https://dergipark.org.tr/en/pub/turkager 2025, 6(1): 89-117 DOI: 10.46592/turkager.1592116

TURKAGER
TURKISH JOURNAL OF AGRICULTURAL ENGINEERING RESEARCH
e-ISSN: 2717 - 8420
https://dergipark.org.tr/tr/pub/turkager

A Critical Review on 'Current Status and Future Implications of Advanced Phenotyping Systems for Monitoring of Agricultural Crops'

Rizwan Ul Zama BANDAY[a], Mohammad MUZAMIL[a*], Danish GUL[a], Seemi LOHANI[b], Sehreen RASOOL[c], Kezia RAJAN[a], Muzamil HAMID[a]

[a]*Division of Farm Machinery and Power Engineering, College of Agricultural Engineering and Technology, Sher e Kashmir University of Agricultural Sciences and Technology of Kashmir, Srinagar, INDIA*
[b]*Department of Students Welfare Office, Faculty of Horticulture, Sher e Kashmir University of Agricultural Sciences and Technology of Kashmir, Srinagar, INDIA*
[c]*Sericulture Production Department, Government of Jammu and Kashmir, Srinagar, INDIA*

ARTICLE INFO: Review Article
Corresponding Author: Mohammad MUZAMIL, E-mail: *muzamil4951@gmail.com*
Received: 27 November 2024 / **Accepted:** 24 March 2025 / **Published:** 30 June 2025

Cite this article: Banday, R.U.Z., Muzamil, M., Gul, D., Lohani, S., Rasool, S., Rajan, K., & Hamid, M. (2025). A Critical Review on 'Current Status and Future Implications of Advanced Phenotyping Systems for Monitoring of Agricultural Crops'. Turkish Journal of Agricultural Engineering Research, 6(1), 89-117. https://doi.org/10.46592/turkager.1592116

ABSTRACT

Phenotyping systems propels the growth of modern agriculture, driving innovations in plant breeding, crop management, precise application of resources and smart agriculture. This review provides a comprehensive analysis of phenotyping systems, exploring their status, technological advancements, challenges and future directions. The evolution from traditional phenotyping to high-throughput phenotyping (HTP) systems with involvement of advanced imaging (visible, infrared, hyperspectral, and thermal), sensors (LIDAR and NIR), data analytics, drones and automated platforms have enabled rapid non-invasive collection of phenotypic information, significantly hastening breeding programs and improving stress tolerance studies. The integration of big data, artificial intelligence (AI) and machine learning (ML) has enhanced data management and interpretation, enabling the development of predictive models and real-time decision-making tools. Despite these advancements, several challenges persist. The technical issues such as data accuracy, resolution and consistency alongside economic concerns related to high cost of implementation, limits the widespread adoption of advanced phenotyping technologies, especially among smallholder farmers. Furthermore, the integration of these technologies with traditional farming practices and the handling of large datasets raises concerns about data privacy, ownership and interpretation. The impending growth of phenotyping lies in advancements such as the integration of AI and genomics, enabling more precise breeding through the linking of genetic information with phenotypic traits. Additionally, the development of low-cost systems is essential to democratize access to precision agriculture, particularly in developing regions. As phenotyping systems continue to advance, they will play a critical role in promoting sustainable agriculture, enhancing resource efficiency, ensuring food security and addressing global climate change.

Keywords: *Phenotyping data, Agriculture, Technologies, Artificial intelligence, Challenges*

INTRODUCTION

Phenotyping intends for comprehensive assessment of observable traits of a crop or organism, such as morphology, development, biochemical properties and behavior in response to environmental conditions (Li *et al.,* 2014). In the context of agriculture and plant sciences, phenotyping is critical for understanding and establishing the relationship between genotype and phenotype, which is fundamental for crop improvement and breeding programs (Furbank and Tester, 2011). The importance of phenotyping in agriculture lies in its ability to facilitate the selection of superior genotypes with desired traits in terms of drought tolerance, disease resistance and yield potential (Reynolds *et al.,* 2020). The measurement of the parameters can provide a basis for the breeders to make informed decisions, leading to the expansion of crops that are better adapted to changing environmental conditions and accelerating the prospectus of feeding 9 billion people in 2050 and 11 billion in 2100 (Araus and Cairns, 2014; Muzamil *et al.,* 2022). Over the years, phenotyping system has gained prominence owing to its association with precision and smart agriculture. The smart agricultural practices are governed by its ability to provide instantaneous and real time data on crop characteristics and performance, that has the potential to augment resource use and enhance productivity (Shakoor *et al.,* 2017). Historically, the emergence of phenotyping system was intended to understand the complex traits in plants growth system. The evolution has been marked by the transformation from manual, labor-intensive and drudgery laced methods to highly automated sensor-based throughput systems, Figure 1.

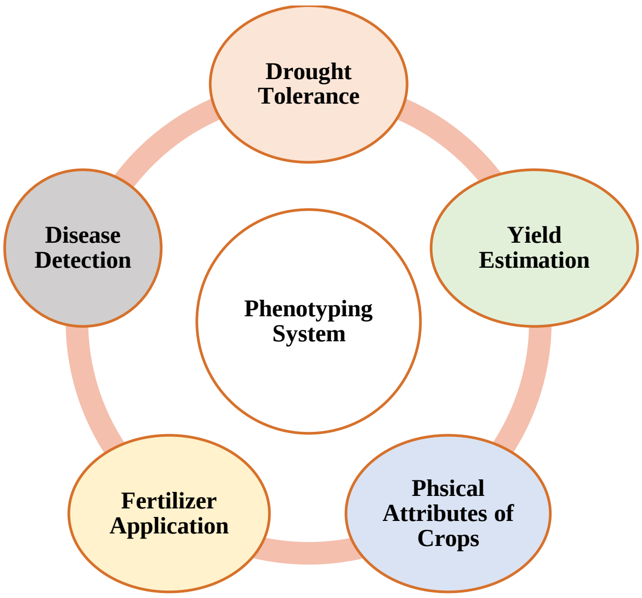

Figure1. *Applications of phenotyping system in agriculture.*

Initially, phenotyping in agriculture was predominantly conducted through manual observations and dimensions of plant traits such as height, leaf size and yield, which were time-consuming and prone to human errors (Xie *et al.,* 2021). The advent of imaging technologies in the late 20th century brought significant advancements, enabling more accurate and objective phenotypic assessments. The arrival and adoption of technologies like such as visible and near-infrared (NIR) imaging promoted non-invasive measurement of traits, providing more consistent and reproducible data (Li *et al.,* 2021). The application of phenotypic technologies in agriculture is enlisted in Table 1.

Table 1. *Application of phenotyping technologies in agriculture.*

Application	Technology	Refrences
1. Detection of disease symptoms in potato plants	Automated machine learning algorithms based high throughput phenotyping (HTP) system	Afzaal *et al.,* 2021
2. Phenotyping canola for plant traits	Automated phenomobile platform equipped with RGB and LiDAR sensors	Cao, 2018
3. Phenotyping wheat for nitrogen use efficiency (NUE)	Multispectral imaging system to measure canopy reflectance and chlorophyll content	Yang *et al.,* 2020
4. Measuring traits in large-scale rice trials	Drone-based HTP system	Panday *et al.,* 2020
5. Screening barley for heat tolerance	Infrared thermography system to capture temperature data from canopies	Kim *et al.,* 2018
6. Root phenotyping for Arabidopsis	Automated root phenotyping system using time-lapse imaging	Satbhai *et al.,* 2017
7. Estimating maize yield potential	LiDAR-based high-throughput phenotyping (HTP) system	Luo *et al.,* 2021
8. Yield and leaf area index estimation for groundnut crop	UAV-based high-throughput phenotyping system with multispectral cameras	Tahir *et al.,* 2020
9. Assessing water-use efficiency in cotton	UAV-based high-throughput phenotyping system for measurement of temperature and spectral reflectance	Lacerda *et al.,* 2022
10.Screening barley for fungal disease resistance	Hyperspectral imaging system	Zhou *et al.,* 2019
11. Screening wheat and rice for drought tolerance	UAV-based systems equipped with thermal and multispectral sensors	Chaturvedi *et al.,* 2019
12. Early-stage detection of stress in maize	Hyperspectral imaging system in high-throughput platform	Asaari *et al.,* 2019
13. Root architecture phenotyping for soybean	X-ray CT imaging to generate 3D root images	Nakhforoosh *et al.,* 2024
14. Evaluating crop phenology in coffee plants	UAV-based phenotyping with RGB and multispectral cameras	Barbosa *et al.,* 2021
15. Phenotyping for drought tolerance in sorghum	UAV-based remote sensing system	Li *et al.,* 2018
16. Estimating yield in rice	Hyperspectral imaging to predict yield from spectral data	Kurihara *et al.,* 2023
17. Monitoring fruit size and color in tomato plants	RGB and hyperspectral imaging in automated greenhouse systems	Deulkar and Barve, 2018
18. Measuring water-use efficiency in wheat	UAV-based thermal and multispectral imaging systems	Bhandari *et al.,* 2021

In recent years, phenotyping systems have further evolved with the integration of high-throughput platforms, which can process and analyze large datasets in a short span of time. These systems utilize advanced sensors, robotics and data analytics to capture, record and analyze phenotypic data at an unprecedented scale (Atefi *et al.,* 2021). The use of drones, UGV (unmanned ground vehicles) and UAV (unmanned aerial vehicles) in field phenotyping has also revolutionized the ability to monitor crops over large areas, providing insights into spatial variability, temporal inconsistencies and environmental interactions (Tanaka *et al.,* 2024). The incorporation of artificial intelligence (AI) and machine learning (ML) in phenotyping systems has heightened the ability to analyze multifaceted datasets, leading to more precise estimates and predictions of plant performance under various conditions (Nabwire *et al.,* 2021). This technological evolution continues to push the boundaries of phenotyping, enabling more efficient breeding programs and precision agriculture practices. The review paper highlights the major advancements in phenotyping systems from last decade with the help of published data. The literature was selected on the basis of availability, relevance, economic viability, technical superiority and feasibility to be deployed at actual fields.

EVOLUTION OF PHENOTYPING SYSTEMS

The phenotyping technologies of the crop system depends on the technological interventions and situations. Initially, there were only two classifications-manual phenotyping and high throughput phenotyping system, Figure 2. However, it has expanded to different sectors of agricultural sections including green house, UAV and precision agriculture, Table 2.

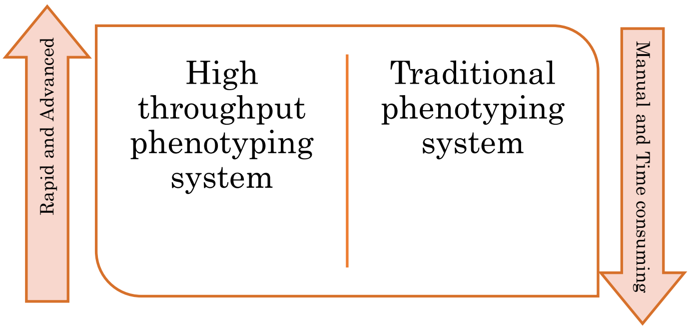

Figure 2. *Types of phenotyping system in agricultural system.*

Table 2. Different types of phenotyping technologies employed in agriculture.

