

000 CURRENT TRENDS IN AI TOOLS DEVELOPMENT IN  
001 PLANT BIOLOGY  
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006 **Anonymous authors**

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011 ABSTRACT

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013 AI tools have revolutionized plant biology and agrobiolgy by enabling high-  
014 throughput analysis of complex biological data, from genomes to phenotypes,  
015 supporting precision breeding and sustainable agriculture. We highlight key ap-  
016 plications in bioimage analysis using YOLO algorithms, crop plant genome anal-  
017 ysis, and computational high-throughput phenotyping tools, discussing recent ad-  
018 vancements. Classical genetic selection demands long time and labor-intensive  
019 opening way to novel computational modeling. Modern omics technologies, high-  
020 throughput genomics, high-throughput plant phenotyping, development of remote  
021 sensing devices on-farm provided vast amount of data available in databases. Such  
022 platforms and associated data generation have contributed to a booming AI indus-  
023 try in agriculture. Computer methods for plant genome data analysis oriented on  
024 stress resistance and crop yield rely on AI approaches including pattern recogni-  
025 tion, neural networks, and LLMs. As an example of the development of AI tools  
026 for crop bioinformatics, we present a collaborative project between Russia and  
027 China “Smart Crop - Cognitive Platform for Reconstruction, Visualization and  
028 Analysis of Stress Response Networks based on ANDSsystem and Multiomics in  
029 Rice and Wheat”. The study of molecular genetic mechanisms of plant resistance  
030 to unfavorable biotic and abiotic factors (high or low temperature, drought, salini-  
031 ty, soil diseases, pathogens and pests) requires the study of the functioning of  
032 entire molecular genetic systems, including complex signaling, regulatory, trans-  
033 port and metabolic pathways. Finally, we discuss the challenges and current trends  
034 of AI applications in computational plant biology.

035 1 INTRODUCTION. PLANT GENOME ANALYSIS AND PROJECT ‘SMART  
036 CROP’

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038 Artificial intelligence (AI) is revolutionizing plant sciences by enabling accurate identification of  
039 plant species, early disease diagnosis, prediction of crop yield, and precision agriculture optimiza-  
040 tion (Gupta et al., 2024; Khan et al., 2025; Kassem, 2025). AI applications in plant research and  
041 agriculture have benefited large-scale industrial farming, with RD investment focused on commod-  
042 ity crops such as wheat, rice, and maize, and high-value horticulture crops such as soft fruits. The  
043 challenge is related to its importance for global food security. Extreme environmental impacts,  
044 including those caused by adverse climate changes, plant diseases and insect pests, lead to signif-  
045 icant crop losses. AI-driven multi-omics integrates genomics, transcriptomics, and metabolomics  
046 for crop improvement, using deep learning to predict traits like yield and stress resistance (Javaid et  
047 al., 2023). Models such as convolutional neural networks analyze pan-genomes in crops like wheat  
048 and maize, identifying QTLs (Quantitative Trait Loci) for seed quality and accelerating breeding.  
049 Recent reviews highlight AI’s role in plant genomics, where ML dissects regulatory networks and  
050 enhances genomic selection for climate-resilient varieties (Eftekhari et al., 2024; Khan et al., 2025).

051 Within the framework of the project, using artificial intelligence methods, a cognitive software and  
052 information platform “Smart Crop” was created, which provides a full cycle of knowledge engi-  
053 neering in the field of plant biology for the reconstruction and analysis of gene networks, focused on  
054 solving problems of studying the molecular genetic mechanisms of the genotype-phenotype relation-  
055 ship - medium for agriculturally valuable crops of rice and wheat (Cheng et al., 2024). The platform

054 is focused on solving such substantive tasks as interpreting the results of omics data (establishing  
055 links between gene sets and biological processes, phenotypic traits, etc.); reconstruction of gene  
056 networks describing the relationship between molecular genetic objects and objects corresponding  
057 to the concepts of selection, phenomics and seed production, phytopathology, diagnostics, means of  
058 protection; identification of regulatory and signaling pathways of plant response to specific growth  
059 conditions, biotic and abiotic stresses (high or low temperature, drought, salinity, soil contamination  
060 with metals, response to fertilizers, the action of hormones, etc.); prediction of candidate genes for  
061 genotyping; search for markers for marker-based selection; candidate targets for the directed action  
062 of substances (including external factors) on plants to solve the problems of early/uniform emer-  
063 gence, better vegetative growth, efficient absorption of nutrients (Kleshchev et al., 2024; Antropova  
064 et al., 2024).

