Advancing Agro-Technology a Comprehensive Assessment of Artificial Intelligence Methodologies for Optimizing the Physicochemical and Functional Attributes of Agricultural Commodities

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Abstract—**The integration of Artificial Intelligence (AI) within agricultural systems signifies a paradigm shift toward data-driven precision and operational efficiency. Convolutional Neural Networks (CNNs) facilitate early-stage detection of Phyto pathological anomalies through image-based classification frameworks, thereby mitigating yield degradation. Long Short-Term Memory (LSTM) architectures enhance predictive analytics for yield estimation and soil fertility dynamics, contributing to optimized resource distribution. Although the global agricultural sector continues to grapple with mechanization and automation constraints, contemporary AI and machine learning (ML) paradigms have redefined agrotechnological methodologies This review synthesizes advancements in AI-enabled systems encompassing ML algorithms, deep learning (DL) architectures, Internet of Things (IoT) frameworks, and Decision Support Systems (DSS), underscoring their contribution to challenges in yield optimization, precision irrigation management, pest diagnostics, and strategic decision-making. Furthermore, it delineates AI-driven innovations in domains such as genomic-assisted plant breeding, smart irrigation networks, supply chain logistics, and post-harvest packaging optimization. Despite substantial progress, large-scale implementation remains hindered by economic constraints, data governance issues, infrastructural deficits, and insufficient digital proficiency. The review provides a critical evaluation of both the transformative potential and the prevailing limitations of AI in contemporary agriculture**

I. INTRODUCTION

The agricultural domain constitutes a cornerstone of national economic resilience and sustainable development. In recent decades, the sector has undergone a paradigm shift due to the accelerated proliferation and implementation of Artificial Intelligence (AI) paradigms. The deployment of AI within agriculture has demonstrated transformative potential across multiple verticals, particularly in precision agronomy and Agri-supply chain optimization (Arjun, 2013). Unmanned Aerial Systems (UAS) are extensively utilized in diverse agrotechnical operations, including Phyto pathological surveillance, yield forecasting, vegetative growth modeling, and automated weed discrimination. Concurrently, the integration of Internet of Things (IoT) sensor networks and AI-driven analytical frameworks has revolutionized soil diagnostics and precision irrigation management, thereby enabling data-centric resource optimization (Tsouros et al., 2019).

AI-embedded robotic systems have substantially enhanced post-harvest processes such as automated harvesting, sorting, and grading, improving throughput, precision, and operational accuracy. In parallel, deep learning (DL)-based image recognition models and satellite-enabled remote sensing techniques facilitate advanced crop phenotyping, land cover analytics, and spatiotemporal moisture mapping (Kamilaris et al., 2018). A notable contribution of AI lies in the computational modeling of engineering properties of agricultural commodities—parameters such as boiling point, density, viscosity, and mass—that underpin product quality, safety compliance, and marketability (Khan, Kumar, Dhingra, & Bhati, 2021). Traditionally, these attributes were assessed via manual procedures, often constrained by human error, lower reproducibility, and high labor intensiveness. AI-driven predictive modeling now enables real-time, scalable, and precise quantification of such physicochemical traits, propelling the agricultural industry toward greater automation and efficiency (Ben-Ayed et al., 2013).

Machine learning (ML) architectures, such as Artificial Neural Networks (ANN) and Support Vector Machines (SVM), have been empirically validated for thermodynamic property estimation. For instance, Yuze et al. (2022) developed an ANN–SVM hybrid framework for predicting the boiling points of 4,550 organic compounds with high statistical accuracy. Likewise, Panwar et al. (2023) proposed an ML-regression model for forecasting the density and viscosity of 305 carbohydrate complexes, yielding coefficients of determination (R^2) of 99.6% and 97.9%, respectively (Abedin et al., 2017). The applicability of ANN models extends to moisture dynamics; Chasiotis et al. (2020) employed a multilayer perceptron (MLP) for predicting the moisture content in quince slices during fluidized bed drying, achieving $R^2 > 0.99$. Similarly, Fajardo-Muñoz et al. (2023) utilized an MLP-ANN model to estimate essential oil yield from orange peel biomass via steam distillation, attaining a prediction accuracy of 97.6%. In another study, dynamic ANN structures with optimized input-output layering achieved a correlation coefficient of 0.9914 for modeling moisture variation in mushrooms, underscoring their predictive robustness and energy efficiency.

The Decision Support System (DSS) bridges the gap between algorithmic intelligence and on-field implementation. It functions as an informatics platform that assimilates soil, climatic, and crop data for predictive analytics and prescriptive recommendations. DSSAT, an established Agro-Technology Transfer Model, exemplifies this integration by delivering yield optimization strategies through simulation-based insights (Mulla et al., 2020). Modern DSS advancements include chatbot-assisted frameworks (Asolo et al., 2024) that utilize ML-driven natural language processing to provide personalized agronomic advisories. Similarly, AgroDSS (Kukar et al., 2019) leverages cloud computing infrastructures to integrate farm management systems with AI-powered analytics, offering farmers predictive tools for performance benchmarking and anomaly detection.

