al.,* 2024). In general, the digital imaging approaches along with computer simulation are very useful for integrating complex data about seed quality parameters in an automated and objective manner (Fig 1). The seed radiography with X-ray imaging and nuclear magnetic resonance techniques (NMR) have proved great potential in evaluating seed quality as well as efficient seed phenotyping in a non-destructive way by providing internal and anatomical features of the examined seeds (Musaev *et al.,* 2020). These techniques offer seed analysts and researcher's detailed information about the seed maturity, internal structures, germination, vigour, insect information and internal damages (Musaev *et al.,* 2021).

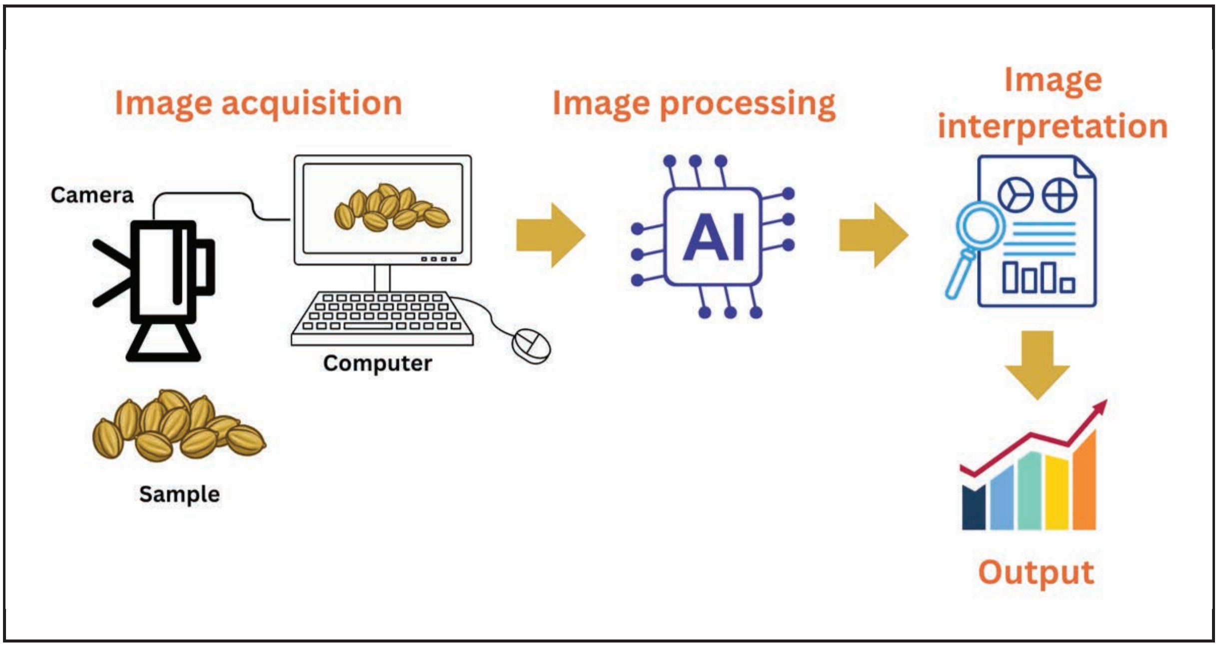

Fig. 1 Stepwise depiction of AI tools in assessment of seed quality

2.1.1. Colour imaging

At present, many ocular techniques are being used to acquire morphological features of seeds. Similar to human eye, traditional colour imaging known also as RGB imaging uses three broad band colour channels (Red, Green and Blue) to produce a single colour value for each pixel in the image. The colour imaging is suitable for collecting morphological data (eg. color, size, shape and surface texture), and can be adopted for analyzing physical integrity (JayaBrindha & Subbu, 2017). However, as a consequence of the broad wavelength band ranges recorded by RGB cameras, RGB imaging has very limited spectral resolution and a large amount of information is lost, which makes RGB imaging unsuitable in differentiating similar samples that only show separate spectral variations within a single broad band range.

2.1.2. X-ray imaging

X-rays having a wavelength of 0.01-10 nm with an energy of 0.1 to 120 keV which has high penetrability. The detector measures the remaining attenuated radiation after the X-ray beam enters the sample, producing a 2D image that can be merged with mathematical concepts to produce a 3D digital image (Chen *et al.*, 2013). Changes in density and composition can be the cause of differences in weakening within a sample (Withers *et al.*, 2021). In addition to standard X-ray CT, soft X-ray radiography has developed as an important non-destructive tool for assessing seed quality. Soft X-ray radiography uses low-energy X-rays which can penetrate seed tissues, resulting in pictures that reveal internal features (Musaev *et al.,* 2020). The approach is based on the differential absorption of X-rays by several seed components, including the embryo, endosperm, and seed coat. This differential absorption causes varied brightness levels in radiographic pictures, which can be examined statistically to determine seed quality. Advances in digital imaging technology have resulted in greatly increased image resolution and clarity, allowing for extensive investigation of seed integrity and viability (Singh *et al.,* 2025).

This method aids in conservation and use of genetic resources by enabling researchers to determine the germination potential based on their internal composition. Also it shown promising results in detecting mechanical damage in seeds by recognizing cracks and other damages.

2.2. Spectroscopy and spectral imaging for seed quality evaluation

Recently optical sensing techniques, including spectroscopy and imaging systems, have been widely utilized for seed quality evaluation. Systems based on spectroscopy provide spectral data either by spectroradiometry or spectrophotometry measurements. In spectrophotometry, the light reflected from a sample is related to the incident light as a measure of spectral reflectance for the sample (Al-Amery *et al.,* 2018). Near Infrared Spectroscopy (NIRS) method has demonstrated its ability to carry out simultaneous assessment of different quality traits with accuracy comparable to that of traditional wet chemistry analytical methods. Due to their advantages, the NIRS techniques have been widely utilized for the quality analysis of crop seeds and kernels including quantitative analyses of oil content, protein, water, sugar, starch and carbohydrate content, viability and vigour detection, purity or variety discrimination, detection of disease and insect infestation, detection of physical damage and other applications (Mortensen *et al.,* 2021).

However, the spectral information extracted by this method is presumably limited to only a little portion of a sample where the measuring probe is positioned, without considering the spatial information. Thus, the sample being analyzed should be reasonable homogenous in order to extract representative spectral information. This disadvantage of conventional spectroscopy can be easily alleviated by combining both spectral and spatial information by using hyperspectral (HIS) and/

or multispectral (MIS) imaging techniques (ElMasry *et al.,* 2019).

Building an integrated computer-aided image analysis system for overall quality evaluation processes of seeds could be realized by combining colour imaging and spectral imaging in one system. The colour imaging system will be used to provide measurements of the morphological features (dimensions, colour shape, texture etc.,) germination capacity (radicle elongation, timing of germination, germination speed, vigour etc.,) and seed health conditions (diseased parts, pest infestation etc.,). Along with colour imaging system, the spectral imaging system will be utilized to provide spectral information about the examined seeds to give detailed information about each chemical composition (protein, lipid, moisture, pigments etc.,) of the examined seeds.

2.2.1. Multispectral imaging

Multispectral imaging gives calibrated reflectance data at many 'discrete' wavelength bands dispersed over a long spectral range from ultraviolet (UV) to near infrared (NIR) area, as opposed to using three broad bands of colour to provide a stack of only three individual greyscale images. The resulting multispectral image is made up of a stack of various grey scale sub-images that accurately depict the relative light reflectance at various non-overlapping wavelength bands over a wider area than is perceptible to the human eye (Jameel *et al.,* 2020). Because it can capture image data at specific multiple wavelengths across the electromagnetic spectrum, the method of acquiring a multispectral image is commonly referred to as "multi-channel imaging," which provides the information necessary for the characterization and identification of the components composing the seeds being studied (Feng *et al.,* 2019).

MSI is able to obtain images at various electromagnetic spectrum wavelengths, enabling the collection of spatio-spectral data that offers important insights into the chemical and physical characteristics of seeds by combining digital imaging with spectroscopy. This method is useful for seed phenotyping and to identify viable seeds. In situations when conventional techniques might not be successful, this technology has also shown promise in identifying coated seeds. Determining seed maturity is another way that MSI is used in the evaluation of seed quality (Singh *et al.,* 2025).

2.2.2. Hyperspectral imaging

When the spectral images are acquired for very narrow spectral bands rather than discrete bands, the system is called hyperspectral imaging. The main difference between multispectral imaging and hyperspectral imaging techniques is number a wave bands at which the spectral image is acquired. In a hyperspectral imaging scenario, the spectral image is recorded by utilizing a great number of wavebands leading to a continuous spectral range (Feng *et al.,* 2019). On the contrary, the spectral image is recorded for a few discrete bands in the case of multispectral imaging. Thus hyperspectral images can provide a full continuous spectrum for every single pixel in the image. While RGB imaging provides information at only within the visible range, the multispectral imaging provides information on different regions of electromagnetic range, hyperspectral imaging facilitates acquiring information not only visible range but also extends outside the visible range into the electromagnetic spectrum (Reddy *et al.,* 2022).

Hyperspectral imaging (HSI) technique captures both spatial and spectral information simultaneously, combines the advantages of spectroscopic and imaging techniques. In other words, it can simultaneously obtain the chemical information of heterogeneous samples and the spatial distribution of chemical components. With a hyperspectral sensor, a wide range of wavelengths, including the ultraviolet (UV), visible (VIS) and near infra-red (NIR) spectra can be obtained. Hyperspectral images are able to convey much more spectral information than RGB or other multispectral data: each pixel is in fact a high-dimensional vector typically containing reflectance measurements from hundreds of contiguous narrow band spectral channels (full width at half maximum, FWHM between 2 and 20 nm) covering one or more relatively wide spectral intervals (typically, but not exclusively in the 400 - 2500 nm wavelength range) (de Juan, 2018). Current HIS acquisition technologies are able to provide high spectral resolution while guaranteeing enough spatial resolution and data throughput for advanced visual data analysis in a variety of quality demanding application contexts.

As HSI allows for rapid, high-throughput analysis on a per-kernel basis, it is a useful technique for assessing seed viability. Because HSI (Hyperspectral Imaging) provides both spectral and spatial information, it can be used to classify a sample's surface quality and anticipate its inside chemical composition.

2.2.3. Near-infrared (NIR) spectroscopy & FT-NIR spectroscopy

The absorption of electromagnetic radiation at wavelengths between 780 and 2500 nm is the basis of near-infrared (NIR) spectroscopy. Wavelength-dependent scattering and absorption mechanisms in samples can change their spectral characteristics through light absorption (Nicolai *et al.*, 2007). The tissue architecture and intra/extracellular environments of living tissues are the causes of this scattering. This method is used to analyze the seed viability, seed moisture content, seed vigour and to quantify hard seed. NIR spectroscopy's analytical capabilities are further improved by the incorporation of chemometric techniques, such as Partial Least Squares Discriminant Analysis (PLS-DA), which enables efficient differentiation between various seed lots (Pandiselvam *et al.*, 2022).

2.3. Software based AI tools

Germination is an essential criteria to be considered during seed quality evaluation. A software tool called GERMINATOR uses the area and positional difference between photographs taken at different time (Joosen *et al.*, 2010) and several settings must be adjusted for different seeds.

Seed vigor Imaging System uses a flatbed scanner to calculate seed length by processing RGB pixels values from scanned pictures. Using a scanner instead of a camera allows for consistent illumination settings, leading to improved performance. However, this method involves manual seed imaging and the researcher's presence during the germination experiment for assessment (Hoffmaster *et al.*, 2005). The YOLO application as a tool for distinguishing germinated and non-germinated seeds proved effective, with a maximum accuracy of 94.58% in seed classification.

Seedgerm is a cost effective system for automated seed imaging and machine learning based phenotypic analysis of seed germination, offering wide utility in large scale seed phenotying (Colmer *et al.*, 2020). Germiscan, camera based system accurately predicts seed germination rates in real time using physical features like size and colour. AISeed is a nondestructive software that accurately identifies seed quality and seed phenotyping (Reddy *et al.*, 2023).

Ensemble based precision farming models improve seed germination quality predictions by combining positive aspects of various models and minimizing negative aspects of individual models (Chalapathi *et al.*, 2023).

2.4. Predictive modelling

Machine learning techniques uses algorithms like Naive Bayes Classifier (NBC), k-Nearest Neighbor (k-NN), Decision Trees, Support Vector Machines (SVM), and Artificial Neural Networks (ANN), for assessing seed germination (Škrubej *et al.,* 2015).

In contrast, Deep Learning, particularly Convolutional Neural Networks (CNNs), is an emerging image processing method. CNNs automatically extract and learn significant characteristics from raw images and have been used to solve a wide range of image classification challenges. One reason for their effectiveness is a reduced reliance on various illuminations and barriers, which leads to greater accuracy in computer vision tasks. CNNs have already been used to automatically assess the germination rate of rice seeds (Nguyen *et al.,* 2018). Modern convolutional neural network configurations can recognize individual seeds with great precision and accurately distinguish between germinated and non-germinated seeds to establish an enhanced germination prediction method that is (1) free of specific color-based limitations and thus applicable to multiple seed cultivars and illumination settings and (2) can be used to better explore the dynamics of seed germination by estimating not only the final germination percentage but also additional indices such as rate and uniformity (Genze *et al.,* 2020).

2.5 Sensor devices

The useful and effective odor scanner E-nose is made up of number of gas sensors, signal preprocessing systems and pattern recognition methods. Since sensors are very sensitive volatiles, it can easily recognize the volatile profiles in the sample. The e-nose device is intended to be used as a detecting tool in the future to identify the volatile organic compounds (VOCs) generated when stored rice ages (Xu *et al.,* 2021). E-nose technology can distinguish the primary factors for rice aging from a variety of volatile organic compounds (VOCs) and accurately classify gas mixes pertinent to a product's physiological, chemistry, and physiochemical performances. Damaged seeds can be identified by analyzing volatile fungi-generated chemicals, such as those produced by *Aspergillus*, *Penicillium*, and *Fusarium (Gancarz et al., 2017)*.

Laser backscattering and deep transfer learning (TL) based photonics sensor depends on acquiring a single backscattered image of a seed sample and processing it using deep learning (DL) techniques (Chalapathi *et al.,* 2023; Thakur *et al.,* 2022).

Conclusion

By harnessing these technologies, AI based seed quality testing is evolving from a supplementary innovation into a core component of modern seed testing infrastructure. These system offer not only improved accuracy and speed but also noninvasive, real time assessment capabilities that are difficult to achieve using traditional methods. As data collection becomes more robust, needs high quality datasets, high initial setup costs, AI models become increasingly sophisticated, the scope and reliability of these application are expected to grow exponentially, paving the way for intelligent, predictive and scalable seed quality management. Further, AI based seed quality testing is not merely a technological upgrade, it represents a change in the perspectives among the seed laboratories, producers and regulatory agencies in seed quality assurance.

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Digital technologies for crop yield estimation: A review

BHAVANI PINJARLA[1], SURANJANA BORAH[1*], SUNIL DUBEY[2] AND S. BANDYOPADHYAY[2]
[1]Technology Implementation Cell-PMFBY, MNCFC, Pusa Campus, New Delhi-110012, India.
[2]Mahalanobis National Crop Forecast Centre (MNCFC), Pusa Campus, New Delhi-110012, India.
Email: bandyo.s@gov.in, bhavani.pinjarla@undp.org, suranjana.borah@undp.org, sunil.dubey86@gov.in,

Lead Author

DR. BHAVANI PINJARLA

Remote Sensing Analyst,
Technology Implementation Cell (TIC)-PMFBY,
MNCFC, UNDP.

Dr. Bhavani Pinjarla currently serving as a Remote Sensing Analyst in the Technology Implementation Cell (TIC), providing technical support for the Pradhan Mantri Fasal Bima Yojana (PMFBY) at the Mahalanobis National Crop Forecast Centre (MNCFC). She is actively involved in integrating geospatial technologies into key PMFBY initiatives, including YES-TECH, WINDS, and CROPIC, among other technology-driven interventions that enhance efficiency and transparency in agricultural insurance.

She holds a Ph.D. specializing in geospatial technology and its applications in agriculture from University of Hyderabad, Telangana, India. Her doctoral research, titled *"Spatio-temporal assessment of agricultural performance and drought vulnerability using long-term satellite, climate, and socio-economic data"*, has significantly contributed to understanding crop dynamics and the impacts of climate variability on agriculture.

With over seven years of experience across CGIAR institutes, worked extensively at ICRISAT and CIMMYT, leading geospatial innovation in climate-resilient agriculture. At CIMMYT, plays a key role in applying advanced geospatial analytics to support CSISA project.

Her technical expertise encompasses a broad spectrum of digital agriculture technologies, including satellite remote sensing, machine learning, deep learning, crop modelling, and high-resolution crop mapping. Her skills also include programming languages such as R, Python, and JavaScript, and leverages powerful cloud-based platforms like Google Earth Engine (GEE) and Google Colab to automate workflows, large-scale data processing, geospatial analysis, and advanced visualization. Through her work, she bridges the gap between scientific research and practical implementation, enabling data-driven decision-making for digital technologies in agriculture.

Abstract

This paper reviews the applications and integration of emerging digital technology tools that are transforming yield estimation system for agricultural crops. Remote sensing data, including satellite imagery and UAV-based observations, offer scalable, non-destructive tools for monitoring crop growth dynamics. Crop simulation models such as DSSAT, APSIM, AquaCrop, and InfoCrop integrate environmental, phenological, and management variables to simulate yield under varying conditions. Concurrently, machine learning such as random forests (RF), support vector machines (SVM), and deep learning algorithms such as convolutional neural networks (CNNs), and long short-term memory (LSTM) networks are being employed to model complex, non-linear relationships in large, multi-source datasets. The integration of IoT sensors enables real-time, ground-level monitoring of soil, weather and crop health parameters, while blockchain technology ensures data integrity, transparency, and traceability across agricultural value chains. Together, these innovations enhance the accuracy and scalability of yield estimation which contribute to resilient, sustainable farming systems. However, challenges remain in data interoperability, field survey data quality, model generalizability, and information dissemination. This article provides a comprehensive synthesis of current technologies, their synergies, limitations, and prospects in advancing precision agriculture.

Keywords: Digital technology, Drones, Satellite, Machine learning, Deep Learning, IoT, Blockchain Technology

Introduction

In recent years, agriculture has witnessed a paradigm shift with the adoption of precision farming - an approach that leverages digital technologies to monitor, measure, and respond to intra-field variability in crops. Precision agriculture (PA) aims to optimize field-level management regarding crop farming by using information technology (IT), remote sensing, and data analytics to increase yield, reduce input costs, and minimize environmental impacts (Zhang & Kovacs, 2012; Mulla, 2013). The integration of precision farming tools facilitates site-specific decision-making, resulting in efficient resource use and sustainable agricultural practices.

One of the critical components of precision agriculture is accurate crop yield estimation, which plays a vital role in food security, policy formulation, market planning, and risk management. Traditional yield prediction methods, which often rely on field surveys and historical statistics, are time-consuming, labour-intensive, and spatially limited (Lobell et al., 2015). With growing global demand for food and increasing climate uncertainties, there is a pressing need for robust, timely, and scalable forecasting systems that can guide stakeholders across the agricultural value chain. In response, a suite of emerging digital technologies has been developed to transform yield prediction from a reactive to a proactive and predictive science. These innovations include aerial imagery from drones and UAVs (Castro et al., 2020), satellite remote sensing, IoT-based soil and crop sensors (Kim et al., 2020), machine learning (ML) and deep learning (DL) algorithms (Jeong et al., 2016; Yang et al., 2019), crop simulation models (Jones et al., 2003), and more recently, blockchain platforms to ensure traceability, data integrity, and integration across heterogeneous sources (Patel et al., 2023).

This review explores the key digital technologies that are shaping the future of crop yield estimation.

Satellite Remote Sensing

Satellite remote sensing (RS) derived inputs has become essential component for crop yield estimation, offering a scalable and cost-effective alternative to traditional field data collection. Field surveys, although accurate, are often expensive, labour-intensive, and impractical for covering large agricultural areas in a timely manner.

In contrast, RS technologies provide frequent, wide-scale coverage and enable non-destructive, repeatable monitoring of vegetation dynamics throughout the crop growth cycle (Abebe et al., 2022; Luciano et al., 2021; Muruganantham et al., 2022).

Lobell et al. (2015) demonstrated that satellite-derived Normalized Difference Vegetation Index (NDVI) can serve as a reliable predictor of wheat yields across various agroecological environments, highlighting its applicability in both data-rich and data-scarce regions. Building on this, Zhu et al. (2020) successfully integrated Sentinel-2 imagery with climatic variables to develop a high-accuracy model for maize yield forecasting, emphasizing the effectiveness of combining remote sensing and weather data for robust yield prediction. Optical satellite imagery such as Sentinel-2 or Landsat has been widely used in yield modelling by deriving vegetation indices like Leaf Area Index (LAI) and NDVI (Qin et al., 2021). More recently, researchers have emphasized the use of additional indices and multi-temporal imagery to improve model sensitivity across different crop stages (Weiss et al., 2020). Similarly, Synthetic Aperture Radar (SAR) offers significant advantages due to its ability to penetrate clouds and operate in all weather conditions, making it particularly valuable during monsoon seasons or in tropical regions (de França et al., 2024).

Despite these advancements, several challenges continue to constrain the full potential of satellite-based yield estimation. Globally, one major limitation is the dependency on accurate ground-truth data for model calibration and validation, small farm area mapping. It is evident that the absence of reliable field data can reduce model accuracy and transferability across regions (You et al., 2017). Furthermore, handling and processing high-resolution satellite data demands significant computational power and expertise, particularly when using cloud-based platforms like Google Earth Engine.

Some extent the high-resolution data platforms such as QuickBird, SPOT5, and Sentinel have addressed the challenges related to monitoring small farm areas, demonstrating reasonable accuracy in yield estimation. Ali et al. (2021) reported strong agreement between observed and predicted rice yields in Egypt, validating the effectiveness of these satellite datasets. Ali et al., (2022) further evaluates the strengths, limitations, and contextual applicability of various remote sensing techniques under different agricultural conditions.

Unmanned Aerial Vehicles (UAVs)

UAVs also known as drones, have significantly advanced the precision and spatial resolution of on-farm crop yield estimation (Steven et al., 2015). Drones offer several advantages over traditional remote sensing platforms. Unlike satellite-based systems, they can operate under cloud cover and provide ultra-high-resolution imagery (Manfreda et al., 2018). Effectiveness of UAVs in precision agriculture, particularly for crop monitoring and forecasting yields was critically emphasized by Zhang and Kovacs (2012). Hunt et al. (2018) utilized multispectral drone data to achieve highly accurate corn yield predictions in USA. The ability of UAVs to conduct low-altitude remote sensing gives them operational flexibility, rapid data collection capability, and superior spatial and temporal resolution (Colomina et al., 2014; Garcia-Ruiz et al., 2013).

Yu et al. (2016) demonstrated the utility of UAV-acquired high-resolution MS imagery across the entire soybean growth cycle to enhance yield predictions.

Recent studies also highlight the multifunctional role of UAVs in agricultural management. Drones are increasingly used for precision irrigation, and targeted pest, weed, and disease control apart from yield estimation and crop monitoring (Rejeb et al., 2022). RGB imagery captured by UAVs has been applied to assess phenotypic traits such as plant height (Lu et al., 2021; Volpato et al., 2021), growth dynamics (Shu et al., 2022), vegetation and canopy coverage (Raman et al., 2022), crop senescence (Buchaillot et al., 2019). Furthermore, drone-based sensing has proven effective in detecting plant diseases (Kerkech et al., 2018; Schirrmann et al., 2021; Sugiura et al., 2016; Tang et al., 2023) and in refining yield estimation models (Castro et al., 2020; Johansen et al., 2020).

Crop Simulation Models

Crop simulation models have emerged as powerful tools in agricultural yield estimation, especially in the face of increasing climate variability. Unlike traditional statistical approaches, these models integrate key variables such as soil characteristics, weather data, crop phenology, and management practices to simulate plant growth and predict yields. These models surpass conventional statistical approaches by integrating a wide range of variables such as soil characteristics, weather data, crop phenology, and management practices to simulate crop growth and predict yields more accurately (Modi et al., 2022). As noted by Lobell and Burke (2010), traditional models often fall short in capturing the complex interactions between crops and their environments, especially under changing climatic conditions. To address these shortcomings, crop simulation models incorporate both qualitative and quantitative inputs, enabling more reliable assessments of crop productivity (Modi et al., 2022).

The most widely adopted simulation model, Decision Support System for Agrotechnology Transfer (DSSAT) framework integrates multiple crop models, including CERES and CROPGRO, allowing simulation of over 40 crops by combining soil, weather, genotype, and management data (Jones et al., 2003, Attia et al., 2016). CERES is one of the earliest and most widely adopted simulation models introduced by Jones and Kiniry (1986). Despite its age, CERES remains an important tool for maize and wheat yield modelling, with Basso et al. (2016) providing a detailed overview of its evolution, validation, and global applications. Other notable models are Agricultural Production Systems simulator (APSIM), extensively applied to assess nutrient cycling, water use efficiency, and climate adaptation strategies in diverse agroecosystems (Holzworth et al., 2014); WOFOST (World Food Studies) developed at Wageningen University (Stockle et al., 2003) widely used for large-scale crop monitoring in Europe (Boogaard et al., 2011); and AquaCrop model, developed by FAO, specifically designed to estimate yield responses to water availability which is frequently applied in regions prone to water scarcity and drought (Steduto et al., 2009).

Another significant advancement in crop simulation model development for Indian agro-ecological conditions is InfoCrop, developed by the Indian Agricultural Research Institute (IARI). Designed to support decision-making in the context of Indian farming systems, InfoCrop is a dynamic cropping system model that simulates crop growth, development, yield, and interactions with pests, diseases, and environmental stresses (Aggarwal et al., 2006). It is calibrated for major Indian crops such as rice, wheat, and maize, and accounts for diverse soil types, climatic variability, and management practices across India's agro-climatic zones.

Banerjee et al., (2024) critically evaluates how these models serve as integrative platforms that bridge experimental knowledge and real-world farming decisions, helping to optimize input use, manage risks, and adapt to climate variability. The review underscores the importance of integrating crop models with emerging technologies such as remote sensing, big data analytics, and machine learning to improve prediction accuracy and scalability.

Ultimately, while crop simulation models are powerful for strategic planning and resource management, their effective adoption depends on user-friendly interfaces, stakeholder engagement, and continued validation across diverse agroecosystems.

Machine Learning (ML)/Deep Learning (DL) approaches

In recent years, ML and DL have emerged as transformative tools in the domain of crop yield estimation, primarily due to their ability to model complex, nonlinear relationships and including satellite-derived vegetation indices, soil properties, weather variables, and sensor data from Internet of Things (IoT) platforms to improve prediction accuracy and model robustness (Mishra et al., 2016; Schwalbert et al., 2020; Herrero-Huerta et al., 2020, Kothamasu Venkata et al., 2024).

A wide array of ML approaches such as random forests (RF), regression trees, k-nearest neighbors (KNN), support vector machines (SVM), multiple linear regression (MLR), artificial neural networks (ANN), and decision trees (DT) have been applied to capture the intricate interactions among climatic, edaphic, and crop-related variables (Jeong, 2016; Basso, 2013; Obsie et al., 2020; Shao et al., 2015; Sharifi, 2021; Suominen et al., 2013; Amankulova et al., 2024). These algorithms are particularly effective at learning from historical data and extrapolating to novel scenarios, thus improving the accuracy and reliability of data-driven agricultural decision-making (Leukel et al., 2023; Stumpe et al., 2024, Sarowar Morshed Shawon et al., 2025).

In parallel, Deep Learning (DL) techniques have demonstrated superior performance in crop yield prediction by automatically learning hierarchical features from raw input data. Among the various DL architectures, Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs) are the most widely adopted, particularly suited for analysing temporal and spatial datasets, respectively (Yang et al., 2019; Yuning Huang, 2022). Other notable DL models applied in agricultural yield forecasting include Artificial Neural Networks (ANNs), Deep Neural Networks (DNNs), Bayesian Neural Networks (BNNs), and Bidirectional LSTM (Joerg et al, 2023; K. Mythilia et al., 2021; K. Pravallika et al., 2021).

IoT Sensors

The rapid advancement of information and communication technologies has significantly influenced modern agricultural practices. Internet of Things (IoT) technologies have enabled real-time environmental monitoring through interconnected smart sensors, facilitating more responsive and precise agricultural management. IoT and Artificial Intelligence (AI) have emerged as pivotal tools in promoting data-driven, sustainable, and efficient farming systems. AI-based automation has demonstrated significant potential in enhancing crop productivity, optimizing resource use, and minimizing environmental impacts key elements for addressing the growing global demand for food in a sustainable manner (Madakam et al., 2015; Mohd Javaid et al., 2023; FAO, 2023).