## 066 2 CROP PLANT GENOME ANALYSIS

068 Extreme environmental effects, diseases and insect pests result in significant crop loss. Therefore,  
069 more researchers turn their attention to the study of crop resistance. Earlier present, research on  
070 single stress-responsive genes in crops has been performed. To date, multiple studies have system-  
071 atically revealed a part of molecular regulatory network in rice and wheat (Li et al., 2025). Recently,  
072 Artificial intelligence (AI) has opened new possibilities for the systematic analysis of molecular  
073 networks. Text-mining is a field in AI that aims to extract information from collections of text docu-  
074 ments based on machine learning and natural language processing (NLP) techniques. Text mining is  
075 considered a useful tool for integrative biological research involving genes, proteins and phenotypes.  
076 In this project we plan to apply ANDSystem - bioinformatics tool that builds molecular networks by  
077 text-mining and data-mining of PubMed indexed publications and multiple omics by Russian part-  
078 ners (Ivanisenko, et al., 2020; Demenkov, et al., 2011; Ivanisenko, et al., 2022), for reconstruction  
079 and analysis of molecular networks under specific growth conditions, biotic and abiotic stresses in  
080 rice and wheat.

081 Therefore, the “Smart Crop” cognitive software and information platform was created, providing a  
082 full cycle of knowledge engineering about the genotype-phenotype-environment relationships in the  
083 field of agriculturally valuable rice and wheat crop research using AI and text-mining methods. The  
084 platform included three modules: (1) a module for automated extraction of knowledge from the texts  
085 of scientific publications, patents, databases; (2) a knowledge base containing extracted information  
086 in the form of a knowledge graph; (3) a module designed for the reconstruction and analysis of gene  
087 networks that describe the molecular mechanisms, regulatory and signaling pathways of a plant’s  
088 response to specific growth conditions, biotic and abiotic stresses (Demenkov et al., 2025).

089 Non-coding RNA (ncRNA) study is an important research field in life sciences. ncRNAs are in-  
090 volved in various biological processes and molecular regulations. Based on AI applications on  
091 plant ncRNAs and their regulatory network construction, we explored high-throughput sequencing  
092 datasets such as Ribo-seq, RNA-seq, sRNA-seq and other genomic/epigenomic data, to develop and  
093 improve molecular networks under stress response in rice and wheat (Shen et al., 2024; Zhou et al.,  
094 2025).

## 096 3 BIOIMAGE ANALYSIS WITH YOLO (YOU ONLY LOOK ONCE) MODELS

098 YOLO (You Only Look Once) models, known for real-time object detection, have been adapted for  
099 plant bioimaging to identify diseases, pests, and structures with high speed and accuracy (Alhwaiti  
100 et al., 2025). YOLOv3 and YOLOv4 excel in localizing diseased areas on leaves, achieving superior  
101 mAP, precision, and recall compared to traditional methods, aiding early intervention in crops like  
102 fruits. Recent 2025 studies demonstrate YOLO’s integration with multispectral imaging for non-  
103 invasive trait extraction, enhancing biodiversity monitoring and precision agriculture.

104 New approaches for detecting plant diseases, based on image processing, Machine Learning (ML),  
105 Deep Learning (DL) techniques, and hyperspectral imaging have been developed as a result of tech-  
106 nological advancements (Kaur et al., 2025). For instance, the applications included multi-class  
107 SVM for detecting three distinct classes of apple diseases, a feed-forward back propagation neural  
network for detecting mildew from grape leaves, machine learning techniques for the prediction

Table 1: Recent works in AI – driven plant bioinformatics (2024-2026)

Area	Key contribution	Publication
Bioimage	Real-time detection	Alhwaiti et al. 2025
Genome	Deep networks for omics	Syeda, 2025
Inter-disciplinary	GPT model for plants	Zhang et al., 2025
Phenotyping	Synthetic data for trait algorithms	Roggiolani et al., 2025
Genome/ Phenotype	Multi-omics for breeding values	Kassem, 2025
Phenotype	Phenotyping in field using drones	Lu et al., 2025
Inter-disciplinary	Plant disease diagnosis	Sheikh et al., 2024
Phenotyping	Yield prediction	Pugh et al., 2024

of crop yield. DL-based approaches for detecting plant diseases have attracted growing interest in recent years due to their capacity to acquire complex representations from vast amounts of data.