The conjunction of AI subdisciplines—machine learning (ML) and deep learning (DL)—with cloud computing platforms establishes the computational infrastructure necessary for large-scale Agri-informatics. ML enables adaptive learning from empirical data, whereas DL leverages hierarchical neural architectures for advanced pattern recognition and predictive analytics (Joshi et al., 2024). Collectively, AI algorithms synthesize insights across the crop value chain, encompassing phenological development, post-harvest logistics, and quality control analytics (Arjun, 2013). As agriculture confronts escalating global challenges, including food security pressures, climate variability, and resource scarcity, AI integration emerges as a critical enabler of resilient, sustainable, and adaptive agricultural ecosystems (Ben-Ayed et al., 2013).

II. AI-BASED SMART IRRIGATION

Smart irrigation represents a data-driven, automated irrigation management paradigm that enhances precision, operational efficiency, and temporal optimization compared to conventional irrigation frameworks. Agricultural yield remains a critical determinant of national food security, serving as a quantitative measure of overall agronomic productivity and economic return. Recent technological advancements in areas such as genomics-assisted breeding, nutrient optimization, and AI-augmented field management systems have markedly elevated crop productivity levels (Luo et al., 2023).

At the institutional level, significant research initiatives are oriented toward the digital transformation of agro-ecosystems through AI-integrated Internet of Things (IoT) infrastructures. IoT-based networks equip farms with interconnected sensors and real-time monitoring capabilities, minimizing inefficiencies while improving agronomic decision-making. However, despite technological affordability, widespread adoption remains constrained by farmers' limited digital literacy and insufficient operational knowledge regarding IoT deployment (Khan, Kumar, Dhingra, & Bhati, 2021). Nevertheless, IoT continues to emerge as a foundational driver of precision and sustainable agriculture, enabling enhanced productivity outcomes through adaptive environmental management.

Smart irrigation, in this context, embodies an evolving scientific discipline that synergistically combines AI analytics, IoT-enabled sensing, and automation to increase agricultural output while reducing ecological footprints (Ben Ayed & Hanana, 2021). Data streams derived from distributed sensors capture critical field variables, including soil moisture gradients, evapotranspiration rates, and meteorological conditions, which facilitate high-resolution modeling and decision optimization. This feedback-driven control architecture allows irrigation schedules to dynamically adapt to fluctuating soil and climatic parameters, conserving water resources while simplifying management complexities (Abedin et al., 2017).

III. AI-DRIVEN APPROACHES FOR YIELD PREDICTION AND REMOTE SENSING

Yield prediction constitutes a pivotal component of precision agriculture, underpinning sustainable production systems and informed agroeconomic decision-making. Accurate and timely yield forecasting enables strategic planning related to sowing schedules, irrigation management, harvesting logistics, and market operations. Machine learning (ML) has emerged as a core computational paradigm for constructing predictive models that infer complex production outcomes from heterogeneous datasets. ML algorithms iteratively learn from historical datasets, optimize parameters through validation against unseen data, and subsequently generate predictive outputs with high statistical confidence (Leukel et al., 2023).

Deep learning (DL) architectures—ranging from convolutional neural networks (CNNs) to recurrent frameworks such as LSTM and GRU—have demonstrated superior performance in yield prediction tasks, as summarized in Table 1. RS-based models are instrumental in large-scale yield estimation, empowering spatially continuous analysis for damage detection, harvest forecasting, and environmental monitoring. Since agricultural productivity is governed by multifactorial biophysical and socio-climatic conditions, comprehensive yield assessment necessitates multidimensional datasets encompassing soil profiles, phenological indicators, and climatological records (Xu et al., 2019).

Predictive frameworks rely on empirically trained models calibrated using historical yield datasets, integrating both statistical and AI-driven approaches. These models facilitate dynamic yield estimation throughout the crop growth cycle (Hara et al., 2021), thereby optimizing operational scheduling, storage management, and input distribution such as fertilizers, machinery, and pesticides. Du et al. (2018) reported that AI-enabled systems enhance crop productivity by an estimated 20 to 150 percent, driving substantial improvements in water-use efficiency and yield sustainability.

Fig. 1. AI-integrated smart irrigation system.