In technologically developed regions, robust infrastructure has supported the wide-scale implementation of IoT solutions, improving their operational effectiveness (Jinyuan Xu et al., 2021). However, promising results have also been reported from resource-limited contexts. For instance, studies on smallholder farms in India demonstrated that IoT-enabled soil monitoring improved water use efficiency by up to 30%, while also contributing to higher crop productivity (Balaji & Ahuja et al., 2020).

Platforms such as Agri-IoT illustrate the practical benefits of integrating multiple data sources ranging from soil properties and weather data to crop health metrics into cloud-based systems to support data-driven decision-making at the farm level (Smith et al., 2019). In parallel, the use of remote sensing technologies like drones and satellites has further complemented ground-based IoT data. The fusion of aerial data with in-situ IoT sensors enhances the reliability of yield predictions by providing both spatial and temporal insights (Kim et al., 2020). Studies by Wolfert et al. (2017) and Aazam et al. (2018) emphasize the integration of real-time sensor networks for monitoring critical soil parameters such as moisture, pH, and conductivity. These smart farming systems reduce waste, optimize resource utilization, and support informed decision-making.

The convergence of AI algorithms with IoT infrastructures has given rise to intelligent agricultural systems capable of performing predictive analytics and adaptive decision-making. These systems enable continuous tracking of environmental variables such as temperature, humidity, soil moisture, radiation, and nutrient levels, thereby supporting site-specific management practices and precision agriculture at scale (Rajak et al., 2023). Furthermore, AI-IoT integration enhances capabilities in pest detection, weather risk prediction, irrigation scheduling, and yield forecasting—ultimately leading to more sustainable and efficient farm operations (Patel et al., 2023). Anand et al. (2025) emphasize the value of integrating IoT with machine learning to address food security challenges in regions like India, where climate variability and population pressures intensify agricultural risks. Their findings underscore the potential of smart farming systems to provide adaptive, scalable, and resilient solutions suited for both resource-rich and resource-constrained agricultural settings.

Blockchain Technology

Traditional yield forecasting models, though increasingly accurate with the help of machine learning and IoT, often face limitations related to data integrity, security, and verification—gaps that blockchain can effectively address (Sumati et al., 2022). Gupta and Patel et al. (2021) proposed a blockchain-enabled system designed to enhance the security and authenticity of crop yield prediction data. To overcome these challenges, Blockchain Technology (BCT)Globally revolutionizing the agriculture and the food supply system. BCT is a decentralized digital system comprising multiple network layers that facilitate secure data capture, storage, and sharing across various stages of the supply chain (Iansiti & Lakhani et al., 2017; Sabir Awan et al., 2024). The integration of blockchain technology in precision agriculture has opened new possibilities in enhancing the transparency, traceability, and reliability of crop yield estimation systems (Panwar et al., 2023, Vignesh B et al., 2024).

The immutable nature of blockchain ensured secure storage of field data, which serves as a critical input for yield modelling. This approach strengthens the credibility of yield estimation models by protecting them from data manipulation and unauthorized modifications. Further, blockchain enhances transparency across stakeholders—from farmers and insurers to agribusinesses and consumers—by ensuring that the data driving yield forecasts is authentic, time-stamped, and auditable ((Menon, Sheeta et al., 2021; Riouali et al., 2024). However, challenges such as scalability, interoperability with existing agricultural platforms, and farmer-level adoption need to be addressed to fully leverage blockchain in yield estimation frameworks.

Conclusion

The current paper briefly reviews the use of individual and combination of multiple digital technologies ranging from satellite remote sensing and unmanned aerial vehicles (UAVs) to crop simulation models, machine learning (ML), deep learning (DL), Internet of Things (IoT) sensors, and blockchain systems that are collectively enhancing the precision, efficiency, and scalability of yield forecasting. Together, these technologies enable farmers to optimize inputs, reduce costs, improve yields, and mitigate climate-related risks. However, challenges persist in user accessibility, interoperability, and digital infrastructure and adapt to changing climates. Despite their potential to transform agriculture, significant challenges remain, particularly in terms of accessibility, system interoperability, and digital infrastructure especially in low-resource settings.

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AI & Spectral Imaging in Modern Seed Quality Assurance for A Digital Future

Vipin Chandra Joshi[1], N.Bhavana Stella[2], Kishore Kumar[3],

[1]Associate Director, Seed Supply chain, AgroStar, Pune.,
[2]Sr.Associate, AgroStar, Pune, AQAL,
[3]Associate Scientist-Digital Innov. CGIAR-ICRISAT, Hyderabad
Email: vipin.joshi@agrostar.in

Lead Author

DR. VIPIN CHANDRA JOSHI

PhD - Associate Director, Seed Supply chain, AgroStar, Pune.

Dr. Vipin Joshi holds a Ph.D. in Seed Science and Technology from GBPUAT, Pantnagar, Uttarakhand. He has held various positions in seed companies across North, Central, and South India, specializing in seed quality assurance within field operations, processing plants, and seed testing laboratories. Dr. Joshi has authored over 7 research papers, 12 research articles, and three book chapters. He has also participated in more than 26 training sessions including International & national conferences, seminars, and workshops organized by various ICAR institutes and SAUs. With extensive experience in the seed supply chain, Dr. Joshi is currently serving as the Associate Director, Seed Supply Chain at AgroStar India Limited in Pune.

Introduction

Ensuring quality assured seed delivery to the farmer is the foundation for productivity and sustainability in agriculture. Traditional testing methods, such as Between Paper Method (BP), Top of the Paper method (TP), True Plant Control (TPC), Field Emergence Test (FET) are lab-based germination tests, which are reliable, laborious, and subjective. The need for rapid, scalable, and objective testing has catalysed the adoption of AI and spectral technologies. Artificial Intelligence (AI) and spectral imaging technologies are revolutionizing seed testing and quality. Seed quality determines crop productivity, farmer success, and food security. Traditional seed testing methods are labour-intensive, time-consuming, and often destructive. Today, **AI and digital tools** are reshaping the landscape enabling **faster, more precise, and non-invasive** seed testing and quality assurance.

1. Role of AI in Seed Testing & Quality Assurance A. Image-Based Seed Analysis

- AI uses computer vision to analyse seed size, shape, colour, and surface defects.
- Identifies physical damage, fungal infections, or foreign materials.

Multispectral imaging combined with AI allows seed analysts to evaluate morphological and biochemical properties non-invasively. This digital transformation is being piloted in progressive seed certification systems globally and offers a pathway for the modernization of India's seed testing infrastructure.

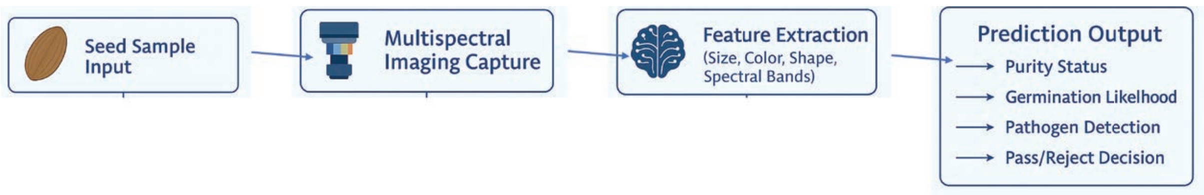

Figure A: Flowchart showing the process of AI and spectral imaging in seed testing from image capture to decision support.

2. Principles of Spectral Imaging in Seed Testing

Spectral imaging captures reflectance from seeds across multiple wavelengths from ultraviolet to near infrared. Each spectral band reveals unique information on seed traits.

- Visible bands: Seed coat colour, surface texture, mechanical damage.
- NIR bands: Internal moisture, oil content, viability indicators.
- UV bands: Fungal contamination, physiological stress.

Instruments like Video Meter Lab utilize LED-based band-sequential illumination, rotating platforms, and CCD sensors to scan each seed. The spectral fingerprint is analysed using AI-based pattern recognition.

In a demonstration by Video meter during the APSA Webinar (2022), spectral imaging was used to accurately classify skinning damage in barley seeds, generating heat maps that correlated strongly with manual assessments of seed coat integrity (Carstensen, 2022).

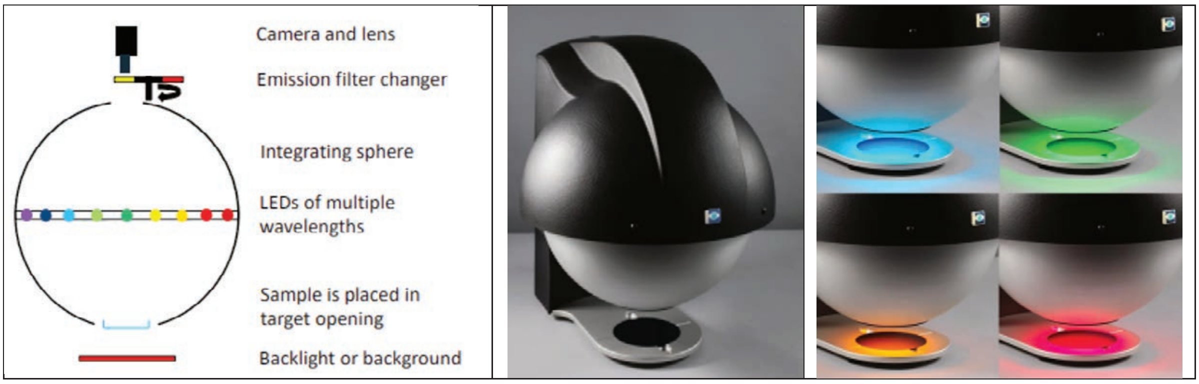

Figure B: Spectral imaging system for rapid seed scanning using multiple LED wavelengths.

A. Germination & Vigor Prediction

- Machine learning models predict seed germination and vigor from historical data and early visual indicators.

B. Seed Classification & Grading

- AI automates seed sorting by quality grade, species, or lot performance — improving batch consistency.

3. Role of AI and Machine Learning in Seed Analysis

Machine learning (ML) models are trained on annotated datasets of seed images. These models learn to classify seed health traits, including:

- Seed purity and varietal identification.

- Detection of seed borne pathogens (e.g., Aspergillus, Fusarium).
- Prediction of germination rate and vigour.
- Assessment of coating, pelleting, or priming uniformity.

Deep learning (CNNs) and supervised algorithms (SVM, Random Forest) are increasingly used to enhance model precision. Cross-validation studies have shown prediction accuracies >90% in crops like Maize, Barley, and Soybean.

According to Video meter's commercial deployment case shared during industry demos, AI-driven classification of treated vs. untreated seed batches enabled automation in a Danish seed testing facility, increasing throughput by nearly 300% (Carstensen, 2022).

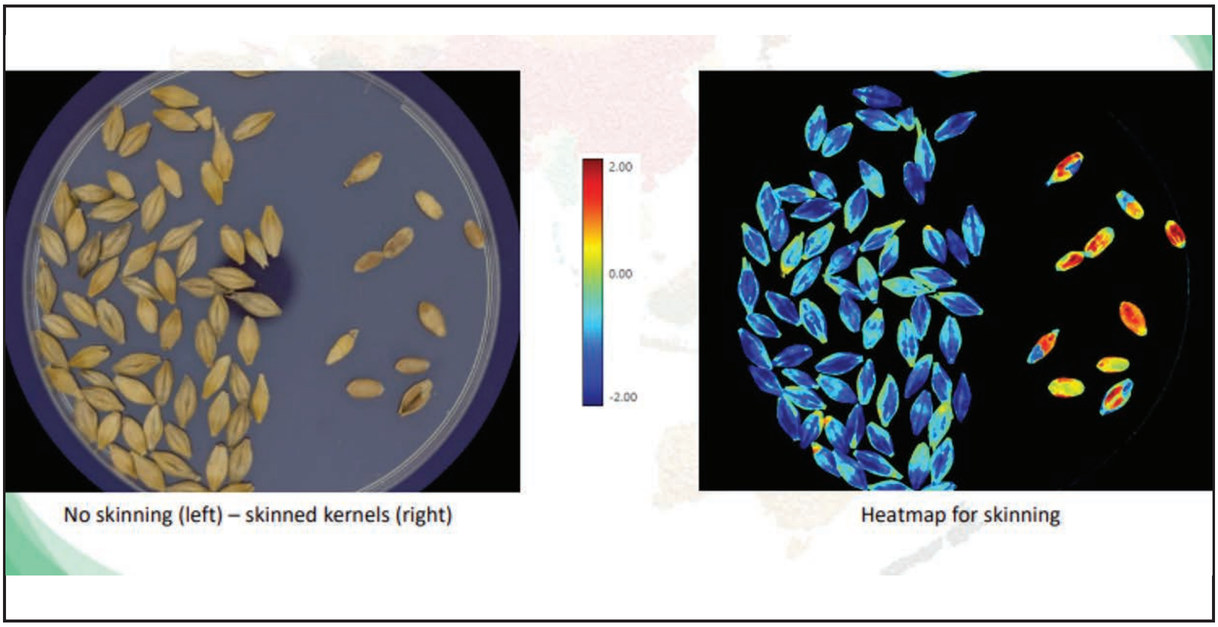

Figure C: Sinking test heat map analysis identifying skinning damage in barley kernels.

4. Key Measured Parameters

Digital seed analysis generates a comprehensive feature set:

Primary Traits:

- Area, length, width, roundness, compactness.
- Colour features (CIE Lab values, hue, saturation).
- Orientation and skewness.

Secondary Traits:

- Germination likelihood (using logistic regression models).
- Mechanical or insect damage.
- Orientation and skewness.

These traits inform automated decision trees used for sorting, grading, or batch rejection.

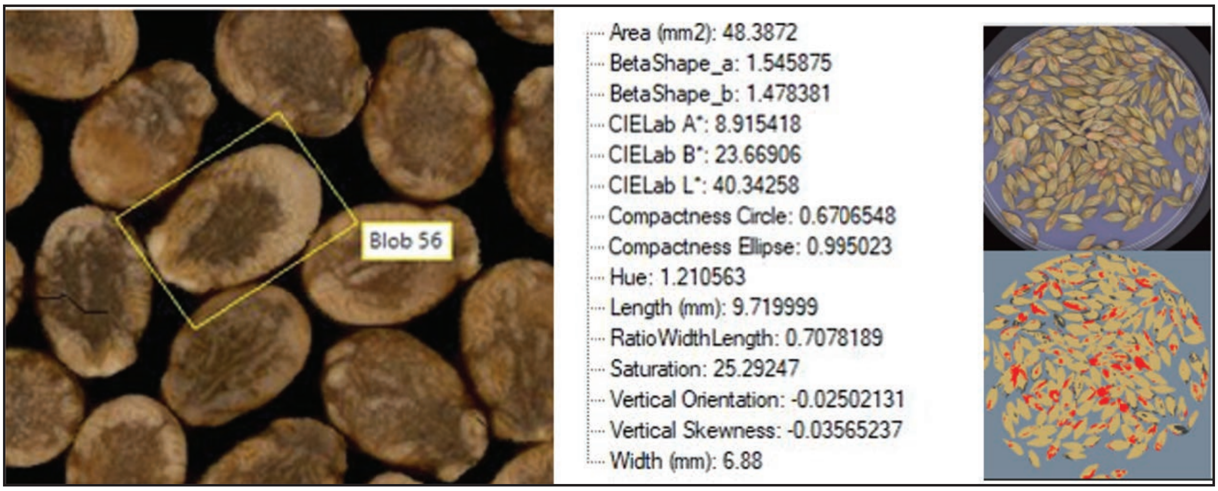

Figure D: AI-driven germination prediction using historical seed data.

5. Applications Across the Seed Value Chain

AI-enabled seed testing is applicable across stages:

- **Breeding Programs**: Off-type detection, DUS trait quantification, parental line purification.
- **Seed Production**: Parent line verification (male & female), seed treatment validation.
- **Processing Units**: Sorting, grading, and packaging QA, advanced colour-based sortex.
- **Certification Labs**: Non-destructive analysis for standard compliance, RO, Certification Tags.
- **Farmer-level Testing**: Portable imaging tools for FPOs and co-operatives.

Govt. Insight: ICAR researchers, particularly at IIMR, have piloted hyperspectral imaging tools to assess pre-harvest sprouting in sorghum and pearl millet (Tonapi et al., 2018). Parallel efforts are underway in other institutions to evaluate non-destructive digital phenotyping tools for millet seed quality.

Farmer-Centric Innovation by Private sector: Private seed companies are using AI for the solution of the farmers in the seed supply chain, which includes (Seed production, Quality Assurance, Processing, Logistics etc.)

AgroStar developed digital app for on-boarding farmers within their business states in different languages at various states and delivering AI-driven solutions. AgroStar implemented AI in agriculture in two ways:

1. Helping farmers to detect their issues automatically using image recognition and suggesting appropriate products to solve their issues. This gives them an instant & quick solution, as opposed to consulting an expert and getting their advice. An instant solution is very important since the farmer's need is urgent.

2. We have built a voice-based agentic AI robot that can answer farmers queries in various languages. This includes queries relating to their product delivery, answers to questions such as "what is the best herbicide to use for Sugarcane," and also weather-related advice, etc.

This is supported by Pune-based AQAL (AgroStar Quality Assurance Lab), a hub of Seed testing for physical quality & germination test (Between Paper-BP, Top of the paper-TP, & Coco peat tray test- TPC) for seed quality assurance. AI-based models of Quality assurance are sustainable, low-cost, quick & helping decentralize seed quality evaluation with accuracy to improve access to advisory services.

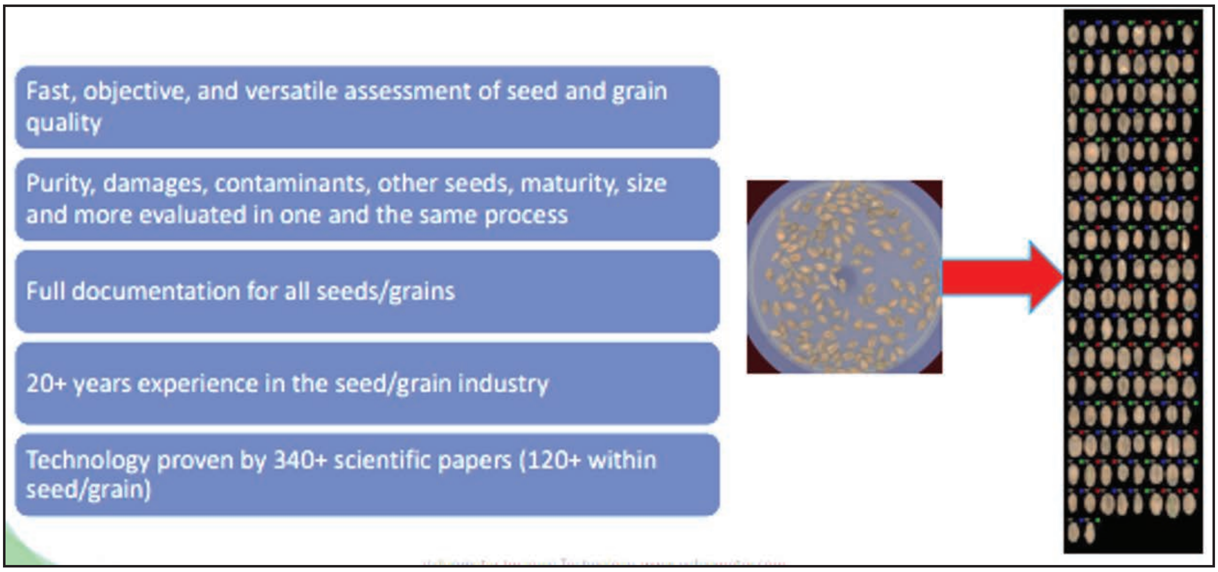

Figure E: Concept illustration of AI and seed digitalization working in tandem.

A. Anomaly Detection

- AI flags abnormal patterns in seed lots using large datasets often faster than human testers.

6. *Masry et al* (2019). Investigate the potential of computer vision and multispectral imaging systems supported with multivariate analysis for high-throughput classification of cowpea (*Vigna unguiculata*) seeds. An automated computer-vision germination system was utilized for uninterrupted monitoring of seeds during imbibition and germination to identify different categories of all individual seeds. By using spectral signatures of single cowpea seeds extracted from multispectral images, different multivariate analysis models based on Linear Discriminant Analysis (LDA) were developed for classifying the seeds into different categories according to ageing, viability, seedling condition and speed of germination etc.

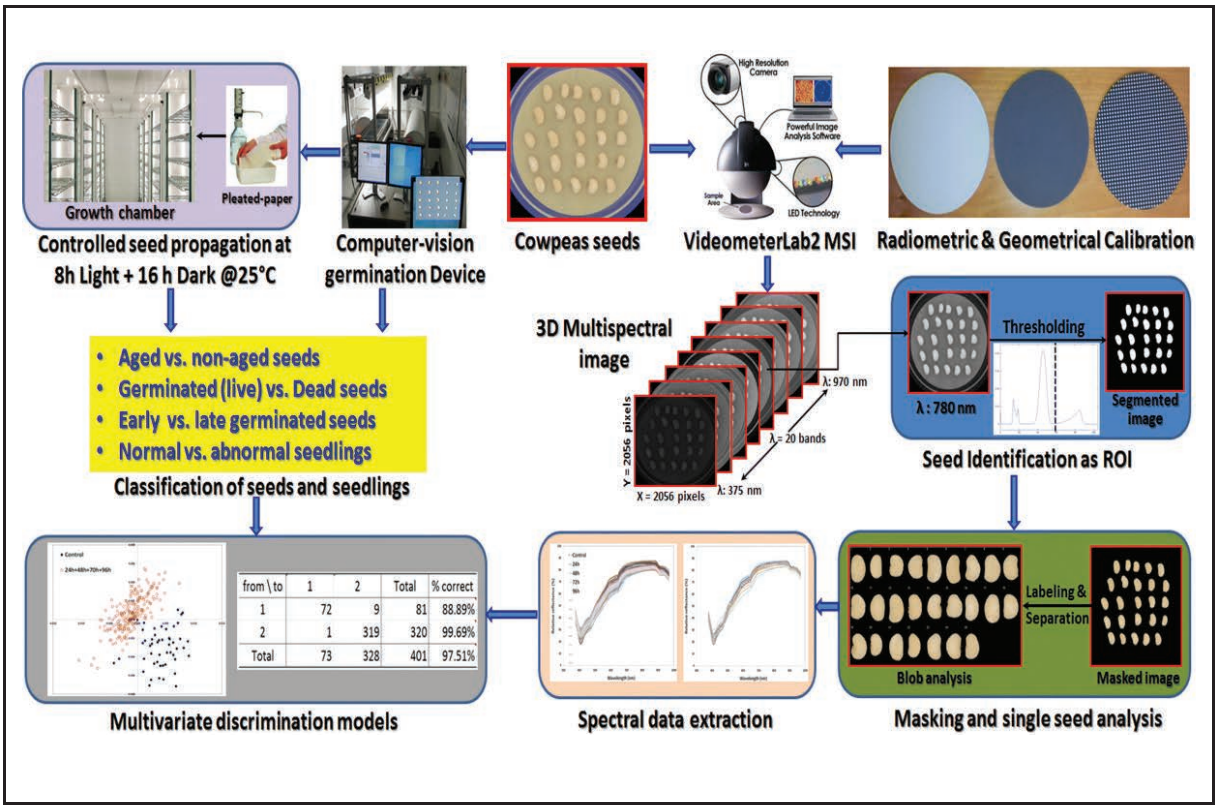

Figure F: Use of a multispectral imaging system for Seed & seedling evaluation.

The results demonstrated the capability of the multispectral imaging system in the ultraviolet, visible, and shortwave near infrared range to provide the required information necessary for the discrimination of individual cowpea seeds into different classes.

7. Comparative Advantage Over Traditional Testing

Criteria	Traditional Testing	AI + Spectral Imaging
Time per sample[1]	30–60 minutes	<10 seconds
Objectivity[2]	Subjective (manual)	High (ML model-based)
Sample damage[3]	Often destructive	Non-destructive
Throughput[4]	Limited	High (>10,000 seeds/hour)
Traceability[5]	Manual logbooks	Digital, timestamped records
Accuracy[6]	Depends on the expertise	The accuracy of observation is high

[1] Average manual purity or blotter test turnaround: ISTA Rules (2021); Videometer Lab demo shows scan & classify in ~8 s/sample. [2] Inter-analyst variation in manual visual tests documented by ISTA (2021); CNN classifiers report >90 % accuracy (Zhang et al., 2019). [3] Traditional germination and cut tests require seed destruction; MSI keeps seeds intact (Videometer White Paper, 2022). The Videometer Lab specification sheet lists a maximum capacity ≈ of 12,000 seeds h[1] in conveyor mode. [5] Digital lab LIMS and cloud dashboards provide automatic audit trails (ISTA Digital Tech Review, 2021). Accuracy is good in AI, if parameters are standardised, vary in traditional methods, Accuracy[6] depends on the expertise of the seed analyst.

8. Challenges and Considerations

Despite its promise, AI-based seed testing requires:

- High-quality annotated datasets for model training
- Periodic recalibration and validation
- Integration with existing IMSCS and DUS protocols
- Capital investment in imaging systems and software

Open standards and public-private collaborations are key to scaling these technologies in India.

9. Future Outlook: Toward Digital Certification, Smart Labs, and Policy

As India modernizes its seed value chain, integrating AI in seed certification (e.g., via NSAI or State Seed Corporations) can ensure faster, accurate, and transparent testing. The concept of "Digital Seed Labs" equipped with imaging stations and cloud analytics, is emerging.

These advancements will strengthen compliance, reduce fraud, and enhance farmer confidence. Adherence to fair principles and emerging seed data standards like MI Seed will ensure interoperability and reuse across labs and jurisdictions.

Future integration of AI-imaging platforms with molecular genotyping (e.g., SNP-based barcode verification) can enable comprehensive digital phenotyping and genotyping for robust varietal authentication.

To scale AI-integrated seed testing nationwide, there is a need for a policy framework that promotes open data standards, affordable imaging technologies, and interoperability with existing seed certification protocols. Public-private partnerships (PPPs), targeted subsidies, and incubation support for agritech startups can accelerate deployment in underserved regions and faster innovation in digital seed quality solutions.

Conclusion

Artificial Intelligence (AI) is emerging as a **game-changer in seed testing and quality assurance** in India, offering scalable, accurate, and cost-effective solutions across the seed value chain. As India aims to ensure high-quality seeds for its vast and diverse agricultural landscape, AI technologies are playing a pivotal role in **modernizing quality protocols, reducing manual dependency, and improving compliance** with national (NSAI, ISTA) and international standards. India can position itself as a global leader in digital seed certification and quality assurance. A multi-stakeholder national pilot led by a consortium of seed corporations, research institutions, and agritech firms can validate the scalability of these technologies. Establishing digital seed testing hubs in every agro-climatic zone would enable real-time certification, enhance transparency.

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SpeedySeed Viability Kit- A rapid colorimetric non-destructive seed viability detection kit

VISHWANATH ROHIDAS YALAMALLE[1*], MANJA NAIK E[2], JITENDER[3] AND GYAN PRAKASH MISHRA[4]

[1]Senior Scientist, Division of Seed Science and Technology, ICAR-Indian Agricultural Research Institute New Delhi -110012

[2]MSc. Scholar, Division of Seed Science and Technology, ICAR-Indian Agricultural Research Institute New Delhi -110012

[3]Technical Assistant, Division of Seed Science and Technology, ICAR-Indian Agricultural Research Institute New Delhi -110012

[4]Principal Scientist & Head, Division of Seed Science and Technology, ICAR-Indian Agricultural Research Institute New Delhi -110012

Email: vishwanath_yal@yahoo.com

Lead Author

DR. VISHWANATH ROHIDAS YALAMALLE

Senior Scientist
Division of Seed Science and Technology
ICAR-Indian Agricultural Research Institute, New Delhi

Dr. Vishwanath Rohidas Yalamalle is a Senior Scientist in the Division of Seed Science and Technology at ICAR-Indian Agricultural Research Institute, New Delhi, with over 14 years of research experience. His expertise spans seed quality enhancement, seed production, and the development of rapid, on-farm applicable technologies. He is currently working on development of seed standards in potential crops like-buckwheat, opium poppy. He has conducted extensive work on seed dormancy and seed storability studies. His latest innovation Speedy Seed Viability Kit ™, a quick viability testing solution for farmers and seed companies has received tremendous response for farmers, seed companies form Indian, research and extension agencies across Africa, Europe, and the USA. Dr. Yalamalle's research focuses on practical innovations that improve seed performance and support sustainable agricultural practices.

