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Breeding 5.0: Artificial intelligence (AI)-decoded germplasm for accelerated crop innovation∞

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ABSTRACT

Crop breeding technologies are vital for global food security. While traditional methods have improved yield, stress tolerance, and nutrition, rising challenges such as climate instability, land loss, and pest pressure now demand new solutions. This study introduces the Breeding 5.0 framework, driven by artificial intelligence (AI) and robotics, marking a shift from empirical selection to intelligent systems. Central to this transformation is AI's emerging ability to deeply "understand germplasm," not merely by identifying genetic markers but also by decoding its architecture, plasticity, regulatory logic, and environmental interactions. This germplasm intelligence enables predictive trait modeling, optimized parental design, and targeted selection. We define four technical paradigms enabling this shift: (i) Multimodal data integration to bridge genotype and phenotype; (ii) Omni-simulated environments for virtual performance testing; (iii) Peopleless data capture for scalable precision; and (iv) Expert, explainable AI for biologically grounded decisions. Together, these technologies algorithmically convert germplasm into actionable breeding insights, accelerating the full cycle from ideal plant type design to elite line development. We further propose the "breeding flywheel," a self-reinforcing system that continuously amplifies phenotypic gains and refines breeding strategies, thereby enabling faster and smarter crop improvement to ensure a sustainable food future.

Keywords: artificial intelligence (AI), breeding, explainable AI, germplasm resources, robotics

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INTRODUCTION

Over the past century, breakthroughs in crop breeding technology have significantly transformed the global food production landscape. Studies have indicated that modern breeding techniques have driven a 50%–200% increase in the yields of major food crops (Pingali, 2012). Moreover, these advancements have bolstered disease and pest resistance in crops, allowing for a 10%–30% reduction in pesticide and fertilizer use (Swarnapriya, 2021; Abebe and Tafa, 2022). The development of drought-resistant and salt-tolerant crop varieties has mitigated climate-related agricultural losses by 20%–40% (Cattivelli et al., 2008; Swarnapriya, 2021). Additionally, molecular marker-assisted breeding technology has significantly shortened the breeding cycle of new varieties from 10–15 years to 5–8 years (Soriano, 2020; Dida, 2022). These advancements have substantially improved global nutrition through biofortification, improved nutritional condition of hundreds of millions of people in the world, and provided crucial support in addressing population growth and land degradation (Ramankutty et al., 2018; Gaikwad et al., 2020).

However, the global food security situation is still challenging. According to the latest report by the Food and Agriculture Organization of the United Nations (FAO et al., 2024), in the year 2024, 733 million people still experienced hunger, with the high undernourishment rate in Africa of 20.4%. Amid the intensification of climate change, arable land degradation, and increasing pressure from pests and diseases, crop breeding is facing unprecedented challenges. Transformative innovations are essential to support the increasingly vulnerable global food security system (Xiong et al., 2022; Pixley et al., 2023). Agricultural research has entered an era of data explosion, marked by exponential growth in genomic, environmental, and phenotypic data. Traditional field trials and manual analysis are increasingly unable to meet the efficiency and precision requirements of modern breeding practices (Van Eeuwijk et al., 2019; Xu et al., 2022). To cope with these challenges and propel breeding science toward intelligence, this study offers a systematic review of the evolution of breeding technologies, outlines the development of artificial intelligence (AI) and robotics technologies and their typical applications in breeding, and summarizes current progress in key areas such as genetic data integration, intelligent algorithm applications, and phenotypic analysis. Through an in-depth analysis of the integration of AI and robotics in crop breeding, this article aims to provide theoretical support and technical reference for constructing a data-driven precision breeding system by incorporating advanced technologies. This technical integration not only significantly enhances the consistency and reproducibility of the breeding process but also pioneers a paradigm shift from "empirical breeding" to "intelligent breeding."

THE DEVELOPMENT OF ARTIFICIAL INTELLIGENCE

Artificial intelligence, a key branch of computer science, simulates human intelligence to empower machines to perform tasks such as language processing, image recognition, and decision-making (Pannu, 2015). Established as an academic discipline at the 1956 Dartmouth Conference (Rajaraman, 2014), AI initially aimed to replicate human-level intelligence. Although its core mission remains centered on mimicking human cognitive functions, technical advancements have broadened AI's capabilities across various domains. Its potential is increasingly evident in modern agriculture, especially through the development of precision breeding systems.

The evolution of AI can be categorized into five distinct developmental phases (Zhang and Lu, 2021). First-generation AI was characterized by rule-based systems, including expert systems and deductive reasoning, which made decisions using manually defined logical rules. Although these systems were effective in specific domains, their lack of self-learning and improvement capabilities results in considerable limitations. (Calegari et al., 2020). Second-generation AI incorporated statistical and data-driven machine learning, enabling computers to make predictions by analyzing historical data. Through algorithmic modeling of data patterns, machines achieved basic pattern recognition. For instance, when we aim for a machine to recognize a cat, the simplest approach is to provide it with numerous cat images. Through data analysis, the machine can summarize common cat features such as ears, whiskers, and fur, which enables it to identify new cat photographs (Sarker, 2021). Third-generation AI marked transformative breakthroughs with the advent of deep learning and neural networks. These systems, utilizing multi-layered architectures for nonlinear hierarchical processing, can autonomously extract high-level features from data to finish complex tasks (Zhang et al., 2023). This advancement substantially enhanced predictive accuracy and led to significant breakthroughs in fields such as computer vision and voice assistance. However, such models require intensive computational resources and large annotated datasets, and their limited explainability remains a challenge. Fourth-generation AI prioritizes self-supervised and reinforcement learning (Jaiswal, 2023). By interacting autonomously with the environment, machines can optimize decision-making process without explicit instruction, demonstrating adaptability in dynamic scenarios.