YOLO-LeafNet approach is proposed for detecting diseases from leaf images of four distinct species, namely, grape, bell pepper, corn, and potato. About 9 thousand leaf images have been acquired for this work from five different publicly available datasets on Kaggle. All the acquired images were pre-processed by applying four different image pre-processing operations. The number of images in the training dataset was tripled for better model performance by applying five different augmentation operations.

#### 4 PLANT PHENOTYPE ESTIMATION TOOLS

Computer vision tools automate phenotyping, quantifying growth, morphology, and physiology from images and 3D models (Kassem, 2025). Recent generative AI creates synthetic 3D leaf point clouds for trait estimation, addressing data scarcity and improving yield predictions (Plant Phenomics, 2025). Platforms like those using CNNs enable field-scale analysis via drones, modeling genotype-phenotype links for nowcasting and forecasting. Tools such as scKAN and AI phenomics pipelines integrate multi-omics for precise seed trait mapping

The study by Roggiolani and colleagues (Roggiolani et al., 2025) introduces a generative model capable of producing lifelike 3D leaf point clouds with known geometric traits, accelerating crop improvement and optimize yield predictions through data-driven modeling.

The research team trained a 3D convolutional neural network to learn how to generate realistic leaf structures from skeletonized representations of real leaves. Using datasets from sugar beet, maize, and tomato plants, they extracted the “skeleton” of each leaf—the petiole and main and lateral axes that define its shape—and then expanded these skeletons into dense point clouds using a Gaussian mixture model. The neural network, designed as a 3D U-Net architecture, predicts per-point offsets to reconstruct the complete leaf shape while maintaining its structural traits.

AI in plant breeding faces significant hurdles like data scarcity and model interpretability but holds promise for predictive breeding and climate resilience. Recent reviews emphasize addressing these to unlock faster genetic gains (Plant Phenomics, 2025).

#### 5 FIELD SURVEILLANCE USING DRONES

Digital phenotyping using drones (Unmanned Aerial Vehicles - UAVs) enables high-throughput, non-destructive trait assessment in breeding plots, accelerating selection for yield, stress tolerance, and maturity (Eftekhari et al., 2024). These applications integrate multispectral/RGB imaging with AI for scalable field data collection. Drones quantify key traits like plant height, biomass, stand count, canopy cover, and relative maturity with 90 percent accuracy, replacing manual labor in crops such as maize, soybean, and dry beans. RGB and multispectral sensors capture vegetation indices (e.g., NDVI) at multiple growth stages, strongly correlated with agronomic performance, such as yield and height.

162 UAVs detect pests, plant diseases and abiotic stresses via hyperspectral imaging, enabling early  
163 selection of resistant genotypes in breeding nurseries. High-resolution imagery identifies symptoms  
164 at the plot level, supporting genomic selection for traits such as drought tolerance through digital  
165 twins.

166 For example, in soybean breeding, drone HTP refines genotype selection via vegetation indices,  
167 optimizing research cycles and reducing costs. Cost-effective solutions like VITO's allow in-  
168 house deployment for large-scale trials, enhancing precision in variety development. Drones bridge  
169 genomics-phenomics gaps, simulating analysis of genotype-environment interactions for predictive  
170 breeding.

## 172 6 KEY CHALLENGES OF AI IN PLANT BIOLOGY

173 Data management is a primary barrier, with issues in standardization, quality, and availability of  
174 high-throughput phenomics and multi-omics datasets, especially for orphan crops (Williamson et  
175 al., 2023). High computational demands, biases in training data, and lack of field validation hinder  
176 model reliability and scalability. Interpretability remains elusive, as "black-box" AI struggles with  
177 explaining predictions for regulatory approval, while ethical concerns like inequality in access and  
178 GMO risks persist.

179 Note current challenges in AI applications in agrobiolology:

180 Data scarcity/quality

181 Federated learning, synthetic data generation

182 Computational cost

183 Field-to-lab

184 Hybrid AI-process-based models will integrate mechanistic simulations with ML for better ex-  
185 trapolation to new environments and traits. Advances in high-throughput phenotyping via drones,  
186 robotics, and digital twins promise real-time, scalable trait assessment. AI-driven gene editing (e.g.,  
187 CRISPR optimization) and predictive simulations could shorten breeding cycles to months, enabling  
188 proactive designs for stress tolerance.

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