Abstract

Seed viability and vigour are critical determinants of crop establishment and yield, yet traditional methods for assessing seed quality are time-consuming and resource intensive. Current standard germination tests, although reliable, can take more than 14 days and require controlled environments and skilled personnel, making them unsuitable for small-scale farmers and rapid decision-making. While the tetrazolium test offers quicker results, it demands technical expertise. To address these limitations, the SpeedySeed Viability Kit™ was developed as a rapid, cost-effective, and user-friendly alternative suitable for on-farm use. The kit operates on the scientific principle that viable and vigorous seeds release more CO_2 during respiration. This CO_2 is captured in an airtight tube containing a colorimetric indicator solution that changes color in response to the CO_2 released. Pre-soaked seeds are incubated for 2–4 hours, and color changes in the indicator solution indicate viability status—green or yellow for viable seeds, and blue for non-viable ones. The test can also quantify seed vigour using optical density (OD) measurements of the indicator solution at 430–450 nm. Higher OD values correlate positively with seed vigour and overall seed lot quality. The kit has been validated across nine crops, including wheat, paddy, maize, and soybean, with over 80% accuracy and over 90% reliability in seed lots exhibiting high germination (>80%).

Keywords: CO_2, non-destructive, rapid test, seed viability, seed vigour

Introduction

Seed is a living entity and loose its viability or ability to germinate with the storage time. The germination and storability of seeds is also affected by the environmental factors during the seed development, harvest and storage. The germination of seeds is high during the physiological maturity and no storage conditions can ensure 100% seed viability. Prior to seed sowing or marketing of the seeds it is desirable to know the viability status of the seeds. By this indication, the quantity of seed used for sowing (seed rate) or its commercial value of can be determined. The viability status will also help in taking decision regarding which seeds lots needs to be marketed first.

One of the key indicators of seed quality is germination, which is typically evaluated through standard germination tests. However, these tests, can take more than

14 days to complete, delaying important decisions for farmers/ seed companies. Additionally, the standard germination test requires infrastructures like BOD incubators and skilled technicians, which may not be feasible for small-scale farmers. While the tetrazolium test provides quicker results, it also requires a high level of expertise to interpret, further limiting its widespread adoption. Therefore, a need exists for a simpler, farmer-friendly test that can be performed on-farm, yielding results within a few hours.

Division of Seed Science and Technology, ICAR-Indian Agriculture Research Institute, New Delhi has developed and released SpeedySeed Viability Kit (Figure 2), which can detect the viability of the pre-soaked seeds within 4 hours depending on the seed type.

Scientific basis of the SpeedySeed Viability Kit

Vigorous and viable seeds release more CO_2 during respiration compared to dead or low-vigour seeds (Figure 1). Respiration-based seed quality assessments have been developed for crops like soybean and okra (Dode *et al*. 2013; Leite *et al*. 2018) which require apparatus or specialized instrument for measuring CO_2. The CO_2 evolved by the seeds is capture in an airtight tube containing an indicator solution which changes colour in response to the CO_2 release by the seeds.

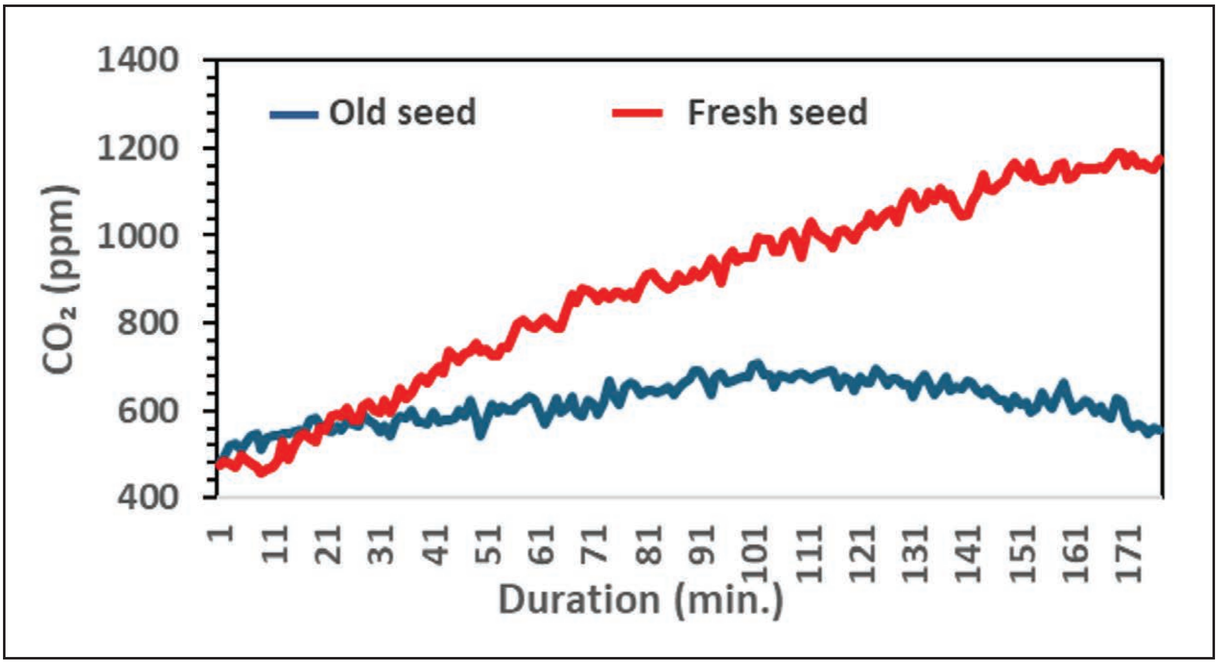

Figure 1: CO_2 evolution by old and fresh seeds in maize, measure by infrared sensor

Figure 2: The SpeedySeed Viability Kit™ was officially released during the 63rd Convocation on 22nd March 2025 by the Hon'ble Minister of State, Shri Ram Nath Thakur, and Shri Bhagirath Choudhary.

The components of the kits

The kit includes an indicator which changes colour in response to pH shifts by capturing the CO_2 released by the respiring viable seeds. The kit includes three indicator concentrates sufficient for testing 300 seed, a dropper bottle, seed holders, and 100 transparent airtight incubation tube (Figure 3). By using one kit 100 seeds can be tested at a time. The kit can be re-used and refill of the indicator concentrate can be purchased separately, machining it cost effective.

Figure 3: SpeedySeed Viability Kit, its components, and interpretation criteria for test results.

Testing procedure

The testing procedure begins by soaking seeds for 2–4 hours, as detailed in Table 1, post soaking empty one indicator concentrate in to the 30 ml dropper bottle provided and dilute it with 30 ml distilled water or RO water of pH (7), afterwards add 5-6 drops (250 μL) of diluted indicator concentrate into the incubation tube. Add one seed holder and single seed into the tube. The seeds are incubated for 3–6 hours, during which the color change in the indicator solution is monitored. If the solution turns green or yellow, it signifies that the seeds are viable and have the potential to germinate. Conversely, if the indicator solution remain blue, the initial color of the indicator, are deemed non-viable. This simple, yet effective, color change visually indicates seed viability, offering a quick and reliable test. The use of this method ensures accurate and straightforward seed quality assessment, making it a valuable tool for both small-scale and large-scale applications (Figures 3 and 4). This process also provides a rapid alternative to traditional, time-consuming germination tests, allowing for immediate results.

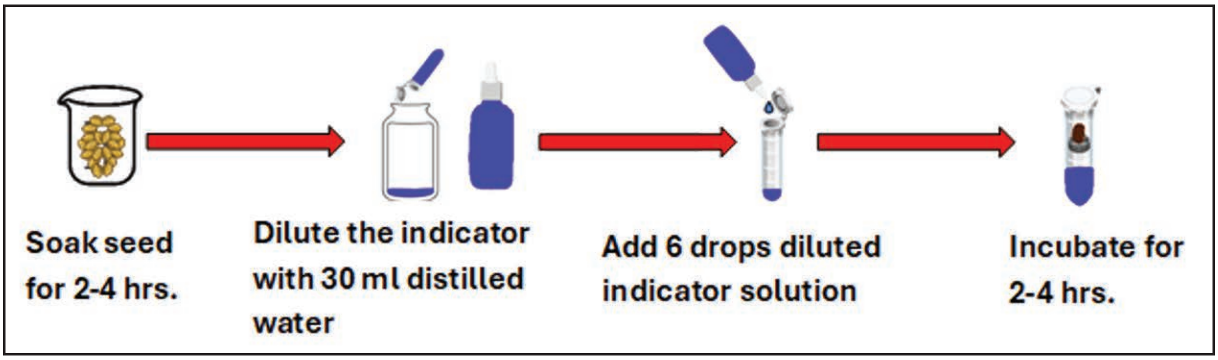

Figure 4: Schematic representation of the steps involved in testing seed viability using the SpeedySeed Viability Kit

Table 1: Soaking and incubation duration in different crops

Crop	Soaking Duration (hours)	Incubation duration (hours)
Maize	4	4
Soybean	2	3
Wheat	4	5
Paddy	4	6
Pumpkin	4	4
Lentil	3	3-3.30
Green gram	3-4	4
Cucumber	3	5
Broccoli	2	2-3

Crops in which test is recommended

This kit can be used for testing seed viability of any crop, the soaking and incubation duration needs to be standardized. Currently this kit is recommended for nine crops including- wheat, paddy, maize, soybean, green gram, lentil, broccoli, cucumber, bottle gourd (Table 1). The standardization for other crops is currently underway.

How the results compare with standard germination test

In a comprehensive study involving nine different crop species, the newly developed seed viability testing kit demonstrated highly reliable results, closely aligning with those obtained from the standard germination test. The accuracy of the kit's results exceeded 80%, indicating its strong potential as an effective tool for assessing seed viability. This high accuracy was consistent across various crop species, suggesting that the kit is versatile and can be used in diverse agricultural contexts (Table 2).

Furthermore, the reliability of the kit is expected to surpass 90% when tested in seed lots with high germination rates, particularly those with germination rates above 80%. This high level of accuracy suggests that the kit could be a particularly useful tool for farmers and researchers working with seeds that are likely to have a high germination potential. In such cases, the kit offers a fast and efficient alternative to the time-consuming traditional germination tests, which often require several days to yield results.

To further corroborate the accuracy of the kit's results, spectrophotometric analysis was employed. The optical density (OD) measurements obtained from the spectrophotometer were found to correlate directly with seed viability. Specifically, seed lots with higher germination potential exhibited significantly higher OD values ($p \leq 0.01$). This spectrophotometric validation adds an extra layer of confidence in the accuracy and reliability of the kit, providing empirical support for its effectiveness.

The findings from this study have significant implications for on-farm seed testing. Traditional germination tests are labour-intensive and time-consuming, often requiring several days to complete. In contrast, the developed seed viability kit offers a rapid and straightforward alternative that can be performed on-site, providing immediate results. This makes it an ideal tool for farmers who need quick assessments of seed quality before planting. Additionally, the kit could be particularly beneficial in regions where access to laboratory facilities is limited, offering a practical solution for farmers to assess seed viability in real-time.

Table 2: Comparison of germination percentage between standard germination test and estimation using indicator

Crop	Standard germination test	Estimated by Speedyseed viability kit
Maize (lot 1)	95%	100%
Maize (lot 2)	63%	60%
Maize (lot 3)	21%	18%
Maize (lot 4)	0%	10%

Measurement of vigour status of individual seed

The SpeedySeed Viability Kit offers a comprehensive approach to not only determining the viability of seeds but also assessing their vigour. This dual functionality makes the kit particularly valuable for researchers, and seed producers, who require a more complete understanding of seed quality. Unlike traditional methods that only provide information on whether seeds are viable or not, the SpeedySeed Viability Kit allows for a more in depth assessment by evaluating the vigour of individual seeds. Seed vigour is a critical factor influencing the overall performance of crops, as it reflects the seed's ability to emerge, grow, and adapt to environmental conditions.

Following the initial testing, transfer 200 µl of the indicator solution from each incubation tube to a 96-well ELISA (Enzyme-Linked Immunosorbent Assay) plate (Figure 5). If automated, the use of a 96-well plate facilitates high-throughput testing, enabling the simultaneous analysis of multiple seed samples, which is ideal for large-scale applications. After the transfer, the optical density (OD) of each well is measured using a spectrophotometer or an ELISA plate reader at a wavelength between 430–450 nm. The OD measurement provides insight into the seed vigour: higher OD values indicate greater seed vigour, as these seeds tend to exhibit higher metabolic activity and a higher likelihood of successful germination and early growth.

Empirical data has demonstrated a strong positive correlation between OD values and seed lot quality (Figure 6-7). Seed lots that exhibit higher viability and vigour consistently show higher OD readings, which are indicative of their potential for good performance in the field. This relationship between OD and seed quality provides a reliable and quantitative method for evaluating not only the germination potential of seeds but also their overall robustness. For example, seed lots with high vigour tend to establish themselves more rapidly after planting, exhibit better resistance to environmental stressors, and ultimately result in healthier and more productive crops.

The data generated through OD measurements can be particularly valuable in various scientific and agricultural applications. One such application is the screening of different seed varieties for vigour. By using the SpeedySeed Viability Kit, breeders and researchers can identify the seed varieties that have the highest vigour, which may be particularly useful for regions with challenging growing conditions. This allows for the selection of seeds that are more likely to thrive under adverse conditions, leading to improved yields and better crop resilience.

In addition to variety screening, the kit can be employed to evaluate the effects of different seed enhancement treatments. For example, seed treatments such as priming, coating, or exposure to growth regulators are commonly used to improve seed performance. By comparing OD values before and after treatment, it is possible to assess the effectiveness of these treatments in improving seed vigour. This is especially useful for companies involved in seed production and treatment, as it provides a quick and reliable means of assessing the impact of their products on seed quality.

Furthermore, the ability to assess seed vigour with high accuracy could play a crucial role in ensuring seed quality control in commercial seed production. Companies can use this data to ensure that only high-quality seed lots are sold to farmers, reducing the risk of poor germination rates and suboptimal crop performance. It also opens up the potential for establishing industry standards for seed vigour, which could help to improve overall seed quality across the agricultural sector.

Figure 5: Measurement of seed vigour by measuring optical density (OD) in ELISA plate reader

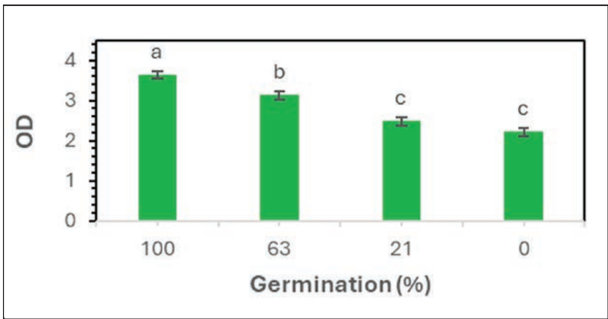

Figure 6: Optical density (OD) of the indicator solution for maize seed lots with different germination percentages

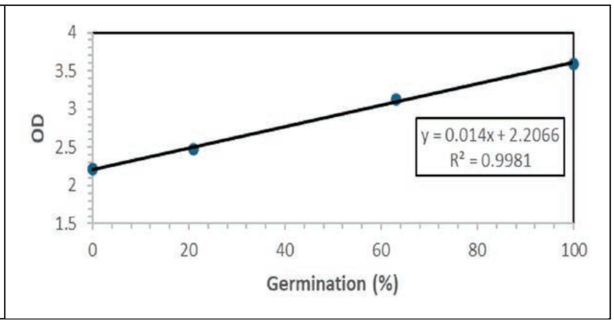

Figure 7: Linear Regression between germination and optical density in maize seed lot with varying germination percentages

Kit availability and technology transfer

The kit is currently sold commercially through our authorized licensee. Enquiries can be made by contacting the Head, Division of Seed Science and Technology, ICAR–Indian Agricultural Research Institute, New Delhi–110012 (Email: head_sst@iari.res.in). The technology has been filed for patent and has been published by the Indian Patent Office under Application No. 202511002330A (Yalamalle *et al*., 2025). It is available for technology transfer on a non-exclusive license basis as per ICAR guidelines.

Conclusion

The SpeedySeed Viability Kit offers a breakthrough in rapid seed quality assessment by providing a simple, reliable, and cost-effective solution for farmers, seed companies, and researchers. Its high accuracy, fast results, and ability to assess both seed viability and vigour make it an invaluable tool in agriculture. The kit's ability to deliver results that closely align with traditional germination tests allows users to confidently determine seed quality, while its quick turnaround time enables timely decision-making, reducing delays in planting schedules. By assessing seed vigour alongside viability, the kit provides deeper insights into seed performance, helping farmers optimize planting strategies and improve crop yields. This dual functionality makes it especially beneficial for selecting seeds that are more likely to thrive in the field. Moreover, the SpeedySeed Viability Kit is an effective tool for scientific research, supporting seed variety screening, treatment evaluations, and advancing seed quality studies.

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Artificial Intelligence and Digital Technologies: Revolutionizing Seed Testing and Quality Assurance

SOHAM MUKHERJEE[1], NUPUR NIHARIKA[1], KUNTAL BERA[1,2], LAVKUSH JOGI[1], BIGYANANDA MUTUM[1], KAJAL MOG CHAUDHURI[1], AND PUSPENDU DUTTA[1]

[1]Department of Seed Science and Technology, Uttar Banga Krishi Viswavidyalaya, Pundibari-736165, Cooch Behar, West Bengal, India.
[2]Plant Molecular Biology Laboratory, Department of Botany, Raiganj University, Raiganj – 733134, Uttar Dinajpur, West Bengal
Email: pdutta.pph@gmail.com

Lead Author

DR. PUSPENDU DUTTA

Assistant Professor (Stage II)
Department of Seed Science and Technology,
Uttar Banga Krishi Viswavidyalaya, Pundibari,
Cooch Behar – 736165, West Bengal

Dr. Puspendu Dutta is engaged as Assistant Professor (Stage II) in the Department of Seed Science and Technology, UBKV, Pundibari, Cooch Behar since 2014 and his role includes teaching and mentoring of undergraduate/post-graduate students in seed science research as per university mandate. Dr. Dutta conducts research in the area of crop seed physiology particularly improvisation of seeds for better plant resilience to environmental stresses. Moreover, seed priming techniques particularly with physical agents are the mainstay of the methodologies being currently used in his research endeavours as evidenced through his peer reviewed publications and grants funding.

Dr. Dutta has completed his Ph.D and M.Sc.(Ag.) in Plant Physiology from Bidhan Chndra Krishi Viswavidyalaya, Mohanpur, Nadia, West Bengal. He has got many

Fellowships, Awards and Recognitions. He has published many research papers or review articles in national and international journals of repute, and also attended several National and International Symposiums, Seminars, Conferences, workshops and Trainings.

Abstract

Modern agriculture has evolved from its nature-based approach to a technology-intensive process that obviously requires careful monitoring and pre-emptive interventions to improve crop production. A solid networking platform for seed testing and management is needed as use of quality seed is the pre-requisite for agricultural production system. Moreover, seed quality and health analysis through interventions of modern technologies such as Artificial Intelligence (AI) is one of the keys to achieve agricultural sustainability. AI is now at the center of most seed testing modules, from image acquisition to biochemical analysis and the construction of digital platforms for integrated seed management. Seed imaging facilitates physical segregation of seeds, while non-destructive testing solutions through application of AI would enabling detailed information on biochemical and genomic properties. An integrated networking platform aids fast and accurate determinations of seed quality including its health and genetic states too. The use of digital technologies in seed testing has a number of benefits like minimizing workload, enhancing time efficiency, and accuracy. With careful monitoring and use of these technologies, efficiency and reliability of seed quality evaluation can significantly be increased that would ultimately, translate into increased agricultural productivity and performance.

Key words: *Seed quality, Health analysis, Artificial Intelligence, Imaging, Non-destructive testing, Genomic properties, Networking, Time efficiency*

Introduction

Agriculture is the backbone of development in the human civilization. Since pre-historic period, the cultivation practice is continuously evolving to increase production of various crops and utilize their by-products for the improvement of human, and to reduce food scarcity. As a result, development of various high-yielding and hybrid crops, use of various chemicals as the source of nutrients and as protective agents against various biotic stresses have evolved. All these developments offer possibilities of increasing crop production as well as quality seeds for generations to come. Up to 21st century, technologies are developing at a faster pace which are capable of conducting multiple analyses in very short time. It helps to work more effectively and in time-saving ways for the agricultural stakeholders, especially the producers or farmers and the researchers.

Seed quality of various crops is tested based on various morpho-physiological and biochemical traits as well as seed health indicators in order to qualify for certification. It requires the use of trained technician, various equipment, chemicals, proper use of all these and most importantly sufficient time to accomplish all these tasks. As such, a speedy and precise technology is required to solve these issues. Therefore, the importance of the most promising technology i.e. Artificial Intelligence or AI of the modern era has drawn the attention of researchers worldwide. AI is the most discussed technology that can be employed for the better management of crops in different phases of production and post-harvest monitoring of the harvested crop through the storing duration. AI helps in monitoring quality of the seeds and can alert in such a way that some signals can be produced at appropriate time, those help to initiate some preventive measures as well as to alert the concerned people for future actions.

Seed Testing- Evolution of the Method of Quality Determination

Good seed testing facility is largely reliant on various aspects, including chemicals, good laboratory arrangement, properly equipped instruments for analysis and observation, skilled man power for conduction of experiment and data acquisition in proper way. All of these and more time-consuming approaches are being put into practice for improved outcome.

But in real scenario of seed testing and quality assessment, conventional method is less efficient and costly, and sometimes is marred by inconsistency of results because of observational errors and biasness (McDonald & Copeland, 2022). Here lies the necessity of using digital technologies and AI to address these challenges.

manual error and biasness can be prevented with these technologies since all the observations are done through instruments.

But their usage facilitates improvement in detection capacity, more extensive data analysis on a larger scale in a better way. Digital technologies with the help of AI capture images of the samples for visual interpretation. Then some non-destructive methods are being utilized to monitor some biochemical parameters and analyze the physiological activities to reach a conclusion. Moreover, various genomic materials such as DNA, RNA and transcriptome analysis provide more decisive results for quality determination with some more sophisticated methods.

Different Seed Testing Routes through AI driven Digital Technologies

With the rapid increasing of application of artificial intelligence and digital technologies in various fields, a new trend of applying these technologies in seed testing is also being observed. The use of these technologies can potentially make a huge difference in the efficiency and precision of the process. Various AI-based approaches are being applied to seed testing today, which can be broadly categorized into four groups:

- **Seed Imaging:** It is the utilization of high-tech imaging technology in combination with AI algorithms to analyze physical parameters of seed quality such as size, shape, and colour.

- **Non-destructive Seed Testing:** These technologies use AI to examine seed viability and quality through the use of spectroscopy and X-ray imaging techniques but without harming the seed.

- **Genetic and Molecular Testing:** AI is also being used to scan genetic information and molecular markers within seeds for disease resistance and favourable traits.

- **Digital Platforms for Seed Testing Management:** These are the AI monitored platforms to automate and control the entire seed testing process from sample tracking to data analysis and reporting.

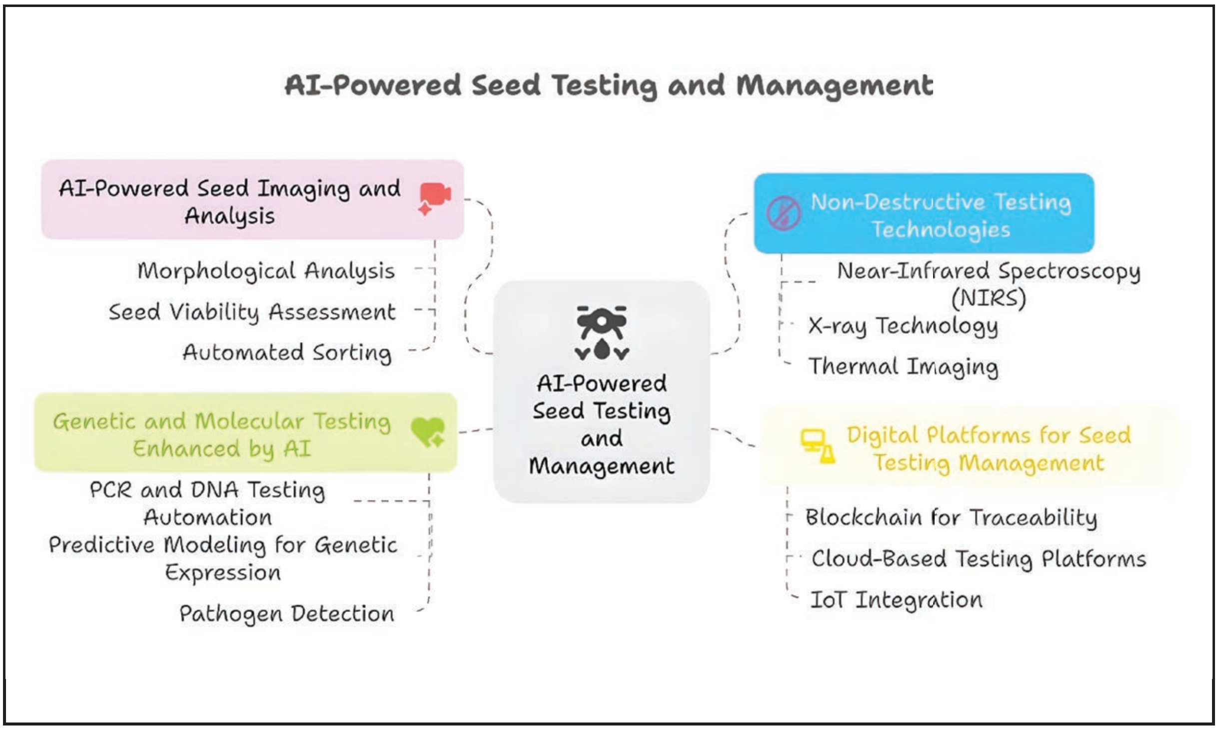

Fig. 1: Role of AI in different aspects of seed quality assessment

1. **AI-Powered Seed Imaging and Analysis:** Machine vision and machine learning have transformed seed quality analysis by observing visual features to a high degree of accuracy (Mishra et al., 2023). Seeds are visually examined during manual or conventional methods, which is generally time-consuming and susceptible to human errors. AI-driven systems can avoid these by taking high-resolution images of the seeds and analyzing them with pre-trained machine learning models. These models are better at detecting slight imperfections like cracks, colour distortion, and bends than human examiners and do so easily and quickly.

- **Morphological Analysis:** AI devices are able to analyze seed size, shape, colour, and surface texture more reliably than human assessors. The devices are able to assess thousands of seeds per minute, detecting physical imperfections or damages that would prevent germination (Zapotoczny et al., 2020).

- **Seed Viability Testing:** Seed viability can be identified non-destructively using advanced imaging and machine learning. Multispectral and hyperspectral images can identify very subtle differences in biochemical content that are seed health-related (Boelt et al., 2021).

- **Sorting:** Mechanized equipment using AI vision technology can sort seeds based on quality characteristics, separating damaged, diseased, or non-viable seeds from seed lots with great accuracy (García-Ruiz et al., 2023).

2. **Non-Destructive Seed Testing:** Advanced technologies make it possible to test the seed without damaging the seed itself (Rahman & Cho, 2021). This is also referred to as hyperspectral imaging based seed testing. Hyperspectral imaging offers rich biochemical information regarding the composition of seeds (ElMasry et al., 2019). AI-based models can identify seed viability, potential for germination, and vigour based on the spectral signature. Based on this non-destructive approach, quick screening can be carried out with large quantities of seeds, and so poor-quality seeds can be separated by seed producers prior to supply to the market.

- **Near-Infrared Spectroscopy (NIRS):** The technology measures seed absorbance and reflectance of various wavelengths of light to determine the chemical composition of seeds. AI algorithms interpret such spectral signatures to forecast moisture content, protein content, and other quality attributes (Chen et al., 2022).

- **X-ray Technology:** Digital X-ray technology with the assistance of AI will show internal structural defects, insect infestation, or development defects not visible to the naked eye (International Seed Testing Association, 2024).

- **Thermal Imaging:** Thermal imaging captures temperature gradients among seed lots. Thermal imaging with AI-aided interpretation can detect seeds of varying metabolic activity, generally signifying vigour and viability (Bewley et al., 2021).

3. **AI-augmented genetic and molecular testing:** DNA sequencing technologies provide accurate information on seed genetic composition. AI software is able to interpret this information to detect genetic markers of desirable traits, including disease resistance, yield, and stress tolerance (Varshney et al., 2005). This helps to ensure that seed lots are genetically pure and of the desired quality.

- **PCR and DNA Testing Automation:** AI technology also automates PCR and DNA testing, identifying certain markers for varietal identification, transgenic composition, or pathogen contamination (FAO, 2023).

- **Genetic Expression Predictive Modelling:** Machine learning models can predict which genetic profiles will translate into field performance and can help in the selection of seeds with best-fit characteristics for a specific environment.