Crop Type	Data Source	Model Used	Key Findings	Reference
Paddy	Satellite imagery	CNN-LSTM	Delivered strong prediction results; effective for early yield forecasting (RMSE = 329, R^2 = 0.78)	Sun et al., 2019
Corn	Hyperspectral imagery	CNN	Achieved 75.5% classification accuracy	Yang, Nigon, et al., 2021
Paddy	Satellite data	Deep Yield (CNN + LSTM hybrid)	Accurately projected yields for past two years (RMSE = 4.79)	Gavahi et al., 2021
Wheat, Corn	Spatial-spectral-temporal data	SSTNN (Spatial-Spectral-Temporal Neural Net)	Notably improved precision in yield prediction (Wheat: RMSE = 0.67, R^2 = 0.83; Corn: RMSE = 0.84, R^2 = 0.68)	Qiao et al., 2021
Wheat, Oats, Barley	High-resolution UAV imagery	UAV-based remote sensing (3D-CNN)	Greater accuracy in intra-field yield estimates (RMSE = 289.5, R^2 = 0.962)	Nevavuori et al., 202X

Table 1: Summary of Deep Learning AI Approaches for Predicting Crop Yield

Remote sensing technology allows spatially explicit monitoring of soil and crop health dynamics across phenological stages, serving as an early-warning mechanism for anomaly detection and targeted intervention. Multiplatform RS acquisitions—via satellites, unmanned aerial systems (UAS), and manned aircraft—enable data capture at varying spatial, spectral, and temporal resolutions (Varela et al., 2018). RS functions by exploiting the spectral, structural, and physicochemical reflectance properties of agricultural surfaces. Multispectral and hyperspectral sensors transmit raw and processed data to centralized repositories for subsequent feature extraction and knowledge discovery (Li & Finch, 2022). Predictive analytics and computational modeling harness these features to derive actionable insights, facilitating intervention at optimal spatial-temporal coordinates to meet specific crop and site requirements with heightened precision (Ennouri et al., 2021).

Robust model validation procedures are indispensable for evaluating the fidelity of ML-driven yield prediction systems. Prity et al. (2024) assessed multiple ML algorithms for crop recommendation using Mean Squared Error (MSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2) (Abedin et al., 2017). These metrics quantify prediction bias, residual variance, and the explanatory strength of independent variables. Similarly, Khodjaev et al. (2025) employed Root Mean Square Error (RMSE) and MAE indicators for model calibration, noting that reduced error values correspond to superior model performance. Complementary metrics such as relative RMSE (rRMSE), Mean Bias Error (MBE), and Model Efficiency (EF) have been employed by Sabo et al. (2023) and Gill et al. (2024) to benchmark DL and ML frameworks under varying agroecological contexts, where ANN-based models consistently achieved the highest predictive accuracy.

IV. ADVANCEMENTS IN CROP ENHANCEMENT LEVERAGING ARTIFICIAL INTELLIGENCE-DRIVEN METHODOLOGIES

The Indian agricultural sector sustains the food security of approximately 1.3 billion individuals and contributes nearly 18 percent to the nation's Gross Domestic Product (GDP). Accounting for roughly 10 percent of India's export economy, agriculture remains the fourth-largest commodity-producing sector (Kumar et al., 2020). Despite advances in industrialization, the sector remains heavily resource-intensive. To meet the escalating demands of a growing population, crop productivity must effectively double by 2025—requiring an average annual growth rate of 1.75 percent in total agricultural output (Steensland & Houle et al., 2010). However, the path toward sustainable intensification faces significant impediments, including climatic fluctuations, hydrological scarcity, declining labor availability, and land fragmentation. Addressing these challenges necessitates dual strategies: genetic crop enhancement and improved agro-management systems. Crop improvement emphasizes the development of climate-resilient, high-yield cultivars capable of tolerating abiotic stressors such as high salinity, whereas advanced farm management prioritizes precision agriculture technologies designed to optimize yield through data-informed input efficiency (Houle et al., 2010).

The transition toward sustainable and intelligent agriculture is supported by emerging digital technologies such as Artificial Intelligence (AI), Internet of Things (IoT), and cloud computing (Ben Ayed & Hanana, 2021). AI-driven frameworks provide algorithmic tools to monitor agricultural performance, detect anomalies such as water overuse, and automate irrigation control via smart irrigation systems (Suprem et al., 2013). Parallel advancements in computational forecasting allow AI applications to perform high-resolution weather predictions, precision pest detection, and automated crop quality assessment. By integrating AI into core agricultural operations—from planting and fertilization to harvesting and commercialization—agro-industries enhance efficiency, reduce uncertainty, and improve profitability (Ben Ayed & Hanana, 2021).

A notable instance of AI-enabled agricultural innovation is the collaboration between Microsoft and the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), which developed an AI-based sowing advisory system. A pilot deployment among 175 groundnut farmers in Andhra Pradesh revealed that those who delayed seed sowing by three weeks as recommended by the algorithm achieved a 30 percent yield increase per acre ($p < 0.05$) compared to control groups (Kumar et al., 2020). Beyond advisory systems, AI-assisted precision weed management technologies utilize robotics, machine learning (ML), and computer vision to localize pesticide application exclusively to infested zones, markedly reducing agrochemical usage and environmental load (Kamilaris et al., 2018).

