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Multi-scale advanced approaches to high-throughput phenotyping in crop improvement

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Abstract
The advent of high-throughput phenotyping (HTP) technologies has revolutionized crop improvement by enabling rapid, non-destructive measurement of multiple plant traits. These advanced methods facilitate the efficient collection of phenotypic data, bridging the gap between traditional phenotyping and modern genomics. These technologies allow for the comprehensive analysis of complex traits, such as growth, yield and stress adaptations, under diverse environmental conditions. By integrating imaging techniques like near infrared, far infrared, thermal and hyper spectral imaging techniques with machine learning algorithms, high throughput phenotyping enhances the accuracy and efficiency of plant characters measurements. This dynamic approach enables the discovery of novel traits and accelerates breeding programs by providing deeper insights into genotype-phenotype relationships. Additionally, these technologies supports the continuous monitoring of plant development, stress responses and adaptive mechanisms, offering a more general perception of plant-environment interactions. The incorporation of robotics and automation in this technology not only increases precision but also allows for repeated, non-invasive measurements, fostering more informed breeding decisions. As these new technologies continue to advance, they hold the capacity to significantly accelerate the development of improved crop varieties, addressing the challenges of modern agriculture.

Keywords: High-throughput phenotyping, robotics, genomics, thermal imaging, modern agriculture

Introduction
The collection of phenotypic data for a large number of phenotypic characters in a large extensive area is labor-intensive and challenging. Technological advancements have given rise to the concept of high-throughput phenotyping methods. High-throughput phenotyping (HTP) rapidly measures multiple plant traits without harm. It tracks growth, yield and stress responses using non-destructive methods (Abebe *et al.*, 2023; Pabuayon *et al.*, 2019) [2, 6]. Plant phenotyping is a more recent and comprehensive definition for plant phenotyping, which assesses complex plant traits such as growth, development, tolerance, resistance, architecture, physiology, ecology, yield (Cadle-Davidson *et al.*, 2019; Chaitra *et al.*, 2017) [15, 18] and the basic measurement of individual quantitative parameters that form the basis for complex trait assessment. These technologies enable researchers to collect vast amounts of phenotypic data quickly and efficiently, allowing for more comprehensive analyses of plant traits (Sheikh *et al.*, 2023; He *et al.*, 2024) [87, 45]. These advanced methods can capture subtle differences in plant characteristics that may be overlooked by traditional phenotyping approaches. By integrating HTP with other cutting-edge technologies, scientists can gain deeper insights into plant biology and accelerate crop improvement efforts (Casto *et al.*, 2021; Sheikh *et al.*, 2023) [17, 87].
High-throughput phenotyping has been implemented primarily to address the following challenges: outdated phenotyping tools, accelerated genomics technologies - a large gap between genotype and phenotype, deriving new traits that were not previously considered for phenotyping on the whole population, dynamic phenotyping, automation and robotics - increase accuracy and non-destructive phenotyping (Chen *et al.*, 2015; Choudhury, 2020; Namin *et al.*, 2017) [21, 23, 65]. The benefits arising from the utilization of HTP technologies facilitate the identification of novel traits that may have been overlooked using traditional phenotyping

methods, potentially leading to new breeding targets and improved crop varieties (Sheikh *et al.*, 2023) [87]. These technologies offer a solution to bridge the gap between rapidly advancing genomic technologies and traditional phenotyping methods. Providing more accurate and detailed phenotypic data enables researchers to correlate genotypic information with observable plant traits (Kiranmai, 2023; Nuzzo *et al.*, 2009) [11, 67]. This enhanced understanding of genotype-phenotype relationships can lead to more targeted and efficient crop breeding strategies, ultimately accelerating the development of improved varieties. These advanced techniques also facilitate dynamic phenotyping, enabling researchers to monitor plant traits over time and in response to various environmental conditions (Dalal *et al.*, 2020; Attia *et al.*, 2020) [26, 10]. This temporal and contextual information can provide valuable insights into plant development, stress responses, and adaptive mechanisms, thereby enhancing our understanding of complex plant-environment interactions. Advanced phenotyping technologies not only improve accuracy through automation and robotics but also enable non-destructive measurements, allowing for repeated observations on the same plants throughout their growth cycle (Van De Zedde, 2022) [97]. This noninvasive approach provides a more comprehensive understanding of plant development and responses to environmental factors, thereby facilitating more informed breeding decisions. The integration of these technologies with machine-learning algorithms can further enhance data analysis, elucidating subtle patterns and relationships that may not be apparent through traditional methods (Gupta *et al.*, 2016; Pathak *et al.*, 2023; Pedro, 2023) [41, 73, 74].