- **Pathogen Detection:** AI-backed molecular diagnosis is able to detect seed-borne pathogens at much earlier stages and higher sensitivity than the conventional approaches (Kumar et al., 2021).

4. **Online platforms for seed Test Management:** These online platforms not only extends digitalization of seed quality analysis but entire management systems too.

- **Blockchain for Traceability:** Distributed ledger technologies ensure proper tracking of seed lots from production through testing and distribution, creating tamper-proof records of quality assurance processes (Zhang et al., 2022). Blockchain technology provides an open and secure platform for seed tracing throughout the supply chain. Each process in the history of the seed, from breeding through processing and distribution, is recorded on a distributed ledger, tracing the seed and preventing counterfeiting. This enhances the level of customer confidence and seed market integrity.

- **Cloud-Based Testing Platforms:** Web-based platforms enable centralized management of testing procedures, data storage, and result sharing among disparate test laboratories for assured standardization and accessibility. Seed testing generates tremendous amounts of data that could be hard to process using traditional tools. AI-driven data analysis tools can process the data to identify trends, predict potential quality flaws, and automate quality control functions. This enables seed producers to make informed choices, improve seed quality, and reduce wastage.

- **IoT integration:** Internet of Things (IoT) sensors track environmental conditions during seed testing and storage, and AI systems interpret this data to guarantee the best conditions and forecast possible quality flaws.

Real-World Impact and Benefits

The coming together of digital and AI technologies in seed testing is paying dividends:

(i) **Efficiency gains:** What used to take hours can now be done in a flash of time, with higher throughput and less labour (Seed Science Center, 2022).

(ii) **Enhanced Accuracy:** Computer testing has proven more consistent and accurate than the older methods, diminishing the possibility of human error and prejudice.

(iii) **Decisions Based on Data:** The volume of data received through digital testing allows for more precise decisions in seed lot certification, storage conditions, and market distribution.

(iv) **Enhanced Traceability:** Blockchain is transparent and traceable throughout the seed supply chain (Sylvester & Kim, 2020).

(v) **Reduced Costs:** Automation and high efficiency result in reduced operation and wastage costs.

(vi) **Increased Crop Yields:** AI enables the forecasting of seed performance, optimization of quality control, and overall enhanced crop yields (Li et al., 2021).

Challenges and Future Directions

Despite the vast potential, AI and digital technology adoption in the seed sector is held back by some challenges:

a) **High Initial Investment:** Sophisticated technologies are expensive to adopt initially.

b) **Availability and Quality of Data:** AI models require large, high-quality datasets for training and validation.

c) **Technical Skill Shortfall:** Skilled personnel are required to run and maintain these technologies.

d) **Standardization and Regulatory Issues:** There should be appropriate standards and regulations in place for the reliability and reproducibility of AI-based seed testing techniques.

e) **Interoperability with legacy systems:** Interoperability with legacy systems may be difficult and expensive (Rao et al., 2022).

However, all the above challenges can be addressed by joint initiatives from governments, research institutions, and the private sector. Some of the future directions for effective implementation of AI and digital technology are pointed out:

- Creating affordable and low-cost AI products for small and medium-sized seed companies.
- Setting up standard processes and data sets for AI-based seed testing.
- Offering training and education courses to build technical skills in the seed business.
- Creating regulatory guidelines that will promote the ethical and responsible use of AI in seed technology.
- Overcoming Data Management Challenges: Secure access to technology and effective data management will be crucial for increased usage.

Conclusion

Artificial intelligence and digital technology are transforming seed testing and quality adherence with greater accuracy, efficacy, and understanding than ever before. As they continue to mature and become widely available, the technologies can be used to ensure world food security by delivering good-quality seeds to farmers globally. The union of AI with old-school seed science is not simply a technological improvement but a transformation in how we go about pursuing seed quality—combining the experience of age-old know-how with the ability of contemporary computing to secure our future agriculture.

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AI and Digital Tools in Seed Testing and Quality Assurance

HARISH M.S[1] AND THOTA JOSEPH RAJU[2]
[1]Assistant Professor, Seed Science and Technology, CCS HAU, College of Agriculture, Bawal-123501
[2]Assistant Professor, Seed Science and Technology, UAS (B), College of Agriculture, Hassan-573225
Email: harishseedtech@gmail.com

Lead Author

DR. HARISH M.S

Assistant professor,
Seed Science and Technology, Chaudhary Charan Singh Haryana Agricultural University, College of Agriculture, Bawal, Haryana

Harish M.S having Ph.D in Seed Science and Technology and presently working as Assistant professor, Seed Science and Technology, Chaudhary Charan Singh Haryana Agricultural University, College of Agriculture, Bawal, Haryana. He has successfully completed post graduate Diploma in Nano biotechnology, Intellectual property rights (IPR) and Agricultural extension management and qualified for National Eligibility Test (NET) of ICAR. He was awarded University gold medal in Master degree and Doctoral degree, He having five year experience in varietal development, characterization, DUS testing, seed production, quality assurance and enhancement techniques in different crop species.

Abstract

Artificial intelligence (AI) and digital tools are transforming seed testing and quality assurance by automating and enhancing traditional processes. AI-powered systems leverage machine learning, computer vision and predictive analytics to assess key seed quality parameters such as germination rate, vigor and disease resistance with unprecedented speed and accuracy. Non-destructive imaging techniques, including spectral and optical analysis, enable rapid and objective evaluation of seed batches, minimizing human error and preserving seed viability for further use. These technologies facilitate high-throughput screening, early defect and disease detection and data-driven decision-making, ultimately improving crop yields, reducing costsand supporting sustainable agriculture. The integration of AI and digital platforms marks a significant advancement in seed quality assurance, ensuring more reliable and efficient outcomes for seed quality managers, seed companies, breeders, producers and farmer.

Introduction

Seed quality is fundamental to agricultural productivity, food security and sustainable farming. Traditionally, seed testing and quality assurance have relied on manual, labor-intensive processes that are time-consuming and prone to human error. The integration of artificial intelligence (AI) and digital tools is revolutionizing these processes, offering automation, speed and unprecedented accuracy. AI in seed testing refers to the use of machine learning, computer vision and data analytics to automate and enhance the evaluation of seed quality. Digital tools encompass a range of technologies, from imaging systems to cloud-based data platforms that support efficient seed analysis and traceability. AI can play role crucial role in seed production, seed certification, seed processing, seed quality control, seed storage and seed marketing. There are numerous challenges and issues in the process of seed production. Seed production is a complex process marked by various factors that can introduce uncertainty and difficulties. These factors encompass fluctuating environmental conditions in the seed production plot, challenges in determining optimal sowing timing and methods, managing seed rates, handling nutrients and irrigation, controlling weeds, identifying off-types, managing soil moisture, isolation distance and addressing pest and disease issues. AI has practical applications in the management of seed production and quality assurance. The utilization of precise sowing techniques through AI is possible which ensures efficient seed placement, minimizes seed wastage and allows for precise control of the seed rate and does not suffer from drought and other adverse climate conditons.AI is making significant strides in the field of seed science, offering innovative solutions to enhance seed production, quality control and overall agricultural productivity. AI can assess seed quality by analyzing factors such as seed sorting and grading, moisture content, genetic purity, and contaminants. This ensures that only high-quality seeds are used for germination. Remote Monitoring Drones equipped with AI technology can capture high-resolution images and data from germination fields. Here are some key applications of AI in seed testing and quality assurance. This article explores how AI and digital technologies are transforming seed testing and quality assurance, detailing the technologies involved, their applications, benefits and future prospects (Jin 2025).

The Key Technologies are Machine Learning (ML) uses algorithms applied in deep learning models are trained on large datasets of seed images and quality parameters to identify patterns, classify seeds and predict performance. Computer vision enables automated visual inspection of seeds, detecting defects, diseases, and morphological traits with high precision. Data Analytics will extract actionable insights from vast datasets, identifying trends, anomalies and correlations to inform decision-making. Digital Traceability Systems and tools like QR codes, block chain and online verification platforms help track seed origin, authenticity and quality throughout the supply chain. Here are some key applications of AI in seed testing and quality assurance.

1. **Automated Seed Analysis**: AI automates repetitive tasks such as counting, sizing, and classifying seeds, drastically increasing efficiency and reducing human error. Automated systems can process large sample sizes quickly, freeing skilled personnel for more complex analyses.

2. **Seed Sorting and Grading**: AI-powered machines can accurately sort and grade seeds based on various attributes such as size, shape, colour and quality. This ensures that only high-quality seeds are planted, leading to better crop yields. AI-powered machines can sort seeds based on their size, weight and quality ensures that only high-quality seeds are planted, increasing the likelihood of successful germination.

3. **Germination prediction and Testing:** Germination Prediction AI models can predict seed germination rates based on various factors including seed quality, environmental conditions and historical data. By analyzing these variables, AI can estimate the likelihood of successful germination, allowing farmers to make informed decisions about seed planting which for remote monitoring of germination progress and the early detection of issues. Data Analysis AI algorithms can process and analyze vast amounts of germination data is helping researchers identify patterns and factors that influence germination success. AI systems can provide real-time feedback to farmers and seed producers during the germination process. AI can recommend customized growing conditions for different seed varieties based on their specific germination requirements with ensured that each seed variety receives optimal treatment. By leveraging AI in seed germination processes, farmers and seed producers can improve the efficiency and success rates of germination, leading to higher crop yields and better resource utilization and AI's ability to analyze and adapt to changing conditions in real time makes it a valuable tool for enhancing seed germination in agriculture (Hamdy, 2024).

4. **Image Analysis for Germination and Vigor**: Computer vision systems analyze time-lapse images to assess germination rates and seedling vigor. These systems offer consistent, objective measurements, improving the reliability of germination tests.

5. **Spectral and X-Ray Imaging**: Advanced imaging technologies, including spectral and 2D X-ray imaging, provide non-destructive analysis of internal and external seed traits. AI models interpret these images to detect internal

defects, measure moisture content and assess chemical composition, often matching or exceeding human performance (Zhu, 2019).

6. **Genetic Purity Analysis:** If the seeds are of a specific crop variety, the algorithm may analyze their genetic characteristics to ensure purity. It compares the genetic profile of each seed with the expected genetic profile for the variety in question.

7. **Moisture Content Assessment:** Seed moisture content is critical for storage and germination. The algorithm measures the moisture content of each seed, comparing it to acceptable ranges for the particular seed type.

8. **Physical Attributes Evaluation:** The algorithm assesses the physical attributes of seeds, including size, shape, colour and surface texture. Deviations from expected physical characteristics can indicate lower quality.

9. **Scoring and Classification**: Using the integrated data, the algorithm calculates a quality score for each seed and then classified into different quality categories based on their scores. The algorithm generates reports that provide detailed information about the quality of each seed. This may include a summary of findings, quality classifications and any identified issues or deviations and can provide recommendations or decision support to seed producers and farmers for planting, which should be discarded or whether specific treatments are needed to improve seed quality. The specific design and features of a seed quality algorithm can vary depending on the goals and requirements of seed producers and the crops being cultivated and are valuable tools in modern agriculture is helping ensure that high-quality seeds are used for planting, which ultimately contributes to better crop yields and agricultural productivity. Additionally, they aid in maintaining the genetic purity of crop varieties, is crucial for seed certification and plant variety protection (PVP) programs.

10. **Defect and Disease Detection**: Deep learning algorithms, such as Convolution

Neural Networks (CNNs), are trained to identify physical defects, fungal infections or other diseases in seeds. These systems can achieve accuracy rates close to 99% in some crops, enabling early intervention and reducing crop losses.

11. **Predictive Analytics for Seed Performance:** By analyzing historical data, environmental factors, and genetic information, AI can predict seed performance, helping breeders and farmers select the best varieties for specific conditions. This supports targeted breeding and optimized planting strategies.

12. **Seed Coating Optimization:** AI can optimize the application of seed coatings, including nutrients, fungicides and insecticides. This ensures uniform and effective coating, enhancing seed protection and germination rates.

13. **Seed Storage Management:** AI-powered sensors and monitoring systems can track environmental conditions in seed storage facilities. If conditions deviate from the ideal, AI can issue alerts to prevent seed deterioration.

14. **Digital Traceability and Anti-Counterfeiting:** Digital platforms and mobile verification tools empower farmers to verify seed authenticity, combating counterfeit seeds and ensuring access to genuine, high-quality products. Systems like AgroTrack and NASC Seed Codex have significantly improved seed traceability and farmer confidence in Africa.

The combination of advanced computational techniques with traditional agricultural practices will unlock new opportunities for sustainable and efficient crop production (Table 1). In conclusion, the integration of Artificial Intelligence (AI) in seed science represents a revolutionary leap forward in agriculture, promising to address critical challenges and unlock new opportunities in seed production, quality control andresearch. AI's application in seed science is multifaceted, spanning various domains, from genetic purity analysis to seed quality assessment, disease detection, and even the optimization of planting and harvesting processes.

Through machine learning, deep learning, computer vision and data analysis, AI algorithms have the capacity to enhance nearly every aspect of seed science.

Table 1: Traditional methods vs AI and Digital tools

Aspect	Traditional Methods	AI and Digital Tools
Speed	Slow, manual	Rapid, automated
Accuracy	Subjective, variable	Objective, highly accurate
Throughput	Limited by human labor	High-throughput, scalable
Cost	Labor-intensive, expensive	Reduced labor, cost-effective
Data Management	Paper-based, fragmented	Centralized, real-time analytics
Traceability	Difficult, error-prone	Digital, transparent

One of the most significant contributions of AI in seed science is in the domain of seed quality control. The automation of these processes not only reduces human error but also accelerates the pace of seed quality assessment, facilitating quicker decisions for seed certification and distribution. Furthermore, AI has empowered seed scientists to tackle one of the most persistent challenges in agriculture.

In the realm of genetic purity assessment, AI has ushered in a new era of accuracy by Through the analysis of genetic markers and DNA sequencing, AI algorithms can verify the genetic purity of seed varieties with unmatched precision. This is particularly crucial in the context of intellectual property rights and seed certification, ensuring that farmers receive seeds of the intended variety and that breeders' rights (IPR) are protected. Moreover, AI has contributed to more sustainable farming practices through precise planting and the adoption of AI may require investment in infrastructure, training and technology access, posing hurdles for small-scale farmers and resource-constrained regions. Additionally, the responsible use of AI related to data privacy regulations and addressing biases in algorithms are paramount concerns. In the context of research and development the AI accelerates the breeding of new crop varieties with desired traits by predict which genetic combinations and vast genome data sets are most likely to yield superior crops is expedites the breeding process, potentially leading to the development of drought-resistant, disease-resistant or higher-yielding crops are essential for global food security.

Future aspects

The future of Artificial Intelligence (AI) in seed science holds immense promise, with numerous exciting aspects poised to shape the agriculture industry and seed production in the coming years. Seed testing and quality assurance lies in further integration of AI, robotics, and digital platforms. Advancements in imaging, cloud computing, and IoT (Internet of Things) will enable even more precise, real-time monitoring of seed quality across the supply chain. Collaborative efforts between research institutions, technology providers, and agricultural stakeholders will drive innovation, making high-quality seeds more accessible worldwide. As AI technologies continue to advance and integrate into the field, we can anticipate several key developments that will revolutionize seed science and its impact on global food security, sustainability and innovation. Enhanced Seed Quality Assurance AI-driven seed quality assessment will become even more sophisticated. As while AI algorithms evolve, they will offer greater accuracy in detecting contaminants, genetic impurities, and diseases. This will provide farmers and seed companies with an unprecedented level of confidence in seed quality, reducing crop failures and increasing overall productivity (Harish M.S, 2017). Customized Seed Varieties with AI will play a pivotal role in personalized agriculture and allow. Farmers will be able to access AI-powered systems that recommend specific seed varieties based on their soil type, climate conditions and historical data. This customization will optimize yields and resource utilization while reducing environmental impact. Presently AI has been exploited in the field of quality control and no research has been done in the aspects of certification, processing as well as storage.

Conclusion

AI and digital tools are reshaping seed testing and quality assurance offering transformative benefits in speed, accuracy, cost, transparency and its role in seed science is transformative, promising to user in a new era of precision agriculture and sustainable food production. By automating manual processes, enabling advanced imaging and analytics and improving traceability useful in technologies ensure that farmers and producers have access to the best possible seeds. By leveraging the power of AI, the agriculture sector can enhance seed quality, detect diseases early, optimize resource use, and accelerate crop breeding. As adoption continues to grow, AI-driven seed quality assurance will play a pivotal role in supporting global food security and sustainable agriculture. While challenges exist, the potential benefits of AI in seed science are vast, offering a path toward meeting the food demands of a growing global population and safeguarding agricultural sustainability for generations to come. As AI continues to evolve and researchers refine its applications in seed science, the future of agriculture is brighter and more resilient than ever before.

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Role of Artificial Intelligence and Digital Technologies for Seed Quality Testing

KUMARI RAJANI[1,2*], RAVI RANJAN KUMAR[2] BINEETA M. BARA[1] AND TUSHAR RANJAN[3]

[1]Dept. of Seed Science and Technology, Sam Higginbottom University of Agriculture, Technology and Sciences, Prayagraj-211007, U.P. India

[2]Bhola Paswan Shastri Agricultural College, Purnea-854302, (Bihar Agricultural University, Sabour), Bihar, India

[3]Dept. of Molecular Biolgoy & Genetic Engineering, Bihar Agricultural University, Sabour-813210, Bihar, India

Email: rajani.dsstiari@gmail.com

Lead Author

MRS. KUMARI RAJANI

Assistant Professor
Bihar Agricultural University (BAU),
Sabour

Mrs. Kumari Rajani is an accomplished academic and researcher in Seed Science and Technology. With a B.Sc. (Ag) from Birsa Agricultural University and an M.Sc. (Ag) from IARI, New Delhi, she joined Bihar Agricultural University (BAU), Sabour, in 2014 as an Assistant Professor. A recipient of ICAR-JRF and ASRB-NET, she played a pivotal role in establishing the Seed Science Department at BAU and introduced quality seed production and testing.

Awarded the prestigious SERB-DST Empowerment and Equity Research Award, she leads a project on seed quality enhancement in pulses using botanicals. As nodal officer for ICAR-IIPR's Seed Hub project, she promoted quality seed production of chickpea, lentil, and mungbean through farmer participation. With over 20 research publications in reputed journals and 05 training manuals for Bihar farmers, her work focuses on farmer empowerment through research, training, and sustainable seed practices. Her contributions significantly advance agricultural development in the region.

Abstract

The use of artificial intelligence and digital technologies in seed quality testing marks a significant change in agricultural science. It tackles important issues in seed certification and crop productivity. Traditional methods, like germination tests and manual phenotyping, face limitations such as subjectivity, low efficiency, and destructive sampling. Deep learning and computer vision based AI solutions, now allow for automated, precise analysis of physical features like size, color, and texture, as well as internal structures using X-ray and micro-CT imaging on a large scale. Hyper spectral imaging paired with convolutional neural networks allows for non-destructive measurement of biochemical traits like oil, protein, and moisture. Predictive machine learning models link spectral signatures to germination capacity. Edge AI devices support real-time assessment of seeds in the field. IoT-enabled sensor networks improve storage conditions by continuously monitoring temperature and humidity. Blockchain platforms boost traceability by creating unchangeable records of seed origin and quality data throughout supply chains. However, barriers persist, including the need for large, annotated multispectral datasets, model interpretability for regulatory approval, and cost-effective deployment in resource-limited settings. New solutions like few-shot learning and digital twins aim to lessen data requirements. At the same time, robotic sorters and drone-based phenotyping broaden testing capabilities. Policy frameworks need to change to standardize AI-assisted certification protocols and ensure fair access to technology. This review highlights technological advancements, commercial uses, and research opportunities. It focuses on AI's role in achieving UN Sustainable Development Goal 2 (Zero Hunger) through next-generation seed systems. Future plans include explainable AI for discovering traits and federated learning for global seed quality databases, which will help connect precision agriculture with food security needs.

1. Introduction

Seed quality is a critical determinant of agricultural productivity, crop performance, and global food security. High-quality seeds ensure better germination rates, uniform crop establishment, and resilience against biotic (pests, diseases) and abiotic (drought, salinity) stresses (Fig. 1). According to the Food and Agriculture

Organization (FAO), poor seed quality can reduce crop yields by 15–30%, significantly impacting food availability, especially in developing nations (FAO, 2024). A study by the International Seed Testing Association (ISTA) revealed that over 25% of seed lots fail quality tests due to low germination rates or contamination, leading to economic losses exceeding $2 billion annually (ISTA, 2022).

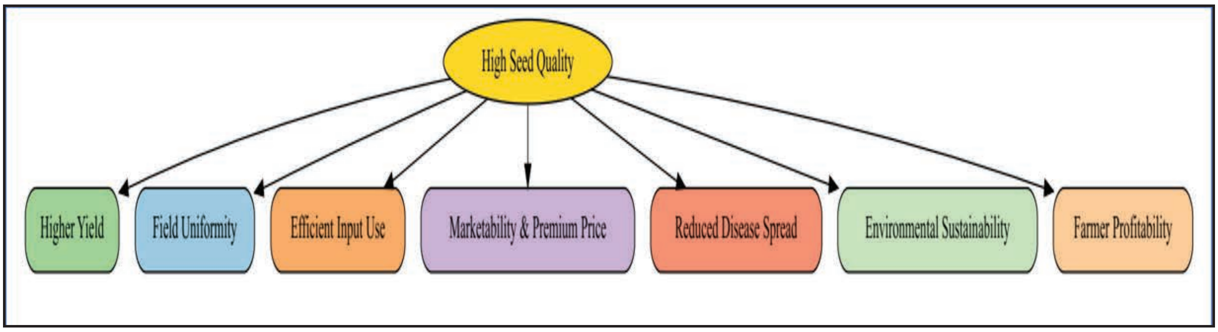

Fig.1 pictorial representation depicting the impact of high quality seed in agricultural system

The role of seed quality becomes even more crucial in the context of climate change and rising global food demand. The United Nations projects that the world population will reach 9.7 billion by 2050, requiring a 70% increase in food production. However, as per the data of world Bank nearly 30% of crop losses occur due to substandard seeds, exacerbating food insecurity. Ensuring seed quality through advanced testing methods is, therefore, essential for sustainable agriculture and meeting Sustainable Development Goal (SDG) **#2 (Zero Hunger)**.

Table 1: Key Impacts of Seed Quality on Agriculture (Ref: ISTA, 2022; FAO, 2023)

Factor	Impact of Poor Seed Quality	Economic Loss (Annual)
Germination Failure	Reduced crop stand density	$800 million
Disease Contamination	Lower yield & higher pesticide use	$500 million
Genetic Impurities	Inconsistent crop performance	$700 million

To address these challenges, artificial intelligence (AI) and digital technologies are emerging as transformative tools for rapid, non-destructive, and high-throughput seed quality assessment. AI-powered image analysis, spectroscopy, and machine learning models can detect defects, predict germination potential, and classify seed health with over 95% accuracy (Zhang et al., 2023). These innovations are crucial for enhancing seed certification programs and ensuring food security in the face of climate uncertainties.

2. Traditional methods of seed quality testing

Seed quality assessment has historically relied on conventional laboratory techniques (Table 2) that, while standardized, present significant operational challenges. The **germination test**, considered the gold standard, requires seeds to be planted under controlled conditions for 7–28 days to evaluate viability (ISTA, 2022). This method requires significant time and resources, which can delay important decisions related to seed certification and distribution. The tetrazolium (TZ) test, another commonly used biochemical assay, stains embryos to evaluate cellular respiration; however, it destroys the seeds in the process, rendering it unsuitable for valuable breeding lines (Bewley et al., 2013). Visual inspection for physical purity—assessing seed size, color, and damage—is highly subjective, with studies reporting **inter-analyst variation of 15–20%** due to human perceptual differences (McDonald & Copeland, 2012). Manual weight measurements (e.g., 1,000-seed weight) and sieving for size uniformity are labor-intensive and prone to sampling errors. For disease detection, **agar plate tests** require culturing pathogens for 3–7 days, risking cross-contamination and false negatives (Mathur & Kongsdal, 2003).

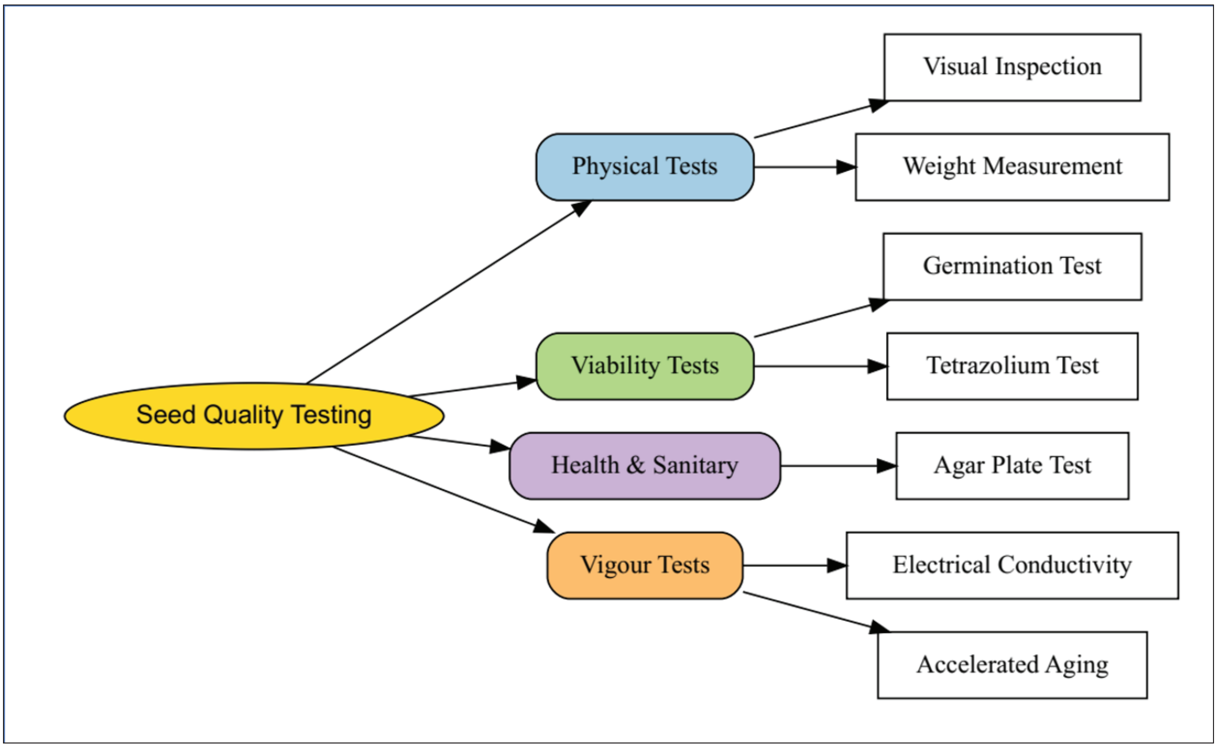

Fig. 2 Different traditionally used methods of seed quality testing

These methods demand specialized facilities, trained personnel, and repetitive workflows, limiting scalability. For instance, the **average throughput of a traditional seed lab is just 50–100 samples per day**, creating bottlenecks in commercial seed production (Marcos-Filho, 2015). Furthermore, environmental factors (e.g., temperature fluctuations during germination tests) can skew results, reducing reliability. Such constraints underscore the need for more efficient alternatives in modern agriculture.

Table 2: Principle, Advantages and Limitations of Traditional Methods of Seed Quality Testing

Method	Principle/Procedure	Advantages	Limitations	Reference
Germination Test	Seeds grown under controlled conditions (7-28 days) to measure sprouting percentage.	- Gold standard for viability - Widely accepted in certification	- Time-consuming (weeks) - Requires lab space & controlled environment	(ISTA, 2020)
Tetrazolium (TZ) Test	Embryos stained with TZ solution; live cells turn red due to dehydrogenase activity.	- Rapid (24-48 hrs) - No need for growth media	- Destructive (seeds unusable post-test) - Subjective color interpretation	(Bewley et al., 2013)
Visual Inspection	Manual examination of seed size, color, damage, and physical purity.	- Low cost - Immediate results	- High subjectivity (15-20% error rate) - Limited to external defects	(McDonald & Copeland, 2012)
Weight Measurement	Weighing 1,000 seeds to estimate uniformity and fill quality.	- Simple equipment (balance) - Indicator of seed maturity	- Labor-intensive - Does not assess viability	(ISTA, 2022)
Agar Plate Test	Seeds placed on agar to culture fungi/bacteria (3-7 days).	- Identifies specific pathogens - Low-tech	- Slow - Risk of contamination - False negatives	(Mathur & Kongsdal, 2003)
Electrical Conductivity Test	Measures solute leakage from damaged seeds in water (high EC = low vigor).	- Fast (24 hrs) - Predicts field performance	- Indirect vigor indicator - Sensitive to seed moisture	(Marcos-Filho, 2015)
Accelerated Aging Test	Seeds exposed to high temp/humidity (41°C, 72 hrs) before germination.	- Predicts storage potential - Correlates with field stress tolerance	- Over-ages seeds artificially - Equipment-dependent	(ISTA, 2022)

3. AI and Digital technologies in agriculture for seed quality testing

The integration of Artificial Intelligence (AI) and digital technologies into agriculture traces back to the 1980s with early computer vision systems for crop monitoring (Eli-Chukwu, 2019). However, significant advancements occurred post-2010, driven by machine learning (ML), IoT sensors, and high-resolution imaging (Liakos et al., 2018) (Table 3). AI in agriculture initially focused on yield prediction and pest detection, but by the mid-2010s, its applications expanded to seed quality testing, addressing the inefficiencies of traditional methods (Mahant and Pal. 2025).

