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REVIEW

## Integrating artificial intelligence and high-throughput phenotyping for crop improvement

Mansoor Sheikh<sup>1</sup>, Farooq Iqra<sup>2</sup>, Hamadani Ambreen<sup>3</sup>, Kumar A Pravin<sup>2</sup>, Manzoor Ikra<sup>4</sup>, Yong Suk Chung<sup>1#</sup>

<sup>1</sup> Phenomics Laboratory, Department of Plant Resources and Environment, Jeju National University, Jeju 63234, Republic of Korea

<sup>2</sup> Council of Scientific & Industrial Research, Indian Institute of Integrative Medicine, Pulwama, J&K 192301, India

<sup>3</sup> Animal and Dairy Science, University of Wisconsin, Madison, WI 530706, United States of America

<sup>4</sup> Division of Fruit Science, Faculty of Horticulture, Sher-e-Kashmir University of Agricultural Sciences and Technology of Kashmir, Srinagar 190025, India

### Abstract

Crop improvement is crucial for addressing the global challenges of food security and sustainable agriculture. Recent advancements in high-throughput phenotyping (HTP) technologies and artificial intelligence (AI) have revolutionized the field, enabling rapid and accurate assessment of crop traits on a large scale. The integration of AI and machine learning algorithms with HTP data has unlocked new opportunities for crop improvement. AI algorithms can analyze and interpret large datasets, and extract meaningful patterns and correlations between phenotypic traits and genetic factors. These technologies have the potential to revolutionize plant breeding programs by providing breeders with efficient and accurate tools for trait selection, thereby reducing the time and cost required for variety development. However, further research and collaboration are needed to overcome the existing challenges and fully unlock the power of HTP and AI in crop improvement. By leveraging AI algorithms, researchers can efficiently analyze phenotypic data, uncover complex patterns, and establish predictive models that enable precise trait selection and crop breeding. The aim of this review is to explore the transformative potential of integrating HTP and AI in crop improvement. This review will encompass an in-depth analysis of recent advances and applications, highlighting the numerous benefits and challenges associated with HTP and AI.

**Keywords:** artificial intelligence, crop improvement, data analysis, high-throughput phenotyping, machine learning, precision agriculture, trait selection

## 1. Introduction

High-throughput phenotyping (HTP) is a revolutionary approach in plant science that aims to assess the phenotypic traits of plants rapidly and accurately on a large scale. It involves the integration of advanced technologies, data analytics, and automation to capture detailed information about various traits, such as

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#Correspondence Yong Suk Chung, E-mail: [yschung@jejunu.ac.kr](mailto:yschung@jejunu.ac.kr)

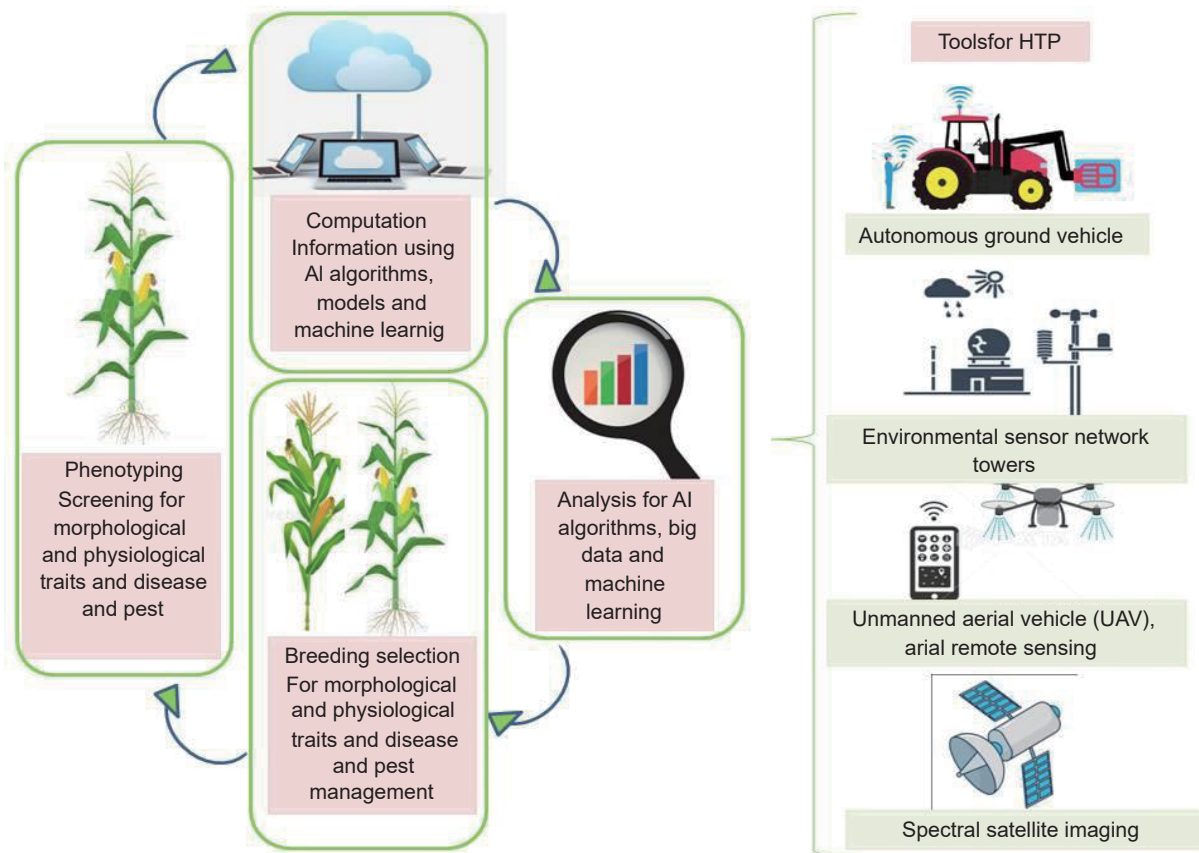
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growth, yield, stress tolerance, and disease resistance (Shakoor *et al.* 2017; Mir *et al.* 2019). This approach has significantly accelerated the progress in plant breeding and crop improvement, as well as our understanding of plant–environment interactions. The traditional methods of phenotyping, which rely on manual measurements and observations, are time-consuming, labor-intensive, and often subject to human error. HTP addresses these challenges by leveraging cutting-edge technologies like remote sensing, imaging, robotics, and sensor networks to collect data from large numbers of plants simultaneously. These technologies enable researchers to capture phenotypic data at multiple scales, ranging from whole plants to the cellular and molecular levels, with unprecedented speed and precision (Fiorani and Schurr 2013; Fahlgren *et al.* 2015). Plant phenotyping is a crucial aspect of studies on the interactions between plants and their environment, with practical implications in crop management and breeding.