High throughput phenotyping

High-throughput phenotyping (HTP) technologies are revolutionizing crop improvement by enabling precise measurements of various traits across thousands of field-grown plants in diverse environments (Shakoor *et al.*, 2017; Jangra *et al.*, 2021; Sheikh *et al.*, 2023) [84, 49, 87]. This approach is critical for selecting superior lines based on yield, disease resistance, and stress tolerance, thereby accelerating breeding programs aimed at enhancing crop performance (Paliwal *et al.*, 2021; Sreenivasulu *et al.*, 2006; Subiramani *et al.*, 2020; Thakkar *et al.*, 2021) [70, 90, 92].

Understanding phenomics

The term "phenomics," introduced by Gerlai in 2002, refers to the comprehensive study of phenotypes at multiple biological levels, from molecular to organismal scales (Biase, 2023; Chen *et al.*, 2013) [14, 22]. High-throughput methods facilitate the analysis of plant growth, architecture, performance and composition, employing advanced imaging technologies such as hyperspectral imaging and 3D scanning. These non-invasive techniques allow researchers to capture detailed morphological and physiological data, significantly enhancing the understanding of plant responses to environmental stimuli (Haase, 2012) [42].

Applications of high-throughput phenotyping

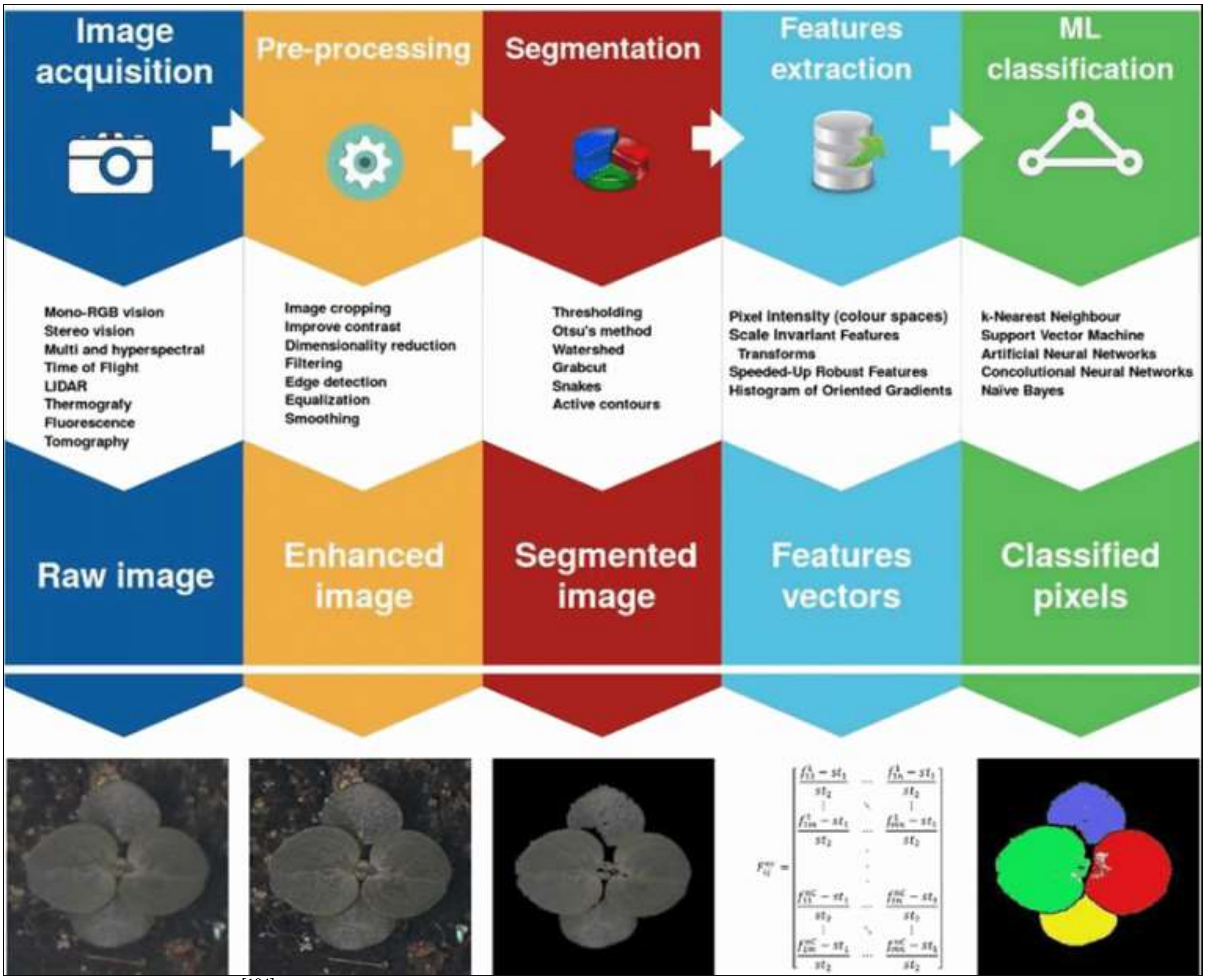
High throughput phenotyping technologies support the simultaneous analysis of multiple traits across various genetic lines and environmental conditions (He *et al.*, 2024; Morota, 2024) [45, 64]. This capability not only expedites the identification of desirable traits but also enriches the understanding of gene functions and interactions within the context of plant responses to stressors. By integrating phenomic data with other omics approaches, researchers can explore the intricate relationships between genotype, phenotype and environment, which is essential for developing targeted crop improvement strategies (Yang *et al.*, 2021; Zaghlool & Attallah, 2022) [103, 105]. Moreover, high-throughput phenotyping is vital for evaluating mutant populations, mapping populations, breeding populations, and germplasm collections. The development of phenotyping devices, including local cameras and infrared thermography, has enabled the assessment of stomatal opening and osmotic stress, providing quantitative data that can detect germplasm resistant to abiotic stresses in various plant species, including cereals and Arabidopsis.