The concept of AI-driven seed testing relies on non-destructive, data-driven approaches:

- **Computer vision** (e.g., hyperspectral imaging) detects internal defects.
- **Machine learning algorithms** classify seed vigor and germination potential.
- **IoT-enabled sensors** monitor real-time storage conditions (humidity, temperature).

By 2020, AI achieved >95% accuracy in seed purity testing, surpassing human capabilities (Singh et al., 2025). The emergence of portable AI devices (e.g., smartphone-based seed analyzers) further democratized seed testing for smallholder farmers (FAO, 2024).

The adoption of **Artificial Intelligence for seed quality testing** has revolutionized agricultural practices by enabling **rapid, non-destructive, and high-throughput analysis** of seeds, overcoming the limitations of traditional methods (Long et al., 2021). Early applications of AI in seed testing emerged in the 2010s with **machine learning (ML)-based image processing** for seed classification, achieving **>90% accuracy** in identifying physical defects. By 2020, advancements in **deep learning (CNNs) and hyperspectral imaging** allowed for real-time detection of internal seed defects and biochemical properties, reducing testing time from **weeks to minutes** (Wang et al., 2025). AI-powered systems, such as **automated seed sorters**, now process **10,000 seeds/hour** with 99% purity classification, significantly enhancing efficiency in commercial seed production (AgTech Review, 2025).

Table 3: Timeline of AI in Seed Quality Testing (1980–2025)

Year	Milestone	Technology	Impact
1980s	Early image processing for seed morphology	Basic computer vision	Limited to lab settings
2005	First ML models for seed classification	Support Vector Machines (SVMs)	Automated defect detection (~80% accuracy)
2015	Hyperspectral imaging for seed health	Deep learning (CNNs)	Non-destructive pathogen detection
2020	AI-powered seed sorters (commercial deployment)	IoT + Robotics	50% faster than manual sorting
2023	Portable AI seed testers (field applications)	Edge AI (TensorFlow Lite)	Affordable smallholder solutions
2025	Blockchain-integrated seed certification	AI + Blockchain	Transparent supply chains

Recent innovations include **portable AI devices** that integrate smartphone-based imaging and edge computing, bringing **lab-quality seed testing to field conditions** (Tao et al., 2023). These tools leverage **predictive analytics** to estimate germination rates and vigor indices within **24 hours**, compared to the **7–28 days** required for conventional germination tests (FAO, 2024). Furthermore, **IoT-enabled sensors** combined with AI provide real-time monitoring of seed storage conditions, preventing post-harvest losses due to mold or temperature fluctuations (Liakos et al., 2022). The integration of **blockchain technology** ensures traceability in seed certification, enhancing transparency in supply chains (Shao et al., 2024).

Studies show that AI-driven seed testing cuts operational costs by 50 to 70 percent and improves accuracy. This makes it crucial for modern agriculture (Singh et al., 2023). As AI models develop further, their importance in precision seed quality management is likely to grow, especially in tackling global food security issues (Zhang et al., 2025).

4. Different Digital and AI driven Technologies for Seed Quality Assessment

The international agri-food sector is facing mounting pressure to enhance productivity, sustainability, and food security, with seed quality being a pivotal corner stone on which successful crop development relies. The recent advances in digital technology have revolutionized the evaluation of seed quality to a great extent, introducing various new methodologies that are characterized by their rapidity, non-invasive nature, and exceptional accuracy. These emerging technologies apply automation, artificial intelligence (AI), and sophisticated imaging methods to solve the problems of conventional testing practices. Conventional tests are mostly lengthy and intrusive in nature, but new technologies seek to improve the process.New seed testing methods are more efficient than conventional methods, which are normally marred by lengthy protocols, subjective diagnosis, and destructive sampling (Marcos-Filho, 2015). As a response to these difficulties, Artificial Intelligence (AI) and digital technologies have emerged as game-changers, supporting rapid, non-destructive, and high-capacity tests of seed quality (Singh et al., 2023). Emerging technologies employ computer vision, machine learning, hyperspectral imaging, and Internet of Things (IoT) sensors to enhance seed testing. These technologies enhance accuracy and efficiency, reducing testing times from weeks to mere minutes. This assists breeders, farmers, and policymakers to make informed choices (FAO, 2024). Incorporating AI in seed testing is a major advancement in agricultural technology. It assists in addressing three primary issues that have rendered it difficult to evaluate seed quality and improve agricultural productivity. The application of new agriculture has brought a lot of improvements in the assessment of seed quality using various AI-based approaches. These state-of-the-art techniques have revolutionized conventional seed testing by providing unprecedented accuracy, efficiency, and scalability (Fig. 3).

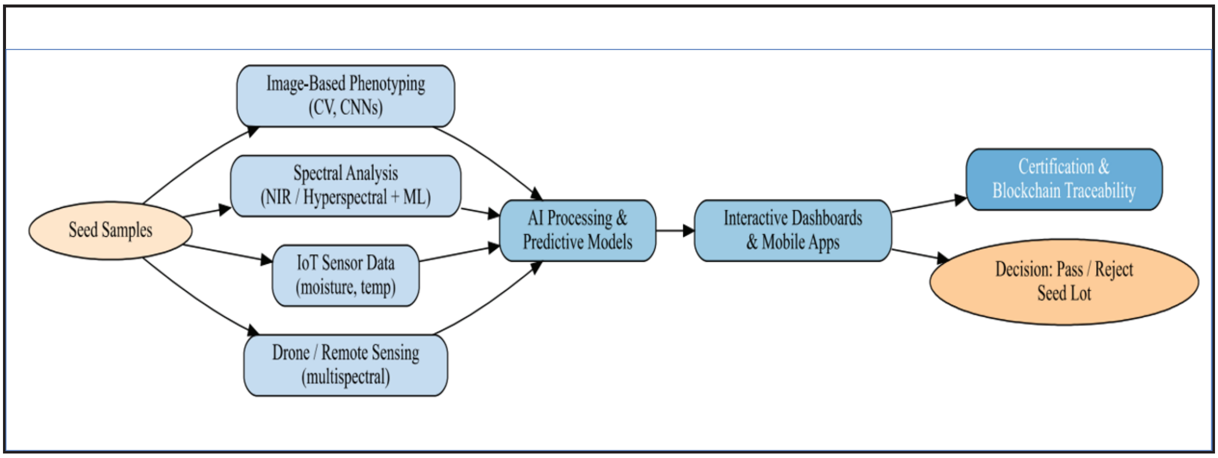

Fig 3. Pictorial representation of use of different digital and AI technologies to access the seed quality

Some of the important digital technologies and AI driven system used to assess seed quality in agriculture system is discussed in this section.

4.1 Computer Vision and Image Analysis

Computer vision systems are among the most widely used applications of artificial intelligence in seed testing (Fig. 4A). These systems use high-resolution cameras combined with machine learning algorithms to conduct several analyses, including:

- Morphological analysis (size, shape, and color)
- Surface defect detection (identifying cracks and discoloration)
- Structural integrity assessment

Advanced implementations take advantage of 3D imaging to assess seed volume and density distribution, which offers insights into potential viability issues. Additionally, the integration of deep learning architectures, such as Convolutional Neural Networks (CNNs), has enabled these systems to achieve classification accuracies of over 98% for common crop seeds.

4.2 X-ray and Micro-CT Imaging

X-ray imaging X-ray imaging offers a non-destructive method for visualizing the internal structures of seeds, allowing for the detection of voids, insect damage, and malformations that can impact viability (Fig. 4B). In contrast, Micro-CT scanning provides high-resolution 3D reconstructions of seed anatomy, facilitating precise analyses of embryo integrity, tissue density, and structural defects. X-ray-based methods deliver exceptional capabilities for internal visualization, including:

- Assessment of embryo development
- Detection of internal voids
- Evaluation of mechanical damage

AI-assisted image analysis automates the identification of seed abnormalities, enhancing both accuracy and throughput compared to manual inspections. This AI-powered analysis can predict germination potential with an accuracy of 90-95% within a matter of hours, whereas conventional germination tests typically require weeks. The latest Micro-CT systems achieve resolutions below 10 micrometers, enabling the detection of microscopic structural defects.

4.3 Hyperspectral and Multispectral Imaging

Hyperspectral and multispectral imaging provide a non-destructive method for assessing seed quality by capturing spectral data across various wavelengths (Fig. 4C)**. This technology reveals biochemical and structural traits that are not visible to the naked eye. It typically captures spectral data in the range of 400 to 2500 nm, allowing for the detection of internal biochemical composition, variations in moisture content, and early-stage pathogen infections. AI algorithms analyze the complex spectral signatures to identify subtle patterns that indicate quality issues. Recent advancements have reduced the scanning time to under five seconds per seed, while still adhering to non-destructive testing protocols.**

4.4 Near-Infrared (NIR) Spectroscopy

AI-driven near-infrared (NIR) spectroscopy allows for rapid and non-destructive assessment of seed quality by analyzing the chemical composition, including moisture, protein, and oil content, through their spectral signatures(Fig. 4D). Machine learning models, such as Partial Least Squares (PLS) and Artificial Neural Networks (ANN), enhance the accuracy of predictions related to seed viability and vigor. Portable NIR devices equipped with edge AI facilitate real-time testing in the field, improving seed sorting and certification while reducing dependence on laboratory methods. These portable NIR devices, with built-in AI interpretation capabilities, have made laboratory-grade testing possible in field conditions, with some models providing results in less than 30 seconds.

4.5 Acoustic Resonance Analysis

Acoustic Resonance Analysis is an emerging non-destructive technique that analyzes the acoustic signatures of seeds when they are mechanically excited. This method evaluates the vibration patterns and sound frequencies emitted by seeds when they are tapped. It is a low-cost, portable approach that shows potential for high-throughput seed sorting and early defect detection(Fig. 4E).

Using AI classifiers, this technique can distinguish between:

- Viable and non-viable seeds
- Degrees of mechanical damage
- Internal insect infestations

AI processes the acoustic signatures to assess internal cracks, density variations, and seed viability, enabling rapid quality screening. This method has shown particular promise for large-seeded crops, with reported accuracy rates ranging from 92% to 96% in preliminary studies.

4.6 Electronic Nose Technology

AI- AI-driven sensor arrays utilize machine learning to analyze volatile organic compounds (VOCs) emitted by seeds, allowing for non-destructive quality assessment. These systems can:

- Identify early fungal infections
- Assess oxidative stress
- Monitor storage conditions

Recent advancements in nanosensor sensitivity, capable of detecting parts per billion, and AI pattern recognition techniques, such as LSTM networks, enable real-time diagnostics that can be deployed in the field. Applications of this technology extend to seed banks and supply chains, helping to reduce post-harvest losses. However, challenges remain, including the calibration of sensors for diverse crop species and the need to mitigate environmental interference.

4.7 Robotic Seed Handling Systems

Robotic Seed Handling Systems combine artificial intelligence, computer vision, and precision robotics to automate the processes of seed sorting, grading, and planting (Fig. 4F). These systems are equipped with high-resolution cameras and machine learning algorithms, such as YOLO and Faster R-CNN, which allow for the classification of seeds based on size, color, and defects at speeds that surpass human capabilities. Soft robotic grippers are designed to minimize damage during handling, while IoT-enabled arms work in conjunction with spectral sensors to perform real-time quality checks. Applications for these systems include high-throughput seed certification labs and precision agriculture. However, challenges remain, such as calibrating the systems for diverse seed morphologies and addressing cost barriers.

Advancements in collaborative robotics, or cobots, are aimed at democratizing access to these technologies, thereby enhancing efficiency in seed supply chains. Automated platforms can integrate multiple testing modalities, providing features such as:

- High-throughput sorting (over 10,000 seeds per hour)
- Precision weighing and sizing
- Automated packaging equipped with QR code tracking

These systems typically use computer vision to facilitate real-time decision-making during sorting operations.

Fig. Different imaging system used to assess the seed quality

The information of Table 4 describes key digital techniques used in seed quality assessment. It includes detailed explanations of their unique benefits, different levels of accuracy, fast processing capabilities, and practical use in various agricultural settings. This overview shows how strongly these technologies impact the progress in modern agriculture.

Table 4: Concise information of different Digital and AI driven technologies used for Seed quality testing (Singh et al., 2025; Zolkin et al., 2024; ElMasry et al., 2019)

Technology	Principle/ Application	Advantages	Accuracy	Speed	Best For
Hyperspectral Imaging	Captures spectral data across multiple wavelengths to detect internal defects & moisture	Non-destructive, detects hidden defects	95–98%	<5 min/ sample	Pathogen detection, nutrient analysis
Machine Learning (ML)	AI algorithms classify seeds based on size, color, and defects using image datasets	High automation, reduces human bias	90–99%	Real-time	Seed sorting, purity testing
X-ray Imaging	Reveals internal seed structures (e.g., embryo damage, hollow seeds)	Non-invasive, detects internal deformities	92–96%	10–30 sec/ seed	Viability assessment
Near-Infrared (NIR) Spectroscopy	Measures chemical composition (moisture, oil, protein)	Rapid, no sample preparation needed	85–95%	<1 min/ sample	Oilseed & grain quality
RGB Imaging + AI	Uses color and shape analysis with convolutional neural networks (CNNs) for defect ID	Low-cost, works with smartphones	88–94%	<2 sec/seed	Smallholder farmers
IoT Sensors	Monitors real-time storage conditions (temp, humidity) to prevent spoilage	Prevents post-harvest losses, cloud-based alerts	90–98% (predictive)	Continuous	Seed storage facilities
3D Imaging & Tomography	Creates 3D models of seeds to assess density and structural integrity	Detailed internal visualization	94–97%	1–2 min/ seed	High-value seeds (hybrids, GMOs)
Laser Sorting	Uses light scattering to separate seeds by size, color, and defects	High-throughput (10,000 seeds/ hour)	96–99%	Real-time	Commercial seed processing

5. Practical Application of AI driven seed quality testing

AI seed testing is revolutionizing the agricultural sector with increased speed, accuracy and scalability for testing seed quality (Fig.5).

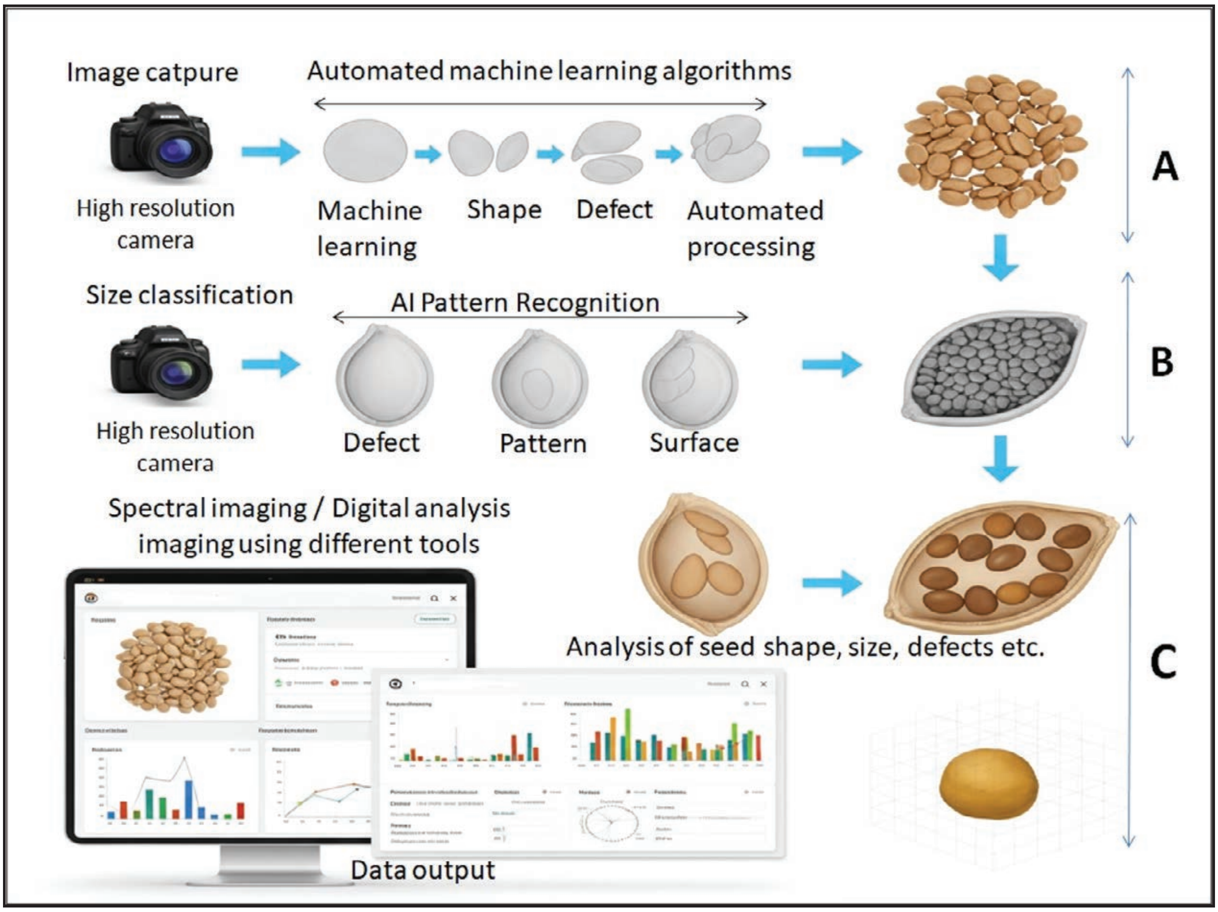

Fig 5: Pictorial representation of use of AI and digital technologies for seed quality assessment. **A.** Processing by machine learning to analyze shape, identify defects, and categorize seeds, **B.** Use of AI to recognize patterns on the seed surface, identify defects, and classify based on size and other features, **C.** use of advanced imaging (spectral) and digital analysis tools, with dashboards for data visualization and comparison of seed health and genetic information.

Such applications serve to improve seed certification, disease detection, and precision breeding; minimizing the occurrence of human error and post-harvest loss. AI is the combination of machine learning with sophisticated imaging, spectroscopy, biology and robotics for non-disruptive, real-time analysis of seed quality, purity and biochemical composition. By doing so, they are able to provide farmers with quality seeds, which increase their crop production and sustainability. Some of the applications of AI driven seed quality testing is listed below (Table 5)

Table 5: Overview of use of AI and related technologies enhance seed quality control, disease detection, sorting, storage, supply chain management, breeding, and field applications **(Singh et al., 2025; Zolkin et al., 2024; Javaid et al., 2023; Rai, 2022)**

Category	Application	Technology/Method	Purpose/Output
Seed Quality Assessment & Certification	Viability & Vigor Testing	Hyperspectral/NIR imaging + AI analysis	Predicts germination potential based on spectral signatures.
	Purity & Defect Detection	Computer Vision (YOLO, Mask R-CNN)	Identifies damaged, immature, or contaminated seeds.
	Biochemical Profiling	NIR spectroscopy + Machine Learning	Quantifies protein, oil, and starch content for nutritional assessment.
Disease & Pathogen Detection	Early Fungal/ Bacterial Identification	VOC sensors + AI (e.g., electronic noses)	Detects pathogen-specific volatile markers (e.g., aflatoxins).
	Internal Defect Mapping	X-ray/Micro-CT imaging + AI analysis	Reveals hidden infections or insect damage inside seeds.
Precision Sorting & Grading	Automated High-Throughput Sorting	Robotic arms + AI vision (CNN-based classifiers)	Classifies seeds by size, color, and health for optimized grading.
	Trait-Based Selection	ML models (e.g., SVM, Random Forest)	Prioritizes seeds with desirable traits (e.g., drought resistance).
Storage & Post-Harvest Management	Real-Time Condition Monitoring	IoT sensors (humidity, temp) + AI analytics	Tracks storage conditions to prevent spoilage.
	Shelf-Life Prediction	Predictive analytics (oxidative stress markers)	Assesses seed aging and predicts longevity.
Supply Chain Optimization	Blockchain Traceability	AI + Blockchain	Verifies seed provenance and quality across supply chains.
	Counterfeit Detection	ML (anomaly detection, clustering)	Identifies adulterated or mislabeled seed batches.
Breeding & Research	Phenotyping Acceleration	AI-based image analysis (e.g., embryo size, coat thickness)	Automates trait measurement for faster breeding decisions.
	Genotype-Phenotype Linking	Deep Learning (e.g., CNNs, Transformers)	Correlates genetic data with seed performance.
Field Deployment & Scalability	Portable AI Tools	Edge AI (smartphone apps, handheld devices)	Enables on-farm seed testing with instant results.
	Drone-Based Monitoring	Multispectral drones + AI analytics	Assesses seed crop health pre-harvest for yield optimization.

The FAO's 2025 AI seed certification protocol, already adopted by 38 countries, represents a major step toward global standardization of these technologies (FAO, 2024). With projections suggesting a 90% reduction in seed-borne disease outbreaks by 2026 and an anticipated $12 billion market for AI seed technologies by 2027 (28% CAGR), the agricultural sector stands on the brink of a technological revolution that will fundamentally transform how we ensure seed quality and food security worldwide.

6. Summary and Conclusions

The use of Artificial Intelligence (AI) and digital technologies in seed quality testing has revolutionized traditional agricultural practices changed traditional farming practices. It allows for faster, more accurate, and non-destructive seed assessments. Techniques like hyperspectral imaging, NIR spectroscopy, X-ray micro-CT, and AI-driven robotics improve the detection of seed viability, defects, and biochemical traits with great precision. Machine learning algorithms such as CNNs, SVMs, and PLSR models examine large datasets to predict germination potential, identify pathogens, and improve sorting processes. Portable devices that connect to the Internet also expand these capabilities for use in the field. This gives farmers tools for making decisions in real time.

Despite these advancements, challenges like high costs, a lack of data for niche crops, and unclear algorithms hold back widespread use, especially in resource-limited areas. Future improvements rely on affordable sensor miniaturization, clear AI, and shared learning to boost accessibility and trust. Plus, adding blockchain can improve seed traceability, and AI-driven predictive models might speed up the creation of climate-resilient seed varieties. In conclusion, AI and digital technologies are changing seed quality testing from a labor-intensive, subjective process into a data-driven, automated system. While obstacles remain, ongoing innovation promises to improve global food security, sustainable farming, and precise agriculture. Collaboration among researchers, policymakers, and agribusinesses will be key to ensuring these technologies reach smallholder farmers and achieve their potential in creating a resilient agricultural future.

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Role of Artificial Intelligence in Enhancing Seed Quality Assurance

RAJNEESH BHARDWAJ[1], ARVIND NEGI[2], VINAY KUMAR CHOURASIYA[3], M.K NAUTIYAL[4]

[1,2,4]School of Agriculture, Graphic Era Hill University, Dehradun
[3]Acharya Narendra Deva University of Agriculture and Technology, Kumarganj, Ayodhya-224229
Email: rajneeshbhardwaj8@gmail.com

Lead Author

DR. RAJNEESH BHARDWAJ

Assistant Professor
Graphic Era Hill University,
Dehradun

Dr. Rajneesh Bhardwaj is an accomplished academician and researcher in the field of Genetics and Plant Breeding, currently serving as Assistant Professor at the School of Agriculture, Graphic Era Hill University, Dehradun. He holds a Ph.D. in Genetics & Plant Breeding from GBPUA&T, Pantnagar, with specialization in molecular biology and seed technology. His expertise spans molecular breeding, genetic variability, seed quality enhancement, and biotic stress resistance, with notable research on botrytis grey mold resistance in chickpea. Dr. Bhardwaj has authored multiple peer-reviewed publications and book chapters and has presented at various national and international conferences. His industry and research experience includes quality control in pharmaceutical biotechnology and gene pyramiding in wheat through marker-assisted selection. He has received accolades such as ICAR-NET and USET qualification, and Student Research Awards. A proactive contributor to academic training and sustainable agriculture initiatives, he is also actively involved in workshops and faculty development programs.

Abstract

Artificial Intelligence (AI) is playing a pivotal role in transforming seed quality assurance by offering precise, efficient, and scalable solutions to overcome limitations of traditional methods. This article explores how AI technologies such as machine learning, computer vision, and Internet of Things (IoT) are used for seed sorting, grading, germination prediction, Vigor assessment, disease detection, genetic purity analysis, and supply chain traceability. These technologies enable real-time, non-invasive evaluations and minimize human error, improving the reliability and consistency of seed quality assessments. The review also discusses the main challenges in adopting AI, including high implementation costs, data constraints, and the need for technical expertise. Furthermore, it highlights future research directions focused on accessibility, integration with emerging technologies, and the development of standardized protocols for broader application in seed science..

Keywords: Artificial Intelligence, Seed Quality, Machine Learning, Computer Vision, Seed Viability, Genetic Purity, IoT, Precision Agriculture, Seed Testing, Smart Farming

1. Introduction

Seed quality assurance is a critical component of modern agriculture, ensuring that only healthy, genetically pure, and viable seeds reach farmers. High-quality seeds contribute significantly to crop yield, uniformity, resistance to pests and diseases, and overall farm productivity. Traditional methods for testing seed quality, including physical inspection, chemical analysis, and laboratory-based germination tests, though effective, are labor-intensive, time-consuming, and subject to human error. Artificial Intelligence (AI), encompassing techniques such as machine learning (ML), deep learning, computer vision, and data analytics, is revolutionizing agricultural practices, particularly in seed quality assurance. AI enables automation, precision, and scalability, making it a powerful tool for improving the accuracy and efficiency of seed evaluation processes. This review aims to examine the current role and potential of AI in transforming seed quality assurance across various stages of the seed value chain.

2. AI technologies in Seed Quality assurance (Fig .1)

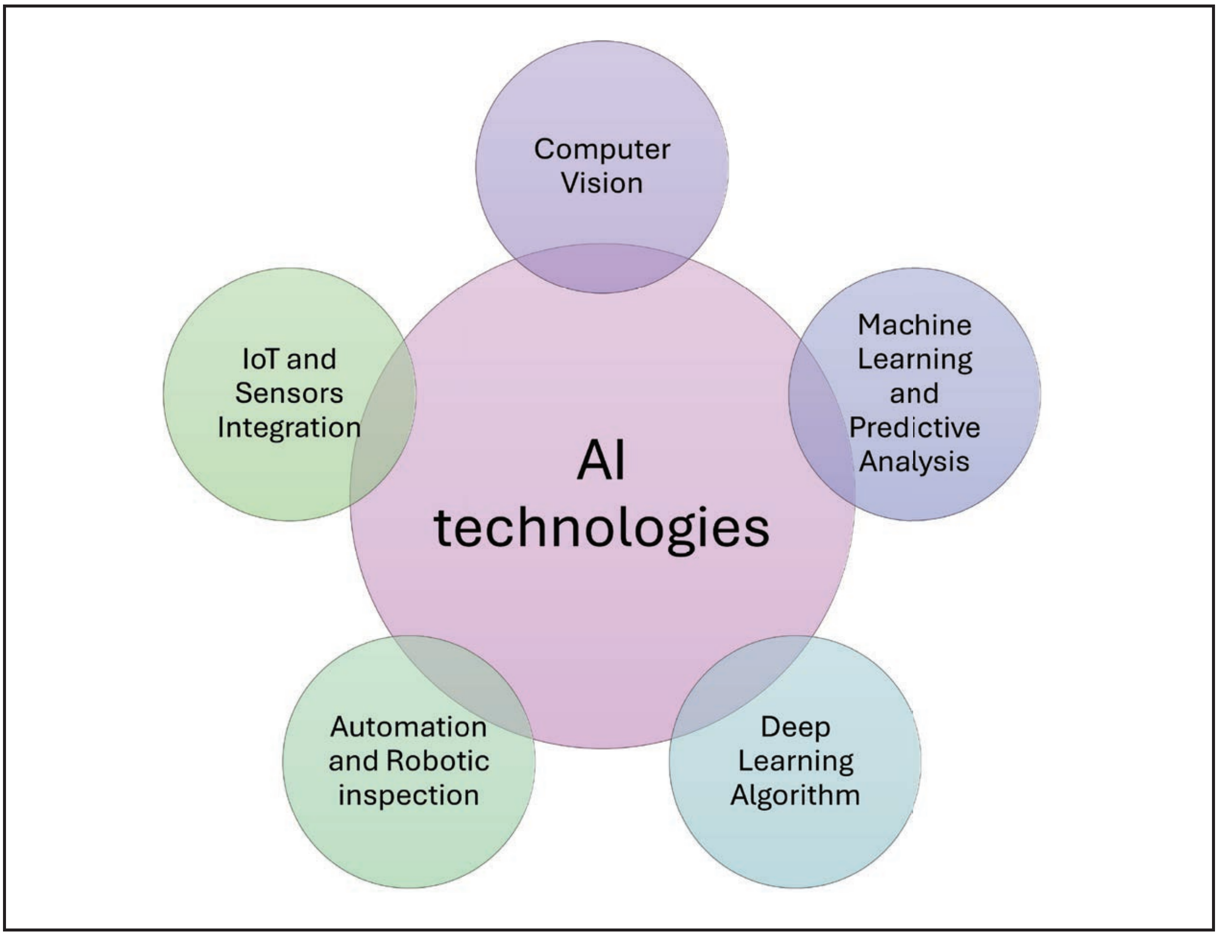

Fig. 1 AI technologies in Seed Quality Assurance

2.1 Computer Vision: Computer vision (CV) significantly enhances seed quality assurance by enabling rapid, non-destructive analysis of seed morphology, defects, and viability through techniques like RGB imaging (85–95% accuracy in sorting), hyperspectral imaging (90–98% accuracy in disease detection), and X-ray microscopy (95–99% accuracy in internal defect identification(Singh et al., 2022; Zhang et al., 2021)(Fig.2). These methods outperform traditional manual inspections in speed (10,000+ seeds/hour), objectivity, and cost-efficiency, with applications ranging from fungal infection detection (e.g., Fusarium in wheat) to germination prediction using deep learning (93% accuracy in 24 hours) (Wang et al., 2023). Challenges include high initial costs (20,000–100,000) and data requirements, but emerging solutions like edge AI and generative models promise wider adoption (FAO, 2023)..