ML algorithms play a pivotal role throughout the agricultural value chain. In pre-production, they are employed for soil fertility modeling, irrigation scheduling, and yield forecasting. During cultivation, ML models facilitate disease recognition and early detection of crop stress. At the post-harvest and supply-chain stages, predictive analytics aid in optimizing harvest planning, storage conditions, and logistics by integrating forecasting models with consumer demand analytics (Hatem et al., 2022). Intelligent greenhouse crop surveillance further exemplifies AI integration, where multi-sensor architectures—including Time-of-Flight (ToF) sensors, soil moisture probes, micro-weather stations, and RGB imaging systems—ensure continuous environmental and phenotypic monitoring to support targeted biological pest management (Huang et al., 2022).

Multiple studies illustrate the efficacy of AI-powered crop improvement tools. One example is “Plan tix,” an AI-based mobile platform that utilizes image recognition for real-time plant disease diagnostics. Validation studies by Akinyemi et al. (2023) reported 90–100 percent diagnostic accuracy across staple crops including maize, okra, cassava, and plantain in southwestern Nigeria. Similarly, AI-based satellite and ML-driven analytics platforms such as a Where and Farm Shots analyze drone and satellite imagery to detect nutrient deficiencies, disease onset, and yield variability patterns with high precision (Giri et al., 2020). Jain et al. (2019) found that the integration of satellite imagery into intervention design could double operational efficiency and yield outcomes, reinforcing the viability of satellite-based predictive agronomy as a sustainable intensification strategy.

AI-driven agricultural transformation is also extending to smallholder systems. The Artificial Intelligence for African Food Systems (AI4AFS) initiative, described by Ozor et al. (2025), implemented on-farm disease detection, IoT-based irrigation, and e-extension services among Nigerian small-scale farmers. Outcomes demonstrated a 40 percent increase in water-use efficiency and an increase in cultivated land area from 1–2 hectares to 4–5 hectares, highlighting AI’s scalability and socio-economic potential. In India, the ITC e-Choupal initiative exemplifies large-scale digital integration, promoting the adoption of AI-enabled weather forecasting, irrigation management, and satellite-assisted monitoring tools. Participating chili farmers in Andhra Pradesh recorded 13 percent higher productivity and a 27 percent increase in net returns following implementation (Rao, 2023)

A comparative assessment of AI-enabled agricultural systems versus conventional practices underscores their differential advantages and constraints, as shown below

Parameter	Traditional Agriculture	AI Driven Agriculture
Decision-Making Approach	Based on empirical experience and observation	Data-driven using predictive modeling and analytics
Resource Utilization	High water, fertilizer, and energy consumption	Optimized usage through sensor and algorithmic control
Pest and Disease Management	Manual identification and blanket chemical spraying	Automated detection with targeted intervention via computer vision and robotics
Yield Forecasting	Static, based on historical averages	Dynamic, real-time prediction using ML and RS data
Scalability	Limited by labor and land expansion	Scalable through digital automation and cloud analytics
Environmental Impact	High carbon and chemical footprint	Reduced environmental load through precision input use
Cost and Accessibility	Lower initial cost but higher operational inefficiency	Higher initial investment with long-term sustainability benefits
Model Transparency	Human-dependent decision process	Requires interpretability frameworks for AI algorithms

V. ECONOMIC ASSESSMENT FRAMEWORKS AND CAPITAL ALLOCATION STRATEGIES FOR ARTIFICIAL INTELLIGENCE INTEGRATION IN AGRONOMIC SYSTEMS.

Variable Rate Nitrogen Fertilizer Application (VRNFA) represents a cornerstone precision agriculture technology that optimizes nitrogen input efficiency while simultaneously enhancing farm profitability and environmental sustainability. Over-application of nitrogen fertilizers elevates operational expenditures, diminishes marginal returns, and contributes to significant ecological degradation through soil acidification and greenhouse gas emissions. Conversely, suboptimal nitrogen dosing impedes crop growth and reduces yield potential, adversely affecting farmers' income stability. The implementation of VRNFA mitigates these inefficiencies by delivering site-specific nitrogen prescriptions tailored to crop nutrient demand, thereby increasing production efficiency and reducing labor and fuel consumption (Biggar et al., 2013).