These phenotyping technologies are indispensable for modern plant breeding, offering a pathway to enhance crop resilience and productivity (Zhou *et al.*, 2021) [109]. By facilitating comprehensive analyses of plant traits in varied growth conditions, these technologies not only streamline the breeding process but also impact the development of crops better suited for future agricultural challenges.

Basics to vision-based plant phenotyping

To know the basics of plant phenotyping we need to consider two main aspects, one is the image type acquired and how to process it and extract information from it. So, we are covering the current and emerging methods of image acquisition and processing allowing image-based phenomics. The high throughput phenotyping is based on images captured using different devices based on different light wavelength ranges and processing them and extracting the information (Danilevicz *et al.*, 2021; Tiwari *et al.*, 2021) [27, 95]. So, before understanding different types of phenotyping methods available it is necessary to understand the step-by-step process of extracting this phenotypic information from images and different softwares and cameras used has to be known to the scientist.

The process of extracting phenotypic information from images involves multiple steps, including image acquisition, preprocessing, segmentation, feature extraction, and data analysis (Guo *et al.*, 2021; Khobragade *et al.*, 2015; Samanta *et al.*, 2018; Zheng, 1994) [39, 51, 82]. Various specialized software tools and algorithms have been developed to facilitate these steps, enabling researchers to efficiently process large volumes of plant images (Knecht *et al.*, 2016) [82]. Understanding the capabilities and limitations of different imaging devices, such as multispectral cameras, thermal imagers, and hyperspectral sensors, is crucial for selecting the most appropriate technology for specific phenotyping applications.