One of the key technologies used in HTP is remote sensing, which involves the use of aerial or satellite-based platforms to capture plant-related data such as canopy temperature, chlorophyll content, and water status. These remote sensing techniques provide a non-destructive

and efficient way to monitor plant growth and health over large areas, enabling researchers to detect stress responses, nutrient deficiencies, and disease outbreaks at an early stage. Another important tool in HTP is imaging, particularly with techniques like hyperspectral imaging and 3D imaging (Ghimire *et al.* 2023; Karunathilake *et al.* 2023). Hyperspectral imaging allows the measurement of a wide range of spectral signatures from plants, and provides detailed information about their biochemical and physiological properties. On the other hand, 3D imaging techniques enable the reconstruction of plant architecture and can be used to quantify traits related to plant structure, such as leaf area, leaf angle, and plant height. Advances in robotics and automation have also played a crucial role in HTP. Automated systems equipped with robotic arms, conveyor belts, and high-resolution cameras can perform repetitive tasks like plant watering, fertilization, and image capture with minimal human intervention. These robotic platforms can handle large numbers of plants simultaneously, enabling high-speed phenotyping and reducing the labor required for data collection (Fig. 1) (Liu *et al.* 2020; Sarić *et al.* 2022; Xu and Li 2022; Ghimire *et al.* 2023). Machine vision is also playing a crucial role in the automation of production



**Fig. 1** Various phenotyping platforms used for crop improvement. AI, artificial intelligence; HTP, high-throughput phenotyping.

(Tian *et al.* 2022).

Leveraging machine learning (ML) algorithms in plant breeding will provide breeders with streamlined and powerful tools to expedite the creation of novel plant varieties and enhance the overall efficiency of the breeding workflow. These advancements are crucial for addressing the agricultural challenges brought about by the realities of climate change (Najafabadi-Yoosefzadeh *et al.* 2023). Advancements in plant phenotyping aim to meet breeding objectives by offering benefits in terms of throughput, applicability in field conditions, and usefulness in the breeding process. The prediction of breeding values using ML could make the practice more popular due to the reduced requirement for computational power as well as expertise for running deployed models (Hamadani *et al.* 2022). Over the past two decades, significant progress has been made in addressing these challenges through the development of novel sensors, automation technologies, and quantitative data analysis methods. These advancements have expanded the scope of analysis, allowing for higher capacity and throughput. Phenotyping can now be conducted on various plants, from model species to crops and forests, at different physical and temporal scales. This has facilitated the study of plant development across different levels, from cellular to canopy, as well as seasonal growth. Overall, these advances have paved the way for a deeper understanding of plant-environment interactions and improved crop management and breeding practices (Furbank and Tester 2011; Busby *et al.* 2017; Rouphael *et al.* 2018; Pieruschka and Schurr 2019). HTP has gained considerable attention and adoption in the plant science community, and it offers great potential for accelerating crop improvement, optimizing resource usage, and developing resilient agricultural systems. Despite its promise, there are still challenges to overcome, including protocol standardization, data integration, and analytical framework development. Nevertheless, HTP is set to revolutionize plant science and contribute to global food security amidst changing climates and increasing population demands. However, the field continues to evolve rapidly, necessitating greater phenotyping capacity, seamless integration of new technologies, improved access for researchers, and robust data management systems.

Artificial intelligence (AI) algorithms can analyze images acquired from high-throughput imaging systems and extract important features and patterns. This capability is particularly valuable in the field of plant phenotyping, where AI can identify leaf shapes, measure plant growth parameters, and detect disease

symptoms. In HTP, multiple types of data are often involved, such as imaging, genomic, and environmental data. AI techniques can integrate these diverse datasets and reveal intricate relationships between genotype, phenotype, and environment. By employing AI algorithms, predictive models can be constructed to establish connections between phenotypic data and other factors, like genotypes or environmental conditions (Xu *et al.* 2022). These models have the potential to predict phenotypic outcomes and provide guidance for breeding programs or experimental designs. Additionally, AI techniques enable the exploration of extensive phenotypic databases to uncover new associations, correlations, or causal relationships that might have been overlooked using traditional analysis methods (Tripodi *et al.* 2022). Therefore, this review provides a comprehensive overview of the power of HTP and AI in crop improvement. By harnessing the synergy between these technologies, breeders and researchers can enhance the efficiency and precision of crop breeding programs, ultimately leading to the development of resilient, high-yielding varieties that can address the global challenges of food security and sustainability.

## 2. Understanding ML

ML, or machine learning, is a combination of advanced modelling approaches that is capable of drawing patterns from data which are not possible using conventional techniques. ML generally uses experiences or case scenarios and projects them to discover underlying patterns in the data to explain or classify a new experience with minimal error. Thus, most ML techniques can generalize trends and patterns after learning from scenarios or data that were previously available. There are many ML tools available, and each has its pros and cons. The choice of a technique depends on the conditions at hand and the expert's discretion. Broadly, ML techniques can solve four possible types of problems: identification/detection, classification, quantification/estimation, and prediction. In addition, all data must be first pre-processed before it can be input into any technique. Pre-processing essentially cleans the data and removes any noise, outliers or unreliable data. It also makes the data better suited to the task at hand. Popular pre-processing methods include dimension reduction, image cropping, clustering, contrast enhancement, de-noising, segmentation, and others. These steps ensure that the outputs obtained are reliable.

The modelling objective is generally either generative or discriminative (Hassan *et al.* 2022). If the model is

being trained to distinguish two different data patterns, the model is said to be discriminative. Sometimes a model is supposed to generate patterns that it learned synthetically. In that case, it is said to be generative. An illustration illustrating the core difference between these two is shown in Fig. 2. The use of a specific model also depends on the task at hand. For example, if the amount of data is very large, discriminative models would function better than generative models in simple classification tasks like comparing rice and wheat plants. With limited training data that has latent features, generative models would be more robust, as they can help in overcoming overfitting.

### 2.1. ML for HTP in plants

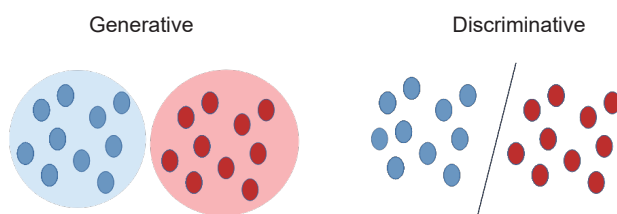
ML algorithms aim to enhance task performance by leveraging examples or historical data. Specifically, ML can establish effective connections between data inputs and build a coherent knowledge framework. Within this data-centric approach, the greater the amount of data utilized, the more effectively ML operates. For this reason, ML is gaining popularity for HTP in plants (Benos *et al.* 2021). The adoption of HTP has opened novel opportunities for non-destructive field-based phenotyping. Autonomous, semi-autonomous, or manually-operated platforms equipped with single or multiple sensors can gather spatial and temporal data, leading to the accumulation of extensive data sets for analysis and storage (Singh *et al.* 2016). Additionally, the integration of unmanned aerial vehicles (UAVs) and other self-operating machines on farms holds significant promise for enhancing the precision (Hamadani and Khan 2015) and effectiveness of crop monitoring processes (Teshome *et al.* 2023).