Type	Description	Reference
Traditional Phenotyping	Manual measurement and visual assessment of plant traits without the use of advanced technologies	Maqbool *et al.*, 2022
High-Throughput Phenotyping (HTP)	Automated systems that use sensors, imaging, and computational tools to rapidly measure plant traits in large-scale studies.	Asaari *et al.*, 2019; Luo *et al.*, 2021
Field-based Phenotyping	HTP conducted in real agricultural fields using drones or mobile platforms.	Chaturvedi *et al.*, 2019; Tahir *et al.*, 2020
Greenhouse-based Phenotyping	Automated platforms in controlled environments like greenhouses that monitor plant traits using imaging and sensors.	Deulkar and Barve, 2018
Root Phenotyping	Specialized techniques for assessing below-ground traits like root architecture and water/nutrient uptake.	Nakhforoosh *et al.*, 2024
UAV-based Phenotyping	Unmanned Aerial Vehicles (drones) equipped with sensors to capture phenotypic data from large agricultural areas.	Bhandari *et al.*, 2021; Asaari *et al.*, 2019
Imaging-based Phenotyping	Use of various imaging techniques (visible, thermal, hyperspectral, multispectral) to assess plant health and physiological traits.	Kurihara *et al.*, 2023
Root and Canopy Phenotyping	Combined systems that measure both above-ground and below-ground plant traits to assess overall plant health and productivity.	Luo *et al.*, 2021
Precision Agriculture Systems	Phenotyping integrated with precision agriculture technologies for real-time decision-making in farm management.	Araus *et al.*, 2022

Traditional Phenotyping

Traditional phenotyping relies on utilizing the manual measurements and visual assessments for plant characterization. This method is based on the skill of the worker to understand the situation and measure or record the parameters accordingly. This method is characterized by cost-effectiveness, simplicity and the ability to capture complex traits that automated systems may overlook. They provide detailed and context-specific data, essential for understanding complex plant traits and interactions. Although high-throughput technologies are rapidly advancing, traditional methods will continue to play a vital role in plant research and breeding, particularly in validating new technologies, conducting detailed trait analyses and supporting agricultural development in resource-limited settings (Brown and Miller, 2019; Zhang *et al.*, 2021). However, traditional phenotyping is valuable, particularly in resource-limited settings, for assessing traits that are difficult to quantify with technology and validating data obtained from high-throughput systems (Dogan *et al.*, 2018).

Despite the advent of advanced phenotyping systems, traditional methods remain indispensable in many agricultural and plant science contexts, Table 1. Traditional phenotyping methods have been the backbone of plant science for decades, providing fundamental insights into plant progress, growth, progress and responses to environmental strains. These methods are highly valuable in regions with limited access to advanced technologies and resources, enabling researchers and farmers to assess crop performance effectively (Singh *et al.,* 2021). Traditional approaches are essential for validating and calibrating data obtained from modern phenotyping platforms, ensuring accuracy and reliability in trait measurements (Reynolds *et al.,* 2020). Traditional phenotyping is also preferred when dealing with complex traits that require detailed and nuanced assessments, which may not be fully captured by automated systems. The traits such as leaf texture, disease symptoms and specific developmental stages often necessitate expert visual evaluation to ensure precise characterization (Lee *et al.,* 2020).

Traditional phenotyping to assess drought tolerance in maize, measuring traits like leaf wilting and chlorosis (Fisher *et al.,* 2015) found that these methods provided reliable data crucial for selecting drought-tolerant varieties for smallholder farmers, Figure 3. Traditional phenotyping was to evaluate wheat cultivars for leaf rust resistance, employing detailed visual inspections and standardized scoring scales. This method enabled precise identification of resistant genotypes and supported effective breeding strategies, as the complexity of disease symptoms required expert interpretation beyond current imaging technologies. Sinesio *et al.* (2021) assessed fruit quality traits like flavor, texture and aroma in various tomato varieties using traditional sensory evaluation with human panels emphasizing that human sensory analysis is important for capturing the subjective and complex aspects of fruit quality that automated systems struggle to quantify. Maqbool *et al.* (2022) studied root architecture in rice by using traditional excavation and manual measurement techniques. Despite its labor-intensive nature, this approach offered detailed and accurate data on root length, density, and branching patterns, which is crucial for breeding programs focused on improving nutrient and water uptake efficiency. Traditional phenotyping was employed to measure plant height, leaf area and biomass in wild populations aiming to understand adaptation to various ecological niches, highlighting that traditional methods provide the flexibility and adaptability needed for field studies in diverse and challenging environments (Diaz-Garcia *et al.* 2024). Traditional observational techniques to track soybean growth stages (Gupta *et al.,* 2020) across various climatic zones showed that manual observations delivered timely and accurate data, which was essential for effectively scheduling irrigation, fertilization and pest control. Manual measurement techniques to evaluate the impact of salinity stress on barley seedlings in controlled environments (Nguyen *et al.,* 2019) enabled detailed analysis of physiological responses under controlled conditions. Enhancing the nutritional quality of crops is a key objective in breeding programs. Traditional laboratory analyses to measure protein, mineral and vitamin content yielded accurate and reliable data imperative for breeding nutritionally enhanced crop varieties.

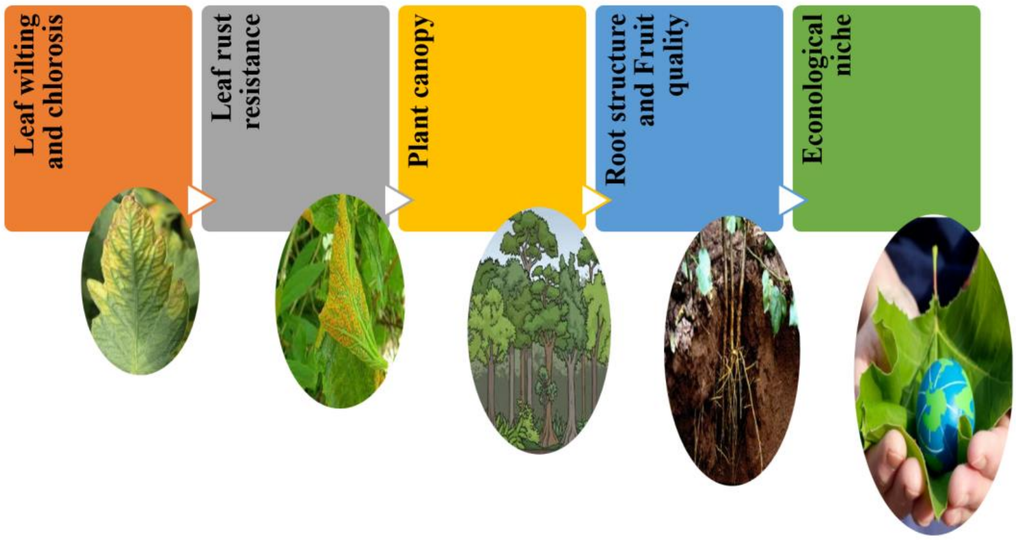

Figure 3*. Phenotyping system for measurement of plant characteristics.*

Traditional phenotyping plays a crucial role in the characterization and conservation of plant genetic resources. Alonso *et al.* (2020) performed manual assessments of morphological and agronomic traits in heirloom vegetable varieties to document and preserve their unique characteristics. The study underscored the importance of traditional methods in maintaining biodiversity and supporting sustainable agriculture. In participatory breeding programs involving farmers and local communities, traditional phenotyping methods are integral. Rodriguez *et al.* (2019) collaborated with farmers to evaluate and select maize varieties based on manual assessments of yield, taste and adaptability. This approach empowered local stakeholders and ensured that selected varieties met the specific needs and preferences of end-users. Müller and Becker (2020) utilized traditional field measurements to assess heat and drought tolerance in sorghum. Parameters such as plant height, leaf area and grain yield were manually recorded under varying stress conditions. The study demonstrated that traditional phenotyping provides robust data critical for developing stress-resilient crop varieties. Understanding interactions between plants and soil microbes often requires traditional assessment methods. Li *et al.* (2021) conducted manual measurements of root exudates and soil nutrient levels to study mutualistic relationships influencing plant health and productivity. The detailed analyses facilitated insights that are challenging to capture through automated systems. In the tea industry, traditional sensory evaluation remains the standard for assessing quality and flavor profiles. Kim and Lee (2019) employed expert tasters to evaluate different tea cultivars, providing nuanced assessments essential for maintaining product standards and guiding breeding efforts aimed at flavor improvement.

Research on phenotypic plasticity often relies on traditional phenotyping to capture variability in plant responses to change in environmental parameters. Fernandez *et al.* (2020) used manual measurements to study how different light conditions affected leaf morphology and photosynthetic rates in forest understory species. Detecting and managing herbicide resistance in weeds is important for crop protection. Thompson and Carter (2019) performed traditional bioassays involving manual observation and measurement of weed growth following herbicide application. This method provided direct and reliable assessments necessary for effective resistance management strategies. In the aftermath of natural disasters, traditional phenotyping methods are often employed to quickly assess crop damage and plan recovery efforts. Oliveira *et al.* (2021) conducted field surveys using manual observations to evaluate the impact of flooding on rice fields, facilitating timely and informed decision-making for restoration. Urban agriculture projects frequently utilize traditional phenotyping due to space and resource constraints. Williams *et al.* (2019) incorporated manual measurement exercises in their curriculum to teach fundamental concepts of plant morphology and physiology, emphasizing hands-on learning and skill development. Traditional methods are important for validating and calibrating data obtained from high-throughput phenotyping systems. Walter *et al.* (2019) conducted parallel manual and automated measurements of wheat canopy traits to ensure the accuracy and reliability of HTP data, highlighting the complementary role of traditional approaches. In many developing countries, traditional phenotyping remains the primary method due to limited access to advanced technologies. Ahmed *et al.* (2021) concluded that extensive manual evaluations of millet varieties under local field conditions contributes valuable data for improving food security and agricultural resilience in resource-constrained regions.

High-throughput Phenotyping (HTP): High-throughput phenotyping (HTP) systems use advanced technologies such as imaging sensors, robotics, and computational tools for rapid and non-invasive measurement of plant traits in large-scale breeding programs. The advent of HTP has also accelerated the process of developing climate-resilient crops that can withstand environmental stresses like drought, heat, and salinity (Nabwire *et al.*, 2021). These systems are designed to handle large volumes of plants while capturing a wide range of phenotypic traits across diverse environments and time points. HTP has revolutionized modern agriculture by enabling the efficient selection of genotypes with superior traits for higher productivity. HTP has improved crop breeding programs by integrating sensors such as RGB cameras, thermal imaging, LiDAR, and hyperspectral imaging to increase the speed and accuracy of phenotypic data collection in terms of plant structure, health, and physiological responses (Mahlein *et al.*, 2018). The ability of HTP to operate in controlled environments like greenhouses, as well as in open fields, makes it versatile for evaluating crops under real-world agricultural conditions, Figure 4. HTP has facilitated the study of complex traits such as water-use efficiency, photosynthetic capacity and root architecture, which are challenging to measure manually.

