



POPULAR ARTICLE

AI meets plant breeding

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Introduction

At the onset of climate change concerns and a rising population, Artificial Intelligence is reviving plant breeding by providing opportunities to secure the future food supply chain. The world's population is rising at an alarming rate. It is estimated that it will reach 10 billion by 2050, which will significantly increase the demand for food, feed, and fiber (Van Dijk *et al.*, 2021). Climate change is already threatening the stability of our food system and eroding limited fertile agricultural land due to adverse weather, soil salinity, and the emergence of minor pests that are becoming major pests (Singh *et al.*, 2023). Plant breeding alone can take more than a decade to improve traits such as yield and disease and pest resistance, even with the help of marker-assisted selection to bring superior-quality genes from the laboratory to the field. (Wu *et al.*, 2025). To overcome such bottlenecks, integration of Modern plant breeding with artificial intelligence is the need of the hour. Artificial intelligence, celebrated for its ability to analyze big datasets and recognize complex patterns, is transforming diverse scientific fields, with plant breeding Convolutional neural networks (CNNs) excel in processing high-resolution plant images,

emerging as a key beneficiary. AI tools have huge potential in various aspects of breeding, which include data collection, unlocking genetic diversity within gene banks, and bridging the genotypic-phenotypic gap to facilitate crop breeding.

AI applications in breeding

Machine learning effectively captures non-linear genotype-phenotype relationships that traditional linear regression models overlook, thereby enhancing predictive accuracy for complex traits (Juan, 2025; Niazian, 2020). Genomic selection is further strengthened by ML algorithms that integrate correlations among genotypes, phenotypes, and environments, enabling data-driven breeding decisions (Yan, 2022; Cheng, 2024; Sivakumar, 2024). Deep learning architectures such as ResNet50 and EfficientNetV2-B4 have demonstrated over 90% accuracy in detecting crop diseases across banana, maize, and wheat. Similarly, AI-powered phenotyping platforms like CropQuant-Air employ deep learning to achieve more than 97% accuracy in wheat spike detection and yield classification (Sivakumar, 2024).

enabling automated trait measurement and disease identification. Computer vision



approaches further advance phenotyping by automatically quantifying thousands of traits such as height, leaf area index, and fruit count from drone and sensor datasets (Wu *et al.*, 2025). Artificial intelligence also accelerates

hybrid performance prediction by forecasting parental combinations likely to produce high yielding crosses, thereby reducing years of conventional field experimentation (Prasanna *et al.*, 2025).

Major AI-driven breeding frameworks

iGEP (Integrated Genomic-Enviromic Prediction)	Extends genomic prediction with multi-omics, enviromics, and spatiotemporal models. It integrates genotype, phenotype, and envirotypes (G-P-E) profiles to enable prediction-based crop design at macro and micro scale (Xu <i>et al.</i> , 2022)
IPDB (Intelligent Precision Design Breeding)	Combines biological big data with AI for precision crop design. (Zhu <i>et al.</i> , 2024)
Breeding 5.0	AI decoded germplasm with multimodal data, omni simulation, and explainable AI (Fu <i>et al.</i> , 2025)
DBTL closed-loop accelerator	Design-build-test-learn cycle integrating AI, gene editing, and Phenotyping. AI to propose optimal designs, gene editing to build them, and high-throughput phenotyping to test results, with each cycle refining the model. (Wu <i>et al.</i> , 2025)
SMART crops	Self-monitoring, adapted, responsive technology via synthetic biology (Zhang <i>et al.</i> , 2024)

Major Challenges and limitations of AI in plant breeding

Despite the promise of AI in plant breeding, several challenges hinder its widespread adoption. A critical challenge persists for orphan crops and understudied traits, as the success of AI models relies heavily on access to extensive, high-quality, and well-annotated training datasets (Wu *et al.*, 2025). Moreover, no universal model currently exists; a comparative evaluation of 12 algorithms across 18 traits and six species revealed that no single approach consistently outperformed others across all contexts. Reported outcomes vary depending on application, dataset, and environmental factors, underscoring that AI alone cannot resolve every breeding challenge.-world feasibility. The transition from empirically driven to AI-driven breeding will

Limitations of the platform, such as a lack of integration with large language models (LLMs) and insufficient data coverage, restrict interactive question answering and the ability to leverage historical datasets. Additionally, high infrastructure costs associated with advanced phenotyping platforms, coupled with computational difficulties in integrating diverse sensor data, present significant barriers to practical implementation.

