A REVIEW OF ARTIFICIAL INTELLIGENCE IN PLANT PHENOTYPING: CURRENT STATE AND FUTURE PERSPECTIVES

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Abstract
One of the main obstacles to contemporary plant breeding and agricultural research is plant phenotyping, or the quantitative study of plant characteristics. The scale and speed of crop improvement are constrained by traditional methods, which are labour-intensive, slow, and frequently damaging. The revolutionary role of artificial intelligence (AI), namely computer vision and machine learning, in transforming plant phenotyping is reviewed in this research. We go over cutting-edge AI applications, ranging from sophisticated data processing for feature extraction and predictive modelling to automated high-throughput data collection employing a variety of sensors. In addition, we discuss the main obstacles, including the quantity and quality of data as well as the "black box" aspect of deep learning models, and we suggest future lines of inquiry for incorporating AI into sustainable farming methods.
***Keywords** – Black Box, Phenotyping, LiDAR, Bottelneck.*

Introduction

A burgeoning population and a changing climate are expected to fuel a major increase in the world's food demand in the ensuing decades. The creation of novel, durable, and high-yielding crop varieties is crucial to supplying this demand. This necessitates a quicker comprehension of the interplay of a plant's phenotype (observable qualities), genotype (genetic composition), and environment. The ability to quantify a vast number of plant phenotypes has trailed behind, resulting in a "phenotyping bottleneck" that impedes agricultural improvement, even while genomics advancements have made genotyping quick and affordable. By automating the phenotyping process and offering non-invasive, high-throughput, and accurate measurements of plant properties, AI-driven technologies are well-positioned to address this.

High-Throughput Data Acquisition

The gathering of large, high-quality datasets is the cornerstone of AI-powered phenotyping. High-Throughput Phenotyping (HTP) platforms, which combine a variety of sensors with automated systems, are used to do this.

1. **Imaging Sensors**: Multi-modal data is collected by a range of sensors, offering a thorough understanding of plant growth and health.
2. **RGB Cameras**: Standard cameras capture visual traits like leaf color, size, and shape, used for basic growth analysis, biomass estimation, and leaf counting.
3. **Hyperspectral and Multispectral Imaging**: For basic growth analysis, biomass estimate, and leaf counting, standard cameras record visual characteristics like as leaf colour, size, and form.
4. **Thermal Imaging**: The surface temperature of a plant is measured using thermal cameras, and this can reveal stomatal activity. AI uses these thermal trends to determine which plants are experiencing heat stress or drought.
5. **LiDAR and 3D Imaging**: LiDAR (Light Detection and Ranging) and stereo cameras create detailed 3D models of plants. AI models use this data to precisely measure plant height, canopy volume, and complex architectural traits.

To effectively cover wide regions, these sensors are frequently installed on automated systems such as Unmanned Aerial Vehicles (UAVs/drones), ground-based phenotyping carts, or gantry robots in greenhouses.

AI-Driven Analysis and Feature Extraction: Once data is collected, AI and machine learning algorithms are employed to extract meaningful information.

1. **Computer Vision and Deep Learning**: This is where AI in phenotyping starts. For image processing applications, Convolutional Neural Networks (CNNs) work especially well. Large, labelled datasets can be used to train them to do the following:
2. **Object Detection and Segmentation**: Accurately identifying and counting individual leaves, fruits, or flowers, even when they are overlapping or occluded.
3. **Classification**: Distinguishing between healthy and diseased plants, or classifying plants by their stress level (e.g., mild vs. severe drought stress).
4. **Regression**: Predicting continuous values like leaf area, biomass, or yield from image data.
5. **Predictive Modeling**: AI models can go beyond simple feature extraction to make powerful predictions by integrating multiple data sources.
6. **Genotype-to-Phenotype Prediction**: By combining phenotypic data with genetic and environmental information, AI can predict how a specific genotype will perform under certain conditions, a process critical for accelerating plant breeding cycles.
7. **Yield Prediction**: Early-season plant traits and environmental data are used to forecast final crop yield, enabling proactive farm management and resource allocation.

Challenges and Future Directions: Notwithstanding the quick developments, a number of obstacles need to be overcome before AI in plant phenotyping is widely used.

1. **Data Scarcity and Annotation**: Large, painstakingly labelled datasets are necessary for building strong deep learning models. One of the biggest obstacles is obtaining and annotating these datasets, particularly in a variety of outdoor settings.
2. **Model Interpretability**: Since many deep learning models are "black boxes," it might be challenging for plant scientists to comprehend the reasoning behind a model's decisions. By emphasising the characteristics that these models rely on to make predictions, the new discipline of explainable AI (XAI) seeks to increase the transparency and reliability of these models.
3. **Scalability and Cost**: Smaller research teams or individual farmers may not be able to use high-throughput phenotyping tools due to their high cost and the substantial computational resources needed to process the large datasets. The development of more scalable and reasonably priced systems must be the main goal of future research.

Conclusion -

Developing more interpretable, flexible, and resource-efficient models is key to the future of AI in plant phenotyping. A more comprehensive understanding of plant biology will result from the integration of multi-omics data (such as transcriptomics, proteomics, and genomics) with phenomic data. In the end, artificial intelligence (AI) will evolve from a potent research tool to a crucial part of self-sufficient agricultural systems, directing in-the-moment choices for more productive and sustainable farming.

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