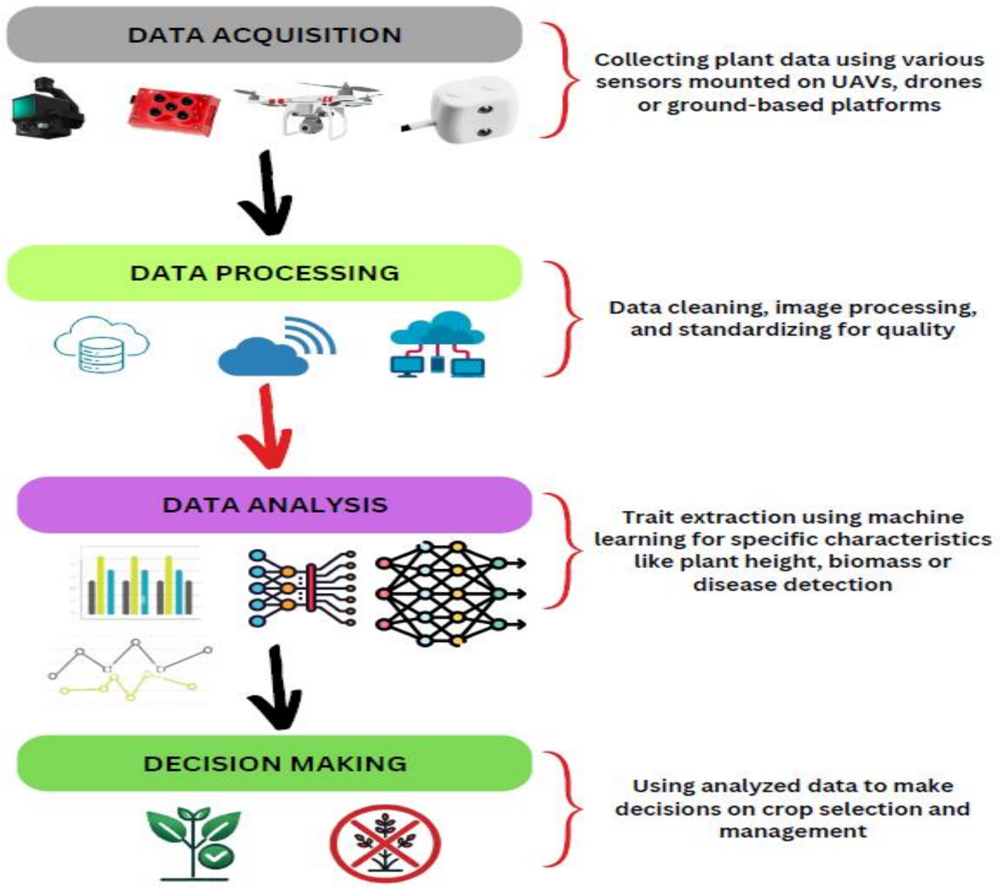

Figure 4. *Process methodology of HTP system.*

Bhandari *et al.* (2021) used UAVs with thermal and multispectral cameras to phenotype wheat genotypes under drought conditions. The UAVs collected canopy temperature and NDVI data, aiding in the identification of drought-tolerant lines. This high-throughput phenotyping (HTP) approach enhanced the accuracy of trait measurement and significantly reduced the time needed for phenotyping. Kurihara *et al.* (2023) utilized hyperspectral imaging to predict rice yield in large field trials by analyzing reflectance data from various spectral bands. This method enabled highly accurate yield estimation before harvest, facilitating earlier selection of high-yielding varieties and shortening the breeding cycle. Deulkar and Barve (2018) used an automated phenotyping platform in a greenhouse study to measure fruit size, shape, and color in tomato plants. By utilizing RGB and hyperspectral imaging, the system continuously monitored the ripening process and detected defects in fruit quality. This high-throughput phenotyping (HTP) system enabled the selection of tomato varieties with superior fruit quality. Asaari *et al.* (2019) employed field-based high-throughput phenotyping (HTP) to assess drought tolerance in maize hybrids. Using a ground-based system with thermal and LiDAR sensors, they collected data on canopy temperature, plant height, and biomass. The study identified drought-tolerant maize hybrids, which were later integrated into breeding programs. Li *et al.* (2018) focused on sorghum, a key crop for food and bioenergy, using an HTP platform with drones and ground-based sensors to measure biomass traits like plant height, leaf area, and chlorophyll content. This system enabled rapid screening of sorghum genotypes, leading to the identification of high-biomass-producing lines.

Nakhforoosh *et al.* (2024) used X-ray CT imaging to phenotype root architecture in soybean, generating detailed 3D images of root structures. This non-destructive method allowed the identification of genotypes with more efficient root systems for water and nutrient uptake, surpassing the limitations of traditional phenotyping techniques. An automated high-throughput phenotyping (HTP) system that used machine learning algorithms (Afzaal *et al.,* 2021) was developed to detect disease symptoms in potato plants. By capturing high-resolution images at various growth stages, the system employed artificial intelligence to identify early signs of disease, significantly reducing the time and labor involved in monitoring large potato fields. An automated phenomobile platform equipped with RGB and LiDAR sensors (Cao, 2018) was used to phenotype canola plants, measuring traits like plant height, leaf area index and flowering time. The platform efficiently covered large field plots, offering high-throughput data to support canola breeding programs. Yang *et al.* (2020) employed multispectral imaging to phenotype wheat plants for nitrogen use efficiency (NUE). The high-throughput system measured canopy reflectance and chlorophyll content, which were linked to NUE. The study successfully identified wheat genotypes with enhanced nitrogen uptake, aiding in the development of more sustainable cropping systems.

Drone-based high-throughput phenotyping (HTP) measured traits like plant height, biomass and leaf area in a large-scale rice cultivation (Panday *et al.,* 2020). The drones enabled rapid data collection across multiple field sites, accelerating the breeding process and facilitating the selection of high-performing rice varieties. Infrared thermography to phenotype heat tolerance in barley (Kim *et al.* 2018) captured temperature data from barley canopies, allowing in identifying genotypes that maintained lower canopy temperatures under heat stress. Satbhai *et al.* (2017) developed an automated root phenotyping system for Arabidopsis using time-lapse imaging to monitor root growth and development. The system captured high-resolution data on root length, branching and angle, allowing for the rapid screening of Arabidopsis mutants with modified root architectures. A Phenotyping tool (RhizOSun) with Raspberry Pi computer and a picamera for acquiring images was employed for automatic recording of the number of tubercles counted on sunflower root (Le Ru *et al.,* 2021).

Luo *et al.* (2021) used LiDAR-based high-throughput phenotyping (HTP) to estimate yield potential in maize. The LiDAR system scans maize fields to create 3D models of plant structures, which are then used to estimate biomass and grain yield. The study showed that LiDAR effectively provided accurate yield predictions for maize breeding programs. The UAV-based high- phenotyping system with multispectral cameras was used to estimate real time leaf area index and yield of groundnut crop utilizing Normalized Difference Vegetation Index (NDVI) (Tahir *et al.,* 2020). The system allowed for rapid phenotyping of large breeding plots, leading to the identification of genotypes with improved yield and disease resistance. A UAV-based HTP system (Lacerda *et al.,* 2022) to assess water-use efficiency in cotton was employed to measure canopy temperature and spectral reflectance which were correlated with water-use efficiency. The HTP approach allowed for the identification of cotton lines with improved drought tolerance and water-use efficiency. An HTP platform (Zhou *et al.,* 2019) to screen barley lines for resistance to fungal diseases employed hyperspectral imaging to detect early symptoms of disease, enabling the identification of resistant genotypes invisible to naked eye. According to Barbosa *et al.* (2021), UAV integrated with RGB camera aligned with computer vision can help to measure coffee tree height/diameter and predict yield of coffee. The system used UAVs equipped with multispectral cameras to collect phenotypic data across a large coffee plantation, supporting breeding efforts for high-yielding and disease-resistant coffee varieties. Chaturvedi *et al.* (2019) utilized high-throughput phenotyping (HTP) to assess rice lines for drought and heat tolerance. UAVs equipped with thermal and multispectral sensors collected data on canopy temperature and NDVI, correlating these with drought and heat tolerance traits. The HTP system facilitated the identification of resilient rice varieties. Some of the applications of phenotyping technology in agriculture are highlighted in Table 2.

TECHNOLOGIES USED IN PHENOTYPING SYSTEM

Sensor Technologies: The use of sensor technologies in HTP systems has revolutionized the ability to collect detailed, real-time data on plant growth, development, and environmental responses. These sensors allow for the non-invasive assessment of a wide range of physiological and structural traits, significantly enhancing the precision of phenotyping. The integration of diverse sensor modalities, including RGB cameras, multispectral and hyperspectral imaging and LIDAR, has significantly improved the precision and efficiency of phenotyping efforts, Figure 5. One of the primary advantages of HTP systems is their ability to automate data collection, which reduces labor costs and human error. Ground-based robots equipped with imaging and LIDAR sensors can accurately measure plant height and biomass at high resolutions, allowing for detailed assessments of crop performance over time (Young *et al.*, 2019; Yao *et al.*, 2021). This automation is crucial for large-scale studies, where traditional manual measurements would be impractical. Moreover, the combination of various sensor types enhances the richness of the data collected, as different sensors can capture complementary information about plant health and growth dynamics (Ma *et al.*, 2022).

Figure 5. *Different sensors used in phenotyping system for agricultural crops.*

The recent advancements in sensor technologies have also facilitated the development of sophisticated technologies and data processing algorithms that can analyze the huge amounts of data generated by HTP systems (Deery *et al.,* 2014), Figure 5. Machine learning techniques have been employed to extract meaningful insights from phenotypic data, enabling researchers to identify genetic traits associated with desirable agronomic characteristics (Tsaftaris *et al.,* 2016; Yang *et al.,* 2020). Studies have demonstrated that integrating genomic data with phenotypic measurements can accelerate the identification of quantitative trait loci (QTLs) linked to yield components in crops like rice (Tanger *et al.,* 2017; Wu *et al.,* 2019). The various types of sensors used in phenotyping system are shown in Table 3.

Table 3. *Different types of sensors used in phenotyping systems.*

Type of Sensor	Description	References
RGB Cameras	Capture visible light in red, green, and blue bands, commonly used for basic morphological traits like plant height, leaf area, and fruit size.	Deulkar and Barve, 2018; Zhang *et al.,* 2023
Thermal Infrared Sensors	Measure plant surface temperature to assess water status and heat stress tolerance by detecting canopy temperature.	Banerjee *et al.,* 2020; Lacerda *et al.,* 2022
Multispectral Sensors	Capture reflectance data across several bands (e.g., NIR, red, and blue) to calculate vegetation indices like NDVI.	Tahir *et al.,* 2020; Panday *et al.,* 2020
Hyperspectral Sensors	Capture data across hundreds of spectral bands to assess physiological traits, such as chlorophyll content and nitrogen status	Asaari *et al.,* 2019; Kurihara *et al.,* 2023
LiDAR (Light Detection and Ranging)	Use laser beams to generate 3D models of plant structures, accurately measuring height, biomass, and canopy traits.	Luo *et al.,* 2021; Yao *et al.,* 2021
X-ray CT (Computed Tomography)	Non-invasive imaging to generate 3D root system models, enabling accurate root phenotyping.	Nakhforoosh *et al.,* 2024
Near-Infrared (NIR) Sensors	Capture near-infrared light, typically used for monitoring water status and photosynthetic activity.	Yang *et al.,* 2020; Araus *et al.,* 2022
Spectral Reflectance Sensors	Measure how much light is reflected by plants, used to evaluate health, nutrient content, and stress levels.	Yang *et al.,* 2020
Fluorescence Sensors	Measure chlorophyll fluorescence to assess photosynthetic efficiency and plant stress responses.	Mahlein *et al.,* 2018
Ultrasound Sensors	Measure root traits such as diameter and length, providing non-invasive phenotyping of roots.	Nguyen *et al.,* 2019

This integration is essential for breeding programs focusing to enhance crop resilience and efficiency in the face of climate change. The application of remote sensing technologies has revolutionized the way phenotyping is conducted. Aerial platforms, such as drones, equipped with multispectral cameras, allow for the monitoring of large fields and the assessment of crop conditions over extensive areas (Thorp *et al.*, 2018; Araus *et al.*, 2022), Figure 6. These technologies not only provide spatially explicit data but also enable real-time monitoring of plant responses to environmental stresses, such as drought or nutrient deficiency. The ability to capture dynamic changes in plant phenotypes is critical for developing strategies to improve water use efficiency and overall crop performance (Thorp *et al.*, 2018; Yuan *et al.*, 2023).