The recent emergence of large-scale foundation models (e.g., ChatGPT) has sparked debates about the imminent realization of Artificial General Intelligence (AGI) (Emmert-Streib, 2024). Fifth-generation AI aims to transcend single-task limitations by advancing toward generative AI and AGI. This paradigm shift enables cross-domain cognitive processing with human-like capacities, such as contextual comprehension, causal reasoning, and multimodal perception (Kumar et al., 2025). Fifth-generation AI integrates four strategic capabilities: generative synthesis (creating novel content from existing data), predictive analytics, autonomous decision-making, and complex logical inference (Sengar et al., 2024). Generative AI focuses on creating new content based on existing data, emphasizing creativity and production. Concurrently, foundation models, as the technical backbone, leverage extensive data and training to provide robust general capabilities, forming the core support of fifth-generation AI and representing a significant direction in technical advancement.

The evolution of AI, which has advanced from rule-based systems to deep learning, reinforcement learning, and affective computing, illustrates a continual rise in technical sophistication (Wang et al., 2022). Future AI systems will integrate multimodal learning, neuro-symbolic computing, and natural language processing to process cross-domain data (text, images, speech, video, etc.) and enable autonomous decision-making (Liang et al., 2024). These systems will feature dual adaptive mechanisms: dynamically optimizing model architectures for environmental changes while reducing reliance on labeled data through semi-supervised learning (Ding et al., 2023). Supported by stream computing, they will achieve real-time cross-industry adaptation and enhance explainability through interactive feedback mechanisms for user intent analysis and decision traceability.

Our analysis has outlined the evolutionary path of AI through the lens of algorithmic generational progression. It is important to note that, even among AI researchers, no unified classification framework has been established to date. This theoretical impasse stems from the multidimensional complexity inherent in AI's theoretical architectures and implementation pathways. From the perspective of the capability spectrum, AI can be categorized into domain-specific narrow AI and general AI with the potential for cross-domain cognition. Analyzing through functional modalities, AI can be further divided into perceptual and interactive subsystems such as computer vision and natural language processing (NLP). Examining from the system integration dimension, AI further distinguishes between "soft intelligence" (algorithmic models) and "hard intelligence" (cyber-physical systems). These taxonomic criteria do not operate in mutual exclusion but rather function like a prism refracting white light, each revealing distinct cognitive boundaries, implementation pathways, and physical interaction paradigms across the various developmental phases of AI.

Inspired by the biological underpinnings of human intelligence, algorithmic systems emulate brain-like higher-order cognitive functions (analogous to the advanced cognitive functions of the human brain), while robotic systems serve as effector organs governed by neural signals (comparable to the human motor system). Their co-evolution is reshaping the paradigm frameworks in modern breeding research, unlocking broader developmental prospects. This article, adopting a diachronic research perspective, systematically elucidates the applications of AI algorithms, which serve as the "digital nucleus" (referred to as AI in accordance with industry conventions unless otherwise specified), and agricultural robots as "physical terminals" across various technical generations in breeding. It further explores how their integration with domain-specific knowledge catalyzes paradigm shifts within breeding science.

EVOLUTION OF BREEDING TECHNOLOGY: COMPARISON AND PROSPECT FROM DIFFERENT PERSPECTIVES

History serves as a valuable mentor for the future. To comprehensively outline the development trajectory and future trends of breeding technologies, we delve into four key dimensions: genetic information utilization, technical evolution drivers, multi-omics data integration, and automated breeding systems. Through in-depth elaboration and systematic summary, we provide a thorough exploration of the evolutionary path of breeding technologies. This multi-level, interdisciplinary analytical framework bridges theoretical models with technical implementations, offering a holistic synthesis of advancements in the field (Figure 1).

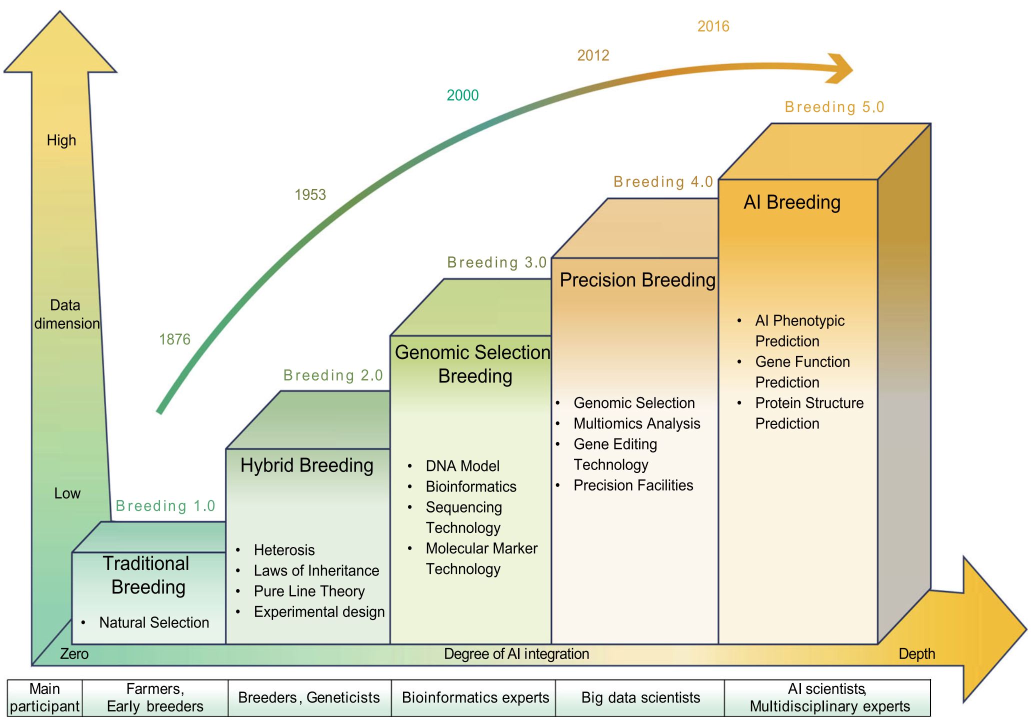

Figure 1. Evolution of breeding technology: From empirical practices to AI-driven paradigms
This stepped diagram outlines five evolutionary stages: Traditional, Hybrid, Genomic Selection, Precision, AI Breeding, within a dual-axis framework: data dimensionality (vertical) and AI integration depth (horizontal). Each ascending tier, annotated with key technologies and main participant, demonstrates progressive synergy between data-driven precision and AI autonomy, transforming breeding from empirical practices to predictive, automated systems.