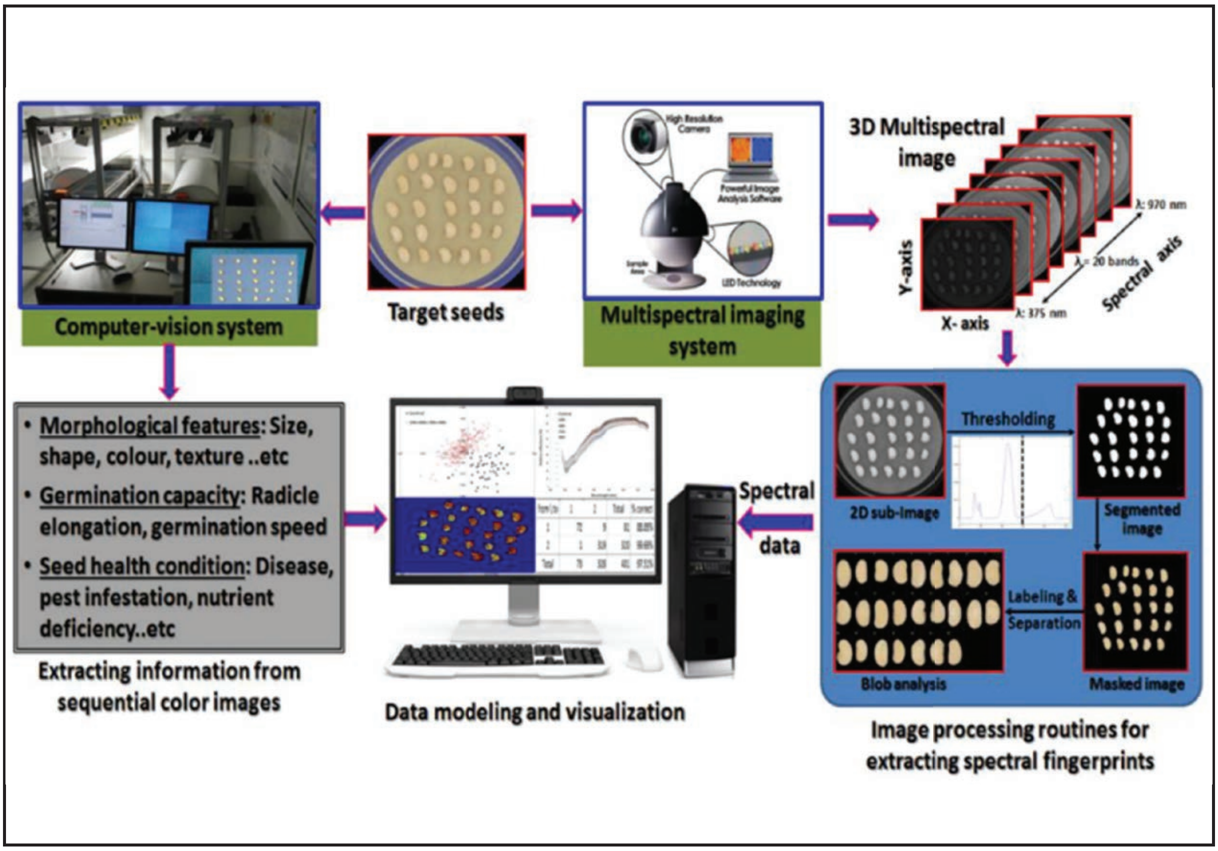

Fig. 2 Schematic representation of a computer-aided image analysis system for seed quality evaluation based on computer-vision and multispectral imaging techniques.(ElMasry et al., 2019)

2.2 Machine Learning And Predictive Analysis: Machine learning (ML) and predictive analytics are transforming seed quality assurance by enabling rapid, data-driven assessment of seed viability, purity, and performance. ML models like convolutional neural networks (CNNs) and random forests analyze seed images, spectral data, and environmental factors to classify varieties (>95% accuracy), detect defects (e.g., fungal infections in <5 seconds), and predict germination rates 24–48 hours faster than lab tests (Wang et al., 2023; Zhang et al., 2022). These methods outperform manual inspections in speed (10,000+ seeds/hour), accuracy (90–98%), and cost-efficiency ($0.001/seed), though challenges remain in data requirements (5,000+ labeled images per category) and model interpretability (Smith et al., 2023). Emerging solutions like generative AI for synthetic data and blockchain for traceability promise to further enhance ML's role in precision seed quality management(Fig. 3).

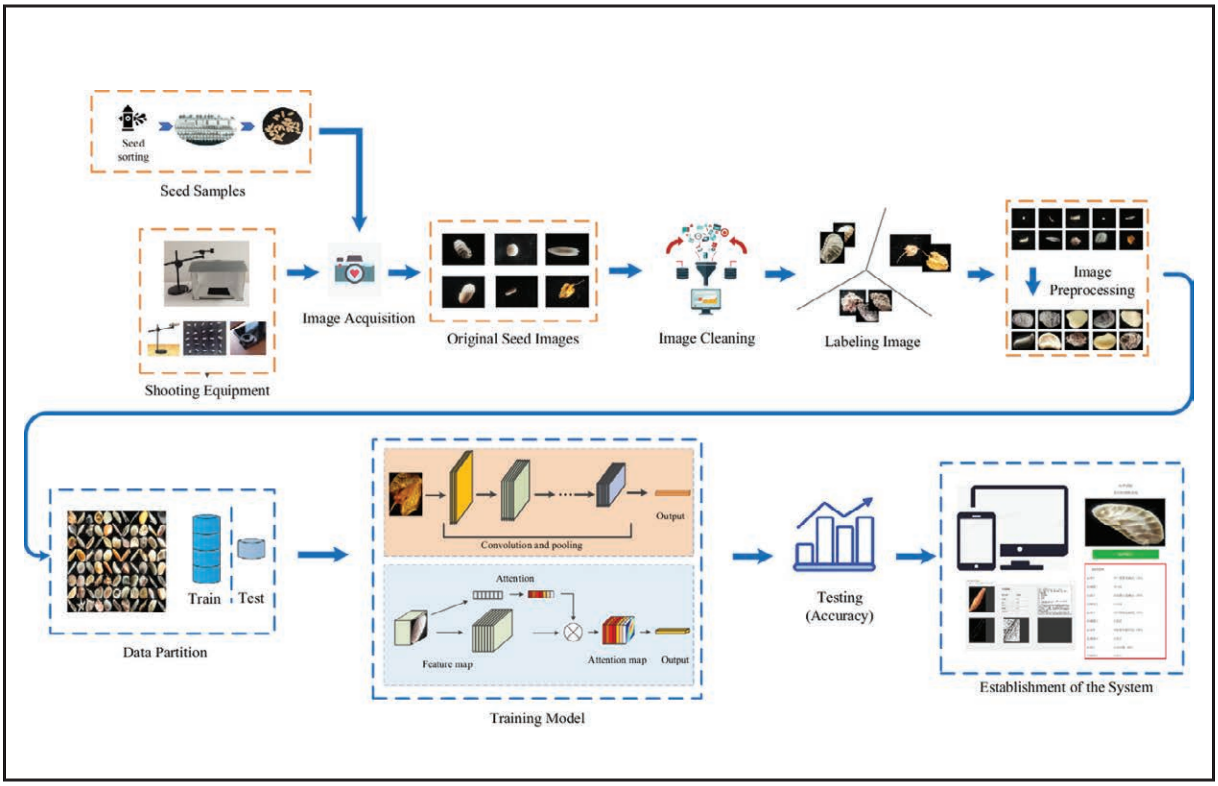

Fig 3 Machine learning training & prediction model for seed quality assurance(Yuan, 2024)

2.3 Deep Learning Algorithms: Deep learning (DL) algorithms are revolutionizing seed quality assurance by enabling automated, high-throughput analysis of seed characteristics with unprecedented accuracy (92-99%). Convolutional neural networks (CNNs) excel in seed classification (96-99% accuracy) and defect detection, while vision transformers and LSTMs predict germination potential days faster than conventional methods. These technologies process 15,000 seeds/hour at a fraction of traditional costs ($0.0002/seed), though they require substantial training data (50,000+ annotated images) and computing resources(Fig 4). Emerging applications include multimodal analysis combining hyperspectral, X-ray, and genomic data, with explainable AI (XAI) techniques building crucial trust among stakeholders. While implementation challenges remain regarding hardware requirements and regulatory standardization, DL's potential to transform global seed certification systems is undeniable, particularly through federated learning approaches that maintain data privacy across organizations (AgriTechX, 2023; Seed AI Labs, 2024; FAO, 2023)

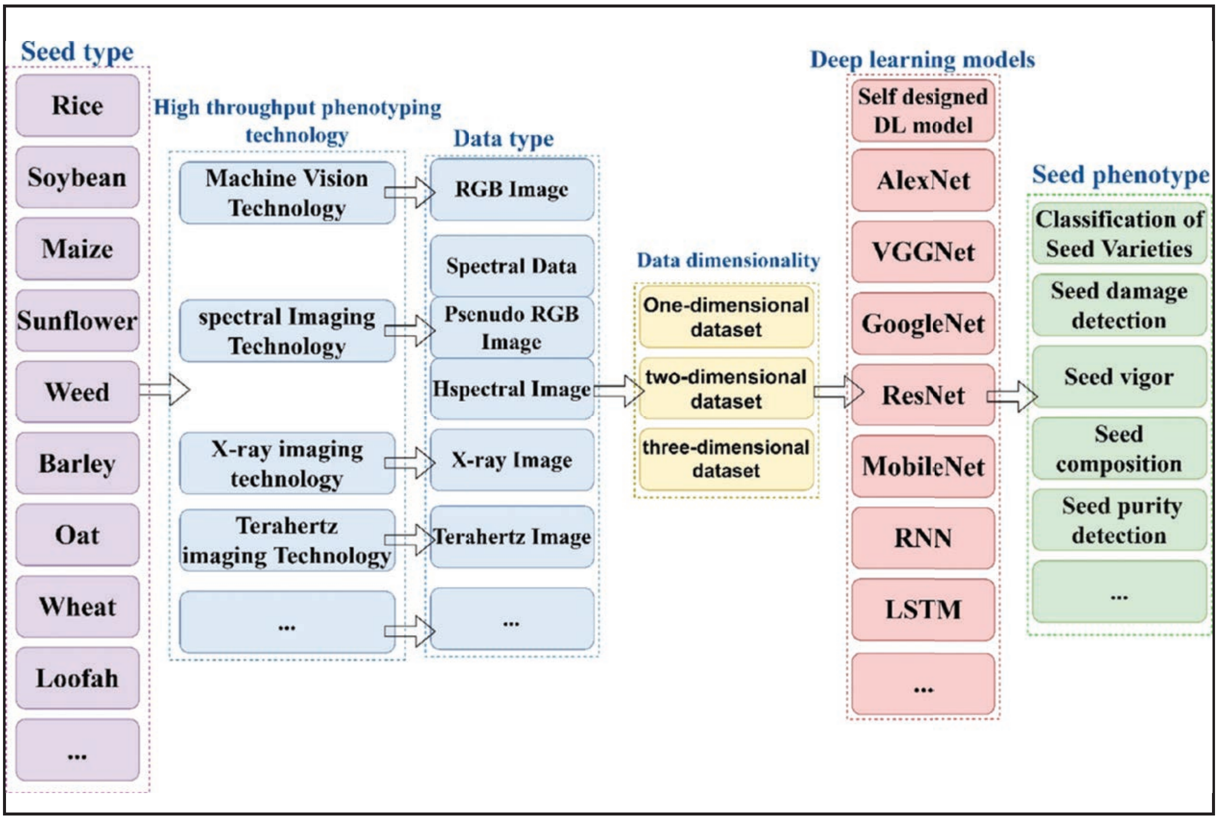

Fig. 4 The general flowchart of deep learning methods for seed phenotyping(Zin et al., 2025)

2.4 Automation and Robotic Inspection: Automation and robotic inspection are revolutionizing seed quality assurance by enabling high-speed, precise, and standardized evaluation of seeds at industrial scales. These systems integrate computer vision, AI-driven sorters, and robotic arms to process 10,000–50,000 seeds/hour with 95–99% accuracy, significantly outperforming manual methods in throughput and consistency (Cimbria, 2023). Applications range from optical defect removal (e.g., cracks, fungal infections) and size/weight grading to automated germination testing and precision seed coating. While initial costs are high (100,000–100,000–500,000), the 60–80% reduction in labour costs and 2–3 year ROI make automation viable for large-scale producers (FAO, 2022). Emerging trends like swarm robotics and blockchain-integrated traceability promise further advancements in seed quality management.

2.5 IoT and Sensor technology: IoT and sensor technologies are revolutionizing seed quality assurance by enabling real-time, data-driven monitoring of storage conditions (temperature, humidity, CO_2), automated seed sorting (via optical/NIR sensors), and predictive germination tracking—improving accuracy to 95–99% while reducing labour costs by 50–70% (FAO, 2023). Integrated with AI and blockchain, these systems ensure traceability from farm to field and prevent spoilage through instant alerts. Challenges like high costs are being addressed by low-cost edge devices and drone-based sensors, paving the way for fully autonomous seed quality management.

3. AI based Seed Testing Methods

AI-based seed testing methods have transformed the seed quality assurance landscape, offering unprecedented speed, accuracy, and non-destructive analysis . The detailed overlook at how these methods work and their practical applications is given below.

3.1 Seed Sorting & Grading

AI-driven seed sorting systems leverage multi-camera machine vision and Convolutional Neural Networks (CNNs) to accurately classify and grade seeds based on features like color, shape, size, and purity. These systems enable real-time, automated sorting with high precision, often combining lightweight or hybrid CNN models for efficiency. Multi-camera setups enhance defect detection by capturing seeds from multiple angles, making the process scalable and adaptable to various crops and quality parameters (Regina et al., 2024). Artificial Intelligence (AI) has revolutionized seed sorting and grading by integrating computer vision, machine learning (CNNs, SVMs), hyperspectral imaging (400-2500nm), and robotic automation to achieve 95–99% accuracy at processing 10,000–50,000 seeds/hour, far surpassing manual methods (FAO, 2023). Advanced systems employ multi-camera arrays (5–20MP resolution) and AI models to analyse morphology, colour, texture, and internal defects (Zhang et al., 2023), while hyperspectral imaging detects fungal infections, moisture content, and chemical composition (IEEE, 2023). Case studies like Bayer's SeedSense (98.2% accuracy, 40% capacity increase) and Syngenta's Quantum Sorter (15,000 seeds/hour, 95% Fusarium detection) demonstrate industrial scalability (Nature Food, 2023). Challenges include high initial costs and data requirements, but emerging solutions like portable edge AI, blockchain traceability, and autonomous robotic sorters promise broader adoption (FAO, 2024). AI-driven systems enhance efficiency, reduce labour costs by 30%, and ensure seed purity and viability, critical for sustainable agriculture (IEEE Transactions on Agri Food Electronics, 2023). The study by de Medeiros et al. (2020) introduced an interactive machine learning approach for classifying soybean seed and seedling quality. By combining interactive and traditional machine learning methods, the researchers achieved high classification accuracies ranging from 0.92 to 0.99 for different seed appearance classes and over 0.90 in independent validation. This method allows for automated, efficient, and non-destructive quality assessment, addressing the limitations of subjective and time-consuming manual inspections. The approach is suitable for integration into seed quality control programs, enabling rapid and accurate sorting of seed lots and identification of quality issues in both industrial and research setting.

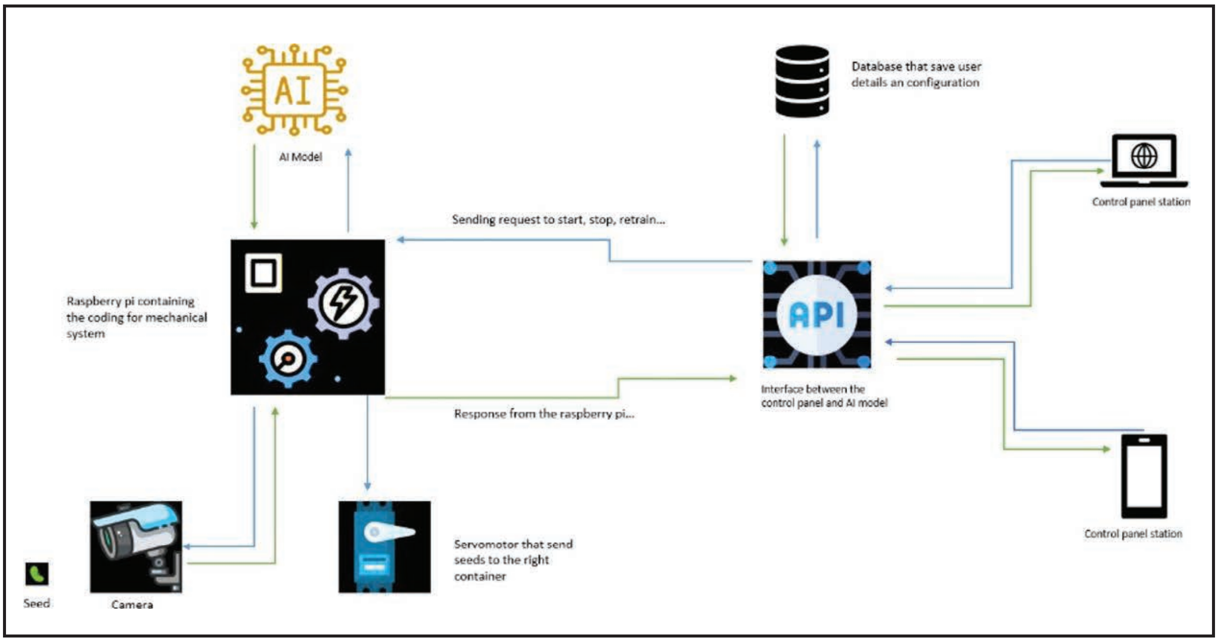

Fig. AI based seed sorting system Setup

3.2 Seed germination Prediction using AI tools:

Artificial intelligence (AI) tools have revolutionized seed germination prediction by offering rapid, non-destructive, and highly accurate assessments of seed viability. Techniques such as Convolutional Neural Networks (CNNs), Support Vector Machines (SVM), and Random Forests are commonly used to analyze seed traits—like image-based features, spectral profiles, and biochemical parameters—to classify germination potential. For instance, Zhang et al., (2022) developed a deep learning model using CNNs to predict maize seed germination from images with 94% accuracy. Similarly, Kumar and Singh (2023) applied hyperspectral imaging combined with SVM to predict soybean germination, achieving over 91% accuracy. These tools outperform traditional germination tests in speed and objectivity and are being increasingly integrated into smart seed testing platforms for crops such as rice, maize, and rapeseed. Despite their effectiveness, model performance can vary depending on seed lot, crop species, and data quality, requiring robust training datasets and validation protocols. The study by Nehoshtan et al. (2021) presents a generic seed germination prediction technology that utilizes deep learning and RGB image data to classify seeds by both germinability and usability. Their approach enables accurate, non-destructive, and high-throughput prediction of seed germination fate across multiple crops and seed lots, using crop-level image data rather than requiring lot-specific training. This technology addresses the challenge of wasteful disqualification of viable seeds, making industrial seed sorting more efficient and reducing financial losses for seed companies by enabling the recovery of good seeds from lots previously deemed unsuitable

3.3 Seed Genetic Purity analysis using AI tools

Artificial intelligence (AI) tools have significantly advanced seed genetic purity analysis by enabling rapid, non-invasive, and high-throughput identification of genetic contaminants and off-types in seed lots. Traditional methods such as grow-out tests or molecular marker-based assays are labour-intensive, time-consuming, and require expert handling, whereas AI-driven approaches analyse phenotypic, spectral, or molecular data using machine learning (ML) and deep learning (DL) models to detect varietal impurities. For example, Rahman et al. (2021) utilized hyperspectral imaging combined with a support vector machine (SVM) algorithm to distinguish between pure and impure hybrid rice seeds with 96% accuracy. Similarly, Singh et al. (2022) applied convolutional neural networks (CNNs) to identify genetic off-types in maize hybrids based on seed morphology and achieved over 93% classification accuracy. These AI tools can be trained on seed images, spectral fingerprints, or molecular profiles, enabling real-time purity checks in seed processing lines, ensuring varietal integrity, and supporting regulatory compliance. However, the effectiveness of AI models depends on robust training datasets, species-specific variability, and integration with validated reference methods.

3.4 Visual inspection of Seeds using AI tools

Visual inspection of seeds using AI tools make use of computer vision and deep learning to automate the assessment of seed quality traits such as size, shape, colour, surface texture, and the presence of mechanical damage or fungal infections. Traditionally performed manually under microscopes or with naked eyes, visual inspection is subjective and prone to inconsistency. AI-powered systems, especially those using Convolutional Neural Networks (CNNs), can process high-resolution images to classify and grade seeds with remarkable speed and accuracy. Chen et al. (2021) developed an AI-based image analysis system that achieved 95% accuracy in identifying damaged wheat kernels. Similarily, Jha and Sinha (2022) used CNN models to inspect soybean seeds for surface defects, achieving precision rates exceeding 93%. These systems can be integrated into seed cleaning and packaging lines for real-time monitoring and sorting, reducing human error and labour costs. Moreover, the combination of multi-angle imaging and deep learning models further enhances detection accuracy and consistency, particularly for heterogeneous seed lots.

3.5 Prediction of Seed health using AI tools

AI-based tools have emerged as powerful solutions for predicting seed health by detecting diseases, fungal infections, insect damage, and physiological deterioration using non-destructive, high-throughput technologies. These systems utilize machine learning (ML) and deep learning (DL) models to analyse visual, spectral, and biochemical data captured through imaging technologies like hyperspectral imaging (HSI), X-ray radiography, and thermal imaging. For example, Baranowski et al. (2020) used hyperspectral imaging combined with machine learning algorithms to detect fungal infection in cereal seeds with over 92% accuracy. Similarly, Soni et al. (2022)

applied convolutional neural networks (CNNs) to identify seed-borne pathogens in chickpea seeds using RGB images, achieving an accuracy of 94%. AI systems can detect subtle visual cues like discoloration, shriveling, or internal voids, often invisible to the human eye, allowing early detection of health issues before sowing. These predictive capabilities improve seed lot quality management, reduce post-sowing losses, and support phytosanitary inspections in seed certification.

4. Advantages of AI-Based Seed Testing

AI-based seed testing offers numerous advantages, including high accuracy, speed, and non-destructive analysis. It enables rapid and consistent evaluation of large seed batches with minimal human intervention, reducing labour costs and errors. AI systems can detect seed defects and viability issues early, generate valuable data insights, and adapt to various crops and traits. Additionally, they are environmentally friendly and can be integrated with smart farming technologies for improved decision-making and efficiency in seed quality assurance.

4.1 Non-Destructive Testing

AI technologies facilitate non-invasive assessment of seed quality, preserving the physiological integrity and viability of seeds. Unlike conventional methods such as tetrazolium staining or germination tests, which may damage or consume the seeds, AI-based methods (e.g., hyperspectral imaging and computer vision) allow for reusable seed material in further production or research.

4.2 High Throughput Capacity

AI systems, especially those integrated with high-resolution imaging and machine learning algorithms, allow for the rapid assessment of thousands of seeds per hour. This scalability is crucial for modern agriculture and seed industries that handle large volumes (Patrício & Rieder, 2018).

4.3 Consistency and Objectivity

Human evaluation of seed traits like color, size, or disease symptoms is prone to subjective errors and fatigue. AI systems operate on pre-trained algorithms that ensure each seed is evaluated under the same parameters, offering reliable and reproducible outcomes (Barbedo, 2016).

4.5 Early and Accurate Defect Detection

AI, particularly deep learning and convolutional neural networks (CNNs), can identify microscopic defects or stress indicators invisible to the naked eye. This leads to early detection of pathogens, physiological deterioration, or genetic anomalies, improving the overall seed quality pipeline (Singh et al., 2020).

4.6 Cost and Labor Efficiency

Although the initial setup for AI tools may be high, the long-term reduction in labor costs, consumables, and human error leads to substantial economic benefits. The automation of repetitive tasks allows skilled personnel to focus on higher-value activities like decision-making and breeding strategy development (Jayas et al., 2010).

5. Traditional vs AI based seed testing Methods

AI-based seed testing offers faster, more accurate, and non-destructive analysis compared to traditional methods, which are often time-consuming, labour-intensive, and prone to human error. While traditional techniques like germination and purity tests rely on manual processes, AI uses technologies such as computer vision, deep learning, and hyperspectral imaging to assess seed quality efficiently. AI systems can process large volumes of data quickly with consistent results, making them highly scalable and cost-effective in the long run. Despite its advantages, AI requires a high initial investment, whereas traditional methods remain useful in settings with limited resources or regulatory requirements.

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Transforming Seeds Supply Chain using QR Codes

MR. DASHMESH SINGH
PROJECTS DIRECTOR
DASH TECHNOLOGIES AND LABELS PVT. LTD
Email : dashmesh@dashtechlabels.com

Lead Author

MR. DASHMESH SINGH

Projects Director
Dash Technologies and Labels Pvt. Ltd

Mr. Dashmesh Singh is a technology leader with a strong background in computer science, design thinking, and artificial intelligence. He began his career as an AI Engineer at Samsung, where he contributed to advanced machine learning solutions. Driven by a passion to apply technology for meaningful social impact, he joined Dash Technologies to lead digital transformation in traditionally underserved sectors. In the seeds industry, he is spearheading initiatives that bring transparency and traceability through digital tools—empowering farmers, enhancing supply chain efficiency, and ensuring product authenticity. His solutions integrate technologies like QR code systems with intuitive interfaces tailored for real-world users. Dashmesh's work reflects a commitment to inclusive innovation, where technology serves not just business goals, but broader community benefits. With a vision to bridge the gap between modern tech and grassroots needs, he continues to explore new ways to create value through responsible and practical digitization.

Executive Summary

Agriculture, once primarily driven by traditional knowledge and manual labour, is undergoing a significant transformation propelled by the adoption of digital technologies. Globally, the agri-tech sector is projected to surpass USD 43 billion by 2030, with a compounded annual growth rate (CAGR) exceeding 12%, driven by the integration of IoT, AI, blockchain, and data analytics in farming practices. In India alone, the agritech market is expected to reach USD 24 billion, yet current penetration is less than 1%, indicating a vast untapped opportunity for innovation-led interventions.

Seeds, being the most fundamental and irreplaceable agricultural input, influence not only crop yield and farm economics but also the national food security. Yet, the sector is tainted by counterfeit seed circulation, opaque distribution networks, and poor access to verified product information by end-users. The Food and Agriculture Organization (FAO) has repeatedly highlighted that seed quality directly impacts up to 30% of agricultural productivity, making the need for trust, traceability, and accountability paramount.