Final verdict

Artificial intelligence is increasingly positioned as a collaborative co-pilot for plant breeders instead of a replacement, offering optimal mathematical solutions while breeders provide critical judgement on real require coordinated institutional partnerships, the development of open-source tools, and



globally harmonized data sharing consortia to ensure equitable access. A key future direction lies in enhancing the explainability of predictive models, enhancing breeders to interpret the biological rationale behind algorithmic outputs. Ultimately, the vision I to

establish a self-reinforcing 'breeding flywheel', where iterative cycles of phenotypic improvement and refined breeding strategies continuously accelerate crop advancement, making breeding faster, smarter and more impactful.

References

1. Cheng, Q., and Wang, X. 2024. Machine Learning for AI Breeding in Plants. *Genomics Proteomics Bioinformatics*, 22. <https://doi.org/10.1093/gpbjnl/qzae051>.
2. Cheng, Z.J., and Cao, Y. 2025. Artificial Intelligence-Assisted Breeding for Plant Disease Resistance. *Int. J. Mol. Sci.*, 26: 5324. <https://doi.org/10.3390/ijms26115324>.
3. Farooq, M., Gao, S., Hassan, M.A., Huang, Z., Rasheed, A., Hearne, S., Prasanna, B., Li, X., and Li, H. 2024. Artificial intelligence in plant breeding. *Trends Genet.* <https://doi.org/10.1016/j.tig.2024.07.001>.
4. Fu, J., Zheng, S., Fan, L., Zheng, X., and Qian, Q. 2025. Breeding 5.0: Artificial intelligence (AI)-decoded germplasm for accelerated crop innovation. *J. Integr. Plant Biol.* <https://doi.org/10.1111/jipb.70008>.
5. Niazian, M., and Niedbala, G. 2020. Machine Learning for Plant Breeding and Biotechnology. *Agriculture*, 10: 436. <https://doi.org/10.3390/agriculture10100436>.
6. Prasanna, G., Joshi, J., Ganesan, S., Shoba, D., and Muralidharan, A. 2025. Advances in Genetics and Plant Breeding with Artificial Intelligence, Data Science and Machine Learning. *Int. J. Agric. Food Sci.* <https://doi.org/10.33545/2664844x.2025.v7.i9e.772>.
7. Sivakumar, T., Bashir, L., and Kumar, S. 2024. AI-Powered Plant Genomics: Revolutionizing Crop Breeding for the Future. *Biotech Today*. <https://doi.org/10.5958/2322-0996.2024.00013.6>.
8. Wu, H., Luo, M., Liu, Y., Yang, J., and Cao, Y. 2025. Integrated biotechnological and artificial intelligence innovations for plant improvement. *Front. Plant Sci.*, 16: 1736707. <https://doi.org/10.3389/fpls.2025.1736707>.
9. Xu, Y., Zhang, X., Li, H., Zheng, H., Zhang, J., Olsen, M.S., Varshney, R., Prasanna, B., and Qian, Q. 2022. Smart breeding driven by big data, artificial intelligence and integrated genomic-environmental prediction. *Mol. Plant.* <https://doi.org/10.1016/j.molp.2022.09.001>.
10. Yan, J., and Wang, X. 2022. Machine learning bridges omics sciences and plant breeding. *Trends Plant Sci.* <https://doi.org/10.1016/j.tplants.2022.08.018>.
11. Zhang, D., Xu, F., Wang, F., Le, L., and Pu, L. 2024. Synthetic biology and artificial intelligence in crop improvement. *Plant Commun.*, 6: 101220. <https://doi.org/10.1016/j.xplc.2024.101220>.
12. Zhu, W., Li, W., Zhang, H., and Li, L. 2024. Big data and artificial intelligence-aided crop breeding: Progress and prospects. *J. Integr. Plant Biol.*, 67: 722-739. <https://doi.org/10.1111/jipb.13791>.