Components
1. Frame
2. Wheel encoders
3. GPS
4. Adjustable height boom
5. Light bank
6. LiDAR sensor
7. RGB stereo camera
8. Spectrometer/hyperspectral camera
9. IR thermometer
10. Generator and electronics
11. Hydraulic drive

Figure 6. *Advanced HTP system with sensor integration (Deery et al., 2014).*

Despite the advancements in sensor technologies, challenges remain in the standardization and integration of data across different platforms. Variability in sensor calibration, environmental conditions, and data processing methodologies can introduce biases that complicate data interpretation (Wang *et al.*, 2018; Roitsch *et al.*, 2019). Therefore, ongoing research is focused on developing standardized protocols and robust data management systems to ensure the reliability and comparability of phenotypic data across studies (Zhao *et al.*, 2019; Ma *et al.*, 2022). Sensor technologies are at the forefront of high-throughput phenotyping systems, providing unprecedented opportunities for crop research and breeding. The integration of diverse sensor modalities, coupled with advanced data analytics, is transforming the landscape of agricultural science. As these technologies continue to grow, they hold the potential to significantly enhance our understanding of plant biology and improve agricultural productivity in a sustainable manner.

Imaging Techniques: Imaging techniques have become fundamental to high-throughput phenotyping (HTP) systems, enabling non-invasive and high-precision data collection on a range of plant traits. These techniques employ different parts of the electromagnetic spectrum to gather information on plant health, growth, stress responses and other important characteristics. The visible imaging, which captures information within the range of the human eye (400-700 nm), is one of the simplest and most cost-effective methods in phenotyping. It provides high-resolution images of plant architecture, including traits like plant height, leaf area, and color (Shakoor *et al.,* 2017). RGB cameras are commonly used to assess morphological traits such as leaf angle and fruit size in crops like maize and tomato (Zhang *et al.,* 2023). Despite its simplicity, visible imaging can be limited in detecting physiological changes, particularly in early stages of stress or disease (Deulkar and Barve, 2018). Infrared (IR) imaging, particularly in the thermal infrared range (8-14 μm), is used to assess plant temperature, which is a proxy for water status and heat stress tolerance. IR imaging systems measure the radiation emitted by plants, enabling the detection of transpiration rates and plant water use efficiency (He *et al.,* 2024). IR imaging has been used to screen for drought-tolerant genotypes by identifying plants that maintain cooler canopy temperatures under water deficit conditions (Banerjee *et al.,* 2020). Hyperspectral imaging captures information from a wide range of wavelengths (typically 400-2500 nm) and is particularly useful for assessing plant physiological traits such as chlorophyll content, nutrient status and disease severity (Sarić *et al.,* 2022).

Hyperspectral cameras divide the light spectrum into hundreds of narrow bands, allowing the detection of subtle differences in plant reflectance that may not be visible to the human eye. Hyperspectral imaging has been successfully used in rice to predict yield and detect nitrogen deficiencies (Kurihara *et al.,* 2023). Multispectral imaging operates in fewer wavelength bands than hyperspectral imaging (typically 3-12 bands), but it still provides valuable insights into plant health. Multispectral sensors measure plant reflectance at key wavelengths, such as near-infrared (NIR), red and blue, which are commonly used to calculate vegetation indices like the NDVI (Normalized Difference Vegetation Index) (Roberts *et al.,* 2018). These indices are highly correlated with photosynthetic activity, biomass, and plant vigor. Multispectral imaging is frequently employed in field-based phenotyping using drones, especially for crops like maize and wheat (Zaman-Allah *et al.,* 2015). Thermal imaging, a type of infrared imaging, focuses specifically on capturing the temperature of plant surfaces. It plays a critical role in monitoring plant responses to heat stress and water availability (Zhu *et al.,* 2018). By measuring canopy temperature, thermal imaging can help breeders select heat-tolerant and drought-resistant crops.

Data Management and Analysis: Effective data management and analysis are critical in modern phenotyping systems, especially in high-throughput phenotyping (HTP), where large volumes of complex data are generated. Technologies like big data, artificial intelligence (AI) and machine learning (ML) are increasingly applied to handle and interpret this data, leading to improved breeding decisions and more efficient crop management. The rise of HTP platforms has resulted in an explosion of data from various sources, including imaging, sensors, environmental monitoring, and genomic information (Fiorani and Schurr, 2019). Managing this data requires advanced big data technologies that can handle the integration of diverse datasets. These technologies allow for the analysis of large-scale phenotypic, environmental, and genetic data, enabling more comprehensive breeding decisions. The use of big data technologies to manage multi-location trials (Tardieu *et al.,* 2017) allows researchers to integrate phenotypic data across varied environmental conditions to identify genotypes with stable performance, helping in understand genotypeenvironment interactions and make more targeted selections in breeding programs. The ability to manage large, diverse datasets is essential in identifying the best-performing crops under different stress conditions (Krause *et al.,* 2019). Artificial Intelligence is revolutionizing phenotyping by automating the interpretation of large datasets. AI algorithms, particularly those based on deep learning, have proven highly effective in analyzing image and sensor data (Singh *et al.,* 2016). Deep learning models can identify subtle patterns in plant images, such as leaf texture or color, which are often early indicators of diseases (Pound *et al.,* 2017). Deep learning models have been used to detect leaf blight in rice by analyzing digital images and comparing them to historical data (Kamilaris and Prenafeta-Boldú, 2018). AI-based systems have been applied to predict crop yields by correlating multispectral images with historical yield data. A study on maize demonstrated that AI models could predict final crop yields based on image data collected during early growth stages, offering real-time insights into crop health and performance (Yang *et al.,* 2022). Such predictive tools are invaluable in improving resource allocation and decision-making for farmers and breeders alike.

Machine learning (ML) methods are essential for processing high-dimensional phenotypic data and identifying non-linear relationships between traits and environmental factors. In crop phenotyping, ML models can predict crop performance based on phenotypic data collected under varying environmental conditions (Araus *et al.,* 2012). ML models have been used to analyze phenotypic traits like canopy temperature and chlorophyll content to predict drought tolerance in maize (Montesinos-López *et al.,* 2021). Machine Learning has also facilitated genotype-phenotype association studies by analyzing large-scale phenotypic data alongside genomic information allowing researchers to identify genes linked to desirable traits such as disease resistance or yield potential (Crossa *et al.,* 2017). ML techniques help in identifying genomic regions associated with high yield, accelerating breeding cycles by enabling breeders to focus on high-potential genotypes early in the process (Li *et al.,* 2024).

CHALLENGES AND LIMITATIONS OF CURRENT PHENOTYPING SYSTEMS

Technical Challenges: High-throughput phenotyping (HTP) systems have brought immense potential for improving agricultural practices and breeding programs. However, they face several technical challenges, particularly related to data accuracy, resolution, and consistency. Addressing these challenges is essential for maximizing the potential of phenotyping technologies. One of the major challenges in phenotyping systems is ensuring data accuracy. Phenotyping platforms rely heavily on sensors, imaging systems, and automated data collection processes, which can introduce errors due to sensor limitations, calibration issues and environmental noise. Inaccurate sensor calibration or poor lighting conditions can result in incorrect measurements of plant height or leaf area, affecting the reliability of the data (Fiorani and Schurr, 2019).

In field-based phenotyping systems, environmental variability further complicates data accuracy. Factors such as wind, rain, and soil heterogeneity can impact the precision of measurements, especially when drones or mobile platforms are used for data collection (Wang *et al.,* 2024). Additionally, plant movements caused by wind can skew measurements in real-time, leading to inaccurate assessments of canopy structure (Feng *et al.,* 2021). Another critical technical limitation is the resolution of data, particularly in imaging-based phenotyping systems. While high-resolution imaging technologies such as hyperspectral or multispectral cameras can capture fine details of plant traits, there is often a trade-off between resolution and the speed of data acquisition. High-resolution imaging systems may slow down the data collection process or increase computational demand for processing, making it difficult to apply these systems in large-scale field trials (Shi *et al.,* 2021). In remote sensing applications, resolution is also limited by the altitude at which drones or satellites operate. Higher altitudes reduce spatial resolution, potentially missing subtle phenotypic traits such as leaf disease spots or early signs of water stress (Xue and Su, 2017). Low-resolution data can also mask small differences between genotypes, making it harder to distinguish superior-performing varieties during selection (Walter *et al.,* 2019).

Ensuring data consistency is another significant challenge in phenotyping. Consistency is affected by the variability of environmental conditions, measurement timing, and differences in phenotyping protocols. The same crop trait measured under different lighting conditions or at different times of day can yield varying results (Gill *et al.,* 2022). Moreover, inconsistency in sensor performance, caused by sensor drift or changes in calibration over time, can reduce the reliability of long-term studies (Ge *et al.,* 2016). Phenotyping systems that are used across multiple locations or seasons face additional consistency challenges. Variations in weather, soil type, and agricultural practices can lead to inconsistent data, making it difficult to compare results across different environments (Araus *et al.,* 2022). Standardizing data collection methods and ensuring uniformity in phenotyping protocols are crucial for improving consistency in multi-location trials.

Economic Considerations: The adoption of advanced phenotyping systems, particularly high-throughput phenotyping (HTP), presents significant economic challenges. The costs associated with implementing and maintaining these systems can be substantial, particularly for small-scale farmers or research institutions with limited budgets. The upfront investment required to establish a phenotyping system, especially HTP platforms, can be prohibitively expensive. The costs include purchasing advanced imaging equipment, sensors, automated platforms, and the necessary computational infrastructure for data storage and analysis (Fiorani and Schurr, 2019). Hyperspectral imaging systems and LiDAR sensors, which are commonly used in phenotyping can cost tens of thousands of dollars (Wang *et al.,* 2024). Additionally, the need for high-powered computing resources to process large datasets further increases the initial cost of implementation (Zhao *et al.,* 2019). Custom-built phenotyping platforms such as phenomobiles (mobile platforms equipped with sensors) or drones require not only specialized equipment but also technical expertise for their operation and maintenance (Shi *et al.,* 2023). Moreover, integrating these platforms with data management systems and ensuring that they are compatible with existing agricultural practices adds to the complexity and cost of implementation (Rico-Chávez *et al.,* 2022).

Jimenez-Berni *et al.* (2018) attempted to design and develop a low cost phenomobile system with sensor attachments for monitoring of crops on real time basis, Figure 7.