Breeding 1.0: Traditional breeding based on experience

Breeding 1.0 marked the inception of crop breeding, relying on empirical observations and ancestral expertise of farmers and early breeders (Wallace et al., 2018) (Figure 1). This phase employed rudimentary techniques in which selection criteria were based on phenotypic traits such as morphology, size, and color to identify superior individuals for propagation. Lacking systematic scientific theories or solid data support, breeding outcomes were contingent upon the accumulation and transmission of individual expertise. Although with low efficiency, this foundational stage established the conceptual bedrock for subsequent technical advancements in the discipline.

Breeding 2.0: Hybrid breeding guided by scientific theory

Breeding 2.0 was initiated by the discovery of Mendelian genetics and the development of quantitative genetics (Wallace et al., 2018) (Figure 1). This stage marked a transition from empirical approaches to scientific methodology, leveraging genetics and statistics to systematically optimize hybridization, field trials, and trait selection. Breeders employed controlled crosses, experimental designs, and statistical tools such as variance analysis to enhance efficiency and predictability. These technical breakthroughs laid the theoretical groundwork for modern molecular breeding and demonstrated the transformative power of interdisciplinary science in agriculture.

Breeding 3.0: Genomic selection driven by molecular biology

Breeding 3.0 is characterized by the defining breakthrough of molecular biology technologies, particularly DNA marker-assisted selection and genome sequencing, ushering agriculture into an era of molecular-level precision (Wallace et al., 2018) (Figure 1). Breeders now systematically screen genotypes using molecular markers, integrating genomic and phenotypic datasets for precision-based selection. The integration of AI, particularly machine learning algorithms, enables high-throughput analysis of complex genetic datasets, significantly enhancing selection accuracy and breeding cycle efficiency (Fang, 2024). The technical breakthroughs during this phase facilitated a shift in breeding from traditional phenotypic selection to genomic selection, significantly enhancing breeding efficiency.

Breeding 4.0: Precision breeding via biotechnology-big data fusion

In the Breeding 4.0 phase, the deep integration of biotechnology and big data emerged as a new norm in the breeding field (Fang, 2024) (Figure 1). Genome editing technologies, such as CRISPR/Cas9, empowered breeders to perform precise manipulations and regulations on plant genomes, significantly enhancing the efficiency and accuracy of gene editing (Sun et al., 2024). Concurrently, AI-based multi-omics data integration technologies began to shine, allowing breeders to not only integrate genomic, phenomic, and environmental data but also leverage AI for data analysis and breeding strategy optimization (Zhu et al., 2024). These technical breakthroughs in this phase make the breeding process more precise and rapid, while providing robust technical support for the development of personalized breeding and sustainable agriculture.

Breeding 5.0: AI-driven intelligent breeding

Breeding 5.0 ushers in a transformative era of hyper-intelligent, cross-disciplinary convergence in crop improvement, underpinned by fifth-generation AI and generative foundation models (Fang, 2024) (Figure 1). This paradigm integrates explainable AI (XAI) with domain expertise to render the breeding process more controllable. It enables real-time optimization of breeding strategies through deep learning-driven analysis of multidimensional data sets, which include genomic, phenomic, and environmental data, along with insights from cross-disciplinary research (Zhu et al., 2024). The rapid advancement of AI technology, particularly its exceptional capability in processing complex biological information, is revolutionizing germplasm resource research, evaluation, and utilization in unprecedented ways (Farooq et al., 2024), providing robust foundational support for Breeding 5.0. AI technology is comprehensively enhancing the efficiency and precision of germplasm resource collection, preservation, evaluation, mining, utilization, and management, transforming these resources from static "gene banks" into dynamic, deeply analyzable "intelligent data sources" (Khan et al., 2022). Technical approaches such as simulated breeding design, fast breeding, and intelligent robotic automation have become standardized processes. AI not only automates these operations but also dynamically optimizes breeding strategies in real time to achieve unparalleled precision and efficiency in crop improvement (Sun et al., 2024). Moreover, breeding 5.0 propels intelligent automation in breeding workflows while facilitating customized breeding solutions tailored to diverse farm conditions, climate adaptability, and consumer preferences. This convergence heralds an unprecedented era characterized by precision-driven methodologies, AI-integrated systems, and sustainable agricultural innovation.

The progression from Breeding 1.0 to 5.0 demonstrates the technical evolution of crop improvement, transitioning from traditional empiricism to scientific methodologies, molecular biology to big data analytics, and precision breeding to comprehensive intelligent systems (Wallace et al., 2018; Fang, 2024) (Figure 1). Each generational breakthrough has systematically enhanced breeding efficiency and selection accuracy, establishing foundational capabilities for sustainable agricultural modernization. Looking ahead, the integration of next-generation AI, functional genomics, and heterogeneous big data will drive breeding technologies toward hyper-intelligent operation and atomic-level precision. These advancements will offer robust technical solutions to critical global challenges including food security imperatives, climate adaptation demands, and resource optimization constraints.

Global crop breeding technologies are currently in a phase of parallel development, with Breeding 4.0 dominating research and applications in developed countries (e.g., AlphaFold, generative models, and biological large-scale models advancing Breeding 5.0), while Africa and developing regions still rely on Breeding 2.0–3.0, where 4.0 adoption remains nascent. The coexistence of multiple breeding generations, both across and within regions, collectively underpins the emergence of Breeding 5.0 (generative breeding). The integration of AI has revitalized traditional frameworks by driving the shift from experience-based methods to data-driven intelligent decision-making, with deepening convergence between AI and agricultural innovation evident across evolving practices.

AI APPLICATIONS IN CROP BREEDING

The advancement of AI serves as a critical engine in breeding technologies.