Source: Yao *et al.*, 2021 [104]

Fig 1: Basic workflow in computer vision-based plant phenotyping:

Steps in the workflow of vision-based plant phenotyping
It involves five steps from image acquisition to ML classification represented in figure 1 and each step is explained below in detail:

A. Image acquisition: This process involves obtaining a digital representation of a scene. The resulting representation is described as image and its constituent elements are known as pixels (picture elements). The electronic device used to capture a scene is known as an imaging sensor. CCD (charge coupled device) and CMOS (complementary metal oxide semiconductor) are the most commonly utilized technologies in image sensors (Mehta *et al.*, 2015; Ardeshirpour *et al.*, 2006) [60, 8]. Recent technological advancements in cameras indicate that manufacturers such as IMEC (India-Middle East-Europe Economic Corridor), a world leader in nanoelectronics, are working to integrate TDI (time delay integration) technology with image sensor characteristics within a single device. TDI technology is anticipated to be applied to high-throughput phenotyping processes in the near future (Bai & Ge, 2021) [12].
Image Acquisition Systems Classification: Image acquisition systems can be categorized into seven groups that are applicable for phenotyping:
1. Mono-RGB (Red green blue) vision
2. Stereo vision
3. Multi and hyper spectral cameras
4. ToF (Time of flight) cameras
5. LIDAR (Light Detection and Ranging) technology
6. Thermography and Fluorescence Imaging
7. Tomography imaging

Image Analysis: Image analysis covers all stages from preprocessing to machine learning in plant image analysis (Zhang & Souri, 2022) [107]. The extraction of information from images is undertaken through the process of segmentation. The objective of a segmentation procedure is to isolate the components of an image that are of interest, *i.e.*, the object or region of interest, from the remainder of the image, *i.e.*, the background or irrelevant components. Consequently, this results in a partitioned image with significant regions.

B. Image pre-processing: Image preprocessing is a crucial component of image analysis. The objective of image preprocessing is to enhance contrast and eliminate noise to accentuate the objects of interest in a given image (Ariateja *et al.*, 2018; Pandey *et al.*, 2023) [9, 71]. Preprocessing techniques can range from basic operations such as image cropping and contrast enhancement to more complex procedures such as dimensionality reduction via Principal Component Analysis or Clustering (Gang & Bajwa, 2021; Zhang *et al.*, 2018) [35, 106]. In a comparative study analysing leaf diseases, histogram equalization was determined to be the most effective method for preprocessing colour images converted to grayscale.

C. Image segmentation: Image segmentation is the core of image processing for artificial vision-based plant phenotyping

(Choudhury, 2020; Patel, 2024) [23, 72]. Segmentation facilitates the isolation and identification of objects of interest from an image and it aims to discriminate background or irrelevant objects (Patel, 2024) [72]. The objects of interest are defined by the internal similarity of pixels in parameters such as texture, colour, statistics, etc. One of the fundamental algorithms utilized is threshold segmentation, based on creating groups of pixels on a grayscale according to the level of intensity, thus separating the background from targets. This approach has been implemented with Android OS (Ap Leaf) to identify plant leaves (Wang *et al.,* 2013) [99].

i) Otsu Method: Minimizes within-class variance to automatically segment images, frequently employed for background subtraction in plant recognition.
ii) Watershed Transformation: Segments images by treating them as topological surfaces, terminating at strong edges.
iii) Grab cut: Separates foreground from background using graph theory, effective with simple backgrounds but encounters difficulties with complex ones.
iv) Snakes: Active contour method that refines segmentation by fitting splines to edges, utilized in plant phenotyping with features such as colour intensity and texture.
v) Active Contours: Employed for precise plant recognition by combining algorithms for image segmentation, particularly effective for flowers.

D. Features extraction: Features extraction constitutes one of the fundamental components of object identification and classification based on computer vision. The features extracted from an image are organized in "feature vectors" (Kumaraguru & Chakravarthy, 2017; Qu, 2019) [54, 77]. The primary features include edges, pixel intensity, geometries, textures, and image transformations. One proposed system utilizes a feature vector composed of a combination of RGB and CIE L*a*b* colour spaces to segment images captured during daylight hours (Jing *et al.,* 2015) [50].