An economic assessment by Tekin (2010) in wheat cultivation demonstrated that VRNFA adoption resulted in yield gains ranging between 1 and 10 percent, accompanied by fertilizer savings of 4 to 37 percent. The annualized cost evaluation, assuming a five-year depreciation period and an interest rate of 21 percent, indicated that the capital investment for precision agriculture technologies varies between 13 and 131 USD per hectare for farms ranging from 50 to 500 hectares. In a related study, Balafoutis et al. (2017) corroborated the economic efficacy of precision farming, showing that integrating AI-driven tools such as soil sensors, drones, and data analytics software reduced water and fertilizer use by 10–15 percent, yielding annual savings of approximately €5,000 to €10,000 per farm.

Though the initial financial barrier is significant—particularly for smallholders whose annual income ranges from €1,000 to €3,000—the return on investment is relatively rapid. Accounting for yield increases of up to 30 percent, the payback period for small farms is typically two to four years. Large-scale commercial agribusinesses, due to their economies of scale and diversified operations, often achieve breakeven within one to two years through the integration of AI solutions across multiple farming domains such as precision spraying, meteorological forecasting, and automated plant disease detection. Liakos et al. (2018) further reported that AI-augmented crop monitoring systems improved production outputs by 10–15 percent and simultaneously lowered input costs by 12–18 percent.

O liveira and Silva (2023) analyzed global trends in AI-enabled agriculture, highlighting that although the initial expenditure on hardware, sensors, drone platforms, autonomous machinery, and software models is high, the long-term economic and environmental returns—through enhanced yield stability, input efficiency, and sustainability—largely outweigh initial costs.

Current financial structuring and resource allocation mechanisms.

Global and national-level funding mechanisms are pivotal in facilitating the implementation and scalability of AI-based agricultural technologies. The United States Department of Agriculture's National Institute of Food and Agriculture (USDA-NIFA) funds AI-driven research initiatives through the Agriculture and Food Research Initiative (AFRI), which supports the development of autonomous systems, robotic platforms, and smart sensing technologies (Van Goor et al., 2019).

Complementing AFRI, several dedicated national AI research institutes have been established to catalyze innovation in agricultural AI systems. complementing AFRI, several dedicated national AI research institutes have been established to catalyze innovation in agricultural AI systems. The Artificial Intelligence for Future Agricultural Resilience, Management, and Sustainability (AIFARMS) institute, founded in 2020, fosters collaboration among academia, government, and industry to advance sustainable AI architectures for the agri-food sector (Adve et al., 2024). Similarly, the AI Institute for Resilient Agriculture (AIIRA) aims to design AI-driven frameworks that enhance crop adaptability, ecological resilience, and input resource optimization. Co-funded by NIFA and the National Science Foundation (NSF), AIIRA received a $20 million endowment to accelerate agricultural digitization through advanced machine learning research (Ganapathy Subramanian et al., 2024) institute, founded in 2020, fosters collaboration among academia, government, and industry to advance sustainable AI architectures for the agri-food sector (Adve et al., 2024). Similarly, the AI Institute for Resilient Agriculture (AIIRA) aims to design AI-driven frameworks that enhance crop adaptability, ecological resilience, and input resource optimization. Co-funded by NIFA and the National Science Foundation (NSF), AIIRA received a $20 million endowment to accelerate agricultural digitization through advanced machine learning research (Ganapathy Subramanian et al., 2024)

Despite the surge in AI-oriented funding and innovation, adoption remains geographically uneven. Low-income countries (LICs) face systemic challenges, including limited access to digital infrastructure, insufficient partnerships with technological providers, inadequate policy frameworks, and a lack of skilled human capital. Consequently, the benefits of AI remain disproportionately concentrated in developed economies that possess robust institutional ecosystems, advanced connectivity, and established regulatory mechanisms (Khan et al., 2024).

Bridging this digital divide necessitates multi-stakeholder efforts focused on capacity-building, infrastructure enhancement, and targeted investment. Strategic technology transfer programs, spearheaded by global institutions such as the World Bank, UNESCO, and USAID, can play a transformative role by supporting localized research, improving technical training, and fostering partnerships between AI-leading economies and developing nations. Building resilient digital infrastructure, coupled with robust policy implementation and education-oriented initiatives, will be essential to achieving inclusive, equitable, and sustainable AI adoption in global agriculture.

VI. ARTIFICIAL INTELLIGENCE APPLICATIONS IN POST-HARVEST OPTIMIZATION AND TEMPERATURE-CONTROLLED SUPPLY CHAIN OPERATIONS

The post-harvest stage marks the commencement of activities immediately following crop harvesting and includes a series of critical processes such as handling, processing, storage, packaging, transportation, and distribution. Despite significant advancements in agricultural production, the post-harvest phase continues to represent a considerable source of inefficiency, particularly due to waste and quality degradation. These losses stem from multiple biophysical and environmental stressors, including physiological deterioration, nutrient imbalances, mechanical damage, temperature deviations, and exposure to suboptimal environmental conditions. Empirical data reveal post-harvest losses ranging between 2 and 20 percent in industrialized nations and escalating to 24–40 percent in developing economies (Ferrandez-Pastor et al., 2016).