Also, with the rapid expansion of computing capabilities and the accessibility of cloud computing resources, automated ML (AutoML) has gained significant traction in both industry and academia. AutoML has emerged as an appealing substitute for traditional manual ML practices. It has the potential to provide high-performance,

comprehensive ML pipelines that encompass various stages, such as data preparation (cleaning and preprocessing), feature engineering (extraction, selection, and construction), model generation (selection and hyperparameter tuning), and model evaluation. Remarkably, AutoML aims to achieve all these steps with minimal user effort or intervention (Koh *et al.* 2021). With the increasing capabilities of machines to process and analyze images, computer vision is also leading to HTP (Tsafaris *et al.* 2016).

Numerous ML algorithms have been used successfully in plants for disease diagnosis, yield prediction, and other applications. To decipher the intricate links between genotype and phenotype, the fields of systems and network biology have found many applications. Network biology, as previously elaborated, has shed light on the intricacies of molecular events within biological systems. Concurrently, ML has played a pivotal role in predicting novel components within plants and pathogens. A promising hybrid approach involves the amalgamation of deep learning and network centrality features extracted from multidimensional omics data. This innovative fusion has the potential to unveil unexplored domains within the realm of plant–microbe interactions (Mishra *et al.* 2019). Image processing has contributed to the disease identification problem, in which thermal and stereo visible light, remote sensing, Kinect RGB depth images, visible and thermal images, hyperspectral images, fluorescence imaging spectroscopy, UAV-based RGB images and multispectral images, and others have successfully been used as data sources.

Agricultural and allied sectors have great potential which can be realized by aligning our data analysis tools with the 4th industrial revolution. Several popular ML algorithms have been used in plants and animals for HTP (Hamadani and Ganai 2022). These include algorithms like SVM, SAM, Gaussian processes classifier (GPC), Bayes factor, DAR, OBIA-based classification, KNN, quadratic discriminant analysis (QDA), linear discriminant analysis (LDA), Naïve Bayes (NB), simple logistic (SL), LibSVM (SVM), LibLINEAR (LINE), MLP (BNN), functional trees (FT), and random forests (RF) for plant species identification and classification in tomato, sugarbeet, apple, spinach, barley, and others (Singh *et al.* 2016; Ataş *et al.* 2022; Hassan *et al.* 2022), and for examining multiple traits and diseases. Recent advances in computation have made possible the use of ML for all four stages of identification, classification, quantification, and prediction (ICQP). It is now possible to use hybrid data that includes phenotypic and genotypic data, like QTL9 (Hassan *et al.* 2022) and genome-wide association studies (GWAS) (Cobb *et al.* 2013).



**Fig. 2** Illustration of the basic difference between generative and discriminative models.

ML algorithms are capable of handling time-series phenotypic data with time-series gene expression data to obtain a steady insight into the complex molecular mechanisms of disease resistance and spatiotemporal differences in the expression of stress.

Although the algorithms use complex computations at the back end, plant scientists can still take advantage of them due to the availability of tools packaged in the graphical user interface (GUI). Thus, they do not have to worry about the underlying mathematical and computational complexities. A major contributor to the seamless integration of ML with conventional phenotyping techniques is the data collection and curation pipeline. Such ecosystems will help in solving many basic problems in agriculture and ensuring food security.

## 2.2. Future of AI and ML in phenotyping

The future of AI for HTP in plants holds tremendous potential for advancements in plant breeding, crop management, and agricultural research. Deep learning techniques, such as deep neural networks, are continuously evolving and have the potential to further enhance the accuracy and efficiency of plant phenotyping. These advanced models can provide more accurate predictions and a better understanding of complex plant traits. Advanced fusion techniques, such as deep multimodal learning and graph-based models, will enable researchers to uncover hidden patterns and relationships between different data sources. Real-time phenotyping allows the continuous monitoring of plant traits throughout the growth cycle, providing valuable insights into dynamic responses to environmental conditions. It will enable rapid decision-making and adaptive management strategies in agriculture by optimizing resource allocation and improving crop yield and quality. ML techniques will facilitate the discovery of genotype–phenotype associations and help in the development of predictive models for trait selection and breeding strategies. Advanced algorithms, such as causal inference methods and Bayesian networks, will aid in unravelling the complex genetic architecture underlying plant traits. ML will drive the development of automated phenotyping platforms that can efficiently collect and analyze plant phenotypic data at large scales. These platforms will combine robotics, sensors, and imaging technologies with advanced machine-learning algorithms to enable HTP in controlled environments or in the field. Such platforms will revolutionize the breeding process, accelerate trait selection, and enhance crop improvement efforts (Fig. 3).

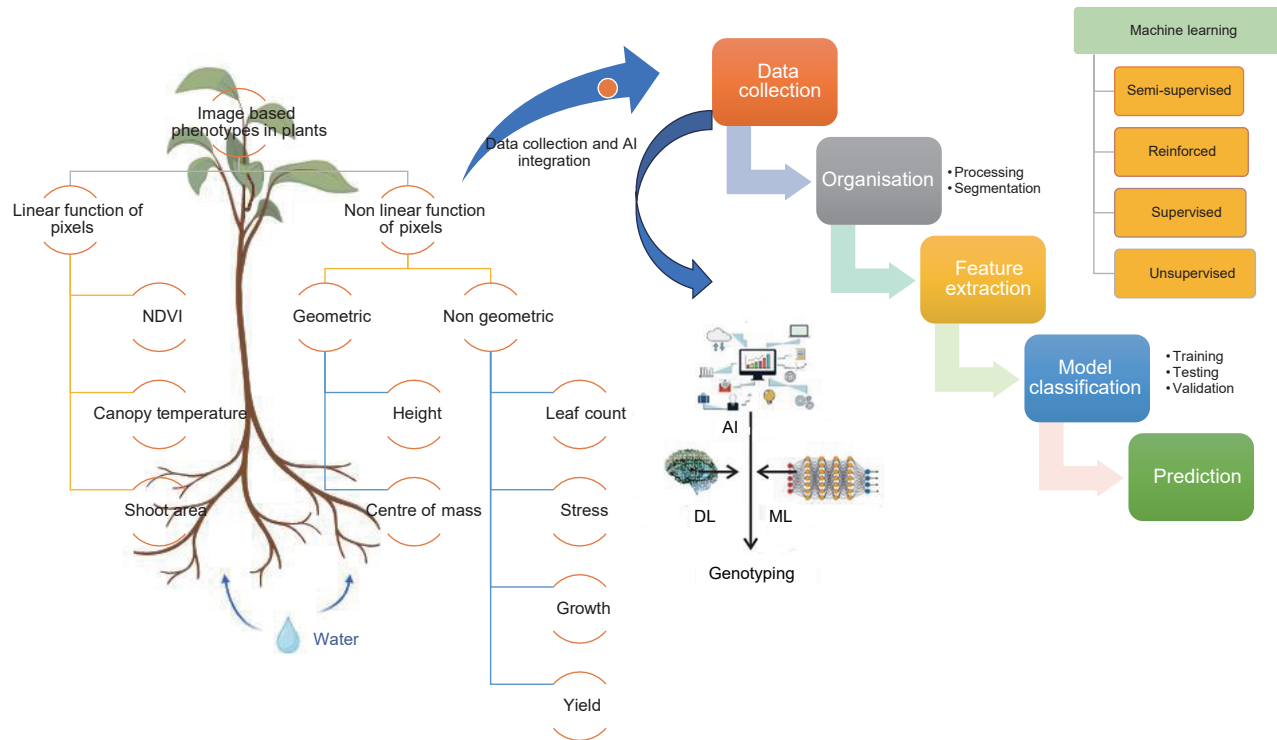
## 3. AI in HTP and its advantages in crop breeding