While precision agriculture and drone-based monitoring often capture headlines, it is the less- glamorous yet foundational technologies—such as traceability platforms—that offer transformational potential for supply chain integrity, especially in the seeds ecosystem, which is the starting point of every harvest.

Traceability in the agricultural seed supply chain is vital for ensuring transparency, trust, quality assurance, regulatory compliance, and combating counterfeit seeds. The use of QR codes linked to digital traceability systems can revolutionize the way seed information is tracked and accessed across the value chain.

QR code-based digital traceability—a practical, scalable, and farmer-friendly solution. When implemented using global standards, QR codes transform seed packets from ordinary packaging into intelligent, interactive data carriers. These codes can store and link to a dynamic digital trail capturing every stage of a seed's journey—from breeding and testing to logistics and retail distribution—accessible with a simple smartphone scan.

The evolution of QR-based traceability also aligns with broader national and international digitization efforts such as India's AgriStack and the Sustainable Development Goals (SDGs).

Key Challenges Faced by the Seed Industry in India

The seed industry in India is at the nucleus of the nation's agricultural economy. Yet despite its strategic importance, the sector is beset by a myriad of complex challenges that span regulatory, operational, technological, and socio-economic dimensions.

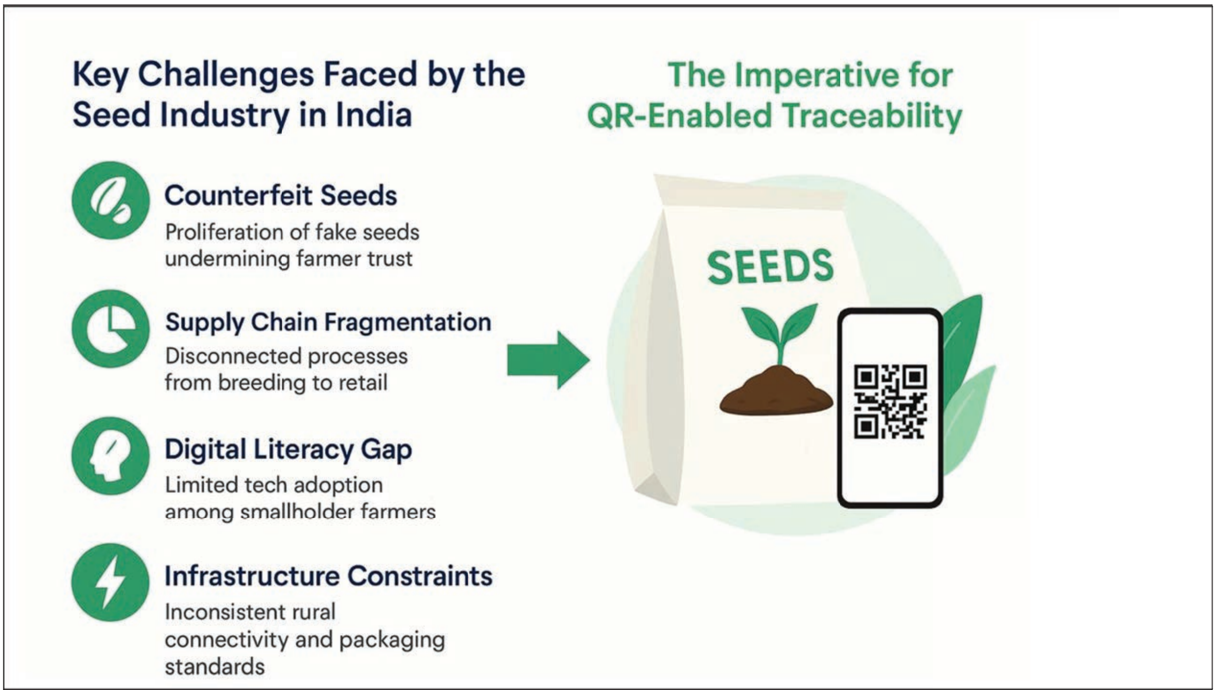
1. Counterfeiting and Substandard Seed Proliferation

Counterfeit and substandard seeds remain perhaps the most pressing issue. In informal or unregulated markets, estimates indicate that up to 20–25% of seed packets are counterfeit, leading to catastrophic crop failures and unprecedented financial hardship for farmers. These fraudulent products often bear forged brand marks, incorrect genetic purity labels, or manipulated germination dates. The absence of a reliable authentication mechanism makes it virtually impossible for farmers to distinguish genuine seeds from imposters. Consequently, lost yields can range from 15% to 50%, directly impacting both rural livelihoods and national food security. In addition, widespread counterfeiting erodes brand reputation, increases legal disputes, and inflates the cost of enforcement for regulatory bodies.

2. Supply Chain Fragmentation and Lack of Data Integration

The seed supply chain in India typically involves a complex network of breeders, contract growers, processing units, distribution channels, and retail outlets. Each stage operates on disparate data systems—if digital records exist at all—leading to massive information silos. For example, a breeder's varietal purity test results may reside in a laboratory's local database, while packaging information is maintained in a separate ERP system, and distributor inventory data may be tracked manually on spreadsheets. This fragmentation prevents end-to-end visibility, making it difficult to reconcile dispatch and receipt records, manage recall operations, or analyze demand patterns.

3. Quality Control Limitations and Recall Inefficiencies



Effective quality control in seeds involves rigorous germination tests, purity analyses, and field trials, all of which generate large volumes of data. Unfortunately, in many processing and packaging facilities, these records are maintained in paper logs or basic spreadsheets, rendering them vulnerable to loss, errors, and tampering. In the event of a quality breach or disease outbreak, tracing a defective batch back to its origin can take weeks or even months. The manual nature of recall processes—issuing circulars, deploying field inspectors, and collecting returned packets—amplifies costs and reduces responsiveness. In worst-case scenarios, delayed recalls exacerbate yield losses, severely impacting farmer incomes and tarnishing brand credibility.

Seeds, being the most fundamental and irreplaceable agricultural input, influence not only crop yield and farm economics but also the national food security. Yet, the sector is tainted by counterfeit seed circulation, opaque distribution networks, and poor access to verified product information by end- users. The Food and Agriculture Organization (FAO) has repeatedly highlighted that seed quality directly impacts up to 30% of agricultural productivity, making the need for trust, traceability, and accountability paramount.

4. Infrastructure Constraints and Technology Adoption Barriers

While larger seed companies have begun investing in automated packaging lines and basic digital platforms, many proprietary or family driven small and medium enterprises (SMEs) still operate with minimal IT infrastructure. High upfront costs for label printers capable of variable data printing, rugged handheld scanners for field operations, and robust internet connectivity in rural warehousing sites pose significant barriers. In regions with unreliable power supply or connectivity, even cloud- based solutions become impractical without fallback mechanisms. These constraints disproportionately affect rural cooperatives and small-scale processors, who form a substantial portion of the industry.

5. Digital Literacy and Farmer Engagement Challenges

The Indian farming community—especially in Tier II and Tier III regions—often has limited experience with digital tools. While smartphone penetration is rising, proficiency in scanning QR codes beyond payment and navigating mobile web pages remains low. Language diversity further complicates matters: India has 22 + languages and hundreds of local dialects, requiring multilanguage support for digital content. Without targeted awareness campaigns, field training, and user-centric design (large fonts, voice prompts, localized content), the intended benefits of traceability systems risk remaining untapped.

6. Cost and Scalability Considerations

Implementing a traceability solution with serialized QR codes involves both capital and operational expenses: hardware procurement (printers, scanners), software development/customization, integration with existing ERPs, and ongoing subscription or hosting fees. For small-volume seed packs—such as specialty horticultural seeds or research samples—the per-unit cost of QR code generation and printing can be prohibitive. Moreover, scaling the solution across multiple product lines and regions requires careful capacity planning to avoid system bottlenecks and ensure high uptime SLAs. Subscription-based pricing models may be attractive initially but can escalate as transaction volumes rise, necessitating clear ROI projections and tiered pricing schemes.

7. Standardisation and Interoperability Gaps

Without adherence to a common data standard, sharing traceability records with regulatory bodies, export partners, or downstream distributors becomes cumbersome. Standardization extends beyond code syntax to include data semantics (defining what constitutes a batch, expiry date format, etc.), requiring industry-wide coordination and adherence to best practices.

8. Market Seasonality and Operational Volatility

Seed demand and distribution are highly seasonal, concentrated around key planting windows. This creates operational spikes in packaging, dispatch, and field distribution. Systems must handle sudden surges in QR code generation and scan events without degradation. Additionally, price volatility—driven by monsoon performance, commodity markets, and crop cycles—can alter SKU priorities and logistic routes on short notice, demanding agile traceability processes.

9. Data Privacy, Security, and Compliance Concerns

Collecting and storing detailed traceability data—ranging from genetic lineage to farmer location— raises privacy and security questions. Companies must implement end-to-end encryption, secure API gateways, and role-based access controls to safeguard sensitive information. Compliance with emerging data protection regulations (such as India's proposed Personal Data Protection Bill) is crucial to avoid legal penalties and maintain stakeholder trust.

Understanding QR Code Technology and Its Role in Traceability

Quick Response (QR) codes have evolved into one of the most practical and versatile tools for identification and authentication across industries. Originating in the 1990s to track automotive parts, their rapid readability and high data storage capacity made them ideal for a broad range of use cases—from mobile payments and e-tickets to pharmaceutical authentication and agricultural traceability.

In the seed industry, where every packet has a high impact on the nation's food security, QR codes offer a transformative approach to ensure transparency, real-time data access, and trust across the value chain. The advent of URL–based QR codes takes this one step further by integrating global standards with scalable, cloud-based data delivery.

Structure and Format of QR Codes

A QR code is a matrix barcode that stores data in a two-dimensional format. It consists of black squares arranged on a white background, which can be scanned using a smartphone or industrial barcode scanner. A single QR code can encode more than 3,000 alphanumeric characters, with URL based QR's, geolocation tracking, batch serialization, and authentication records becomes more feasible.

Static vs Dynamic QR Codes

- **Static QR** Codes are hardcoded with data and cannot be changed once printed. They are suited for one-time, non-updatable applications such as basic product info.
- **Dynamic QR** Codes point to a cloud-hosted link (redirect URL) which can be updated anytime, enabling version control, real-time alerts, and scan analytics.

Key Features in Seed Industry Applications

Individual Serialization

Each seed packet is assigned a unique identity (UID) encoded into its QR code. This enables packet- level traceability for anti-counterfeit, returns, and complaint management.

Dynamic Content Hosting

Scanned codes can reveal multilingual sowing guides, certification documents, videos, and field advisories customized by region or crop.

Real-Time Authentication

When scanned by CFA, retailers, or farmers, the system cross-verifies the scanned data with expected distribution zones, flagging any unauthorized or suspicious scans.

Regulatory Compliance

QR codes can serve as digital compliance carriers by embedding testing reports, certification details, and origin trace—all accessible by inspectors or exporters.

Recall Management

If a batch fails post-market testing, affected farmers and retailers can be notified through scan history, SMS alerts, or in-app notifications.

Geo-Analytics

Every scan can be timestamped and geotagged, allowing analytics dashboards to show heatmaps of usage, distribution density, or counterfeiting clusters.

Integration with Packaging & ERP Systems

- Modern seed packaging facilities can integrate QR printing inline using:
- Thermal Inkjet Printers for flexible printing on paper and plastic
- Laser Etching for permanent, tamper-proof codes
- Label Applicators with pre-printed QR stickers

These systems can pull serial numbers from a central database and update dispatch records via middleware linked to ERP (SAP, Tally, Zoho, etc.), ensuring no duplication or misuse.

Security and Anti-Counterfeit Mechanisms

QR-based traceability platforms also offer anti-counterfeit features:

- Scan-limit enforcement: Detects abnormal scanning frequency
- Location intelligence: Flags scans from out-of-territory regions

- Duplicate scan detection: Warns if the same code is reused
- Blockchain add-ons: Immutable audit trail for premium-grade seeds
- QR Scanning & Farmer Interface

For the end user—the farmer—scanning a QR code should be seamless. On scanning:

- A browser opens with the product's digital identity page.
- Multilingual content loads based on the user's device language.
- Farmers can see sowing dates, storage instructions, and warranty.
- Optional fields may also collect farmer feedback, sowing confirmation, or images, closing the traceability loop.
- Offline Use and Inclusion
- QR solutions are increasingly inclusive:
- QR codes can include SMS fallback instructions for non-smartphone users.
- Offline scanning apps cache data and sync when internet resumes.

Technical Infrastructure requirements

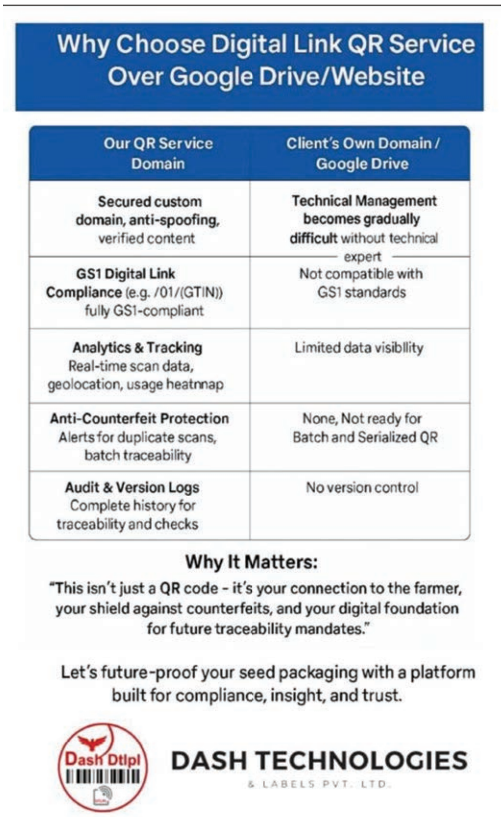
The ideal traceability application involves the following components:

a. QR Generation Engine

- Hosted on secure cloud
- Able to scale and manage millions of QR code
- Structured using global standards

b. Content Management

- Upload brochures, test results, and advisories
- Version history for audit trail
- Language selector and download options



Our QR Service Domain	Client's Own Domain / Google Drive
Secured custom domain, anti-spoofing, verified content	**Technical Management becomes gradually difficult** without technical expert
GS1 Digital Link Compliance (e.g. /01/(GTIN)) fully GS1-compliant	Not compatible with GS1 standards
Analytics & Tracking Real-time scan data, geolocation, usage heatnnap	Limited data visiblity
Anti-Counterfeit Protection Alerts for duplicate scans, batch traceability	None, Not ready for Batch and Serialized QR
Audit & Version Logs Complete history for traceability and checks	No version control

c. APIs for Integration

- Connect to seed ERP systems
- Share data with regulators via public APIs
- Distributor app integrations for scan tracking

d. Mobile App Interface

- Multilingual
- Offline scan cache
- Farmer help button, feedback module

e. Dashboard & Analytics

- Heatmap of scans by region
- Fraud detection via scan anomalies
- Report builder for compliance reviews

Hardware Infrastructure Requirements

- QR Code Printers: Thermal inkjet or laser printers capable of variable data printing
- Labeling Systems: Integrated with packaging lines
- Handheld Scanners: For warehouse, distributors, and audit teams
- Mobile Devices: Android/iOS for farmer scan access
- Servers or Cloud Hosting: High uptime cloud platform for QR redirection and file storage

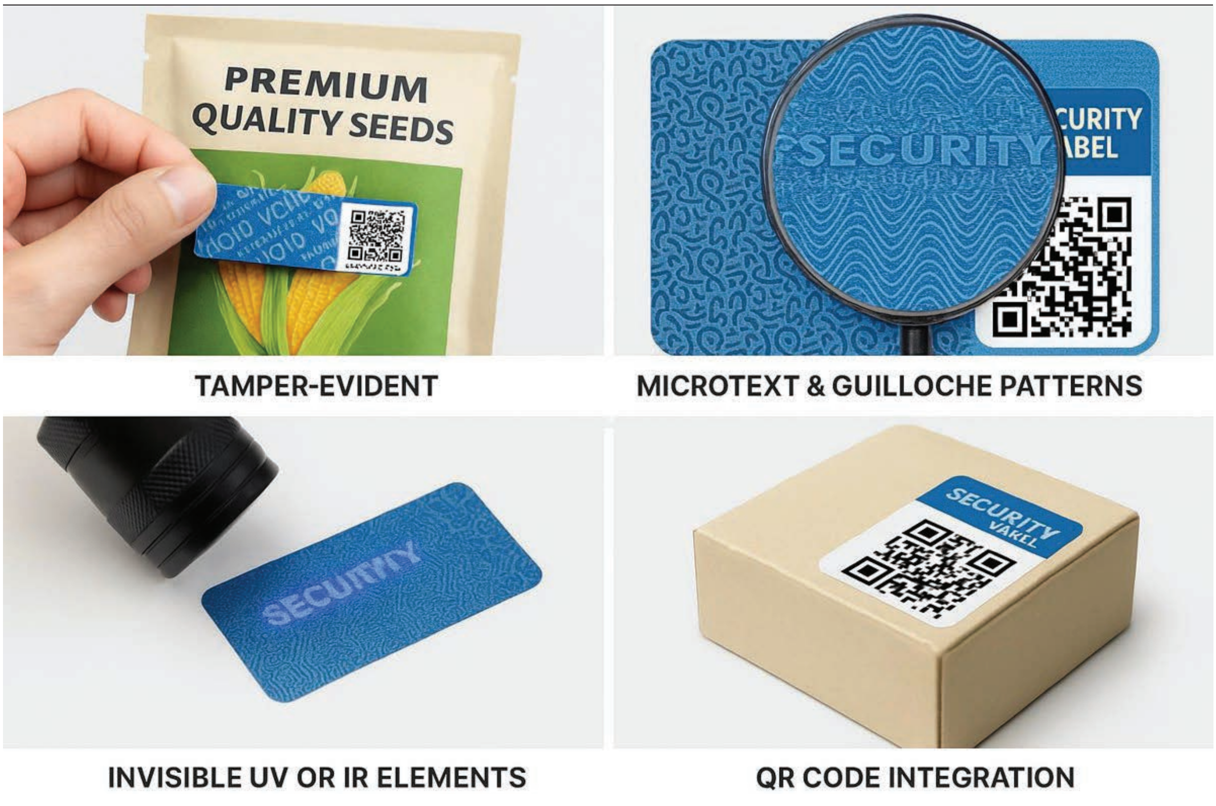
Covet Security features on QR code labels

While QR code–based traceability has emerged as a powerful digital solution for serialization and lifecycle tracking, there's an increasing need for physical security to complement digital intelligence.

Covet Security Label—a next-generation, tamper-evident, multi-layered security label that integrates seamlessly with QR codes to form a robust authentication system. Covet labels act as the physical shield to a product's digital soul, ensuring that any physical compromise to the seed packet is immediately visible while enabling real-time validation through QR scanning.

1. What is a Covet Security Label?

A Covet Security Label is a specialized security tag applied to seed packaging, designed to provide visual authentication, tamper indication, and brand integrity assurance. These labels are often made using advanced materials and printing technologies that combine overt and covert security features.



2. Key Features of Covet Security Labels

a. Tamper-Evident Construction

Covet labels are built with tamper-evident adhesives that leave visible marks if someone attempts to peel or reposition them. For example, they may:

- Break apart into fragments when tampered with (“destructible labels”)
- Leave behind text like “VOID” or “OPENED”
- Change color upon attempted removal

This ensures that once applied to the seed packet, any unauthorized access or reuse of the packaging is immediately visible, deterring repackaging fraud or resale of used bags.

b. Microtext and Guilloche Patterns

Covet labels often include microprinting and guilloche lines—fine, intricate patterns that are extremely difficult to replicate without precision equipment. Microtext appears as a solid line to the naked eye but reveals legible text under magnification.

These features are nearly impossible for counterfeiters to duplicate accurately, thus providing a visual line of defense against copied or fake labels in the market.

c. Invisible UV or IR Elements

Certain versions of Covet labels incorporate invisible inks that become visible only under UV light or infrared scanning devices. These covert features are especially useful during spot checks by regulatory bodies or during warehouse audits where packaging may appear genuine but lacks hidden markers.

d. QR Code Integration

At the heart of the system is a serialized QR code, which is either printed on or embedded within the Covet label. Each code is uniquely tied to a seed packet via Unique item code+ serial number + batch number (e.g. https://yourdomain.com/01/6151234567890/21/XYZ123). Points to a cloud-based landing page containing dynamic product data, test reports, and certification documents

Records scan events (time, location, device) for analytical reporting

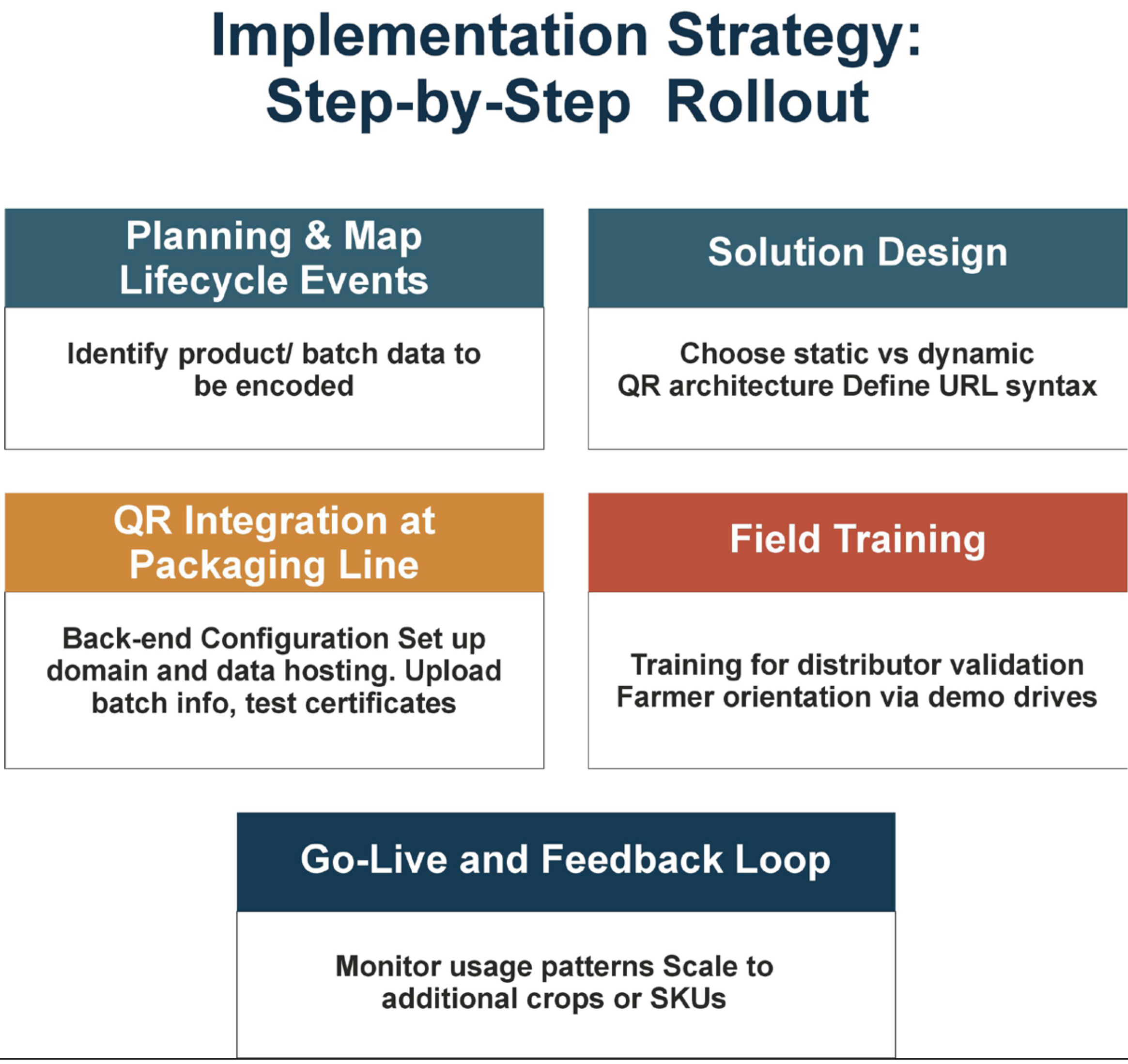
By integrating physical (Covet label) and digital (QR code) verification, the system provides dual- layer authentication for end-users and regulators alike.

Additional options include:

- Holographic foils with pattern shifting
- Nano-text or forensic taggants
- Digital watermarks visible under software filters

These make the label function as a fingerprint for the product, providing track-and-trace visibility throughout the seed's lifecycle.

Implementation Strategy:



1. Planning & Map Lifecycle Events

This initial step involves documenting all critical touchpoints in the seed's journey—from production, packaging, and warehousing to distributor dispatch and farmer delivery. Teams must define who scans what and when, and what data needs to be captured at each event. A clear lifecycle map forms the foundation for designing the QR system architecture. It ensures that no data node is missed, enabling accurate traceability and seamless data flow. This stage also includes identifying stakeholders (internal teams, CFA, field officers) who will be trained or affected during rollout.

2. Identify Product / Batch Data to Be Encoded

Here, you finalize the set of product-specific and batch-level details that will be embedded in or linked to the QR code. Typically, this includes GTIN (product ID), batch number, manufacturing date, expiry, and serial number. Optional fields could be test reports, sowing advisories, and storage instructions. This step ensures consistency across packaging lines, databases, and cloud platforms. The data structure must also meet regulatory standards (like GS1 Digital Link format) and allow easy updates post-printing where dynamic QR codes are used.

3. Solution Design

In this phase, the solution blueprint is developed to suit business requirements. Decisions include the type of QR system (static, dynamic, or hybrid), hosting preferences (cloud or on-premise), and integration needs (ERP, distributor apps, scan dashboards). Workflows are defined for each actor in the supply chain. UI/UX wireframes for scan landing pages are created. The outcome is a complete solution design document including architecture, roles, permissions, and user stories, which then becomes the implementation playbook.

4. Choose Static vs Dynamic QR Architecture

You must now determine the architecture best suited for your needs. Static QR codes embed fixed data directly into the code (e.g., a PDF link or label text), whereas dynamic codes point to a cloud- hosted URL that can be updated after printing. Dynamic QR offers flexibility, analytics, content personalization, and version control—ideal for compliance and traceability. This step involves considering cost, scalability, security, and control over data updates. Many firms prefer a hybrid model: static base with dynamic fallback.

5. Define URL Syntax

Standardizing your QR URLs is critical for compliance, interoperability, and downstream integration. Following GS1 Digital Link syntax is best practice. The structure typically includes GTIN, serial, batch, and expiry parameters (e.g., /01/{GTIN}/21/{Serial}/10/{Batch}). This structure enables auto- extraction by compatible software and audit systems. Proper syntax also reduces scanning errors and ensures traceability across systems. This step also considers domain choices (your brand or QR provider) and the need for multilanguage or region-specific landing pages.

6. QR Integration at Packaging Line

Once architecture and URLs are ready, integration at the packaging line begins. QR codes are printed on labels or directly on seed packets using Thermal Inkjet or Laser printers. Print management software links each QR to the central database. Staff are trained to handle variable data printing, verify correct placement, and test code readability. Automated QA ensures that printed QR codes pass verification checks. This is where physical meets digital—turning packaging into a traceable asset.

7. Back-End Configuration

Here, the system backend is configured to host and serve QR data securely. Content Management Systems (CMS) are connected to QR databases, batch upload tools are enabled, and admin rights are set up. SSL certificates, domain DNS, and user access layers are implemented to safeguard data.

Workflow automation for uploads, alerts for duplicate scans, and dashboards for real-time analytics are activated. Testing is done to ensure system readiness before data is pushed live.

8. Set Up Domain and Data Hosting

A critical part of the backend is selecting and setting up a branded domain (e.g., https://qr.yourcompany.com) that hosts the scan data and landing pages. Secure cloud hosting (AWS, Azure, etc.) ensures uptime, global reach, and scale. Redirection logic for multilingual access, expired codes, or batch recalls is also configured here. A strong domain presence lends authenticity and professionalism, differentiating your brand from competitors using free or insecure QR URLs like Google Drive links.

9. Upload Batch Info, Test Certificates

In this stage, seed batch information—lot size, genetic test reports, germination certificates, and handling instructions—are uploaded to the CMS or database. Each QR code is linked to this unique data, ensuring traceability and transparency. This info may be hosted as PDFs, mobile-friendly pages, or media files. Version logs ensure audit trail compliance. The goal is to create rich, accessible content that farmers, distributors, and regulators can view instantly after scanning the code.

10. Field Training, Training for Distributor Validation

To ensure system adoption, training must be rolled out for field staff and distributors. This includes hands-on practice with scanning devices, how to verify code authenticity, report anomalies, and handle returns using the system. Simulations and mock dispatches are run to test understanding. Training materials include videos, FAQs, manuals, and demo kits. Field validation ensures distributors do not misuse or bypass the system and helps in collecting feedback to refine processes.