Artificial Intelligence (AI) frameworks and digital sensing technologies are transforming post-harvest management within the agri-food supply chain by enabling real-time monitoring and intelligent control systems. The adoption of Radio Frequency Identification (RFID), Internet of Things (IoT) sensors, and automated diagnostics allows continuous tracking of perishable goods, monitoring their physical and chemical states throughout transport and storage phases (Zhang, 2021). These AI-enabled frameworks facilitate the detection of compromised food quality, microbial spoilage, and fruit degradation, contributing to greater efficiency in food preservation and logistics.

Kollia et al. (2021) applied deep learning (DL) models, specifically Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, to optimize yield estimation and energy-efficient refrigeration systems. Their results confirmed that the LSTM-AM model outperformed conventional Machine Learning (ML) methods such as Support Vector Regression (SVR) and Random Forest Regression (RFR), achieving a significantly lower Mean Squared Error (MSE) of 0.002 compared to 0.015 and 0.040, respectively. Fully Convolutional Networks (FCNs) demonstrated a classification accuracy of 98.2 percent for shelf-life and expiry date prediction tasks. Furthermore, Mamidala (2023) proposed an ML-based dynamic spoilage prediction system incorporating visual (color and texture) and olfactory features to determine deterioration rates, effectively reducing food waste through freshness monitoring.

Li et al. (2021) developed a CNN-based apple grading framework, achieving 99 percent training accuracy and 98.9 percent validation accuracy in fruit quality assessment. Similarly, Wang and Zhang (2019) constructed an automated apple classification model detecting surface defects and size variations with high consistency and minimal human intervention. For tropical fruit inspection, Patel et al. (2021) utilized a Support Vector Machine (SVM)-based model to identify defective mangoes during packing operations, enhancing post-harvest quality and minimizing manual labor requirements. An integral element of post-harvest management is Cold Chain Logistics (CCL), designed to ensure the integrity of perishable commodities such as fruits, vegetables, dairy products, meat, and seafood by maintaining optimal thermal and humidity conditions throughout the supply chain. Accurate visualization of CCL data flow, as illustrated in Fig. 2, underscores the complexity of this system. Improper cold storage management may lead to post-harvest losses exceeding 30 percent (Kitinoja et al., 2011). CCL systems rely on advanced refrigeration and climate regulation units to sustain consistent microenvironments critical for extending shelf life (Ndraha et al., 2018). However, maintaining temperature stability continues to impose substantial energy costs across stakeholders—including producers, logistics providers, and retail chains—making energy optimization a central research objective (Han, Zhao, et al., 2018).

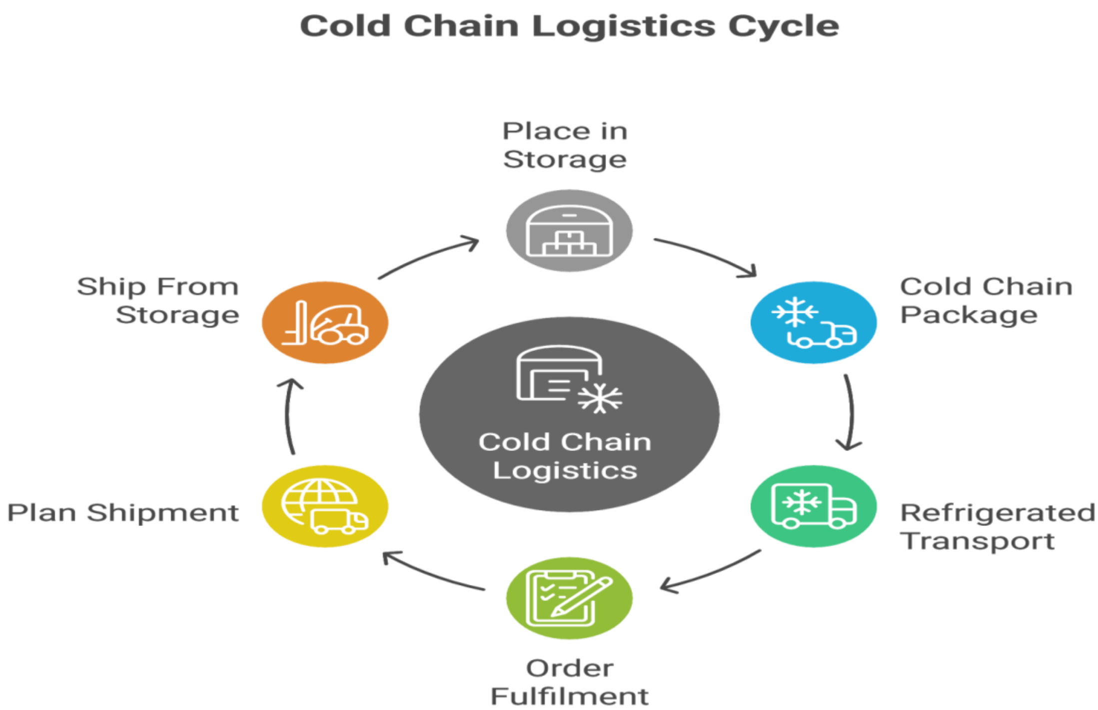

Fig. 2. Flowchart of cold chain logistics operations.