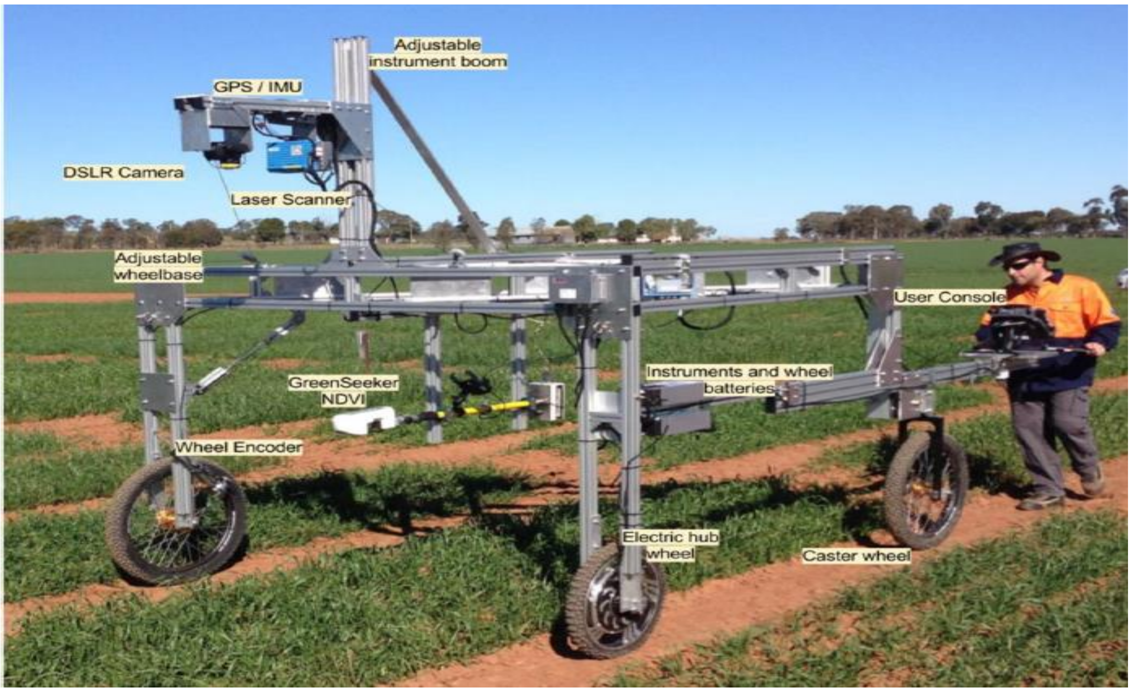

Figure 7. *Low cost phenomobile platform and sensor attachments (Jimenez Berni et al., 2018).*

The maintenance of phenotyping systems is another important economic factor. Advanced phenotyping platforms, such as drones, robotic systems and automated imaging equipment, require regular calibration and servicing to maintain data accuracy (Kamarianakis *et al.,* 2024). Sensor performance can degrade over time, necessitating frequent recalibration or replacement. The cost of maintaining these systems is compounded by the need for skilled technicians to operate and troubleshoot them (Mao *et al.,* 2017). In field-based systems, environmental factors such as dust, humidity, and extreme weather conditions can affect the durability and performance of equipment, leading to higher maintenance costs. Drones used in field phenotyping may require frequent repairs or part replacements due to exposure to harsh outdoor conditions (Washburn *et al.,* 2024). Similarly, automated greenhouse systems, which involve moving platforms and robotic arms need regular upkeep to ensure smooth operation.

The operation of HTP systems often requires highly trained personnel to manage both the hardware and software components. Training staff to operate advanced imaging systems, interpret sensor data, and manage big data infrastructure incurs additional costs (Kim *et al.,* 2020). Even with automation, skilled labor is required to oversee data collection, analyze results, and troubleshoot technical issues (Araus *et al.,* 2022). Smaller institutions or research farms may not have the resources to hire specialized staff, making the operation of such systems more costly and less feasible. While HTP systems offer tremendous benefits for large-scale breeding programs and research, their high costs make them less accessible for smallholder farmers and low-resource institutions (Kaur *et al.,* 2024). Scaling down these systems to make them affordable for broader use remains a challenge. Small-scale implementations may still require significant investment, and while these costs may be justifiable for large research programs, they are often too high for smaller operations.

Despite the high costs of implementation and maintenance, the potential economic benefits of phenotyping systems cannot be ignored. By improving the efficiency of breeding programs, increasing crop yields, and reducing input costs, HTP platforms can lead to long-term economic gains (Costa *et al.,* 2019). However, realizing these benefits requires a significant upfront investment, which may be a barrier for widespread adoption, especially in developing countries or regions with limited agricultural funding (Feng *et al.,* 2021).

Integration with Existing Agricultural Practices: High-throughput phenotyping (HTP) systems are reshaping agricultural research and crop improvement, but integrating these technologies into traditional farming practices poses several challenges. Smallholder farmers continue to rely on manual labor, conventional tools, and historical knowledge, making the transition to advanced phenotyping more complex. Several factors must be addressed for successful integration. One significant barrier is the complexity of advanced phenotyping systems. HTP platforms involve sophisticated tools such as drones, multispectral cameras, and environmental sensors that require specialized knowledge to operate effectively. Traditional farmers familiar with visual assessments may struggle with systems that rely on machine learning algorithms for decision-making. Studies have highlighted the need for comprehensive training programs to ensure that farmers can adapt to these technologies and maximize their utility in field settings (Mir *et al.,* 2019; Ruzzante *et al.,* 2021). Infrastructure deficits are another roadblock. In many regions, particularly in developing countries, access to reliable electricity, internet connectivity, and data management systems remains inadequate (Singh, 2022). This lack of infrastructure impedes the adoption of HTP platforms, which rely on consistent data transmission and analysis. Furthermore, the high cost of equipment poses an economic barrier for smallholder farmers, making external support crucial for adoption (Hatem *et al.,* 2022).

The lack of standardization across phenotyping systems is a significant issue for integration. Current technologies vary widely in their data formats, making it difficult for farmers to incorporate these systems into their existing workflows. Moreover, traditional farming often involves multiple crop varieties and environmental conditions, which complicates the implementation of generalized phenotyping solutions (Wang *et al.,* 2024). Customization of phenotyping systems for specific crops or regions is essential for widespread adoption. There is a notable gap between the technical knowledge required for modern phenotyping systems and the traditional expertise of farmers. Traditional farmers are skilled at observing visual signs of plant health, but they may find sensor-generated data challenging to interpret (Jimenez-Berni *et al.,* 2018). Bridging this knowledge gap requires investment in educational initiatives to help farmers understand the benefits and practical applications of phenotyping data (Marwaha *et al.,* 2023). Economic barriers are significant, particularly for smallholder farmers. Even when the long-term benefits of phenotyping technologies are evident, the initial investment costs can be prohibitive. Financial subsidies, microfinancing, and government incentives may be necessary to make these technologies accessible at the farm level (Rose *et al.,* 2021). Large-scale farms and research institutions have had more success in implementing these technologies, but smallholder farmers need financial support to bridge the gap (Lipper *et al.,* 2017). Despite the challenges, successful case studies exist in regions such as India and parts of Africa, partnerships between agricultural research institutions and local farmers have enabled the adoption of drone-based phenotyping to monitor crop health. This has improved water use efficiency and increased yields (Chawade *et al.,* 2019). Research collaborations have shown how tailored solutions, paired with strong farmer education programs, can overcome many of the integration barriers (Balota and Oakes, 2017).

Data Management and Interpretation: Phenotyping systems generate massive amounts of data that require efficient management, interpretation and storage solutions. With the advent of high-throughput phenotyping (HTP) platforms, the volume and complexity of the datasets have increased exponentially. Managing these large datasets presents challenges in terms of storage capacity, computational power, and the ability to extract meaningful insights.

HTP platforms generate multispectral, hyperspectral and 3D imaging data as well as environmental and sensor data, which results in terabytes of information per growing season (Tong and Nikoloski, 2021). The effective management of these datasets requires high-performance computing (HPC) and cloud-based solutions which can process large-scale data in real time (Fiorani and Schurr, 2019). Image processing algorithms are often used to analyze large sets of visual data from various sensors and cameras. However, the quality of the output relies on the precision and accuracy of these algorithms, as even minor discrepancies in sensor calibration or environmental factors can lead to errors in the final analysis (Singh *et al.,* 2021). Data collection is just the first step, proper curation and storage are essential for long-term use. Phenotypic data needs to be organized into databases that can be easily accessed and queried by researchers, breeders, and farmers (Dwivedi *et al.,* 2020). The sheer volume of data makes it difficult to maintain without specialized tools and infrastructure, leading to the development of centralized platforms such as the European Plant Phenotyping Network (EPPN) and the Integrated Breeding Platform (IBP), which provide shared resources for data management and dissemination (Daviet *et al.,* 2022).

Sharing large datasets across institutions and countries is critical for advancing crop research and breeding programs. Open access to phenotyping data facilitates collaboration and speeds up the development of new crop varieties. However, data sharing is hampered by several factors, including the lack of standardization in data formats, which makes it difficult for different systems to interpret and exchange information (Chenu *et al.,* 2018). Data collected by different HTP systems or field phenotyping platforms might be incompatible due to variations in measurement protocols or sensor technologies (Hu and Schmidhalter, 2023). To address these challenges, efforts have been made to develop standardized protocols and metadata structures for phenotypic data sharing. Initiatives such as MIAPPE (Minimum Information About a Plant Phenotyping Experiment) have been established to provide guidelines for data sharing, helping researchers and breeders to collaborate more effectively (Papoutsoglou *et al.,* 2020). Another challenge in data sharing is the proprietary nature of some phenotypic datasets, particularly in commercial agriculture. Companies may be reluctant to share data due to competitive concerns or intellectual property rights. To overcome this, public-private partnerships have been proposed to facilitate the sharing of non-sensitive data while protecting the commercial interests of the stakeholders (Pieruschka and Schurr, 2019).

In addition to the technical and logistical challenges of data sharing, there are privacy concerns related to the ownership and use of phenotypic data. Farmers and researchers may be wary of sharing data, especially when it contains information about crop yields, soil health, or farm management practices, which could be exploited by competitors or used for profit without their consent (Kotal *et al.,* 2023). The growing reliance on cloud-based systems for data storage also raises concerns about data security. Breaches in these systems could expose sensitive agricultural information, including proprietary breeding lines or field-level data on crop performance. Ensuring that phenotypic data is protected by robust security protocols, such as encryption and user authentication, is essential for maintaining trust among data providers (Kuriakose *et al.,* 2020). Legal frameworks surrounding data ownership and intellectual property rights are still evolving in the context of phenotyping. Clarifying who owns the data collected by phenotyping systems-whether it be the farmers, researchers or technology providers-remains a pressing issue that requires regulatory oversight (Lassoued *et al.,* 2021). Ensuring fair access to and control over data will be crucial for the continued growth of phenotyping as a tool for crop improvement and precision agriculture.

FUTURE PROSPECTUS, IMPLICATIONS AND DIRECTIONS

Advancements in Phenotyping Technologies: AI and machine learning are playing a transformative role in modern phenotyping. Enhanced predictive models and decision support systems are improving the efficiency of plant breeding programs by rapidly analyzing large datasets and predicting phenotypic traits based on environmental and genetic factors (Sahoo *et al.,* 2024). These advancements have enabled real-time monitoring of crops and early detection of stress responses (Centorame *et al.,* 2024). Deep learning models have been successful in identifying complex traits with high accuracy, reducing the time needed for manual phenotyping (Arya *et al.,* 2022). The integration of phenotyping with genomics holds significant promise for enhancing the precision of plant breeding (Shakshi *et al.,* 2024). By linking phenotypic data with genetic information, researchers can better understand gene-trait relationships, enabling the advancement of more resilient crop varieties (Mir *et al.,* 2019). This integration also facilitates genome-wide association studies, where phenotypic traits are mapped to specific genomic regions, helping to identify key genes responsible for desirable traits (Xiao *et al.,* 2022). To ensure the widespread adoption of advanced phenotyping technologies, it is crucial to develop low-cost systems, particularly for smallholder farmers in developing regions (Reynolds *et al.,* 2019). Recent innovations include handheld devices and smartphone-based applications that offer affordable alternatives to expensive imaging systems (Nguyen *et al.,* 2023). These systems democratize access to precision agriculture tools, empowering small-scale farmers to monitor crop health and make data-driven decisions without significant financial investment (Karunathilake *et al.,* 2023).

Role in Sustainable Agriculture: Advanced phenotyping technologies are playing a crucial role in promoting sustainable agriculture by refining resource use efficiency and reducing the environmental footprint of farming practices. These technologies empower farmers to better monitor crop health, optimize the use of water, nutrients, and other inputs, and reduce wastage, ultimately leading to more sustainable farming systems (Janni and Pieruschka, 2022).