For night-time image segmentation, a vector comprising statistical features over two decomposition levels of the wavelet transform using IR images was computed. Numerous algorithms exist to identify invariant feature detectors and descriptors. This type of image analysis ensures the detection of points of interest in a scale- and rotation-independent manner. The Scale Invariant Features Transforms (SIFT), Speeded-Up Robust Features (SURF), and the Histograms of Oriented Gradients (HoG) are algorithms employed to extract characteristics in computer vision, and they have been extended to plant phenotyping (Agarwal *et al*., 2017; Bakhshi *et al.,* 2013; Routray *et al.,* 2017) [4, 13, 79]. SIFT and SURF algorithms have been evaluated for detecting local invariant features to obtain a 3D plant model from multi-view stereo images.

E. Machine learning in plant image analysis: The proliferation of data generated in current and future phenomic setups with high-throughput imaging technologies has necessitated the utilization of Machine Learning (ML) statistical approaches (Hruška *et al.,* 2018; Mayerich *et al.,* 2011; Rehman *et al.,* 2018; Singh *et al.,* 2015) [46, 59, 78, 88]. A significant advantage of ML is its capacity to explore large datasets to identify patterns, employing combinations of factors rather than conducting independent analyses. A contemporary concept derived from ML is Deep Learning (DL), encompassing a set of algorithms designed to model with a high level of abstraction. Convolutional Neural Networks (CNN) are an exemplar of DL derived from Artificial Neural Networks (ANN) (Dhaka *et al.,* 2021; Ghongade & Nagpur, 2024) [30, 36]. CNN has been employed to detect plant pathogen attacks (Abade *et al.,* 2020; Almeida *et al.,* 2019; Tugrul *et al.,* 2022) [1, 81, 96].

The factors essential for accelerating plant phenomics

1. High-throughput screens
2. Advanced imaging techniques and sensor technologies
3. Machine learning algorithms for data analysis and interpretation.
4. Multiple camera units
5. Non-destructive measurements
6. Quantitative analysis
7. Monitor growth dynamics
8. Stress assessment
9. Link to genomics

Different key technologies which enable high throughput phenotyping

There are different technologies available for high throughput phenotyping in plants which enables noninvasive and non-destructive phenotyping which saves time and labour. The different key technologies available for phenotyping at field level or green or glass house or laboratory level and benefits arousing from these technologies were discussed below.

1. Color imaging (2D and 3D)
2. Near infrared imaging
3. Far infrared imaging
4. Chlorophyll fluorescence imaging
5. Hyperspectral imaging
6. SONAR
7. LIDAR
8. Computed X ray tomography (CT scan)
9. MRI scan
10. Ground penetrating radar imaging or proximal sensing principle

Color imaging (2D and 3D)

2-dimensional imaging

Color imaging primarily relies on visible light spectra. The process involves creating images based on digital representations that aim to replicate human visual perception. These images provide data for plant phenotyping applications in trait-based physiological breeding. The most widespread use of visible imaging employs silicon sensors (CCD or CMOS arrays) that respond to visible light wavelengths (400-750 nm) and capture two-dimensional images (Harvey & Bähr, 2004; Waltham, 2013) [44, 99]. This technique represents the most basic imaging technology for plant sensing. Typically, raw image data is presented as spatial matrices of intensity values corresponding to photon fluxes in the red (~600 nm), green (~550 nm), and blue (~450 nm) spectral ranges of visible light. Cameras operating in the visible spectrum, such as standard digital cameras or RGB/CIR cameras, are commonly used due to their ability to provide quick measurements and cost-effective solutions for plant phenotyping applications (Nijland *et al.,* 2013) [66].