While Breeding 1.0 and 2.0 primarily relied on empirical phenotyping, the subsequent stages, which include genomic selection, molecular marker-assisted breeding, multi-omics integration, and deep learning predictive models, have continuously improved efficiency and accuracy through data-driven technical innovations. This section systematically reviews AI's applications across these generational stages (Figure 2).

Second-generation AI (Breeding 3.0) is exemplified by Bayesian networks and Hidden Markov models (HMMs). Bayesian network model conditional dependencies, via directed acyclic graphs, have been applied to rice phenotypic dimensionality reduction (Yu et al., 2019), maize agronomic trait causal inference (Valleggi et al., 2024), and yield prediction in crops/livestock (Gianola et al., 2011). HMM was used to latent state sequences, enabling weed life cycle prediction (Borgy et al., 2015), plant stress classification (Blumenthal et al., 2017), protein functional site identification

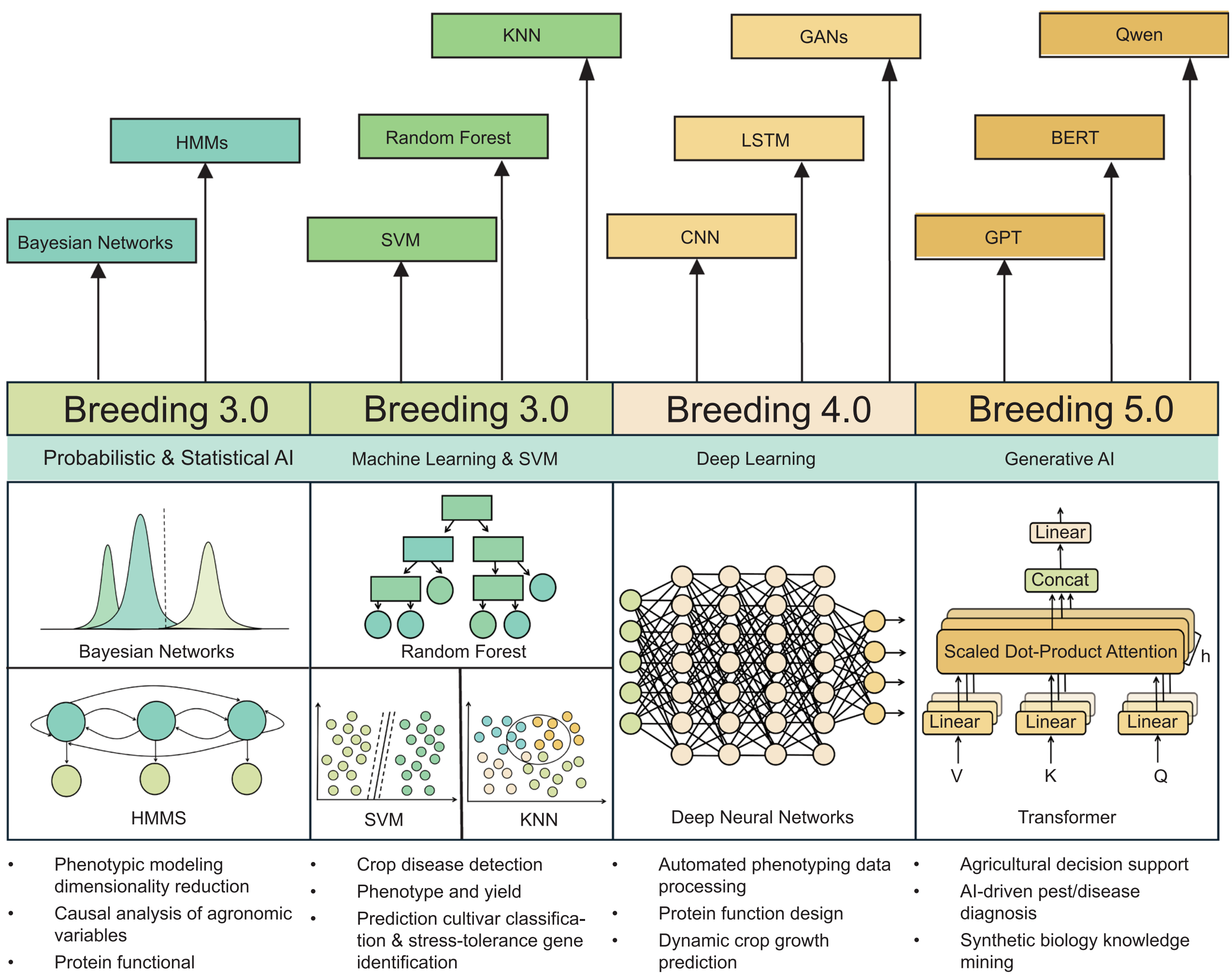

Figure 2. AI application in crop breeding
This evolutionary bar illustrates the integration of AI into crop breeding, structured into three phases aligned with methodological advancements: Probabilistic and Statistical AI, Machine Learning and SVM, Deep Learning, and Generative AI. Schematic diagrams below each phase depict AI application contexts and model architectures. The progression underscores AI's transformative role in transitioning from auxiliary decision support to autonomous breeding system design.

(Podell and Gribskov, 2004), and haplotype genome reconstruction (Campos-Martin et al., 2023) (Figure 2).

Third-generation AI (Breeding 3.0) integrates Support Vector Machines (SVM) for high-dimensional data classification and regression, Random Forest (RF) for overfitting-resistant ensemble learning, and K-Nearest Neighbors (KNN), enabling crop phenotype, yield, and stress tolerance prediction; disease-resistant gene identification; growth stage classification (e.g., disease detection and chlorophyll content evaluation); and rapid species/pest recognition (Shah et al., 2019; Singh and Kaur, 2019; Rabanus-Wallace et al., 2021; Picek et al., 2022; Sabouri and Sajadi, 2022) (Figure 2).