One of the primary areas where phenotyping contributes to sustainability is in water management. By accurately measuring crop water use and stress responses, farmers can implement precision irrigation techniques, which minimize water use while maintaining crop yields (Thorp *et al.,* 2018). This is particularly important in regions fronting water shortage due to climate change and increasing agricultural demands. Similarly, nutrient management is another area where phenotyping can enhance sustainability. Real-time monitoring of plant nutrient status allows for the precise application of fertilizers, reducing the risk of over-application and nutrient runoff, which can lead to soil degradation and water pollution (Shi *et al.,* 2020). Integrating phenotyping with precision agriculture practices can help in reducing the environmental impact of excessive chemical use. Phenotyping also aids in the expansion of climate-resilient crops, which are critical for addressing the challenges posed by global climate change (Cvejić *et al.,* 2022). By identifying traits associated with resilience to extreme temperatures, drought, and pests, researchers can breed crops that require fewer inputs while maintaining high productivity, contributing to both ecological sustainability and food security (Bohra *et al.,* 2021).

Policy and Regulatory Considerations: As phenotyping technologies evolve, there are important policy and regulatory issues that need to be addressed, particularly around data ownership, standardization, and ethical concerns. With the growing use of phenotyping platforms, including drones and IoT devices, large amounts of data are being generated. The question of who owns this data is becoming increasingly significant. Farmers, researchers, and technology providers may have different stakes in the data, raising concerns about intellectual property rights and the commercialization of agricultural data (Lajoie-O'Malley *et al.,* 2020). Policies need to clearly define ownership rights, ensuring that farmers retain control over their data while allowing for the responsible sharing of information for research and development purposes. There is a lack of standardized protocols for data collection and analysis in phenotyping, which creates challenges in comparing results across different studies and technologies (Tomičić *et al.,* 2022). Regulatory frameworks should work towards developing industry-wide standards to ensure consistency and reliability in phenotyping data. Standardization will also facilitate the integration of phenotypic data with other datasets, such as genomic or environmental data, enabling more comprehensive analyses. The use of AI and automation in phenotyping raises ethical concerns, particularly around the potential displacement of human labor and the unequal access to technology. Smallholder farmers in developing regions may be left behind if policies do not promote equitable access to advanced phenotyping tools (Ryan, 2023). Additionally, the use of sensitive genetic data in phenotyping could lead to privacy breaches or misuse if not properly regulated (Stanghellini and Leoni, 2020). Ethical guidelines are needed to ensure that these technologies are used responsibly and do not exacerbate social or economic inequalities.

Future Research Directions: There are several promising areas for future research in phenotyping that can help address current gaps and explore new applications. Despite the significant advances in phenotyping, some gaps remain that need to be addressed there. Phenotyping for below-ground traits, such as root structure and function, lags above-ground phenotyping (Blanchy *et al.,* 2024). Research should focus on developing tools and methodologies for non-invasive root phenotyping, which is essential for understanding water and nutrient uptake and improving drought tolerance (Wasaya *et al.,* 2018). Additionally, current phenotyping systems are often expensive, limiting their accessibility to resource-constrained farmers. Developing low-cost, scalable systems should be a priority for future research (Thrash *et al.,* 2022). Future research should also explore new applications of phenotyping, such as its potential role in biodiversity conservation and ecosystem monitoring. By identifying and characterizing plant species based on their phenotypic traits, phenotyping could help monitor changes in biodiversity due to climate change or human activities (Karaca and Ince, 2019). Moreover, integrating phenotyping with precision agriculture tools such as drones and satellite imagery and decision making tools could enable large-scale environmental monitoring, offering insights into ecosystem health and sustainability (Sweet *et al.,* 2022). The possibility of low-cost AI driven phenotyping system can also be explored to benefit small and marginal farmers.

CONCLUSION

Phenotyping systems have evolved significantly over the past few decades, from traditional manual methods to high-throughput, AI-driven technologies. The integration of advanced imaging techniques, sensor technologies, and big data analytics has revolutionized how phenotypic traits are monitored and measured. Despite these advancements, several challenges remain, including technical issues such as data accuracy and consistency, economic considerations around the cost of implementation, and the need for better data management and interpretation. Moreover, compatibility with traditional farming practices and ethical concerns, such as data privacy and ownership, present additional hurdles. However, the future holds exciting prospects, with advancements in AI, machine learning and genomics integration promising to enhance the precision of plant breeding. The development of low-cost phenotyping systems also offers hope for smallholder farmers, allowing them to adopt precision agriculture without significant financial strain. The continued evolution of phenotyping technologies will play a necessary role in addressing most demanding challenges in global agriculture, particularly in ensuring food security amidst climate change and population growth. By enabling more efficient resource use, promoting sustainability, and accelerating the development of climate-resilient crops, phenotyping will be at the forefront of agricultural innovation. Moreover, as technology becomes more accessible, especially with the development of affordable systems for smallholder farmers, the gap between high-tech and traditional farming practices may narrow. This could lead to a more equitable agricultural system where all farmers, regardless of scale, can profit from scientific and technological advancements. In this way, phenotyping will continue to be a driving force in the future of global agriculture, contributing to a more sustainable, productive and resilient food system.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no conflict of interest.

CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

The author declared that the following contributions is correct.
Rizwan Ul Zama BANDAY: Conceptualization, investigation, writing (original draft),
Mohammad MUZAMIL: Supervision, writing (review and editing),
Danish Gul: Methodology, validation,
Seemi LOHANI: Methodology, validation,
Sehreen RASOOL: Software, visualization,
Kezia RAJAN: Formal analysis, data curation,
Muzamil HAMID: Formal analysis, data curation.

ETHICS COMMITTEE DECISION

This article does not require any Ethical Committee Decision.

REFERENCES

Afzaal H, Farooque AA, Schumann AW, Hussain N, McKenzie-Gopsill A, Esau T and Acharya B (2021). Detection of a potato disease (early blight) using artificial intelligence. *Remote Sensing*, *13(3): 411.*

Ahmed S, Rahman M and Hossain M (2021). Evaluation of millet varieties under drought conditions using traditional phenotyping methods. *Journal of Agricultural Science, 13(2): 85-94.*

Alonso J, Perez L and Gomez M (2020). Conservation and characterization of heirloom vegetable varieties using traditional phenotyping approaches. *Genetic Resources and Crop Evolution, 67(5): 1023-1035.*

Araus JL, Serret MD and Edmeades GO (2012). Phenotyping maize for adaptation to drought. *Frontiers in Physiology, 3: 305.*

Araus JL and Cairns JE (2014). Field high-throughput phenotyping: the new crop breeding frontier. *Trends in Plant Science, 19(1): 52-61.*

Araus JL, Buchaillot ML and Kefauver SC (2022). High throughput field phenotyping. In wheat improvement: Food security in a changing climate (pp. 495-512). Cham: *Springer International Publishing.*

Arya S, Sandhu KS, Singh J and Kumar S (2022). Deep learning: As the new frontier in high-throughput plant phenotyping. *Euphytica*, *218(4): 47.*

Asaari MSM, Mertens S, Dhondt S, Inzé D, Wuyts N and Scheunders P (2019). Analysis of hyperspectral images for detection of drought stress and recovery in maize plants in a high-throughput phenotyping platform. *Computers and Electronics in Agriculture*, *162: 749-758.*

Atefi A, Ge Y, Pitla S and Schnable J (2021). Robotic technologies for high-throughput plant phenotyping: Contemporary reviews and future perspectives. *Frontiers in Plant Science*, *12: 611940.*

Bailey-Serres J, Parker JE, Ainsworth EA, Oldroyd GE and Schroeder JI (2019). Genetic strategies for improving crop yields. *Nature, 575 (7781): 109-118.*

Balota M and Oakes J (2017). UAV remote sensing for phenotyping drought tolerance in peanuts. In *Autonomous air and ground sensing systems for agricultural optimization and phenotyping II* (Vol. 10218, pp. 81-87). SPIE.

Banerjee K, Krishnan P and Das B (2020). Thermal imaging and multivariate techniques for characterizing and screening wheat genotypes under water stress condition. *Ecological Indicators, 119: 106829.*

Barbosa BDS, Costa L, Ampatzidis Y, Vijayakumar V and dos Santos LM (2021). UAV-based coffee yield prediction utilizing feature selection and deep learning. *Smart Agricultural Technology, 1: 100010.*

Bhandari M, Baker S, Rudd JC, Ibrahim AM, Chang A, Xue Q and Auvermann B (2021). Assessing the effect of drought on winter wheat growth using unmanned aerial system (UAS)-based phenotyping. *Remote Sensing, 13(6): 1144.*

Blanchy G, Deroo W, De Swaef T, Lootens P, Quataert P, Roldán-Ruíz I and Garré S (2024). Closing the phenotyping gap with non-invasive below ground field phenotyping. *EGUsphere, 1-30.*

Bohra A, Naik SJ, Kumari A, Tiwari A and Joshi R (2021). Integrating phenomics with breeding for climate-smart agriculture. *Omics Technologies for Sustainable Agriculture and Global Food Security (Vol II): 1-24.*

Brown D and Miller S (2019). The enduring relevance of traditional phenotyping in the era of precision agriculture. *Plant Science Today, 6(3): 200-207.*

Cabrera-Bosquet L, Fournier C, et al (2020). Advances in HTP and its application in breeding. *Journal of Experimental Botany, 71(16): 4687-4705.*

Cao HT (2018). *A low-cost depth imaging mobile platform for canola phenotyping* (Doctoral dissertation, University of Saskatchewan).

Centorame L, Gasperini T, Ilari A, Del Gatto A and Foppa Pedretti E (2024). An overview of machine learning applications on plant phenotyping, with a focus on sunflower. *Agronomy, 14(4): 719.*

Chaturvedi SK, Sekhar R, Banerjee S and Kamal H (2019). Comparative review study of military and civilian Unmanned Aerial Vehicle. *INCAS Bulletin, 11(3): 183-198.*

Chawade A, van Ham J, Blomquist H, Bagge O, Alexandersson E and Ortiz R (2019). High-throughput field-phenotyping tools for plant breeding and precision agriculture. *Agronomy, 9(5): 258.*

Chenu K, Van Oosterom EJ, McLean G, Deifel KS, Fletcher A, Geetika G and Hammer GL (2018). Integrating modelling and phenotyping approaches to identify and screen complex traits: transpiration efficiency in cereals. *Journal of experimental botany, 69(13): 3181-3194.*

Costa JM, Marques da Silva J, Pinheiro C, Barón M, Mylona P, Centritto, M and Oliveira MM (2019). Opportunities and limitations of crop phenotyping in southern European countries. *Frontiers in Plant Science, 10: 1125.*

Crossa J, Pérez-Rodríguez P, Cuevas J, Montesinos-López O, Jarquín D, De Los Campos G, and Varshney RK (2017). Genomic selection in plant breeding: methods, models, and perspectives. *Trends in Plant Science, 22(11): 961-975.*

Cvejić S, Jocić S, Mitrović B, Bekavac G, Mirosavljević M, Jeromela A M and Miladinović D (2022). Innovative approaches in the breeding of climate-resilient crops. climate change and agriculture: Perspectives, sustainability and resilience, *Wiley, Online Library, 111-156.*

Daviet B, Fernandez R, Cabrera-Bosquet L, Pradal C and Fournier C (2022). PhenoTrack3D: an automatic high-throughput phenotyping pipeline to track maize organs over time. *Plant Methods, 18(1): 130.*

Deery D, Jimenez-Berni J, Jones H, Sirault X and Furbank R (2014). Proximal remote sensing buggies and potential applications for field-based phenotyping. *Agronomy, 5: 349-379.*

Deulkar SS and Barve SS (2018). An automated tomato quality grading using clustering-based support vector machine. In *2018 3rd International Conference on Communication and Electronics Systems (ICCES)* (pp. 1128-1133). IEEE.

