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MINI REVIEW

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Rapid in vitro propagation protocol standardized for an endangered medicinal plant – Picrorhiza kurroa

Ananya Mishra

Centre for Medicinal Plant Research, Department of Botany, Banaras Hindu University, Varanasi, Uttar Pradesh, India

ABSTRACT

The agricultural sector faces unprecedented 21st-century challenges due to climate change, resource limitations, and a growing global population. Developing high-yielding, stress-resilient, and nutrient-rich crops has become more critical than ever. Accurate, high-throughput phenotyping, quantifying plant traits that reflect genetic and environmental interactions, is essential for accelerating crop improvement. Traditional phenotyping methods are labor-intensive, time-consuming, and prone to human error. Advances in artificial intelligence (AI), particularly deep learning, are revolutionizing plant phenotyping by leveraging imaging technologies such as RGB, hyperspectral, thermal, and 3D systems. These tools enable automated, precise analysis of complex traits at scale. This review highlights AI-driven phenotyping approaches in crop breeding, with emphasis on convolutional neural networks (CNNs), vision transformers, and multi-modal learning through UAVs, ground-based platforms, and integrated sensor arrays. Key applications include early disease detection, biomass estimation, canopy modeling, and yield prediction. Integrating phenotypic, genotypic, and environmental data using AI will significantly enhance genomic selection, driving more efficient and sustainable crop breeding strategies.

KEYWORDS

AI phenotyping; Crop breeding; Precision agriculture; Hyperspectral imaging; Deep learning

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Introduction

Crop improvement has always been fundamental to agricultural development and food security. However, the complexity and urgency of current agricultural challenges demand a paradigm shift in how breeding programs are executed. With the global population projected to exceed 9.7 billion by 2050 and agricultural land and water resources becoming increasingly constrained, the demand for high-yielding, stress-tolerant, and climate-resilient crops has never been greater [1]. Compounding these demands are the unpredictable effects of climate change, including altered rainfall patterns, rising temperatures, and increased pest and disease pressures.

While the advent of next-generation sequencing (NGS), marker-assisted selection (MAS), and genomic selection (GS) has accelerated the identification of favorable alleles and genes, breeding success ultimately hinges on the accurate evaluation of plant phenotypes, the physical and physiological traits that result from genotype–environment interactions [2]. Phenotyping, however, remains a major bottleneck in crop improvement. Traditional methods of measuring plant traits, whether in greenhouses or field conditions, are typically slow, manual, and error-prone. Such limitations hinder the throughput and objectivity required for modern breeding programs, especially when screening thousands of genotypes across multiple environments [3].

To address these limitations, the field of high-throughput phenotyping (HTP) has evolved, integrating remote sensing, sensor networks, robotics, and informatics to scale data acquisition. Yet, the full potential of HTP is being realized only now with the advent of artificial intelligence (AI), particularly deep learning. AI algorithms have the capacity to analyze large, complex, and noisy datasets with a high degree of precision, making them well-suited for automated trait extraction from diverse imaging modalities.

Deep learning models, especially convolutional neural networks (CNNs), can learn intricate patterns from images without requiring manual feature engineering. These capabilities have enabled breakthroughs in automated detection of diseases, prediction of yield traits, classification of growth stages, and even estimation of plant biomass [4]. Emerging technologies like vision transformers, generative adversarial networks (GANs), and graph neural networks (GNNs) are further expanding AI's potential in multi-modal and spatio-temporal phenotypic analysis [5].

Moreover, AI's synergy with modern imaging systems, such as hyperspectral sensors, LiDAR scanners, thermal cameras, and UAVs (unmanned aerial vehicles), has unlocked new frontiers in field-based phenotyping. These tools enable real-time monitoring of large breeding plots, capturing subtle physiological signals and dynamic developmental changes that are otherwise undetectable [6]. This review presents a comprehensive overview of how AI and advanced imaging technologies are transforming crop phenotyping. It highlights the major platforms, models, and applications being deployed and how they are reshaping the efficiency, scale, and accuracy of modern crop breeding.