Fourth-generation AI (Breeding 4.0), characterized by deep learning, transcends traditional dimensional constraints: Convolutional Neural Networks (CNNs) extract spatial features to facilitate phenotypic data processing, protein structure resolution, and RNA–protein binding prediction (Lärm et al., 2023; Zhu et al., 2023; Draizen et al., 2024; Freschlin et al., 2024); Recurrent Neural Networks (LSTM/GRU) model temporal dependencies for environmental dynamics forecasting, protein trajectory simulation, and DNA base modification analysis (Liu et al., 2019; López-Correa et al., 2023; Kaplun et al., 2024); Generative Adversarial Networks (GANs) enable de novo protein design (Lan et al., 2024) (Figure 2).

Fifth-generation AI (Breeding 5.0), marked by multimodal foundation models (GPT, BERT, Qwen), integrates natural language perception and cross-modal data processing to enable agricultural decision support (flood assessment, disease risk prediction), DNA sequence feature extraction (miRNA promoter prediction, transcription factor identification), and germplasm data mining (wheat germplasm analysis, synthetic biology knowledge graphs) (Wang et al., 2023; Zhao et al., 2023; Kadiyala et al., 2024). These capabilities span the entire breeding chain, including phenotype–gene association modeling, environmental adaptability analysis, and germplasm innovation, thereby establishing AI as the backbone of modern crop improvement (Figure 2).

It is particularly noteworthy that fifth-generation AI demonstrates profound potential in germplasm resource data mining, with its applications spanning the entire research chain to significantly enhance utilization efficiency. The deep integration of AI with multi-omics (genomics, phenomics, and enviromics) is unprecedentedly advancing the mechanistic understanding of crop functional responses (Harfouche et al., 2023). These studies indicated that AI technologies are reshaping the paradigm of germplasm resource research by strengthening data analytics, optimizing decision-making processes, and accelerating genetic studies. More importantly, the deep analysis and design ability of AI on germplasm resources directly serves the transformation of resources to breeding practice (Khan et al., 2022). Through precise prediction of superior allelic combinations, targeted genotype design, and optimization of hybridization schemes, AI is substantially accelerating the development of innovative parental materials, thereby providing an efficient source for precision breeding. It can be asserted that "enabling AI to decipher germplasm and accelerating germplasm innovation" epitomizes the core value of this integrated technology.

ROBOTICS IN BREEDING

As previously discussed, drawing inspiration from the biological basis of human intelligence, algorithmic systems undertake brain-like higher cognitive functions (corresponding to advanced cognitive capabilities of the human cerebrum), while robotic systems serve as effector organs governed by neural signal analogs (analogous to the human motor system). The term "robots" here encompasses not merely embodied humanoid robots but includes various intelligent automation-driven products such as unmanned aerial vehicles, autonomous driving systems, unmanned ground vehicles, quadruped robots, and embodied intelligence. In the field of breeding, robotic systems can be applied across multiple scenarios: phenotypic trait collection, cultivation management and automated production, harvesting operations, speed breeding, and gene editing assistance (Figure 3).

Robotic applications at the microscale technical level

Robotic technology is progressively advancing into the microscale applications of crop breeding, encompassing critical stages such as gene editing, genetic transformation, tissue culture, and protein engineering. These applications significantly shorten breeding cycles while enhancing efficiency and precision, thereby providing robust support for developing crops with high yield, superior quality, and stress resilience (Li et al., 2024) (Figure 3). Current advancements in medical and animal research offer valuable insights for agricultural breeding. For instance, embryo microinjection platforms integrating machine vision and automated injection systems (Alegria et al., 2024; Guo et al., 2024) and automated single-cell isolation systems (Ungai-Salánki et al., 2016) have demonstrated exceptional stability and high-throughput operation potential. Concurrently, protein engineering is gaining momentum in agriculture. AI-driven automated protein modification platforms have substantially improved protein redesign efficiency, offering novel pathways for developing crop varieties with enhanced resistance and functionality (Rao, 2008; Lin et al., 2024).

Additionally, the convergence of robotic technology and novel materials science has yielded innovative solutions for plant cell engineering and nutrient regulation. For instance, the Tomato-Biobots developed by Huska et al. (2022) enable the precise delivery of nutrients and pesticides, significantly enhancing tissue culture efficiency. Automated micropropagation and genetic transformation systems, such as the Bright Yellow 2 platform, have enabled contamination-free and high-throughput plant production workflows (Lee et al., 2019). As these technologies continue to integrate and evolve, crop breeding is rapidly advancing into a new era characterized by precision, automation, and intelligence,