Post-harvest biochemical and physiological dynamics play a pivotal role in defining food shelf stability. Even after harvest, fruits and vegetables remain physiologically active, undergoing metabolic processes such as respiration, evapotranspiration, and ethylene emission. These activities consume vital organic substrates, contributing to the depletion of nutrient content, texture firmness, and sensory quality, ultimately reducing market value (Han, Li, et al., 2018). External stressors such as pressure, vibration, and fluctuating gas concentrations (O_2, CO_2, and ethylene), coupled with internal factors like moisture translocation and heat diffusion, induce complex biochemical alterations that accelerate spoilage across the supply chain continuum (Mercier et al., 2019).

The Food and Agriculture Organization (FAO) identifies post-harvest losses as a primary bottleneck in developing economies. These losses are typically attributed to inadequate infrastructure, poor transport facilities, lack of cold storage systems, and insufficient knowledge of perishable goods handling (Goedhals-Gerber & Khumalo, 2020). FAO projections for 2025 estimate that 30–40 percent of total agricultural produce may be lost before reaching the consumer market. Distribution patterns vary by product category: fruits, vegetables, and root crops account for 40–50 percent of losses; fish and cereals approximately 30 percent; and oilseeds around 20 percent (FAO, 2025).

The future of cold chain logistics lies in the integration of cutting-edge digital technologies—IoT, AI, big data analytics, and cloud computing—which are central to establishing resilient, intelligent, and environmentally adaptive CCL systems (Han, Zhao, et al., 2018). These next-generation infrastructures will enhance predictive maintenance, real-time process optimization, and resource-efficiency analytics, paving the way for sustainable food distribution networks. As global Agri-supply chains expand, digital cold chain ecosystems will play an increasingly vital role in achieving food security, minimizing waste, and ensuring quality retention across every stage from harvest to consumption.

6.1. Real-time monitoring and early warning systems in cold chain logistics

perishable and fresh agricultural commodities, the efficiency and reliability of cold chain logistics (CCL) systems are highly dependent on the continuous acquisition and real-time processing of environmental data, particularly temperature, humidity, and transport conditions. The emergence of Internet of Things (IoT)-enabled infrastructures has revolutionized cold chain management by integrating advanced monitoring technologies such as wireless sensor networks (WSNs), Radio Frequency Identification (RFID) systems, and Global Positioning System (GPS) trackers. These components collectively facilitate end-to-end visibility, enabling the maintenance of optimal storage parameters throughout the transportation process and prolonging the shelf life of perishable goods during extended distribution cycles (Yu et al., 2021).

Qi Lin et al. (2012) developed a WSN-based aquatic cold chain monitoring architecture designed for precision tracking of environmental variables during transport. The model demonstrated superior accuracy in data acquisition and transmission, ensuring consistent product quality across the logistics chain. Further advancements have been achieved through hybrid AI-IoT approaches. For instance, Wang and Du (2025) introduced an intelligent energy and temperature management framework for IoT-based CCL systems integrating Long Short-Term Memory (LSTM) neural networks with the Particle Swarm Optimization (PSO) algorithm. By employing a distributed sensor network and adaptive communication protocols, the proposed framework optimizes energy consumption while maintaining stringent environmental control standards.

Experimental evaluation within a simulated cold chain environment demonstrated the model's superiority over conventional approaches. Traditional control architectures achieved 85 percent accuracy with temperature-humidity variation confined to ±2.5°C, whereas systems using fixed power regulation recorded 82 percent accuracy and a wider deviation of ±2.8°C. Conversely, the LSTM–PSO hybrid model achieved 91 percent regulation accuracy and constrained variations to ±1.8°C, representing a 7.1 percent improvement in energy optimization and stability over traditional schemes. These findings affirm the efficacy of self-learning, data-driven control mechanisms in maintaining consistent cold chain performance under dynamically changing operational contexts