11. Farmer Orientation via Demo Drives

Farmers, as the ultimate users, need basic digital awareness to extract value from QR codes. Demo drives in villages, co-operative centers, and agri-retail stores help introduce scanning practices, landing page use, and information access. Visual aids, local-language instructions, and voice-over tools enhance understanding. Collaborations with local agri-dealers or NGOs can drive adoption faster. Some companies also incentivize farmers for scanning via loyalty points, warranty activation, or mobile recharge coupons.

12. Go-Live and Feedback Loop

With everything configured and field-tested, the system is deployed. Early go-live is done in selected geographies or SKUs as a pilot. A feedback loop is established to monitor bugs, correct print errors, and assess scan volume. Teams are on alert to manage returns, farmer complaints, or analytics gaps. QR scan dashboards are monitored daily. Farmer feedback is logged to assess user-friendliness and informational value. This stage marks the live test of end-to-end QR traceability.

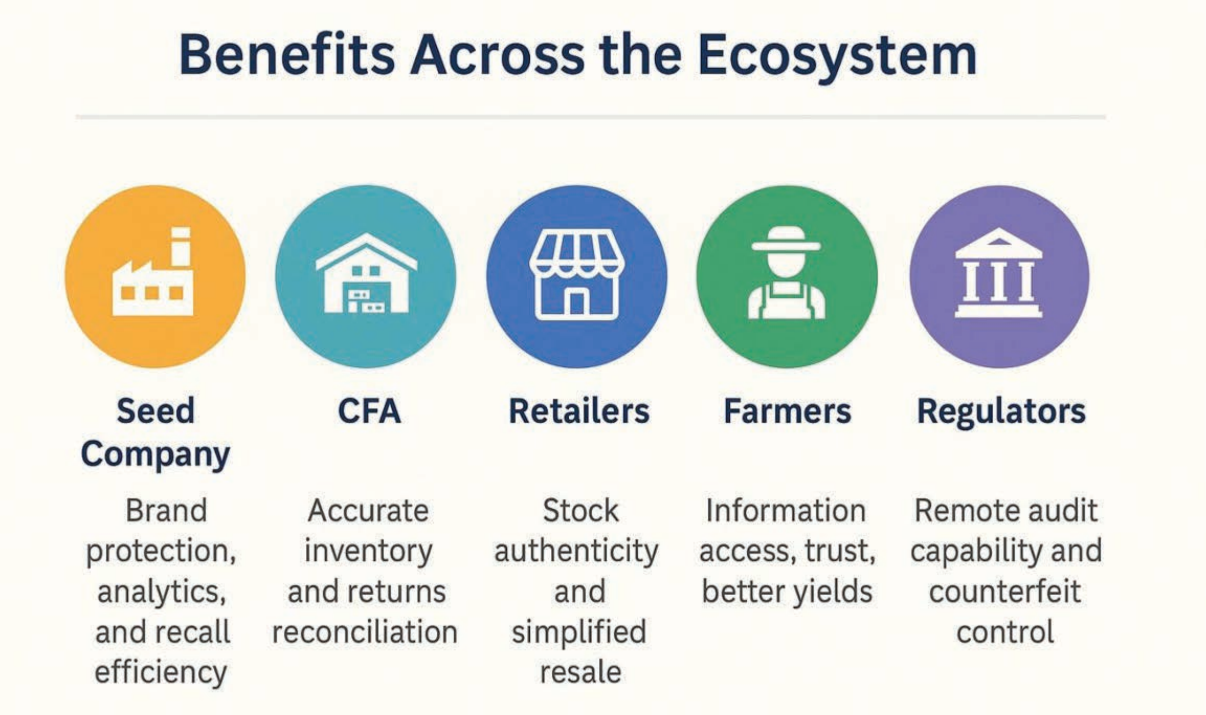
13. Monitor Usage Patterns

Post-deployment, the system continuously collects data on scan counts, location heatmaps, bounce rates, and engagement time. Abnormal patterns (e.g., many scans from one region, duplicate scans) can indicate fraud or misuse. Regular reports are generated for internal teams and compliance officers. KPIs like farmer reach, average scan frequency, and QR code error rates are monitored to guide future upgrades. This analytics layer closes the feedback loop and feeds into product and marketing decisions.

14. Scale to Additional Crops or SKUs

Once the system stabilizes, scale-up begins. Additional crops, seed categories, geographies, or business units are onboarded. Templates, training modules, and backend configurations are reused for faster implementation. Learnings from pilot rollouts are incorporated to streamline future projects. Strategic planning ensures hosting capacity, print infrastructure, and training bandwidth can support increased volume. Partnerships with retailers and agri-fintech players can help extend traceability into the post-sale advisory ecosystem as well.

Benefits of QR code implementation:



The benefits of implementing a QR-based traceability system in the seed industry include:

- **Real-Time Verification**: Allow farmers, officials, and retailers to verify the authenticity of seeds using smartphone-based QR scans.
- **Transparency:** Offer end-to-end visibility of the seed journey from breeder to field.
- **Enhanced Farmer's Trust:** Empower farmers with access to relevant information like certification, shelf life, and usage guidelines.
- **Data-Driven Decisions**: Help manufacturers use scan data to assess regional trends and improve logistics.
- **Anti-Counterfeit:** Prevent fraudulent repackaging and distribution of low-quality seeds.
- **Compliance:** Ensure that seed packets comply with Seed Act, govt norms, and export documentation requirements as applicable.

Cost and ROI Perspective

While implementing QR code infrastructure does involve initial investments in printers, hosting, and software, it creates long-term value across the entire ecosystem. The return on investment is reflected not just in financial gains, but in enhanced trust, transparency, and operational efficiency.

Benefits include fewer customer complaints and legal disputes, stronger brand reputation that supports premium positioning, smoother audit and compliance processes, and significant reductions in product returns, misrouting, and counterfeiting—ultimately empowering businesses, distributors, and farmers alike.

- Reduced complaints and litigations
- Brand credibility and premium pricing
- Streamlined audits and reporting
- Lower returns and misrouting

Future Innovations

As Covet labels evolve, integration with NFC chips**,** blockchain**, and** dynamic visual **elements (like color-changing ink or app-based verification) is becoming feasible—even for high-volume, low-cost units like seeds. Companies can customize** label security based on geography, crop type, or distributor profile.

Conclusion

The use of QR codes is no longer a cosmetic packaging upgrade — it is the backbone of an accountable, modern, and farmer-friendly seed supply chain. With evolving government mandates, increasing farmer digital literacy, and growing concerns about input authenticity, the time to invest in QR-based traceability is now.

Companies that take the lead in building robust digital trust infrastructure will not only meet compliance but build long-term relationships with the farming community.

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SPECIAL ARTICLE

Status of Breeder Seed Indent for new varieties of Coarse Cereals under NFSNM

ANUPAM BARIK[1], DEEPA BENIWAL[2]
[1]EX-ADDITIONAL COMMISSIONER (CROPS), MOA & FW, DA&FW. &
[2]KVSSL, GURUGRAM, HARYANA
EMAIL: anupam.barik@kvssmscs.com

Lead Author

DR. ANUPAM BARIK

Ex-Additional Commissioner (Crops), DAFW, MoA&FW, GoI

Dr. Anupam Barik (Phd. in Agronomy) has more than 27 years' experience in Central Government Service and served at Ministry of Agriculture and Farmers Welfare, (Crops Division), Government of India, Krishi Bhavan, New Delhi since 1998 in different capacities. He retired in August 2020 as Additional Commissioner (Crops).

Dr. Barik was actively involved in formulation of policy documents and implementation of various crop specific schemes of DA&FW with special reference to Cotton, Jute, Sugarcane, Oilseeds, Pulses, Maize, Nutri Cereals, Oil palm and Tree Borne Oilseeds. He has visited more than 19 countries on Official capacity as Country representative in various Plenary Meetings, Conferences, international cooperations working group, exposure visit & studies.

At National Level he was closely associated with formulation and implementation of flagship schemes of DA&FW namely Technology Mission on Cotton (TMC) in 2000, National Food Security Mission (NFSM) in 2011, National Mission on Oilseeds & Oil Palm (NMOOP) in 2014, National Mission on Edible Oils- Oil Palm (NMEO-OP) and National Mission on Edible Oils- Oil Seeds (NMEO-OS) in 2021.

Dr. Barik also acted as Board of Director/ Member in various organisations like CAB, CCI, ICAR-CIRCOT, CAI, AICOSCA, OPIL, SEA, SOPA, SEA-IPOS Council, STAR Society.

He has published more than 40 scientific /research/extension articles in various Indian/International journals and more than 85 proceedings of National level seminars/ workshops/ Conferences in last 30 years. He is author of a Book **"Plam oil Chronicles-The crucial insights we need"** which was launched in June 2024 by Solideridad & APOA at Indore.

After retirement he was engaged with Patanjali Foods Limited (PFL), Noida, U.P as Advisor-Palm Plantation and looked after the oil palm plantation programme under NNEO-OP and 202 FPOs formation under 10K FPOs scheme on behalf of PFL. Currently associated with Krishi Vikas Sahakari Samiti Limited, Gurugram, Haryana as Head-Seed Division since February 2025.

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1. Introduction

1.1 Seed is the basic and most critical input for sustainable agriculture. The response of all other inputs depends on quality of seeds to a large extent. It is estimated that the direct contribution of quality seed alone to the total production is about 15–20% depending upon the crop, yet only 30-40% of farmers use certified seeds. The yield can be further raised up to 45% with efficient management of other inputs.

1.2 Accordingly, for giving impetus on the objective of improving the Seed Replacement Rate (SRR) and Varietal Replacement Rate (VRR) a new, revised and comprehensive scheme namely **National Food Security and Nutrition Mission (NFSNM)"** has launched by DA&FW in October 2024. NSFNM is under implementation to increase the productivity of Pulses, Nutri Cereals, Coarse Cereals, Commercial crops and Fodder crops through adoption of newly released varieties, restoring soil fertility and dissemination of improved production technologies in identified areas mainly high area low productivity districts of the country.

1.3 Under the NFSNM emphasis has been given to promote less than 5 years old varieties of Breeder seeds production, less than 8 years old varieties for Foundation & Certified seeds production and less than 10 years old varieties for Certified seed distribution. To boost Breeder seed production, GOI is providing financial assistance of 50% on the Breeder Seed cost decided by Seed Division, DA&FW, GOI for distribution of Breeder Seed of newly released varieties/hybrids which are < 5 years old (from the date of notification) to States and Central seed agencies for foundation seed production.

1.4 The Scheme aims to develop/strengthen seed sector and to enhance production and multiplication of certified/quality seeds of agricultural crops and make it available affordable to the farmers. Hence it helps in catering the Sustainable Development Goals i.e End hunger, achieve food security and improved nutrition and promote agriculture.

2. Breeder Seed Indent & Allocation

2.1 Breeder seed is the progeny of nucleus seed of a variety and is produced by the originating breeder or by a sponsored breeder. Breeder seed production is the mandate of the Indian Council of Agricultural Research (ICAR) through its network.

2.2 NFSNM focus on the incorporation of seeds of newly released and notified high-yielding, climate-resilient, bio-fortified, resistant to insect, pest and diseases, short and medium duration varieties/hybrids in the seed chain including enhancement of infrastructure facilities in the Seed Sector.

2.3 State Government (State Seed Corporation) and Central agencies obtain breeder seed of different crops placing indent in SATHI portal and thereafter, allotted by Seed Division of DA&FW, GOI and lifting the same from respective ICAR Institutions and SAUs. Breeder seed serves as the foundational link in the seed-multiplication program and strengthening the program's efficiency & effectiveness demands meticulous attention.

2.4 In accordance with the National interest to promote recently released varieties/hybrids, Seed Division of DA&FW is allocating Breeder seeds to various states and Central agencies in kharif and rabi season separately for production of foundation & certified seeds respectively. The production of breeder seed is reviewed every year by ICAR-DAC in the annual seed review meeting.

3. Issues related to Breeder seed indent & production

3.1 A lot of research and development work is being carried out by ICAR, SAUs, CAUs and other organizations for development of new and high yielding varieties which are bio-fortified and climate resilient. The rate of incorporation of these varieties in the seed chain must be expedited and the old varieties needs to be phased out. One of the important reasons for this was lack of awareness of new varieties, reluctance of farmers to leave old varieties

3.2 A considerable work has been done in last 4-5 years to improve the awareness among different stakeholders about the newly released varieties. For incorporation of seeds of newly released and notified varieties in seed chain the cost of breeder seed is a big factor. The cost of breeder seed is generally high and assistance on the cost of breeder seed of new varieties under NFSNM will give a boost in rapid incorporation of new varieties in seed chain and ultimately improving the Varietal Replacement Rate (VRR). It will further help the implementing agencies to popularize the new varieties and in reducing the cost of foundation seed production.

4. Coarse Cereals production scenario in India

4.1 A variety of coarse cereals are grown throughout the country in different ecology, agroclimatic condition, but mostly as rainfed crop. Sorghum, pearl millet, maize, barley, finger millet and several small millets such as kodo millet, little millet, foxtail millet, proso millet and barnyard millet together called coarse cereals. NFSNM has several interventions for increasing the yield of Coarse cereals and to support promotion of new high yielding varieties.

4.2 In India, Nutri/coarse cereals are grown over an area of 22.65 million ha (17.42% of total food grains), with a production of 50.90 million tonnes during 2021-22 with 2247 kg/ha productivity and contributed about 17% to national food basket (Table 1). More than 90% coarse cereals are produced in Rajasthan, Maharashtra, Karnataka, Uttar Pradesh, Madhya Pradesh, West Bengal, Andhra Pradesh, Telangana, Bihar and Tamil Nadu States

4.3 Even as area under millet cultivation dropped by 56% in India, production increased from 11.3 to 15.3 million tonnes. This was due to the development and adoption of improved varieties and hybrids, and better crop management practices. Overall, millet productivity has increased by more than two times, and pearl millet productivity has tripled.

4.4 The area of coarse cereals except maize has declined after inception of green revolution and the area of coarse cereals reduced from 44.35 million ha in 1965-66 to 22.65 million ha in 2021-22 i.e. 51%. In 2021, India's millet cultivation covered 9.76 million hectares, accounting for 31.55% of the world's total area. The total production in India was 13.21 million tonnes, contributing 43.90% to the world's total production. The average yield in India is around 1239 kg/ha. Rajasthan contributed a significant portion of the total area, with around 36% in 2021-22.

Table 1: Area production & Yield of Coarse Cereals in India (2021-22)

Crop	Area (Million ha)	Production (Million Tons)	Yield (kg/ha)
Sorghum	3.81	4.23	1110
Pearl Millets	6.70	9.62	1436
Finger Millets	1.21	1,70	1404
Maize	10.04	33.62	3349
Others	0.89	1.73	1943
All India	**22.65**	**50.90**	**2247**

Source: Agricultural Statistics at a glance, 2022, DA&FW

4.5 In 2022, a total of 17.63 million hectares was sown with coarse cereals like Maize and Barley, producing around 50 million tonnes in India. The average yield for coarse cereals was approximately 2,245 kilograms per hectare. Rajasthan, Maharashtra, Karnataka, Uttar Pradesh, Madhya Pradesh, and Gujarat are major coarse cereal-growing regions, contributing to about 90% of the total area.

5. Status of Breeder seed indent of Coarse cereals

5.1 Every year, several improved varieties of Coarse cereals are being released by Indian Council of Agricultural Research and State Agricultural Universities for the benefit of the farming community. The seed plays a vital role in agriculture and acts as a carrier of the genetic potential of improved varieties. The quality seed with high genetic and physical purity, germination, vigour and viability assures the potential of crop production under suitable and favorable agro-climatic conditions.

5.2 The Breeder seeds indent from various States & Central seeds producing agencies indicates that, the % of indent of < 5 years old varieties are not upto mark as compared to total indent and not to that extent as desired under NFSNM. To understand the indent status of different states and central agencies to promote < 5 years old varieties based on breeder seed indent of Coarse Cereals and Nutri cereals have been worked out in the present analysis as per seed zonal review meeting held on 20-21 March 2025 and indent placed for Kharif 2026. The crop wise status of newly released varieties of Breeder seed indent placed by various states and Central nodal agencies are described below.

5.1 Breeder seed indent of Maize:

5.1.1 Maize cultivation is significant due to its role as a staple food for both humans and livestock, as well as a crucial raw material for various industrial products. It's a highly productive cereal, important in both food and non-food applications, and a key source of nutrition and income for many.

5.1.2 It was noted thar Breeder seed indent for Kharif 2026 was placed for 49 varieties of Maize by States & agencies of which 20 varieties are less than 5 years **(Annexure 1).** Therefore, sufficient varieties below 5 years are available to promote new varieties under the seed chain. The breeder seed indent by various states for Maize for Kharif 2026 was 63.63 quintals of which less than 5 years old varieties is 28.75 quintals i.e. 45% of total indent (Table2). The states like Rajasthan, Orissa, Jharkhand, J&K have placed 100% indent for new varieties while Assam, Karnataka, Kashmir, Maharashtra, Madhya Pradesh, Uttarakhand and Uttar Pradesh are still placing indent for old varieties (over 5 years old).

Table 2: Status of Less than 5 years old varieties of indent of Breeder Seeds of Maize

States	Breeder Seeds (Q)			Agencies	Breeder Seeds (Q)		
	Total indent	Indent for <5 years	% of total indent		Total indent	Indent for <5 years	% of total indent
Assam	3.0	0	0	KVSSL	9.35	4.35	46
Himachal Pradesh	2.08	0.25	12	NDDB	0.66	0	0
Jharkhand	1.00	1.00	100	NSAI	9.14	6.40	70
J& K	1.00	1.00	100	NSC	5.40	4.80	89
Karnataka	0.56	0	0	**Total**	**24.55**	**15.55**	**63**
Kashmir	5.24	0	0				
Maharashtra	0.85	0	0				
M. Pradesh	24.40	0	0				
Odisha	2.00	2.00	100				
Punjab	0.50	0.50	100				
Rajasthan	24.00	24.00	100				
Uttarakhand	1.00	0	0				
Uttar Pradesh	1.00	0	0				
Total	**63.63**	**28.75**	**45**				

Source: Seed Zonal meeting, March 2025, DA&FW

5.1.3 Among the Central nodal agencies, KVSSL, NSAI and NSC are giving indent for less than 5 years old varieties to the tune of 63% of total indent while NDDB is still using old varieties. The total indent of Breeder seed of Maize by 4 central agencies was 24.55 quintals of which 15.55 quintals belong to less than 5 years old category. In case of Maize, States are placing 45% of total indent for new varieties while agencies are 63%.

5.2 Breeder seed indent of Pearl Millets

5.2.1 Pearl millet cultivation is crucial for food and nutritional security, especially in arid and semi-arid regions, due to its drought tolerance and adaptability to harsh conditions. It provides a reliable source of food and fodder, contributing to the livelihoods of smallholder farmers and livestock-based agricultural systems.

5.2.2 The Breeder seed indent was placed for 22 varieties of Pearl Millets by States & agencies of which 9 varieties are less than 5 years **(Annexure II).** Therefore, varieties are available to promote new varieties under the seed chain.

5.2.3 The total indent of Breeder seeds for Pearl Millets was 13.11 quintals of which only 0.63 quintals were below 5 years old and among the states, only Karnataka placed more than 95% indent for new varieties (Table 3). The rest of the states are not showing interest in the same and still using old varieties.

Table 3: Status of Less than 5 years old varieties of Breeder Seeds of Pearl Millets

States	Breeder Seeds (Q)			Agencies	Breeder Seeds (Q)		
	Total indent	Indent for <5 years	% of total indent		Total indent	Indent for <5 years	% of total indent
Bihar	8.50	0	0	DADF	0.40	0	0
Karnataka	0.66	0.63	95	HIL	0.60	0.10	16
Maharashtra	0.18	0	0	KVSSL	4.95	4.75	95
Tamil Nadu	0.77	0	0	NSC	2.40	1.20	50
Uttar Pradesh	3.00	0	0	NSAI	0.18	0	0
Total	**13.11**	**0.63**	**5**	**Total**	**8.53**	**5.95**	**69**

Source: Seed Zonal meeting, March 2025

5.2.4 In the case of central nodal agencies, total indent was 8.53 quintals of which 70% are below 5 years. Among the agencies, KVSSL has placed more than 95% of its indent for under 5 years followed by NSC 50%. Agencies like DADF, HIL and NSAI are placing less quantity of indent for old varieties. In the case of Pearl Millets, States are placing only 5% of total indent for new varieties while agencies are 69%.

5.3 Breeder seed indent of Sorghum

5.3.1 Sorghum is a vital crop in India, particularly in semi-arid regions, for its nutritional value, drought tolerance, and ability to be used as food, feed, and fodder. It's a staple food and fodder for many, especially in rural areas, and can contribute significantly to food security and livestock support, especially under adverse conditions.

Table 4: Status of Less than 5 years old varieties of indent of Breeder Seeds of Sorghum

States	Breeder Seeds (Q)			Agencies	Breeder Seeds (Q)		
	Total indent	Indent for <5 years	% of total indent		Total indent	Indent for <5 years	% of total indent
Karnataka	0.81	0.06	7	HIL	1.00	1.00	100
Maharashtra	3.88	0.20	5	IFFDC	0.20	0	0
M. Pradesh	2.50	2.50	100	KVSSL	25.12	17.12	68
Odisha	1.50	1.50	100	NSAI	13.05	5.25	40
Rajasthan	15.00	10.00	66	NSC	7.75	3.75	48
Telangana	0.18	0.12	66	**Total**	**66.72**	**27.12**	**40**
Tamil Nadu	0.50	0.50	100				
Uttar Pradesh	0.20	0.20	100				
Total	**24.57**	**15.08**	**61**				

Source: Seed Zonal meeting, March 2025

5.3.2 Indent was placed for 44 varieties of Sorghum of which 22 are less than 5 years old **(Annexure III).** The total indent by various states was 24.57 quintals out of which 15.08 quintals are below 5 years old i.e. 61 % of total indent (Table 4). As per Table 4, all the states showed interest in promoting new generation varieties except Maharashtra & Karnataka.

5.3.3 Among the agencies HIL placed indent for 100% new varieties followed by KVSSL (68%), NSC (40%). The total indent by various agencies were 66.72 quintals out of which 27.12 quintals are below 5 years old i.e.40 % of total indent. In case of Sorghum, States are placing 61% of total indent for new varieties while agencies are 40%.

5.4 Breeder seed indent of Finger Millets.

5.4 Finger millets, like Ragi, are crucial in India due to their nutritional value, ability to thrive in dry regions, and cultural significance. They are a staple food, especially in southern India, and are known for their high calcium and iron content, making them a valuable food source, particularly for children and those with nutrient deficiencies.

5.5 The states and central agencies placed indent for 39 varieties of which 20 varieties are below 5 years old (Annexure IV). The total indent of Breeder seed of Finger millets was 69.77 quintals of which indent of State Government was 60.22 quintals and by agencies were 9.55 quintals (Table 5). In Both the cases the indent for less than 5 years was around 40% of total indent. Among the states Odisha, Maharashtra and West Bengal recorded 80-100% indent of new varieties and among the agencies KVSSL showed 50% of total indent followed of NSC (37%) for 5 years old varieties. In the case of Finger Millets, States are placing 40% of total indent for new varieties while agencies are 39%.

Table 5: Status of Less than 5 years old varieties of indent of Breeder Seeds of Finger Millets.

States	Breeder Seeds (Q)			Agencies	Breeder Seeds (Q)		
	Total indent	Indent for <5 years	% of total indent		Total indent	Indent for <5 years	% of total indent
A. Pradesh	0.10	0.04	4	HIL	0.60	0	0
Assam	2.80	1.40	50	KVSSL	4.00	2.00	50
Bihar	20.00	9.00	45	NSAI	0.40	0	0
Chhattisgarh	16.70	0	0	NSC	4.55	1.70	37
H. Pradesh	0.15	0	0	**Total**	**9.55**	**3.70**	**39**
Karnataka	2.20	0.35	16				
Maharashtra	0.40	0.40	100	HIL	Hindustan India Limited		
M. Pradesh	0.40	0	0	KVSSL	Krishi Vikas Sahakari Samity Ltd.		
Odisha	9.00	8.00	89	NSAI	National Seed Association of India		
Telangana	0.04	0	0	NSC	National Seeds Corporation		
Tamil Nadu	2.12	0.32	15	IFFDC	Indian Farm Forestry Dev. Coop Ltd		
Uttarakhand	0.90	0.20	22	DADF	Dept of AH Dairying and Fisheries		
U. Pradesh	5.20	4.00	77				
WB	0.20	0.20	100				
Total	**60.22**	**23.91**	**40**				

Source: Seed Zonal meeting, March 2025

6. Conclusion:

6.1 On the basis of the seed zonal review meeting, March 2025, total indent of Breeder Seeds of Course & Nutri Cereals was 270.88 quintals both by States and agencies of which 120.69 quintals were below 5 years old varieties having only 39.57% contribution of total indent. The maximum indent for new varieties were noticed for Maize (50%) followed by Sorghum (46.22%). Finger Millets (39.57%) and Pearl Millets. (30.40%) (Table 6)

Table 6: Status of < 5 years old varieties of Breeder Seeds indent of Coarse Cereals.

Crops	Breeder Seeds (Q)		
	Total indent	Indent for <5 years	% of total indent
Maize	88.18	44.30	50.23
Sorghum	91.29	42.20	46.22
Finger Millets	69.77	27.61	39.57
Pearl Millets	21.64	6.58	30.40
Total	**270.88**	**120.69**	**41.60**

6.2 The breeder seed indent had been placed to meet state demands based on the Seed Replacement Rate (SRR). However. the SRR of Course & Nutri Cereals in many states remains very low. High cost of seeds from private companies could be reduced by increasing the public sector's share in seed availability. There is need to increase the indented quantity of breeder seed and emphasized the need to focus more on new varieties, as it takes 3-4 years' time for production and multiplication system before reaching farmers.

6.3 Among the states, Jharkhand, Jammu & Kashmir, Odisha, Punjab and Rajasthan are placing 100% indent for new varieties for Maize (Table 7) and all other states are 0-12%. In case of Sorghum 4 states namely Madhya Pradesh, Odisha, Tamil Nadu and Uttar Pradesh are promoting < 5 years varieties showing 100% of total indent. Maharashtra, Odisha, West Bengal and Uttar Pradesh showing >70% indent for Finger Millets while Karnataka is the only state maintaining >90% for Pearl Millets.

6.4 In case of Central agencies NSAI and NSC showed >70% indent for Maize followed by KVSSL (46%). HIL & KVSSL maintained >60% indent of new varieties for Sorghum while NSAI & NSC are placing 40-48% of total indent for new varieties. KVSSL in the only agency placing >50% indent for Finger Millets and >90% indent for Pearl Millets (Table 7). NSC is maintain 50% and 37% indent for Pearl Millets and Finger Millets respectively.

Table 7: Performance of different states and agencies for BS indent of Coarse Cereals

States placing indent for new varieties			
Maize (100%)	***Sorghum (100%)***	***Finger Millets (>70%)***	***Pearl Millets (>90%)***
Jharkhand	Madhya Pradesh	Maharashtra	Karnataka
J& K	Odisha	Odisha	
Odisha	Tamil Nadu	West Bengal	
Punjab	Uttar Pradesh	Uttar Pradesh	
Rajasthan			
Agencies placing indent for new varieties			
Maize (>70%)	***Sorghum (>60%)***	***Finger Millets (> 50%)***	***Pearl Millets (>90%)***
NSAI	HIL	KVSSL	KVSSL
NSC	KVSSL		

6.5 State governments/ Central agencies are crucial in initiating Foundation seed production through Breeder seed indent requests. To ensure access to improved varieties, states/ Agencies should develop five-year seed rolling plans. These plans prioritize replacing outdated varieties with high-yielding, bio-fortified, and disease-resistant alternatives. Production, Promotion & Demonstrations on varieties not older than 5-10 years old. As par minutes of the meeting "Finalization of Breeder Seed indent Kharif 2026 dated 07.05.2025, the minimum breeder seeds indented quantity placed by state/agency should be latest for I acre or 20 kg for new variety and 50 kg for old varieties. Only public sector variety/hybrid breeder seed indent will be considered under NFSNM. The breeder seed indent of newly released varieties should be increased for achieving the Seed Replacement Rate of Coarse cereals.

nsa National Seed Association of India

The National Seed Association of India

909, Surya Kiran Building,
19 Kasturba Gandhi Marg, New Delhi - 110001 (INDIA)

Ph.: 011-43553241-43, Fax.: 011-43533248
Email: info@nsai.co.in | Web: www.nsai.co.in