Diaz-Garcia G, Lozoya-Saldaña H, Bamberg J and Diaz-Garcia L (2024). Morphometric analysis of wild potato leaves. *Genetic Resources and Crop Evolution, 1-16.*

Dogan A, Uyak C, Keskin N, Akcay A, Sensoy R I G and Ercisli S (2018). Grapevine leaf area measurements by using pixel values. *Comptes rendus de l'Acade'mie bulgare des Sciences, 71(6): 772-779.*

Dwivedi SL, Goldman I, Ceccarelli S and Ortiz R (2020). Advanced analytics, phenomics and biotechnology approaches to enhance genetic gains in plant breeding. *Advances in Agronomy*, *162: 89-142.*

Feng L, Chen S, Zhang C, Zhang Y and He Y (2021). A comprehensive review on recent applications of unmanned aerial vehicle remote sensing with various sensors for high-throughput plant phenotyping. *Computers and electronics in agriculture*, *182: 106033.*

Fernandez A, Lopez R and Martinez J (2020). Phenotypic plasticity in response to light variability in understory plants assessed through traditional measurements. *Ecology and Evolution, 10(15): 8421-8432.*

Fiorani F and Schurr U (2019). Future scenarios for plant phenotyping. *Annual Review of Plant Biology*, *64(1): 267-291.*

Fisher M, Abate T, Lunduka RW, Asnake W, Alemayehu Y and Madulu RB (2015). Drought tolerant maize for farmer adaptation to drought in sub-Saharan Africa: Determinants of adoption in eastern and southern Africa. *Climatic Change, 133: 283-299.*

Furbank RT and Tester M (2011). Phenomics-technologies to relieve the phenotyping bottleneck. *Trends in Plant Science*, *16(12): 635-644.*

Ge Y, Bai G, Stoerger V and Schnable JC (2016). Temporal dynamics of maize plant growth, water use, and leaf water content using automated high throughput RGB and hyperspectral imaging. *Computers and Electronics in Agriculture, 127: 625-632.*

Gill T, Gill SK, Saini DK, Chopra Y, de Koff J P and Sandhu KS (2022). A comprehensive review of high throughput phenotyping and machine learning for plant stress phenotyping. *Phenomics*, *2(3): 156-183.*

Gupta N, Sharma R and Verma S (2020). Monitoring soybean development stages through manual observation for improved crop management. *Agricultural Research, 9(4): 541-550.*

Hatem Y, Hammad G and Safwat G (2022). Artificial intelligence for plant genomics and crop improvement. *Egyptian Journal of Botany*, *62(2): 291-303.*

He S, Li X, Chen M, Xu X, Tang F, Gong T and Liu W (2024). Crop HTP Technologies: Applications and Prospects. *Agriculture, 14(5): 723.*

Hu Y and Schmidhalter U (2023). Opportunity and challenges of phenotyping plant salt tolerance. *Trends in plant science, 28(5): 552-566.*

Janni M and Pieruschka R (2022). Plant phenotyping for a sustainable future. *Journal of Experimental Botany, 73(15): 5085-5088.*

Jimenez-Berni JA, David MD, Rozas-Larraondo, Anthony (Tony) G, Condon GJR, Richard AJ, William DB, Robert TF and Xavier RRS (2018). High throughput determination of plant height, ground cover, and above-ground biomass in wheat with LiDAR. *Frontiers in Plant Science, 9: 1-18.*

Kamarianakis Z, Perdikakis S, Daliakopoulos IN, Papadimitriou DM and Panagiotakis S (2024). Design and implementation of a low-cost, linear robotic camera system, targeting greenhouse plant growth monitoring. *Future Internet*, *16(5): 145.*

Kamilaris A and Prenafeta-Boldú FX (2018). Deep learning in agriculture: A survey. *Computers and electronics in agriculture*, *147: 70-90.*

Karaca M and Ince AG (2019). Conservation of biodiversity and genetic resources for sustainable agriculture. *Innovations In Sustainable Agriculture*, *363-410.*

Karunathilake EMBM, Le AT, Heo S, Chung YS and Mansoor S (2023). The path to smart farming: Innovations and opportunities in precision agriculture. *Agriculture*, *13(8): 1593.*

Kaur S, Kakani VG, Carver B, Jarquin D and Singh A (2024). Hyperspectral imaging combined with machine learning for high-throughput phenotyping in winter wheat. *The Plant Phenome Journal*, *7(1): e20111.*

Kim Y, Still CJ, Roberts DA and Goulden ML (2018). Thermal infrared imaging of conifer leaf temperatures: comparison to thermocouple measurements and assessment of environmental influences. *Agricultural and Forest Meteorology, 248: 361-371.*

Kim J and Lee S (2019). Sensory evaluation methods in assessing tea quality: A traditional approach. *Food Quality and Preference, 71: 87-95.*

Kim KD, Kang Y and Kim C (2020). Application of genomic big data in plant breeding: Past, present, and future. *Plants*, *9(11): 1454.*

Kotal A, Elluri L, Gupta D, Mandalapu V and Joshi A (2023). Privacy-preserving data sharing in agriculture: enforcing policy rules for secure and confidential data synthesis. In *2023 IEEE International Conference on Big Data (BigData)* (pp. 5519-5528). IEEE.

Krause MR, González-Pérez L, Crossa J, Pérez-Rodríguez P, Montesinos-López O, Singh RP and Mondal S (2019). Hyperspectral reflectance-derived relationship matrices for genomic prediction of grain yield in wheat. *G3: Genes, Genomes, Genetics*, *9(4): 1231-1247.*

Kuriakose SV, Pushker R and Hyde EM (2020). Data-driven decisions for accelerated plant breeding. *Accelerated Plant Breeding, Volume 1: Cereal Crops, 89-119.*

Kurihara J, Nagata T and Tomiyama H (2023). Rice yield prediction in different growth environments using unmanned aerial vehicle-based hyperspectral imaging. *Remote Sensing*, *15(8): 2004.*

Lacerda LN, Snider JL, Cohen Y, Liakos V, Gobbo S and Vellidis G (2022). Using UAV-based thermal imagery to detect crop water status variability in cotton. *Smart Agricultural Technology*, *2:* 100029.

Lajoie-O'Malley A, Bronson K, van der Burg S and Klerkx L (2020). The future (s) of digital agriculture and sustainable food systems: An analysis of high-level policy documents. *Ecosystem Services*, *45: 101183.*

Lassoued R, Macall DM, Smyth SJ, Phillips PW and Hesseln H (2021). Data challenges for future plant gene editing: expert opinion. *Transgenic Research*, *30(6): 765-780.*

Le Ru A, Ibarcq G, Boniface MC, Baussart A, Muños S and Chabaud M (2021). Image analysis for the automatic phenotyping of *Orobanche cumana* tubercles on sunflower roots. *Plant methods*, *17: 1-14.*

Lee SH, Goëau H, Bonnet P and Joly A (2020). New perspectives on plant disease characterization based on deep learning. *Computers and Electronics in Agriculture, 170: 105220.*

Li D, Quan C, Song Z, Li X, Yu G, Li C and Muhammad A (2021). High-throughput plant phenotyping platform (HT3P) as a novel tool for estimating agronomic traits from the lab to the field. *Frontiers in Bioengineering and Biotechnology*, *8: 623705.*

Li J, Shi Y, Veeranampalayam-Sivakumar A N and Schachtman D P (2018). Elucidating sorghum biomass, nitrogen and chlorophyll contents with spectral and morphological traits derived from unmanned aircraft system. *Frontiers in Plant Science*, *9: 1406.*

Li L, Zhang Q and Huang D (2014). A review of imaging techniques for plant phenotyping. *Sensors*, *14(11): 20078-20111.*

Li X, Chen M, He S, Xu X, He L, Wang L and Yang W (2024). Estimation of soybean yield based on high-throughput phenotyping and machine learning. *Frontiers in Plant Science*, *15:* 1395760.

Lipper L, Thornton P, Campbell BM, Baedeker T, Braimoh A, Bwalya M and Torquebiau EF (2017). Climate-smart agriculture for food security. *Nature climate change*, *4(12): 1068-1072.*

Luo S, Liu W, Zhang Y, Wang C, Xi X, Nie S and Zhou G (2021). Maize and soybean heights estimation from unmanned aerial vehicle (UAV) LiDAR data. *Computers and Electronics in Agriculture*, *182: 106005.*

Ma Z, Rayhana R, Feng K, Liu Z, Xiao G, Ruan Y and Sangha JS (2022). A review on sensing technologies for high-throughput plant phenotyping. *IEEE Open Journal of Instrumentation and Measurement*, *1: 1-21.*

Mahlein AK, Kuska MT, Behmann J, Polder G and Walter A (2018). Hyperspectral sensors and imaging technologies in phytopathology: state of the art. *Annual review of phytopathology*, *56(1): 535-558.*

Mao Y, You C, Zhang J, Huang K and Letaief KB (2017). A survey on mobile edge computing: The communication perspective. *IEEE communications surveys & tutorials*, *19(4): 2322-2358.*

Maqbool S, Hassan MA, Xia X, York LM, Rasheed A and He Z (2022). Root system architecture in cereals: progress, challenges and perspective. *The Plant Journal*, *110(1): 23-42.*

Marwaha S, Deb CK, Haque MA, Naha S and Maji AK (2023). Application of artificial intelligence and machine learning in agriculture. In translating physiological tools to augment crop breeding (pp. 441-457). Singapore: *Springer Nature* Singapore.

Mir RR, Reynolds M, Pinto F, Khan MA and Bhat MA (2019). High-throughput phenotyping for crop improvement in the genomics era. *Plant Science, 282: 60-72.*

Montesinos-López OA, Montesinos-López A, Pérez-Rodríguez P, Barrón-López JA, Martini JW, Fajardo-Flores SB and Crossa J (2021). A review of deep learning applications for genomic selection. *BMC genomics*, *22: 1-23.*

Müller J and Becker H (2020). Manual phenotyping of sorghum under abiotic stress conditions for breeding resilience. *Journal of Agronomy and Crop Science, 206(5): 609-620.*

Muzamil M, Rasool S and Ummyiah HM (2022). Insitu and Exsitu agricultural waste management system, 45-63. Agricultural waste-New Insights. *IntechOpen.* ISBN: 978-1- 80356-966-6.

Nabwire S, Suh HK, Kim MS, Baek I and Cho BK (2021). Application of artificial intelligence in phenomics. *Sensors*, *21(13): 4363.*

Nakhforoosh A, Hallin E, Karunakaran C, Korbas M, Stobbs J and Kochian L (2024). Visualization and quantitative evaluation of functional structures of soybean root nodules via synchrotron X-ray imaging. *Plant Phenomics, 6: 0203.*

Nguyen T, Tran H and Le P (2019). Traditional assessment of salinity stress responses in barley seedlings under controlled conditions. *Plant Physiology and Biochemistry, 141: 259-266.*

Nguyen LQ, Shin J, Ryu S, Dang LM, Park HY, Lee ON and Moon H (2023). Innovative cucumber phenotyping: A smartphone-based and data-labeling-free model. *Electronics, 12(23): 4775.*

Oliveira R, Santos L and Pereira J (2021). Rapid assessment of flood damage in rice fields using traditional field surveys. *Natural Hazards, 107(1): 495-508.*

Panday US, Pratihast AK, Aryal J and Kayastha RB (2020). A review on drone-based data solutions for cereal crops. *Drones, 4(3): 41.*

Papoutsoglou EA, Faria D, Arend D, Arnaud E, Athanasiadis IN, Chaves I and Pommier C (2020). Enabling reusability of plant phenomic datasets with MIAPPE 1.1. *New Phytologist, 227(1): 260-273.*

Park S, Lee J and Choi H (2020). Validation of high-throughput phenotyping data through traditional measurement techniques in wheat. *Plant Methods, 16(1): 83.*

Pieruschka R and Schurr U (2019). Plant phenotyping: past, present, and future. *Plant Phenomics*.