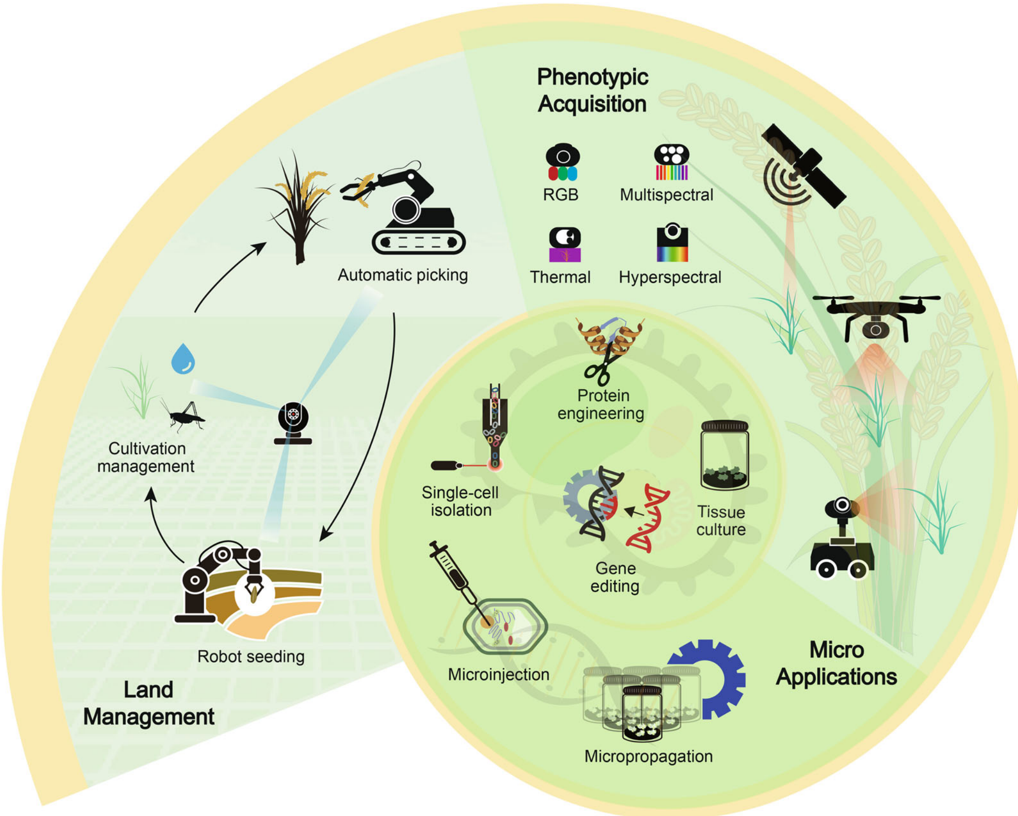

Figure 3. Robotics in breeding: Cross-scale integration from molecular to field systems
This spiral schematic illustrates the cross-scale integration of robotics in breeding, spanning molecular, plant phenotyping, and field management dimensions. The spiral structure highlights a progressive transition from laboratory-based research to scalable industrial implementation, underscoring robotics' transformative role in reinforcing the 'design-analysis-control' continuum of modern breeding practices.

thereby establishing an efficient and sustainable framework for germplasm resource innovation.

Robotic applications in phenotypic data acquisition

Phenotypic data collection plays a pivotal role in breeding processes, not only accelerating the screening of individuals with desirable traits but also providing critical data for genotype–phenotype association analysis and precision breeding. The integration of modern sensors, computer vision, and automated equipment has transformed phenotypic collection from traditional manual measurements to high-throughput, high-precision digital acquisition, enhancing both efficiency and reliability (Zhang et al., 2024) (Figure 3). The integration of robotic technology with AI-based vision systems has not only revolutionized methods of phenotypic data acquisition but also provided automated solutions for germplasm resource surveys, identification, and core sample collection, emerging as a pivotal tool for the establishment of intelligent germplasm repositories. Ground-based robotic platforms are ideal for close-range observation of low-stature crops (Xu and Li, 2022), while aerial platforms such as unmanned aerial vehicles (UAVs) enable rapid large-scale crop monitoring (Gano et al., 2023). When combined with satellite remote sensing, these systems further expand environmental omics applications (Resende et al., 2024). Multimodal feature extraction—spanning color, texture, and thermal properties—is achievable through diverse sensor types, including RGB, multispectral, hyperspectral, and thermal imaging technologies (Sun et al., 2022). The collected resource information is processed by an AI-driven intelligent archiving and labeling system to realize rapid input and standardized management of information.

In recent years, the applications of phenotypic robots have continued to expand. For example, the Pheno-Robot, which integrates 3D detection and NeRF (Neural Radiance Field) reconstruction technology, has enhanced in situ phenotypic analysis capabilities (Pan et al., 2024). In strawberry research, the SSM semantic segmentation model enables precise fruit classification (Yang et al., 2024), while UAV-based chlorophyll monitoring has revealed complex relationships between high chlorophyll levels and crop yield (Gu et al., 2024). Additionally, phenotypic robotic platforms for crops such as maize, wheat, and soybean are undergoing continuous refinement (Song et al., 2021; Hu et al., 2025). These advancements exemplify the deep integration of robotics, vision systems, and AI algorithms, propelling phenotypic analysis in breeding toward a new era characterized by precision, efficiency, and intelligence.

Robotic applications in field management

In the breeding process, cultivation management and automated production hold significant importance for enhancing efficiency and precision. By implementing precise regulation of environmental parameters such as water and nutrient supply, light exposure, and temperature, optimal growth conditions for crops can be ensured, facilitating phenotypic evaluation and superior cultivar selection. Advances in automation technology have driven the intelligent transformation of operations such as seeding, irrigation, fertilization, and harvesting. For instance, the *Autonomous Precision Crop Planting Robot* achieves autonomous navigation and precision seeding (Nataraj et al., 2024) (Figure 3), while autonomous ridging robots demonstrate superior cost-effectiveness and accuracy compared to traditional machinery (Kang et al., 2024). Robotic arms also exhibit high-efficiency operational potential in greenhouse and orchard settings (Jin and Han, 2024). These intelligent systems not only reduce labor costs but also enhance data acquisition capabilities, providing real-time, dynamic data support for breeding programs.

Furthermore, fully automated cultivation systems such as *SPECULARIA* have achieved end-to-end automated management from seeding to harvest (Car et al., 2023). In harvesting applications, robotic systems for crops such as gerbera, lettuce, and tomatoes have seen continuous breakthroughs. Platforms like Vegebot and AHPPEBot employ machine vision and deep learning models to perform fruit detection and ripeness assessment (Birrell et al., 2020; Li et al., 2024). These robotic systems significantly improve harvesting efficiency and precision while mitigating risks associated with human intervention. Collectively, intelligent cultivation management and automated operations are emerging as pivotal enablers for advancing smart and efficient breeding processes.

VISION FOR CROP BREEDING 5.0

The breeding flywheel driven by AI–robotic synergy

The flywheel metaphor illustrates a process transitioning from initiation to sustained growth. Initially requiring substantial impetus, the system gradually accumulates kinetic energy, enters a self-sustaining acceleration phase, and ultimately establishes a self-reinforcing growth cycle (Figure 4).

Artificial intelligence-driven breeding signifies the advent of the flywheel era in modern agricultural technology, where the core lies in establishing a self-reinforcing intelligent breeding system through the synergy of data, algorithms, and hardware. During the initial phase, substantial investments are required for deploying data acquisition infrastructure, training multimodal AI models, and calibrating automated robotic systems. This stage serves as a critical energy-accumulation period to initiate the flywheel. Once in operation, high-speed breeding robots execute AI-generated instructions with precision, performing tasks such as seeding, phenotypic scanning, and sample collection in greenhouses or field conditions. Equipped with high-throughput sensors, these systems continuously capture plant growth parameters (leaf area, plant height, spectral reflectance), environmental metrics (temperature-humidity indices, soil moisture content) and molecular-level data (spatiotemporal gene expression profiles).