***Correspondence:** Dr. Priya S. Mehta, Department of Plant Sciences, Indian Agricultural Research Institute, New Delhi, India. e-mail: priya_mehta@iari.res.in

Imaging Technologies in Modern Phenotyping

The success of AI in phenotyping hinges on the quality, resolution, and diversity of image data obtained from multiple imaging platforms. Each imaging modality captures unique physiological, morphological, or biochemical aspects of plant development. The integration of multiple imaging types across time points and spatial scales allows for the development of holistic phenotyping pipelines capable of tracking dynamic crop performance [7].

RGB imaging

RGB imaging is the foundation of most phenotyping systems due to its affordability and ease of use. Modern RGB cameras can capture high-resolution images under controlled or field conditions, allowing visual assessment of traits such as leaf number, plant height, color changes, and damage from pests or diseases [8]. With proper calibration and lighting conditions, RGB imaging has been shown to be effective in detecting early signs of leaf senescence, chlorosis, and necrosis. AI models, especially CNNs, are often trained on RGB datasets to classify disease symptoms, segment plant organs, or count structures such as flowers or seed pods [9].

Hyperspectral imaging (HSI)

Hyperspectral imaging captures data across hundreds of narrow spectral bands, typically ranging from the visible (400–700 nm) to near-infrared (700–1100 nm) and shortwave infrared regions. This allows detailed characterization of plant biochemistry, such as pigment content, water status, and nutrient deficiencies. Unlike RGB, which provides limited color information, HSI can detect subtle spectral signatures indicative of physiological stress even before visual symptoms appear [10].

HSI is particularly valuable for identifying biotic and abiotic stress responses. AI models such as 1D and 3D CNNs, support vector machines (SVMs), and ensemble classifiers have been trained to interpret hyperspectral data for classification tasks. These models help identify disease infections (e.g., powdery mildew in wheat), nitrogen deficiency, and water stress with high precision [11].

Thermal imaging

Thermal cameras detect infrared radiation emitted by plant surfaces, translating it into temperature maps. Since plant transpiration cools leaf surfaces, canopy temperature is often inversely related to stomatal conductance and water availability. Thermal imaging can thus detect drought stress or stomatal closure far earlier than visual cues can [12].

Thermal data are commonly used to compute indices like the Crop Water Stress Index (CWSI) or used directly in AI models for trait prediction. For instance, deep neural networks have been trained on thermal data to assess heat tolerance in wheat and maize, identifying cultivars that maintain cooler canopies under heat stress [13].

Imaging and LiDAR

Three-dimensional imaging provides detailed structural data on plant architecture. LiDAR systems emit laser pulses and measure the return time to reconstruct 3D point clouds. These models can assess traits such as plant height, canopy volume, internode spacing, and biomass [14].

Stereo imaging and structured light systems are alternatives to LiDAR and are often used in indoor phenotyping platforms. The output from 3D imaging can be further analyzed using computer vision algorithms or AI models for dynamic growth modeling. Studies using 3D LiDAR have been able to monitor changes in canopy structure over time to predict yield potential in rice and maize fields [15].

UAV and satellite imaging

Unmanned Aerial Vehicles (UAVs), or drones, equipped with RGB, multispectral, or thermal sensors, offer cost-effective, scalable phenotyping tools for field trials. These platforms allow the collection of high-resolution data over hundreds of plots within minutes [16]. Compared to ground-based systems, UAVs provide a bird's-eye view that captures spatial variability in canopy structure, chlorophyll content, and stress gradients.
Satellites offer similar advantages over larger scales, although with lower spatial resolution. Integrating satellite-based data with AI has shown promise in regional yield forecasting, crop mapping, and disease outbreak prediction [17]. In breeding contexts, UAVs are routinely used for canopy cover estimation, flowering detection, and growth monitoring using AI-based image segmentation and regression techniques [18].

Deep Learning Models for Image-Based Phenotyping

AI algorithms play a critical role in extracting and interpreting phenotypic features from diverse image data. Deep learning models, particularly convolutional neural networks (CNNs), excel at recognizing patterns in high-dimensional and noisy datasets, making them well-suited for real-world agricultural applications [19].

Convolutional neural networks (CNNs)

CNNs are among the most widely used deep learning architectures in plant phenotyping. They are composed of convolutional layers that automatically extract hierarchical features, starting from edges and textures to complex shapes and spatial patterns. CNNs eliminate the need for manual feature engineering, which is time-consuming and error-prone [20].