HTP methods are a major scientific advancement, with their ability to monitor and measure multiple phenotypic traits related to various aspects of plant growth and yield, as well as their adaptability to stress. HTP unlocks new prospects for phenotypic analyses with the many advantages it offers. It is non-destructive and collects massive amounts of spatial and temporal data through sensors (Pabuayon *et al.* 2019).

The use of automated systems for data collection is leading to the creation of extensive volumes of data and images that are destined for storage, processing, and analytical purposes. This phenomenon qualifies as big data due to its substantial volume, diverse range, and high speed of generation. Consequently, drawing inferences or interpreting this data becomes a challenging task (Younas 2019). In response to this situation, AI is increasingly garnering attention within the field. AI's capacity to provide rapid, effective, and enhanced data analytics is making significant strides in the realm of biology. Leveraging ML tools has shown many advantages (Hassan *et al.* 2022) since such tools enable data assimilation, feature identification, prediction, and other uses. ML can handle all four stages of plant phenotyping, i.e., ICQP. Some notable studies on the use of AI in HTP for crop breeding are detailed in Table 1.

ML can also handle the multidimensional data obtained from diverse sources, as well as complex mathematical models. This is especially useful for plant phenotyping for stress and yield which are challenging to model efficiently and holistically given the many factors involved, including genetic, economic, agronomic, meteorological, and even human inputs. HTP platforms have been used across various crops such as cotton (*Gossypium hirsutum* L.), triticale (*×Triticum secale* Wittmack L.), and maize (*Zea mays* L.). Recent strides have been made in plant imaging sensors, encompassing a spectrum from remote sensing, including techniques like spectroradiometry and light detection and ranging (LIDAR), to technologies such as hyperspectral, thermal, fluorescence, and 3D laser scanning. These innovations, combined with advancements in autonomous vehicle technology, have paved the way for high-throughput stress phenotyping (HTSP) approaches (Hassan *et al.* 2022). For example, many variants of artificial neural networks have been used for predicting the effects of the morphological responses of melatonin on citrus due to drought stress (Jafari and Shahsavari 2020).

High-throughput field phenotyping, substantiated by AI technology, has been beneficial for precision agriculture



**Fig. 3** Workflow illustrating the synergy between various high-throughput techniques, artificial intelligence (AI), machine learning (ML), and deep learning (DL) in the context of precise plant phenotyping in a comprehensive and dynamic workflow. It begins with the acquisition of diverse plant images using high-throughput systems, followed by preprocessing, advanced segmentation, and the training of machine learning models, particularly deep learning architectures. These models then have the capacity to predict intricate phenotypic traits accurately, ultimately leading to a nuanced and precise quantification of various plant characteristics. NDVI, normalized difference vegetation index.

**Table 1** Notable studies in the area of artificial intelligence (AI) applications in high-throughput phenotyping (HTP)

Focus	Methodology	Key findings
Plant phenotyping with deep learning	Image analysis+CNN	Accurate leaf segmentation and trait quantification (Minervini <i>et al.</i> 2015)
Automated HTP	Hyperspectral imaging+machine learning	Rapid assessment of crop performance (Montes 2007)
Disease detection using AI	UAV imagery+deep learning	Early identification of diseases in wheat (Singh <i>et al.</i> 2021)
Genomic selection in plant breeding	Genomic data+machine learning	Enhanced prediction of breeding outcomes (Crossa <i>et al.</i> 2017)
Optimizing crop breeding with AI	Bayesian optimization+genomic prediction	Improved selection of high-yielding genotypes (Merrick <i>et al.</i> 2022)
Weed detection using computer vision	UAV imagery+Convolutional Neural Networks	Efficient identification of weed presence (Haq 2022)

and plant breeding. Recent developments in data analysis, sensors, and the advancement of robots have enabled quick, efficient, non-destructive, non-invasive, measurable, repeatable, and objective phenotyping (Chawade *et al.* 2019). The study of identifying crop phenotypes on a wide scale at a low cost and with greater precision than human vision is made possible by computer vision, while ML helps researchers to identify significant trends in plant data. Combining, contrasting, and visualizing huge datasets from various sources

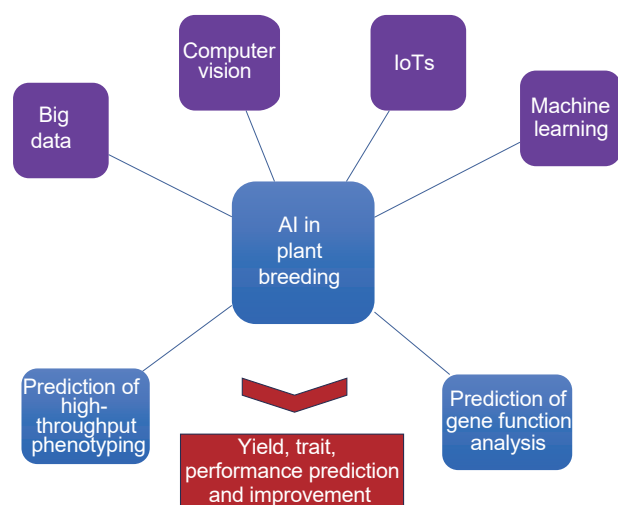
requires big data management and internet of things (IoT). Effective data management systems play a vital role in facilitating data exchange and knowledge sharing across different installations, locations, and experiments. Developing reliable systems for data storage, sharing, and analysis is crucial for harnessing the vast amounts of phenotypic data generated by different phenotyping facilities and experiments. This entails addressing issues of data standardization, interoperability, and privacy while promoting data-driven discoveries and advancements