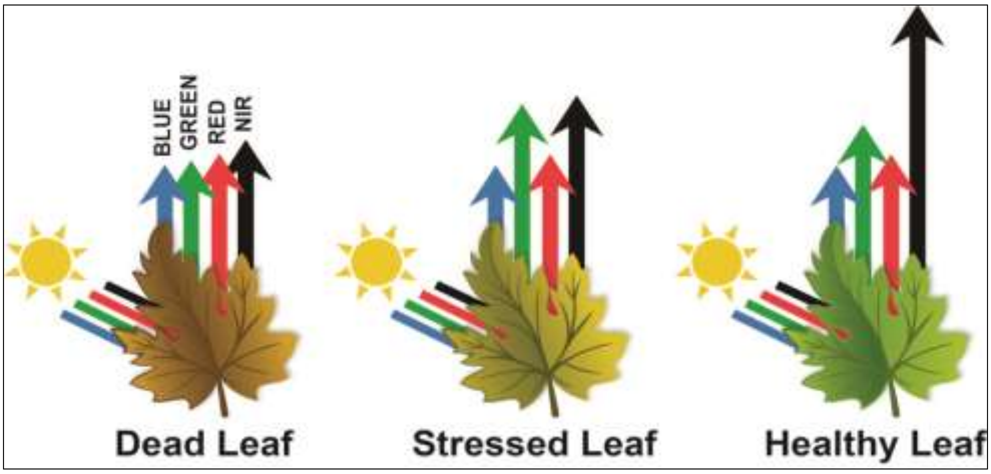
This colour information give estimation of the degree of senescence. By examining the colors, we can find the senescence of older leaves during drought and then suggest an escape or avoidance. Genotypes with stay-green type can be detected that would be able to continue photosynthesis under water stress. It also measures the aspects of plant architecture such as image-based projected biomass, leaf disease severity assessments, seed morphology, root architecture, leaf area, colour, growth dynamics, seedling vigour, yield, and fruit number and distribution.

3-Dimensional imaging

In this method firstly the digital photos of the plants on top and side views were taken and combined into 3D image (Guo *et al.*, 2018) [38]. The different measurements taken using 3-D were Shoot mass, Leaf number, Shape and angle, Leaf colour and Leaf health which are useful for constructing the final image in 3-dimensional representation.

Near infrared imaging (NIR)

NIR spectroscopy is a method that makes use of the near-infrared region of the electromagnetic spectrum (from about 700 to 2500 nanometers) (Ali *et al.*, 2010; Chapman *et al.*, 2019; Engelhardt & Gillam-Krakauer, 2012) [5, 19, 32]. NIR Capable of examining irregular surfaces with the same ease as a carefully prepared sample. NIR is non-destructive and requires little or no sample preparation. It can also be used to analyse multiple constituents in a single scan (Chelladurai & Jayas, 2014; Cozzolino, 2009) [20, 25]. NIR reflectance can be influenced by leaf thickness in addition to leaf water content.



Source: https://midopt.com/healthy-crop/

Fig 2: Near infrared imaging in Plants showing colour variations for a dead leaf, stressed leaf and dead leaf

Benefits of NIR:

The NIR and short-wave infrared (SWIR) subranges contains several major and minor water absorption troughs that can be used as an index of leaf relative water content, more the presence of chlorophyll more will be reflectance in NIR range, it also facilitates estimation of water content and movement within leaves and soil and Carbohydrate content of leaves.

Far-infrared imaging (FIR)

Thermal imaging allows for the visualization of infrared radiation, indicating an object as the temperature across the object's surface. Far-infrared (FIR) spectroscopy utilizes the electromagnetic spectrum's far-infrared region, ranging from approximately 10µm to 1 mm. Thermal cameras typically operate within a sensitive spectral range of 3-14 µm (Ozaki, 2021; Ruan *et al.*, 2001), with the most frequently employed wavelengths being 3-5 µm or 7-14 µm. These cameras are capable of detecting long-wave infrared (LWIR) radiation emitted by objects based on their temperature.

Benefits of FIR

FIR technology offers several advantages, including the ability to measure temperature differences between leaves and plants, identify cooler plants that absorb more water, and assess individual plants or entire plant systems. The temperature variations observed can be used to evaluate photosynthetic activity, salinity tolerance, and effective water use efficiency.

Fluorescence imaging

Plant metabolic status can be assessed by artificially stimulating plant photosystems and observing their responses. Fluorescence, which is the emission of light during radiation absorption at shorter wavelengths, occurs when chloroplasts are exposed to blue or actinic light. This re-emitted light serves as an effective indicator of a plant's ability to assimilate actinic light. The imaging of these fluorescence signals, known as fluorescence imaging, typically utilizes charge-coupled device (CCD) cameras that can detect fluorescence signals (Colarusso & Spring, 2003; Webb & Brown, 2012) [24, 100]. UV (ultraviolet) illumination (340-360 nm range) produces two types of fluorescence: red to far-red and blue to green. This forms the basis of multicolour fluorescence imaging, which allows for the simultaneous capture of fluorescence emission from four spectral bands (blue (440 nm, F440), green (520 nm, F520), red (690 nm, F690), and far-red (740 nm, 740)) using a single excitation wavelength.