These models are used for:

- **Disease detection:** Classifying various plant diseases with high precision
- **Segmentation tasks:** Delineating leaves, roots, stems, or fruits from complex backgrounds
- **Trait estimation:** Predicting plant height, leaf area index, or biomass from aerial or ground images

Vision transformers and attention models

Transformers, initially designed for language processing, have recently been adapted for computer vision tasks. Vision transformers (ViTs) treat images as sequences of patches and use self-attention to model relationships between different parts of an image.

In phenotyping, ViTs are particularly effective in:

- Integrating multi-source data (e.g., imagery, weather, genotype)

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- Handling variable input resolutions
- Understanding global context within field-scale images

Attention mechanisms enable the model to "focus" on relevant image regions, improving interpretability and performance in complex environments [21].

Generative adversarial networks (GANs) and synthetic data

GANs are used for creating synthetic images that resemble real plant images, helping in data augmentation for training robust models. They are particularly useful when real datasets are limited or imbalanced. GANs have also been used to simulate rare stress conditions, generate phenotypic diversity, and explore genotype-phenotype spaces virtually. By enriching datasets with diverse synthetic images, GANs help mitigate overfitting and improve model generalizability across environments [22].

Applications in Crop Breeding and Trait Selection

AI-powered phenotyping is already being used in breeding pipelines to accelerate selection, improve genetic gain, and reduce breeding cycle time. Below are key application areas:

Disease detection and resistance screening

AI models trained on large image datasets can classify plant diseases with remarkable accuracy. Tools developed using CNNs and HSI have been successfully deployed to detect early signs of foliar diseases like wheat rust, soybean blight, and maize leaf spot. Early detection enables breeders to evaluate resistance without waiting for full symptom expression, increasing the selection accuracy. Moreover, hyperspectral imaging coupled with AI allows discrimination between different pathogens based on spectral fingerprints, even under overlapping symptoms [23].

Monitoring of growth and developmental stages

Phenological traits such as flowering time, maturity, and growth rate are crucial for climate adaptation. AI models analyze time-series data from UAVs or ground cameras to track developmental changes. Automated monitoring of growth curves allows breeders to assess trait stability across environments and select genotypes with optimal phenology. Additionally, AI can detect abnormalities in development, such as delayed flowering or asynchronous tillering, that may not be obvious in manual observation [24].

Structural trait measurement and biomass estimation

Accurate estimation of biomass, plant height, and canopy volume is critical in breeding for yield and stress tolerance. AI models, especially those trained on 3D LiDAR or UAV images, can estimate these traits non-destructively. In rice, maize, and sorghum, biomass estimation using AI has been correlated with final grain yield, making it a useful proxy for early-stage selection [25].

Root architecture analysis

Root traits like length, branching pattern, and angle are important for water and nutrient uptake but difficult to phenotype. AI-powered segmentation and skeletonization techniques can extract these traits from rhizotron images or soil profile scans. These data inform breeding decisions for drought tolerance and efficient resource use.

Conclusion

AI-powered phenotyping marks a transformative shift in plant science and crop breeding, enabling researchers to analyze complex plant traits with unmatched speed, accuracy, and scale. By integrating artificial intelligence with advanced imaging technologies, such as drones, hyperspectral cameras, and 3D scanners, it significantly reduces the time and labor associated with traditional manual phenotyping, resolving a key bottleneck in breeding pipelines.

Deep learning models, especially convolutional neural networks (CNNs), vision transformers (ViTs), and generative approaches—have proven highly effective in extracting meaningful biological information from complex, high-dimensional datasets. These models excel under real-world conditions, handling variability, noise, and incomplete data to assess traits like disease presence, canopy structure, biomass, and root development in real time.

A key advancement lies in integrating phenomic, genomic, and environmental data to support predictive breeding and improve genotype-by-environment interaction models. This facilitates more accurate genomic selection, essential for addressing climate-induced stresses such as drought, salinity, and heat. Accessibility is also expanding, with affordable UAVs, open-source tools, and edge computing making AI-powered phenotyping feasible even for resource-constrained regions. This democratization is vital for bridging yield gaps in smallholder agriculture.

Ultimately, AI enhances, not replaces, the role of plant breeders. With collaborative, interdisciplinary efforts and standardized frameworks, AI-powered phenotyping will drive more efficient, resilient, and sustainable crop improvement globally.

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No potential conflict of interest was reported by the authors.

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