Multidimensional data streams continuously feed the AI breeding brain, driving iterative improvements in deep learning to analyze disease-resistant traits, predict environmental impacts on yield, and simulate genetic combinations. Enhanced accuracy enables AI to optimize hybridization strategies, compressing breeding cycles from 5–8 years to 2–3 years while identifying drought-tolerant, pest-resistant, or nutrient-enhanced candidates. Elite varieties deployed in fields generate new IoT-collected data, fueling a closed-loop system: *rapid cultivar release → expanded data scale → smarter models → accelerated breeding iteration*. This framework allows rapid climate adaptation and targeted breeding (e.g., high-protein wheat, salt-tolerant rice), offering sustainable solutions for food security. By transforming traditional agriculture into a computable, data-driven science, AI–robotic systems redefine crop breeding as a promising tool for global food resilience.

HOPE driven by AI

With the advancement of AI technology, the vision of Breeding 5.0 is to seamlessly integrate multiple key processes through AI, creating an intelligent breeding management system.

With the rapid advancement of technology, breeding is entering an unprecedented era of intelligent innovation. In this transformative age, AI will play a pivotal role in propelling crop breeding toward a future characterized by greater efficiency, precision, and sustainability. Four core technologies are emerging as foundational pillars of Breeding 5.0: High-Dimensional and Multi-Modal Data, Omni-simulated Breeding, Peopleless Management and Data Collection, Expert and Explainable AI (Figure 4).

High-dimensional and multimodal data integration and analysis

Future crop breeding will witness exponential growth in both data volume dimensionality and modality. AI will be the key in this process by integrating multi-source datasets to achieve a comprehensive understanding of every aspect of crop growth. These data encompass not only genomics and phenomics but also environmental parameters, climate change patterns, sensor-derived metrics, and simulation models, forming a multimodal information ecosystem (Figure 4).

In the temporal dimension, AI enhances predictive accuracy by continuously aggregating historical data and tracking detailed variations in crop development. Spatially, AI expands data acquisition to incorporate not only ground-based sensors but also remote sensing technologies (e.g., satellite imagery), extending to environments ranging from soilless

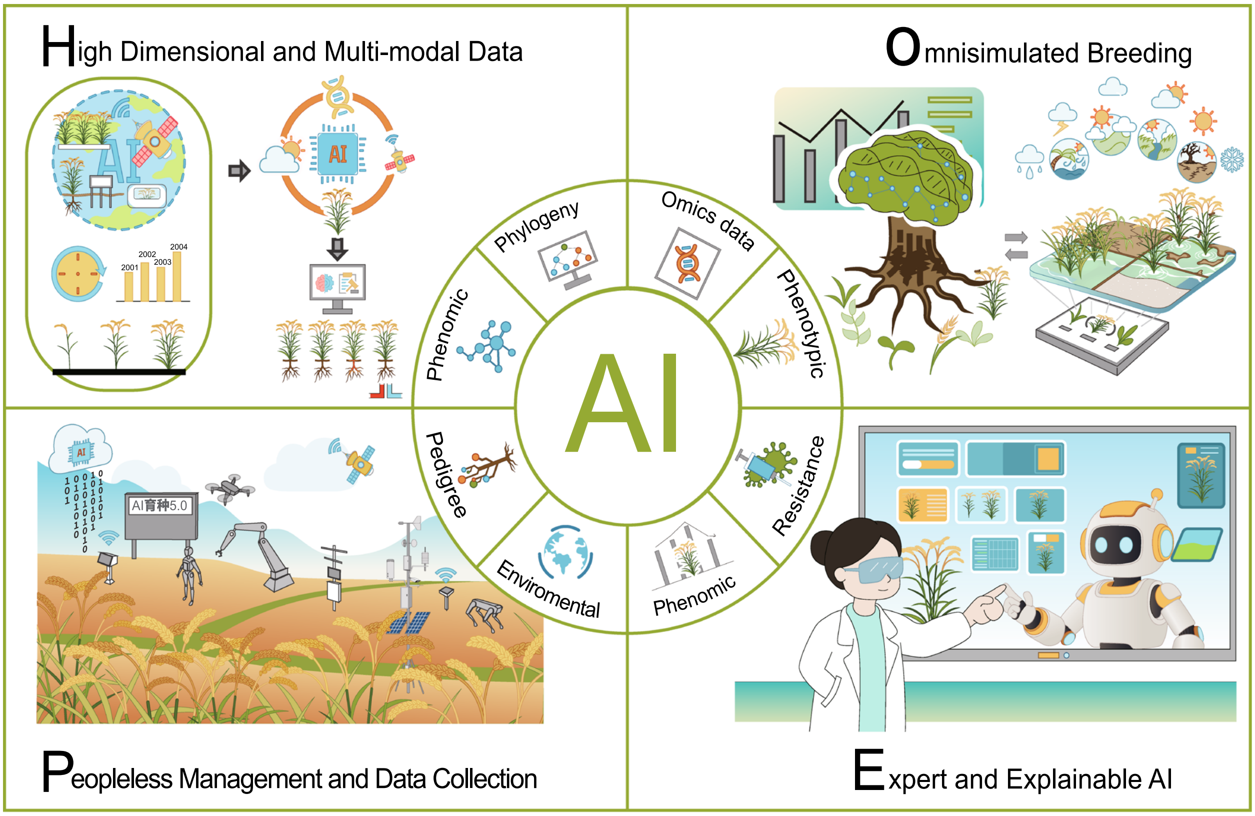

Figure 4. HOPE: An AI-driven framework for the future of smart agriculture

This schematic illustrates the HOPE framework, an integrated approach leveraging advanced technologies to accelerate crop breeding and enhance agricultural productivity. The framework comprises four synergistic components: H (Hyper-dimensional and Multimodal Data): Integrates diverse genomic, environmental, and phenotypic datasets for precise trait selection. O (Omni-simulated Breeding): Employs predictive models and simulations to optimize breeding outcomes across varied scenarios. P (Peopleless Management and Data Collection): Utilizes robotics, drones, and automation for efficient, accurate farm data acquisition and management. E (Expert and Explainable AI): Combines transparent AI analysis with human expertise for validated, scientifically sound decisions. Together, these components form a self-reinforcing cycle known as the "breeding flywheel," which continuously improves strategies, accelerates variety development, boosts yields, and enhances stress resistance. The HOPE framework aims to meet rising food demands sustainably and address global food security challenges.