The blue and green fluorescence signals (with peaks near 440 and 520 nm) originate from cinnamic acids, primarily ferulic acid, found mostly in cell walls (Fincher, 1976; Lichtenthaler & Schweiger, 1998; Morales *et al.*, 1996) [33, 55, 63].

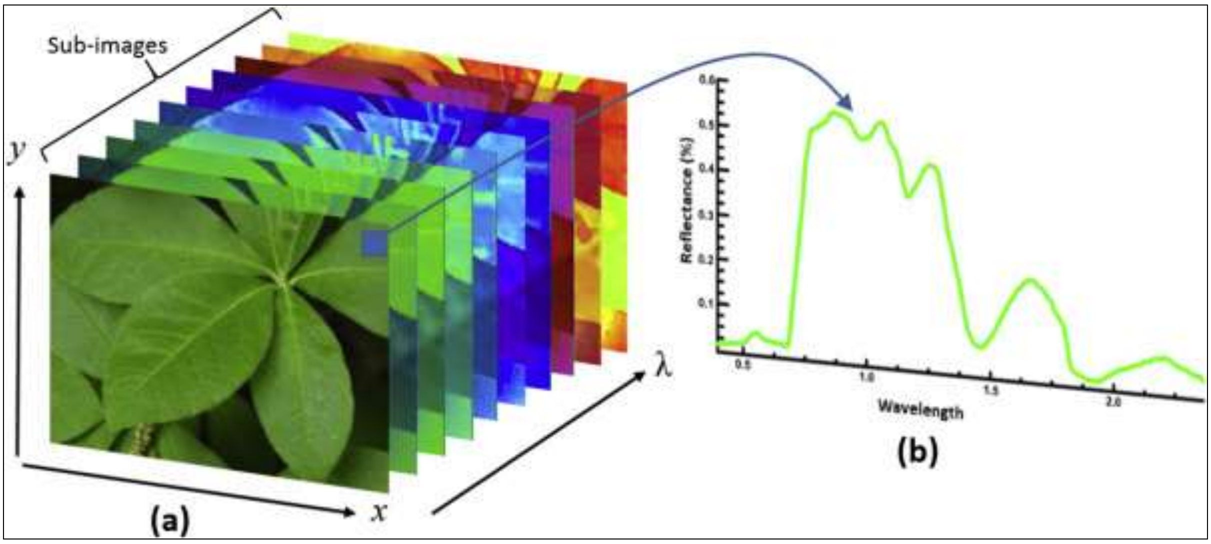
The red and far-red fluorescence emissions (with peaks near 690 and 740 nm) come from chlorophyll α molecules in the antenna and reaction centre of photosynthetic photosystem II, located in chloroplasts within mesophyll cells (Van Dorssen *et al.*, 1987).

Benefits of FI

It measures photosynthesis rate, biotic and abiotic stress responses and chlorophyll content.

Hyperspectral imaging

Hyperspectral imaging combines spectral (λ) and spatial (x, y) data into a three-dimensional structure known as a 'hyperspectral data cube' or 'hypercube' (Sharma *et al.*, 2021; Xu *et al.*, 2016) [21, 102]. This 3D hypercube consists of two dimensions of spatial information and one spectral dimension, which contains data for numerous spectral bands.



Source: Mishra *et al*., 2017

Fig 3: Hyperspectral imaging in plants

Benefits of Hyperspectral imaging: This technology has been utilized to identify abiotic, biotic, and quality characteristics in plants under both indoor and outdoor growing conditions. It can be employed across various scales, from cellular to landscape levels, to determine plant traits. The tools for data processing and mining are continuously evolving, with scientists employing machine learning and deep learning algorithms to aid in trait prediction. Imaging spectroscopy creates new opportunities for extracting spectral features associated with plant health and disease status. Spectral reflectance refers to the proportion of light reflected by a non-transparent surface. Scientists utilize this spectral reflectance to detect plants under stress from saline soil or drought, often before such stress becomes visible to the naked eye.