in the field (Arend *et al.* 2022; Morisse *et al.* 2022; Nagasubramanian *et al.* 2022). These developments in envirotyping data and AI technologies open new possibilities for breeding in the future (van Dijk *et al.* 2021; Karunathilake *et al.* 2023). Various aspects of the use of AI in plant breeding are represented in Fig. 4. Through the analysis of vast amounts of complex genetic data, ML has completely changed plant breeding. Big data and ML in plant breeding have the potential to revolutionize the sector and increase food security. In the past five years, various ML techniques have been proposed, highlighting both their advantages and disadvantages (Veeragandham and Santhi 2020; van Dijk *et al.* 2021; Varshney 2021). For instance, the productivity of crops like oil palm has grown due to ML approaches (Latif *et al.* 2021). The classification and regression algorithm methods used for agricultural enhancement produce crop type recommendations and yield projections, respectively (Sundari *et al.* 2022). Decision tree regression (DTR) and random forest regression (RFR) can accurately predict wheat productivity using datasets for training and testing, with evaluation metrics such as  $R^2$ , RMSE, Akaike information criterion (AIC) with weights (AICW), evidence ratio (E.R), and decompositions of prediction error (Islam and Shehzad 2022). Classifiers such as k-Nearest Neighbor (kNN), Naive Bayes (NB), Decision Tree (DT), Support Vector Machines (SVM), Random Forests (RF), and Bagging can be used to recommend the most well-suited cultivatable crop(s) for a particular piece of land, depending on soil and environmental variables (Ganesan *et al.* 2022). A ML technique called ensemble learning combines several basic models to improve prediction

accuracy (Najafabadi-Yoosefzadeh *et al.* 2023). These algorithms can be employed in a variety of agricultural applications, such as crop recommendation, yield forecasting, or determining whether a particular location is suitable for agricultural cultivation.

To recognize changes in plants, computer vision algorithms are employed in plant phenotyping to extract data from photos and videos. ML, plant recognition, and computer vision-based phenotyping are a few of the methods (Šulc and Matas 2017; Mochida *et al.* 2019). Taxonomic hierarchical classification is frequently related to the fine-grained classification challenge of plant recognition, which has substantial intra-class variability and frequently minor inter-class variations. HTP has benefited from the recent developments in image analysis enabled by ML-based techniques, such as convolutional neural network-based modeling (Mochida *et al.* 2019). For example, TasselNet, a computer vision-based system, can count maize tassels, while CycleGAN, an algorithm for generating and transforming unpaired pictures through generative learning, was used to partition tomato developing trusses (Jung *et al.* 2022). Deep learning has made challenging phenotyping tasks achievable, and an image processing pipeline for high-throughput plant phenotyping has been developed. Big data management is crucial for crop improvement and plant breeding since it enables changes in fundamental plant traits. Plant breeders now rely on high-performance computing, bioinformatics tools, and machine-learning techniques to examine the massive volumes of genomic data produced by high-throughput omics technologies (Najafabadi-Yoosefzadeh *et al.* 2023). This field may undergo a revolution thanks to this strategy, which would also improve food security.

Studies have found that big data analysis and ML approaches are effective at solving agricultural problems (Parmley *et al.* 2019; Najafabadi-Yoosefzadeh *et al.* 2023). Envirotypic data, in general, is a crucial part of the big data in plant breeding because it can aid in predicting how different plant varieties will behave under various environmental circumstances and direct the creation of new varieties that are better adapted to certain environmental challenges (Taranto *et al.* 2018). Calibration difficulties can be overcome when using near-earth hyperspectral data for agriculture. For instance, a data-driven, fully automated calibration workflow with a suite of reliable algorithms for radiometric calibration, bidirectional reflectance distribution function (BRDF) correction and normalization, soil and shadow masking, and image quality evaluations was developed (Sagan *et al.* 2021). By delivering real-time environmental data that affect crop yield and productivity, IoT technology



**Fig. 4** Different aspects of artificial intelligence (AI) use in high-throughput phenotyping in plant breeding. IoT's, internet of things.

has the potential to enhance plant breeding and crop production. IoT, sensor networks, and data analysis can be used to construct a smart agricultural system. This approach emphasizes crop selection, nutrient content and humidity maintenance, effective fertilizer application, and quality control. Agricultural IoT applications can provide cutting-edge solutions, including remote monitoring, decision support, automatic irrigation, frost protection, and fertilization management (Mentsiev and Amirova 2020; Gowda *et al.* 2021; Sagan *et al.* 2021).

To hasten the development of climate-resilient crops, boost pest control, and improve plant phenotyping, AI is being employed progressively in plant breeding. For instance, speed breeding combined with AI is being used to generate crops that are climate smart (Rai 2022). Modernized plant breeding operations have the potential to benefit greatly from AI since it offers a mechanism to quickly assess the massive volumes of complicated data produced by high-throughput omics technologies. HTP and gene functional analysis problems can be solved using AI, which can also be used to predict or even explain phenotypes from the underlying genotypes in various contexts. However, to fully realize the promise of AI in crop and agronomic research, data management issues must be resolved. Applications of AI in plant breeding have the potential to enhance the effectiveness and precision of breeding programs as well as assist in addressing the issues of food security and climate change. The development of novel plant varieties with improved yield performance and increased resistance to pests, diseases, and climate change can also be aided by AI, which will help small-scale farmers by giving them access to more productive and resilient crops. In conclusion, by enhancing the effectiveness and precision of breeding programs and creating crops that are better adapted to local conditions, the application of AI in plant breeding has the potential to strengthen food security and enhance the livelihoods of small-scale farmers.

Plant high-throughput genotyping has the potential to quickly provide genetic data and to foster the growth of large mapping populations and a variety of phenotyping lines (McMullen *et al.* 2009). For enhancing photosynthesis, it can be useful for assessing new crop genotypes and identifying crucial genes (Parry *et al.* 2011). Previous research has demonstrated that the interactions between a crop's genetic make-up and environmental factors results in its phenotype (Yang *et al.* 2017). Traditional phenotyping techniques are destructive, time-consuming, inefficient and expensive. Plant HTP traits, such as yield, disease resistance, drought resistance, and salt resistance, have been studied using new techniques

like machine vision, imaging spectroscopy, and thermal infrared imaging (Li *et al.* 2014). In crop breeding and phenotyping, collecting data at extremely high resolution is critical for assessing and choosing the cultivars that perform the best. Plant breeding greatly benefits from quick methods for assessing crop response. High-throughput remote sensing can offer a great way to quickly identify the crop response. This means that the genotype to phenotype relationship can be successfully established using a HTP platform. The use of handheld and ground-mounted sensors for plant phenotyping has garnered growing research interest in recent years. However, ground vehicles are typically constrained by crop types and locations, and they can also destroy the crops and fields, and handheld-based phenotyping does not have a high throughput. Because of their inefficiency and time requirements, these methods cannot be used widely. Imaging from satellites is dependent on the weather. Additionally, the relatively low image resolution of satellites prevents them from being used in situations where high resolution is required (Jannoura *et al.* 2005).