cultivation systems to extraterrestrial settings. This enables AI to holistically process and analyze multifaceted crop growth information, including macroscopic phenotypic traits, microscopic genetic profiles, infrared imaging, and internal fluid dynamics monitoring. Such comprehensive data integration empowers breeders to make data-driven decisions with enhanced precision.

Omni-simulated breeding

Omni-simulated breeding represents another major breakthrough of AI in Breeding 5.0. AI-driven computational simulation systems enable breeders to test the potential outcomes of diverse breeding strategies through virtual cultivation environments. By simulating varied environmental conditions and growth scenarios, AI predicts crop performance under future constraints and guides strategic adjustments to achieve breeding objectives (Figure 4).

The core advantage of this technology lies in its ability to significantly shorten experimental cycles and mitigate risks associated with field trials. Furthermore, AI-powered simulation systems dynamically adapt virtual environments based on real-time data, enhancing predictive accuracy. Through virtual experimentation, breeders can conduct extensive testing and optimization beyond laboratory settings, drastically reducing time and costs while accelerating breeding efficiency.

Peopleless management and data collection

Advancements in robotics and automation technologies will drastically reduce human intervention in breeding processes. Intelligent cultivation systems will autonomously manage all operational phases, including planting, irrigation, fertilization, and pest control, thereby achieving fully automated field management. Through real-time decision-making and precise execution, AI systems ensure optimal growth conditions for crops, thereby enhancing operational precision and optimizing crop management efficiency.

Powered by fifth-generation AI and advanced sensor technologies, intelligent cultivation systems now simultaneously guide robotic routine maintenance operations and execute automated data collection. These systems dynamically collect multidimensional and multimodal datasets tailored to the demands of intelligent decision-making and analytical workflows, thereby continuously strengthening the data infrastructure of AI-driven agricultural platforms (Figure 4).

The superiority of peopleless management lies not only in enhanced efficiency and cost reduction but also in minimizing human-induced disturbances to crop growth. AI-driven systems autonomously refine breeding strategies and environmental conditions through continuous monitoring and real-time feedback, ensuring optimal crop development. Furthermore, these systems deliver customized management protocols tailored to species traits, enabling precision agriculture at scale.

Expert and explainable AI

While AI exhibits exceptional data-processing capabilities and decision-making advantages in breeding applications, its transparency and interpretability remain equally critical. Particularly in domains impacting human ethics and well-being, AI decision-making processes must be comprehensible and traceable to ensure technical advancement aligns with societal values and ethical principles.

Explainable AI technologies will play a pivotal role in enabling experts and breeders to elucidate the rationale behind AI-driven decisions, thereby fostering trust in AI systems (Figure 4). In the Breeding 5.0 era, AI must synthesize not only global expertise and empirical knowledge but also ensure transparent and controllable decision-making processes. This knowledge integration empowers breeders to address multifaceted challenges spanning biology, ecology, and ethics with evidence-based decisions, effectively mitigating risks and unintended consequences.

Breeding 5.0: silicon-based systems serving carbon-based sustainability

At present, our understanding of computer and AI principles now in many ways surpasses our comprehension of human biology and plants on which we live. This phenomenon arises from two key factors: the rise of AI as a globally prioritized field attracting substantial human and financial investments, and the inherent complexity of carbon-based organisms, whose intrinsic mechanisms remain scientifically challenging to decipher despite their status as highly sophisticated systems.

Under the robust drive of fifth-generation AI, breeding 5.0 and flywheel breeding technologies are revolutionizing crop breeding with unprecedented speed and efficiency. Through precise data analysis and predictive modeling, scientists can rapidly identify varieties with superior traits, such as high yield, stress resilience, and reduced pesticide dependency, significantly enhancing agricultural productivity and sustainability.

Simultaneously, the rise of peopleless management and vertical farming has ushered in revolutionary transformations for modern agriculture. Leveraging advanced sensor technologies and automated control systems, agricultural production now achieves precision-based and intelligent management, ensuring both product quality and safety. Furthermore, these innovations dramatically reduce water and fertilizer inputs, achieving savings rates exceeding 90%. Such advancements hold profound significance for alleviating global water scarcity, mitigating environmental pollution, and advancing sustainable agricultural practices. Even more inspiring, these technical advancements offer potential agricultural solutions for future human migration to Mars. Under extreme environmental conditions, the deep integration of technology and biological systems could enable the establishment of self-sustaining agricultural ecosystems on Mars. Such systems would provide essential material foundations for interplanetary exploration and colonization, demonstrating how Earth-derived innovations in precision agriculture and closed-loop resource management can be adapted to sustain life beyond our planet.

Looking ahead, we have every reason to believe that with continuous technological advancements and innovations, humanity will gain a deeper understanding and better utilization of natural laws, achieving harmony with the environment. We will bequeath to future generations a more prosperous, healthy, and sustainable world, empowering them to continue exploring the mysteries of the universe and writing the brilliant chapters of human history under the guidance of technology. Let us work together to forge a future brimming with hope and possibilities.

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CONFLICTS OF INTEREST

The authors declare no competing interests.

AUTHOR CONTRIBUTIONS

Q.Q. provided significant academic guidance. X.Z. was responsible for the conception and supervision of the project.

L.F. participated in the conception, supervision, and writing the manuscript. J.F. contributed to writing the manuscript and drawing the figures. S.Z. contributed to writing the manuscript. All authors read and approved of its content.

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