Sonar

An ultrasonic sensor is an electronic device that determines the distance to a target object by sending out ultrasonic sound waves and transforming the reflected sound into an electrical signal (Canali *et al*., 1982; Kulkarni *et al*., 2019; Punia, 2014; Srijith, 2021; Tanaka, 1987) [16, 53, 76, 91]. A CTFM ultrasonic sensor generates a signal containing information about the geometric structure of plants (Darwito *et al*., 2019; Dorr, 1991; Gupta & Agarwal, 2018) [28, 31, 40]. By correlating echoes from various angles, plants can be identified with enough precision for navigation purposes (Magori *et al.*, 1995; Olayinka *et al.*, 2021) [57, 3].

LIDAR

Lidar, also known as 'laser radar', 'laser scanner', 'laser profiler', 'range finder', or 'laser ranger' (Archibald & Petriu, 1993; Iman & Rashid, 2016; Schwarte & Singh, 2004) [7, 47, 83], has emerged as an innovative active sensing technology for three-dimensional measurement of plant morphology and canopy structures. This technology accurately determines the distance between the sensor and a target by measuring either the time elapsed between laser pulse emission and return (the 'time of flight' method) or through trigonometric calculations (the 'optical probe' or 'light section' methods) (Fu *et al.*, 2011; Hardesty, 1991) [34, 43]. Airborne lidar systems typically achieve accuracies of ~0.1-1 m, while ground-based systems offer precision ranging from ~0.05-10 cm, making lidar a superior alternative to traditional passive 3D measurement techniques. Various categories of lidar systems exist, classified according to their specific characteristics.

Computed tomography (CT)

X-ray digital radiography serves as the foundation for this imaging technique. It is commonly employed to evaluate tissue density, count tiller numbers, and assess grain quality, among other applications. Nevertheless, the processes of CT scanning, reconstruction, and extracting roots from X-ray CT volumes are time-consuming (Michael, 2001) [61]. For genetic studies, such as quantitative trait locus mapping, which necessitate large population sizes, a method that can visualize RSA rapidly and efficiently is essential.

Magnetic resonance imaging (MRI)

This imaging method aims to display metabolites, offer structural insights, and track internal physiological activities occurring within living organisms (Wirestam, 2021) [101]. This innovative approach allows researchers to visualize and analyse the distribution of various biochemical compounds within the body. By providing detailed metabolic mapping, it enables a deeper understanding of tissue composition and physiological processes. Moreover, this technique offers the potential to monitor real-time changes in metabolic activity, which could be invaluable for diagnosing and tracking disease progression.

Ground penentrating RADAR

Ground Penetrating Radar (GPR) is a non-invasive geophysical method that uses electromagnetic waves to detect subsurface objects, structures, and changes in material properties (Ismail *et al.*, 2016; Slob *et al*., 2010) [48, 89]. It is commonly used in archaeology, geology, and civil engineering to map underground features without excavation. GPR systems emit high-frequency radio waves into the ground, which reflect back upon hitting different materials, creating detailed images of subsurface layers. Its applications range from locating buried utilities to assessing soil conditions and detecting hidden artifacts.

Future prospects: The future of high-throughput phenotyping (HTP) in plant science holds great promise, propelled by rapid advancements in sensor technologies, artificial intelligence, and data analytics, which are transforming the way we assess plant traits on a large scale (Ma *et al.*, 2022; Sharma & Shivandu, 2024) [56, 86]. These innovations, including mobile phenotyping platforms, UAVs, and satellite imaging, are enhancing the precision and efficiency of phenotypic data collection across diverse environments. As HTP methods evolve, the integration of multi-omics data, including genomic and metabolomic information, is expected to provide deeper insights into plant responses to environmental challenges, aiding the development of more resilient crop varieties. However, to fully harness the potential of HTP, the field must address key challenges, such as standardizing phenotyping protocols, managing the vast amounts of data generated, and overcoming the high costs of infrastructure, particularly for researchers in resource-limited settings. Addressing these challenges will be crucial in leveraging HTP to advance crop breeding, especially in the face of climate change.

Conclusion

In conclusion, the future of high-throughput phenotyping is bright, with technological advancements and innovative approaches paving the way for improved agricultural practices. Addressing existing challenges and focusing on integration and automation will be key to unlocking the full potential of these methods in plant science.

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