UAV has been used in agriculture and general plant sciences over the past few years. To achieve HTP, more researchers are fusing airborne remote sensing methods with plant science. The use of unmanned aerial systems (UAS) has introduced a fresh method for crop management and observation, and UAS-based phenotyping is a good replacement for the earlier techniques, as it can avoid their limitations.

HTP has sped up plant breeding efforts by allowing for the rapid screening of numerous plants at various phenological stages. As a result, there is no need to wait for plant maturity in the field since this method can quickly screen for desired traits at the beginning of the process. It can be applied in controlled and natural settings in both the lab and the field. Plant performance can be quickly evaluated in the field, which encourages a thorough evaluation of the entire life cycle using less destructive methods. In addition, data recording is enhanced and environment-controlled high-throughput facilities require fewer replications. Phenotypic data are unquestionably the best predictors of biological outcomes, such as plant health, disease-related traits, and mortality, in most cases. They are also particularly helpful for obtaining precise measurements of plant characteristics, which enhances the abilities of plant breeders and agronomists (Mir *et al.* 2019; Rebetzke *et al.* 2019; Zhao *et al.* 2019; Ku *et al.* 2023).

### 3.1. Crop modeling and simulation linked with HTP

AI algorithms can be used to develop crop models that

simulate plant growth and predict crop performance under different environmental conditions. These models can aid in optimizing cultivation practices, predicting yield outcomes, and adapting cropping systems to changing climatic conditions (Hassan *et al.* 2022). HTP and crop modeling are closely linked. The data obtained from HTP, such as plant trait measurements, can be used as inputs for crop models to improve their accuracy and predictive capabilities. In turn, crop models can provide a framework for interpreting and analyzing the large volumes of data generated by HTP, allowing for a better understanding of crop performance and optimizing agricultural practices. By combining HTP and crop modeling, researchers and farmers can gain deeper insights into crop physiology, identify key traits for breeding programs, optimize resource allocation, enhance crop productivity, and develop sustainable and resilient agricultural systems (Bustos-Korts *et al.* 2019; York 2019; Gill *et al.* 2022).

### 3.2. Phenotypic platforms

Numerous HTP platforms are currently available for assessing diverse biotic and abiotic stress-related characteristics in various crops. These platforms are pivotal in advancing our understanding of plant responses to stressors. Several such platforms include:

1) “PHENOPSIS”: An automated platform developed for analyzing plant responses to soil water stress in *Arabidopsis*.

2) “GROWSCREEN FLUORO”: Designed to phenotype leaf growth and chlorophyll fluorescence, enabling the identification of abiotic stress tolerance in *Arabidopsis*.

3) “LemnaTec 3D Scanalyzer System”: Employed for non-invasive screening of salinity tolerance traits in rice, facilitating comprehensive assessments.

4) “HyperART”: Enables non-destructive quantification of leaf traits, including chlorophyll content and disease severity, in various crop.

5) “PhenoBox”: Identifies diseases such as head smut and corn smut in *Brachypodium* and maize, respectively, along with assessing salt stress responses in tobacco.

6) “PHENOVI-SION”: Developed for detecting drought stress and recovery patterns in maize plants, contributing to stress response analyses.

7) “PhénoField”: Geared towards characterizing various abiotic stresses in wheat, advancing insights into stress-related plant traits.

8) “PlantScreen™ Robotic XYZ System”: Used to analyze diverse traits associated with drought tolerance in rice, enhancing our understanding of resilience mechanisms.

These platforms collectively contribute to the

systematic assessment of stress-associated traits in a range of crops, fostering insights into plant responses and stress tolerance mechanisms (Gill *et al.* 2022).

## 4. Advances in imaging technologies and AI for crop improvement

Advanced imaging technologies, HTP, and AI have emerged as powerful tools for crop improvement. They enable researchers and breeders to assess the traits and performance of large populations of plants rapidly and accurately, leading to more efficient and targeted breeding strategies. High-resolution imaging technologies such as hyperspectral imaging, thermal imaging, 3D imaging, and fluorescence imaging allow researchers to capture detailed information about various plant characteristics, including leaf morphology, canopy structure, physiological processes, and stress responses (Fahlgren *et al.* 2015; Ampatzidis and Partel 2019; Nabwire *et al.* 2021). Advanced imaging technologies, such as hyperspectral imaging, thermal imaging, LiDAR (light detection and ranging), and drones equipped with high-resolution cameras, can provide detailed and real-time data on crops. These technologies allow researchers and farmers to monitor crop growth, detect stress factors, and identify diseases or pests at an early stage (Ampatzidis and Partel 2019; Nabwire *et al.* 2021; Hassan *et al.* 2022). By capturing information about plant health, nutrient status, water availability, and other vital parameters, imaging technologies enable precise and targeted interventions for better crop management. For example, hyperspectral imaging can analyze the reflected light spectrum from plants and identify specific biochemical markers related to stress or diseases. This enables farmers to address these issues promptly and prevent yield losses. Thermal imaging can detect variations in plant temperature, indicating stress caused by factors such as water shortage or disease. LiDAR technology can assist in creating 3D models of crop canopies, which can aid in estimating biomass, canopy structure, and crop density (Guo *et al.* 2018; Kim *et al.* 2023). Drones equipped with cameras or other sensors can capture high-resolution images of vast agricultural areas, providing comprehensive information for monitoring and decision-making.

HTP involves the automated and non-destructive measurement of plant traits on a large scale. It enables researchers to collect phenotypic data from thousands of plants quickly and accurately. These data can include traits related to growth, yield, disease resistance, nutrient status, and stress tolerance. HTP involves capturing large amounts of data on plant traits, such as leaf area, plant height, biomass, flowering time, and disease resistance,

on a large scale and in a time-efficient manner (Kim 2020; Yang *et al.* 2020). Traditional manual phenotyping methods are labor-intensive, time-consuming, and may not capture accurate data due to human error or subjectivity. HTP addresses these challenges by employing automated systems, robotic platforms, and non-destructive imaging techniques. By using imaging technologies and machine vision algorithms, HTP platforms can rapidly measure and analyze multiple traits across thousands of plants. This enables researchers and breeders to conduct large-scale screening experiments, assess the performance of diverse germplasms, identify desirable traits, and accelerate the breeding process. It also facilitates the collection of data in diverse environmental conditions, which can aid in understanding genotype–environment interactions and the development of more resilient and adaptable crop varieties (Parry *et al.* 2011; Yang *et al.* 2017; Xu and Li 2022). AI plays a crucial role in analyzing the vast amounts of data generated by advanced imaging technologies and HTP. AI algorithms, including ML and deep learning techniques, can process and interpret complex datasets, identify patterns, and make predictions or recommendations (Yang *et al.* 2021; Hassan *et al.* 2022). This enables AI to assist in various aspects of crop improvement.