Pound MP, Atkinson JA, Townsend AJ, Wilson MH, Griffiths M, Jackson AS and French AP (2017). Deep machine learning provides state-of-the-art performance in image-based plant phenotyping. *Gigascience, 6(10), gix083.*

Reynolds D, Baret F, Welcker C, Bostrom A, Ball J, Cellini F and Tardieu F (2019). What is cost-efficient phenotyping? Optimizing costs for different scenarios. *Plant Science, 282*: 14-22.

Reynolds M, Chapman S, Crespo-Herrera L, Molero G, Mondal S, Pequeno D N and Sukumaran S (2020). Breeder friendly phenotyping. *Plant Science, 295, 110396.*

Rico-Chávez AK, Franco JA, Fernandez-Jaramillo AA, Contreras-Medina LM, Guevara-González RG and Hernandez-Escobedo Q (2022). Machine learning for plant stress modeling: A perspective towards hormesis management. *Plants, 11(7): 970.*

Roberts DA, Roth KL, Wetherley EB, Meerdink SK and Perroy RL (2018). Hyperspectral vegetation indices. In *Hyperspectral indices and image classifications for agriculture and vegetation* (pp. 3-26). CRC press.

Rodriguez M, Hernandez L and Gomez R (2019). Participatory breeding in maize: The continued relevance of traditional phenotyping methods. *Agriculture and Human Values, 36(4): 799-810.*

Roitsch T, Cabrera-Bosquet L, Fournier A, Ghamkhar K, Jiménez-Berni J, Pinto F and Ober E S (2019). New sensors and data-driven approaches-A path to next generation phenomics. *Plant Science, 282: 2-10.*

Rose DC, Wheeler R, Winter M, Lobley M and Chivers CA (2021). Agriculture 4.0: Making it work for people, production, and the planet. *Land use policy, 100, 104933.*

Ruzzante S, Labarta R and Bilton A (2021). Adoption of agricultural technology in the developing world: A meta-analysis of the empirical literature. *World Development, 146, 105599.*

Ryan M (2023). The social and ethical impacts of artificial intelligence in agriculture: mapping the agricultural AI literature. *AI & SOCIETY, 38(6): 2473-2485.*

Sahoo L, Mohapatra D, Raghuvanshi HR, Kumar S, Kaur R, Chawla R and Afreen N (2024). transforming agriculture through artificial intelligence: Advancements in plant disease detection, applications, and challenges. *Journal of Advances in Biology & Biotechnology, 27(5): 381-388.*

Sarić R, Nguyen V D, Burge T, Berkowitz O, Trtílek M, Whelan J and Čustović E (2022). Applications of hyperspectral imaging in plant phenotyping. *Trends in plant science, 27(3): 301-315.*

Satbhai SB, Göschl C and Busch W (2017). Automated high-throughput root phenotyping of Arabidopsis thaliana under nutrient deficiency conditions. *Plant Genomics: Methods and Protocols, 135-153.*

Shakoor N, Lee, S and Mockler TC (2017). High throughput phenotyping to accelerate crop breeding and monitoring of diseases in the field. *Current opinion in plant biology, 38: 184-192.*

Shakshi RP, Yadav S and Singh MK (2024). Integrating genomics and phenomics in agricultural breeding: A comprehensive review. *Asian Research Journal of Agriculture,17(4):116-125.*

Shi Y, Zhu Y, Wang X, Sun X, Ding Y, Cao W and Hu Z (2020). Progress and development on biological information of crop phenotype research applied to real-time variable-rate fertilization. *Plant methods, 16: 1-15.*

Shi Y, Thomasson JA, Murray SC, Pugh NA, Rooney WL, Shafian S and Yang C (2021). Unmanned aerial vehicles for high-throughput phenotyping and agronomic research. *PloS one, 11(7), e0159781.*

Shi T, Liu Y, Zheng X, Hu K, Huang H, Liu H and Huang H (2023). Recent advances in plant disease severity assessment using convolutional neural networks. *Scientific Reports*, *13(1): 2336.*

Sinesio F, Cammareri M, Cottet V, Fontanet L, Jost M, Moneta E and Grandillo S (2021). Sensory traits and consumer's perceived quality of traditional and modern fresh market tomato varieties: a study in three European countries. *Foods, 10(11): 2521.*

Singh A, Ganapathysubramanian B, Singh A K and Sarkar S (2016). Machine learning for high-throughput stress phenotyping in plants. *Trends in Plant Science, 21(2): 110-124.*

Singh D, Bhatia S and Rehman A (2021). Big data analytics for phenotyping: Tackling the challenge of high-throughput data. *Computers and Electronics in Agriculture, 182: 106-111.*

Singh AK (2022). Precision agriculture in India-opportunities and challenges. *Indian Journal of Fertilisers, 18(4): 308-331.*

Stanghellini G and Leoni F (2020). Digital phenotyping: Ethical issues, opportunities, and threats. *Frontiers in Psychiatry, 11: 473.*

Sweet DD, Tirado SB, Springer NM, Hirsch CN and Hirsch CD (2022). Opportunities and challenges in phenotyping row crops using drone-based RGB imaging. *The Plant Phenome Journal*, *5(1): e20044.*

Tahir MN, Lan Y, Zhang Y, Wang Y, Nawaz F, Shah MAA and Naqvi SZA (2020). Real time estimation of leaf area index and groundnut yield using multispectral UAV. *International Journal of Precision Agricultural Aviation*, *3(1): 1-6.*

Tanaka TST, Wang S, Jørgensen JR, Gentili M, Vidal AZ, Mortensen AK and Gislum R (2024). Review of crop phenotyping in field plot experiments using UAV-Mounted sensors and algorithms. *Drones, 8(6): 212.*

Tanger P, Klassen S, Mojica JP, Lovell JT, Moyers BT, Baraoidan M and McKay JK (2017). Field-based high throughput phenotyping rapidly identifies genomic regions controlling yield components in rice. *Scientific Reports*, *7(1): 42839.*

Tardieu F, Cabrera-Bosquet L, Pridmore T and Bennett M (2017). Plant phenomics, from sensors to Aknowledge. *Current Biology*, *27(15): R770-R783.*

Thompson G and Carter J (2019). Traditional bioassays for detecting herbicide resistance in weed populations. *Weed Science, 67(4): 498-507.*

Thorp KR, Thompson AL, Harders SJ, French AN and Ward RW (2018). High-throughput phenotyping of crop water use efficiency via multispectral drone imagery and a daily soil water balance model. *Remote Sensing*, *10(11): 1682.*

Thrash T, Lee H and Baker RL (2022). A low-cost high-throughput phenotyping system for automatically quantifying foliar area and greenness. *Applications in Plant Sciences*, *10(6): e11502.*

Tomičić A, Malešević A and Čartolovni A (2022). Ethical, legal and social issues of digital phenotyping as a future solution for present-day challenges: A scoping review. *Science and Engineering Ethics*, *28: 1-25.*

Tong H and Nikoloski Z (2021). Machine learning approaches for crop improvement: Leveraging phenotypic and genotypic big data. *Journal of plant physiology, 257: 153354.*

Tsaftaris S, Minervini M and Scharr H (2016). Machine learning for plant phenotyping needs image processing. *Trends in plant science, 21(12): 989-991.*

Walter A, Scharr H, Gilmer F, Zierer R, Nagel K A, Ernst M and Schurr U (2019). Dynamics of seedling growth acclimation towards altered light conditions can be quantified via GROWSCREEN: a setup and procedure designed for rapid optical phenotyping of different plant species. *New Phytologist*, *174(2): 447-455.*

Wang Y, Wen W, Wu S, Wang C, Yu Z, Guo X and Zhao C (2018). Maize plant phenotyping: Comparing 3D laser scanning, multi-view stereo reconstruction, and 3D digitizing estimates. *Remote Sensing*, *11(1): 63.*

Wang X, Zhou X, Ji L and Shen K (2024). Artificial intelligence/machine learning-assisted near-infrared/optical biosensing for plant phenotyping. In *Machine Learning and Artificial Intelligence in Chemical and Biological Sensing* (pp. 203-225).

Wasaya A, Zhang X, Fang Q and Yan Z (2018). Root phenotyping for drought tolerance: a review. *Agronomy*, *8(11): 241.*

Washburn JD, Adak A, DeSalvio AJ, Arik MA and Murray SC (2024). High temporal resolution unoccupied aerial systems phenotyping provides unique information between flight dates. *The Plant Phenome Journal*, *7(1): e20113.*

Williams E, Brown S and Miller D (2019). Incorporating traditional phenotyping techniques in plant science education. *Journal of Natural Resources and Life Sciences Education, 48(1): 45-52.*

Wu D, Guo Z, Ye J, Feng H, Liu J, Chen G and Yang W (2019). Combining high-throughput micro-CT-RGB phenotyping and genome-wide association study to dissect the genetic architecture of tiller growth in rice. *Journal of Experimental Botany, 70(2): 545-561.*

Xiao Q, Bai X, Zhang C and He Y (2022). Advanced high-throughput plant phenotyping techniques for genome-wide association studies: A review. *Journal of advanced research, 35: 215-230.*

Xie T, Li J, Yang C, Jiang Z, Chen Y, Guo L and Zhang J (2021). Crop height estimation based on UAV images: Methods, errors, and strategies. *Computers and Electronics in Agriculture*, *185, 106155.*

Xue J and Su B (2017). Significant remote sensing vegetation indices: A review of developments and applications. *Journal of sensors*, *2017(1): 1353691.*

Yang W, Feng H, Zhang X, Zhang J, Doonan J H, Batchelor W D and Yan J (2020). Crop phenomics and high-throughput phenotyping: past decades, current challenges, and future perspectives. *Molecular plant*, *13(2): 187-214.*

Yang B, Zhu W, Rezaei EE, Li J, Sun Z and Zhang J (2022). The optimal phenological phase of maize for yield prediction with high-frequency UAV remote sensing. *Remote Sensing*, *14(7): 1559.*

Yao L, Van De Zedde R and Kowalchuk G (2021). Recent developments and potential of robotics in plant eco-phenotyping. *Emerging topics in life sciences*, *5(2): 289-300.*

Young SN, Kayacan E and Peschel JM (2019). Design and field evaluation of a ground robot for high-throughput phenotyping of energy sorghum. *Precision Agriculture*, *20(4): 697-722.*

Yuan H, Song M, Liu Y, Xie Q, Cao W, Zhu Y and Ni J (2023). Field phenotyping monitoring systems for high-throughput: A survey of enabling technologies, equipment, and research challenges. *Agronomy*, *13(11): 2832.*

Zaman-Allah M, Vergara O, Araus JL, Tarekegne A, Magorokosho C, Zarco-Tejada PJ and Cairns J (2015). Unmanned aerial platform-based multi-spectral imaging for field phenotyping of maize. *Plant methods*, *11: 1-10.*

Zhang L, Zhao H and Li D (2021). Integrating traditional and modern phenotyping methods for comprehensive plant trait analysis. *Frontiers in Plant Science, 12: 640.*

Zhang H, Wang L, Jin X, Bian L and Ge Y (2023). High-throughput phenotyping of plant leaf morphological, physiological, and biochemical traits on multiple scales using optical sensing. *The Crop Journal, 11(5): 1303-1318.*

Zhao C, Zhang Y, Du J, Guo X, Wen W, Gu S and Fan J (2019). Crop phenomics: current status and perspectives. *Frontiers in Plant Science*, *10: 714.*

Zhou RQ, Jin JJ, Li QM, Su ZZ, Yu XJ, Tang Y and Li XL (2019). Early detection of magnaporthe oryzae-infected barley leaves and lesion visualization based on hyperspectral imaging. *Frontiers in Plant Science, 9: 1962.*

Zhu W, Chen H, Ciechanowska I and Spaner D (2018). Application of infrared thermal imaging for the rapid diagnosis of crop disease. *IFAC-PapersOnLine*, *51(17): 424-430.*