#### 4.1. HTP and AI in disease detection

Using the integrated phenotypic data and AI algorithms, disease detection models have been built. These models can identify subtle relationships and associations between phenotypic patterns and specific diseases. They can be trained on large, labeled datasets to learn the patterns and characteristics associated with different diseases. HTP and AI algorithms together can analyze images or sensor data to identify signs of diseases or pests, allowing for early detection and targeted interventions. For example, ML models trained on large datasets of diseased plant images can accurately classify and diagnose plant diseases (Nabwire *et al.* 2021; Hassan *et al.* 2022; Kim *et al.* 2023).

#### 4.2. Trait discovery and quantification

Advanced imaging technologies combined with AI can facilitate the discovery and quantification of novel or complex traits that are otherwise challenging to measure. For example, AI algorithms can identify subtle differences in leaf coloration, texture, or disease symptoms that may be indicative of specific genetic traits. By analyzing historical data, weather patterns, and crop traits using HTP, AI models can predict crop yields and help to

optimize management practices. This information allows farmers to effectively plan their harvesting, storage, and marketing strategies (Shakoor *et al.* 2017; Harfouche *et al.* 2019; Karunathilake *et al.* 2023; Kim *et al.* 2023).

#### 4.3. Crop management and precision agriculture

Advanced imaging technologies combined with AI can provide real-time recommendations for irrigation scheduling, fertilizer application, and pest control based on sensor data, weather conditions, and plant responses. This optimization of crop management practices contributes to resource conservation and increased productivity. Advanced imaging technologies and AI can also be applied to monitor and optimize crop growth in real time. By continuously analyzing plant health, stress levels, and nutrient requirements, farmers can make informed decisions regarding irrigation, fertilization, and pest management, leading to improved resource efficiency and higher crop yields (Chawade *et al.* 2019; Maes and Steppe 2019; Kim *et al.* 2020; Karunathilake *et al.* 2023; Kim *et al.* 2023).

### 5. Challenges in implementing HTP and AI in crop breeding programs

Employing HTP techniques provide an assessment of the desired characteristics of ample genotypes indirectly *via* robust, cost-effective, and concurrent techniques (Kim *et al.* 2023). However, certain aspects restrict the implementation of this technology in plant breeding in a major way. In this context, impediments such as traits of quantitative origin, phenotyping of roots, impacts of the environment, and trials (multilocation and replicated) at field plot levels are still challenging. The use of HTP resolutions at the spatial and temporal levels for tissues or cells, morphological aspects, phenotypes of small size, and the characters which are below the soil are also risky (Zhao *et al.* 2019). Besides, the data which is generated is difficult to store, manage, and process along with the creation of worthwhile information at biological levels (Ates and Bukowski 2021; Jo *et al.* 2021). Various aspects, like phenotyping using crop models, involve occlusion which could not be avoided while the structure of the canopy is estimated, especially during the later stages of crop growth, in which the architecture of the foliage is a challenge (Karunathilake *et al.* 2023). Also, during the later growing season of soybean crops, measuring the total area of leaves and number of leaves using unmanned aerial systems (UAS) imaging is inaccurate compared to measurements in the early period of growth (Liu *et al.* 2021). Root phenotyping involves the core-

break method for obtaining the depth of roots (Wasson *et al.* 2017) and minirhizotrons having sensors for observing the growth of roots (Svane *et al.* 2019). But in both methods only a few roots can be detected along with the measured roots based on the position of the sample. Non-destructive tools of detection, such as ground-penetrating radar (Delgado *et al.* 2017) and electrical impedance tomography (Corona-Lopez *et al.* 2019), can detect the biomass of roots and help to capture the development of roots. But the spatial resolution for both is reduced (~1 cm/pixel), with low detection of fine roots at the individual level. The genetic architecture of abiotic tolerance, such as drought resistance (DR), is complex and influenced by many alleles with small effects (Fukao and Xiong 2013). Thus, the search for generic drought tolerance using single major-effect genes has almost always been unproductive (Passioura *et al.* 2012). There are many constraints which need to be properly addressed with respect to HTP along with high-throughput analysis of imagery and AI which will create an exact list of 2- and 3-dimensional traits of various phenotypes regarding the stress aspects with the latent knowledge of tolerability with time. Collecting data under field conditions *via* HTP and AI has been in an advanced phase for only a few years. But, the management and mining of the data collected in vast amounts is quite complicated. First, the study needs clear-cut aims and objectives at the biological level. Secondly, robust and convenient methods for the processing and analytical aspects need to be improved at a larger scale in order to interpret the raw data (Poorter *et al.* 2012).

Meanwhile, every year, large amounts of phenotypic data are generated through experiments of phenotypes under controlled environments or in the field. But, replicating the output by the same researcher or reproducing results from various labs in different studies is not satisfactory in many cases due to the uncontrolled variability in environmental conditions (Kim *et al.* 2023). Therefore, environmental parameters have a great impact and must receive similar attention from researchers as the traits which need to be measured. Envirotyping is a next-generation technology for environmental aspects that helps in addressing this issue (Xu 2016). Besides, through the integration and multiplication of the information, the impact of genotype×environment×management (G×E×M) can be calculated, and phenomic predictions might be possible (Xu 2016; Araus *et al.* 2018). For many years, the yield of crop growth, i.e., genetic gain, is quite slow and influenced by various aspects, such as population, genotypic data, heritable traits, geospatial (GS) data, and breeding strategy (Xu *et al.* 2020). The format of image data has changed broadly depending on various imaging sensors, such

as RGB, thermal aspects, hyperspectral, and computed tomography (CT), making a general view for analyzing image data challenging (Yang *et al.* 2020). Also, the re-use of data of phenotypic origin is quite rare compared to data at the omics level. Data at the phenotypic level must also comply to the FAIR criteria, so it is not readily accessible (Goff *et al.* 2011). Elaborate descriptive metadata and ideologies which can be agreed upon are required for constructing a database system that can store multiomics data. However, the vast amounts of data which are collected are either scattered in various laboratories or they differ in key formatting and quality aspects (Li *et al.* 2018). Sharing and standardization of data among various communities is still an impediment. Another problem is insufficient funds and infrastructure for data handling (Bolger *et al.* 2019). The challenges of implementing HTP and AI in crop breeding programs are depicted in Table 2.

In the next decade, these challenges must be addressed, which will emphasize innovative below-ground tools, advanced technology for dissecting stress like abiotic aspects or other complicated features, robust and feasible phenotyping at field levels, standardized data, and dissecting data for multiomics approaches. However, the need for experienced and trained manpower for phenotyping is still an issue to be resolved, along with finding trained research personnel (e.g., data imagery analysts) (Tsafaris and Scharr 2019). The phenotyping of plants is achieving big-data levels with the advanced high-throughput platforms. Information of phenotypes at individual stages does not suffice for associational analysis. Therefore, exact and accurate phenomic data, multi-scale interactions (e.g., physiological, structural, omics approaches), and the environment will form the basis of research in the coming years. To overcome the interference of environmental issues on the phenotyping of plants, we should create novel low-cost techniques based on AI/remote sensing (RS) to advance the imagery-based phenotyping approaches. Deep or ML models along with simulation platforms are the most urgent need for developing the latest applications for HTP and AI. In addition, an automatic model for phenotyping should be identified for the precise tasks among the novel species of the plant kingdom with robust and vibrant outputs based on large sampling statistical analysis with their relationships to traits of agronomic origin (Tayade *et al.* 2022). With the availability of multi-disciplinary information at phenotypic levels, there is a need to employ recent applications of AI for in-depth learning, the fusion of data, hybrid intelligence and swarm intelligence for generating big-data management systems to support integrated data, coordination, and universality. The obvious method to influence (genotype×environment×management)

**Table 2** Applications of HTP Platforms in various crops and their limitations

Crop	Trait	Technique	Challenges	Reference
Common bean ( <i>Phaseolus vulgaris</i> L. cv. 'Shiny Fardenlosa')	Phenotyping of roots	X-ray mediated computed tomography (CT) and Magnetic Resonance Imaging (MRI)	Cost and time-intensive; specialized prototype not available to study a crop	Metzner <i>et al.</i> (2015)
Rapeseed seed ( <i>Brassica napus</i> ) genotypes (Wotan, Expert, and Pirola) Barley seed ( <i>Hordeum vulgare</i> ) genotypes (Barke, HOR13719, and HOR9707) <i>Arabidopsis</i> seed ( <i>Arabidopsis thaliana</i> ) genotypes (Co1-0, lag2-2 and Agu-1)	Automatic individual seed handling and phenotyping	PhenoSeeder	Slow measurement speed; Threshing needed	Jahnke <i>et al.</i> (2016)
Maize ( <i>Zea mays</i> ) hybrids (Pioneer P1223, Syngenta GSS1477)	Canopy analysis structure with a smartphone	PocketPlant3D	Fewer features and single function; reliable models needed for complicated field situations	Confalonieri <i>et al.</i> (2017)
Spring wheat ( <i>Triticum aestivum</i> cv. Paragon)	Morphometric traits of spikes and grains	X-ray mediated micro computed tomography	Cost-intensive; time-intensive; bespoke image analysis needed for pipelining novel species types	Hughes <i>et al.</i> (2017)
Wheat ( <i>T. aestivum</i> L.) cvs. Avalon, Cadenza, Crusoe, Gatsby, Soissons and Maris Widgeon	Heading and flowering	AutomaticFieldScanalyzer, a rail-based gantry phenotyping system	Cost-intensive; less imaging area; varied ambient light	Yoosefzadeh-Najafabadi <i>et al.</i> (2023)
<i>Zea mays</i> genotypes EGB seeds (Olds Seeds, Madison, WI, USA) <i>Nicotiana benthamiana</i> , <i>Brachypodium distachyon</i> ecotype ABR4 seeds	Phenotyping of shoots	PhenoBox	Requires labor for screening at large level	Sadeghi-Tehran <i>et al.</i> (2017)
237 grains of <i>Triticum monococcum</i> subsp. <i>aegilopoides</i> (wild) and 513 for <i>T. monococcum</i> subsp. <i>monococcum</i> (domesticated), grain traits of wild ( <i>Hordeum spontaneum</i> ) and domesticated ( <i>Hordeum vulgare</i> ) 2-row barley	Morphometric variations	μ Computed tomography (CT) analysis of traits	Cost-intensive; time-intensive; bespoke image analysis needed to pipeline new species	Hughes <i>et al.</i> (2019)
Cultivated rice ( <i>Oryza sativa</i> L.)	Concentration of protein	Hyperspectral analysis	Cost-intensive; bespoke image analysis required and updating model for novel species, recent indicators for physiology or biochemical based features	Sun <i>et al.</i> (2019)
Rice ( <i>O. sativa</i> )	Chalkiness	Convolutional Neural Networks (CNNs) and Gradient-weighted Class Activation Mapping (Grad-CAM)	Colored rice cannot be screened, needs extra training and fine-tuning for quantifying chalkiness under varied proportions of grain overlapping	Wang <i>et al.</i> (2022)

interactions is to find the desired traits for a particular environment. Although there are many problems at scientific and technological levels which need remedies (Zhao *et al.* 2019). The path of (G×P×E) requires elaborated analytical tools. Therefore, Coppens *et al.* (2017) suggested that “phenotyping of plants has a future by synergising the national and global scenarios”. Since HTP and AI is still in their early inception, the pioneers and the leaders of research are combining the unmanned aerial system-based HTP platforms with spaceborne systems (RS), AI, and simulation modelling for crops to monitor agricultural features over larger areas. Also, there is a need to build multi-disciplinary groups which can tackle different challenges throughout the fields of biology,

environmental sciences, and computer sciences. There is an urgent need for efforts in developing standardized methods for the collection, processing, and interpretation of data. Meanwhile, as the core of digital data-based agriculture, the need for good quality raw-data cannot be neglected (Jung *et al.* 2021).

## 6. Conclusion and future perspective

Despite rapid advancements in robust and high-quality genetic and genomic technologies, the quality and speed of HTP are currently limiting crop genome functional analysis. Continuous advances in genomics and HTP are generating multiple layers of valuable information that can be used to

advance crop breeding and disease monitoring at a rapid pace. Significant contributions have been made in recent years by governments and private organizations in the development and use of HTP tools that can accelerate the development and deployment of phenotyping and breeding technologies to the benefit of researchers and farmers. Integrating heterogeneous data from reliable, automated, multifunctional, and HTP platforms will necessitate the continuing development of novel technologies, with a greater emphasis on developing low-cost, high-performance HTP technologies. With multifunctional phenotyping platforms generating massive amounts of sensor data and images, crop HTP will face new challenges in data storage, management, and analysis. The data volume is determined by the sensor/imager resolution and the number of acquired readings. To further promote the use of HTP in crop improvement programs, data analysis infrastructure that is less expensive and more accessible will need to be developed.

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## Declaration of competing interest

The authors declare that they have no conflict of interest.

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