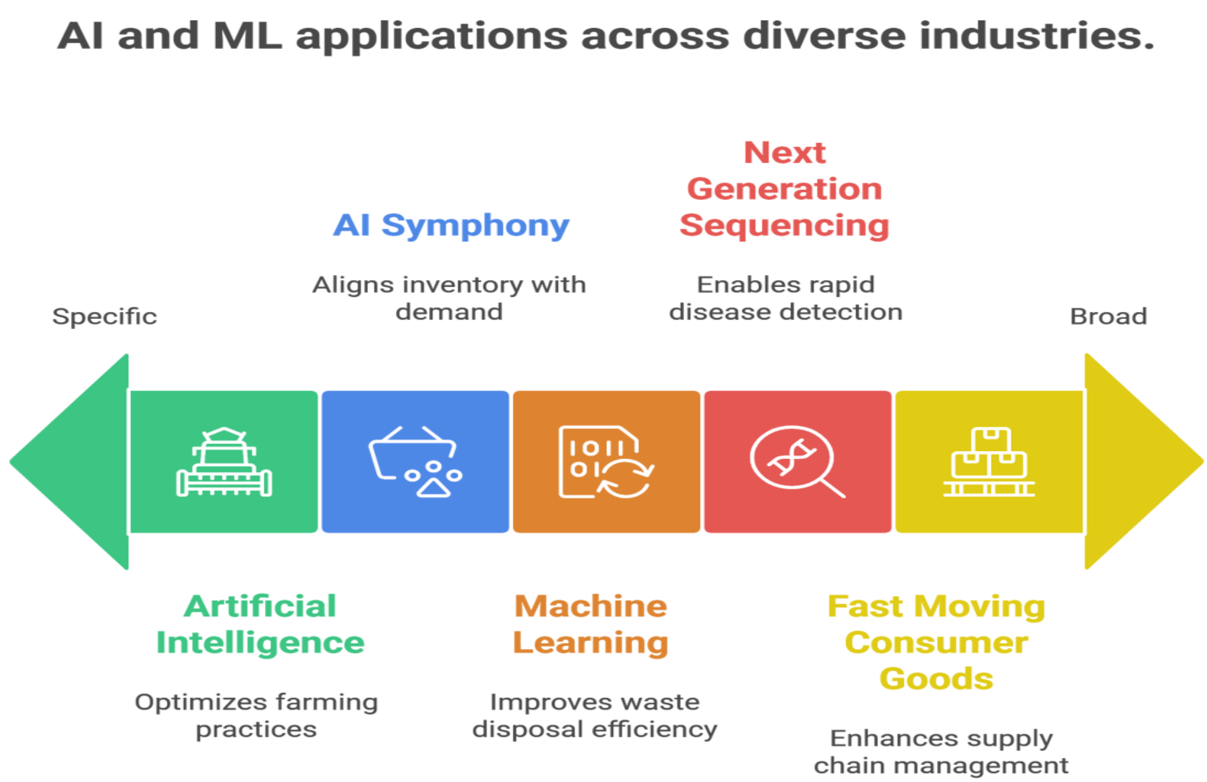

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Fig. 3. AI application in FMCG and food industries in Argo

Given the complex nature of product degradation, cold chains remain highly susceptible to thermal fluctuations, mechanical stress, and handling inconsistencies. Such deviations can accelerate biochemical reactions, resulting in rapid spoilage or quality decline. AI-assisted analytics integrated within CCL systems enhance food safety monitoring by performing predictive modeling, anomaly detection, and rule-based alerts. These mechanisms, supported through mobile applications and wireless communication networks, issue automated notifications when deviations from predefined thresholds are detected, enabling rapid corrective interventions (Kale, 2022).

Recent innovations in cold chain technology have also emphasized the incorporation of blockchain frameworks. Blockchain-integrated CCL architectures ensure immutable, transparent, and decentralized data recording across all logistics transactions. As described by Tian (2016), every operational event—ranging from temperature logging to cargo transfers—is encrypted and stored in a tamper-proof distributed ledger. This approach not only secures data authenticity but also enhances trust, accountability, and traceability among stakeholders by immediately exposing supply chain vulnerabilities. Such transparent and decentralized information ecosystems are poised to become the backbone of next-generation intelligent Agri-logistics networks, enabling auditable, resilient, and energy-optimized post-harvest system.

VII. APPLICATIONS OF AI IN FOOD SUPPLY CHAIN AND POST-HARVEST MANAGEMENT

7.1. Fast-moving consumer goods and AI

The agricultural sector has adopted a range of AI-driven farming methods, with cognitive computing technology emulating human reasoning patterns on digital platforms. This evolution has facilitated the development of intelligent agricultural systems capable of learning, interpreting diverse operational scenarios, and autonomously optimizing efficiency (Xia et al., 2019). Serving as the foundation of the food industry, agriculture directly supports the fast-moving consumer goods (FMCG) sector by supplying essential raw materials for product manufacturing—thus, greater food output improves raw material availability for FMCG enterprises.

The COVID-19 pandemic disrupted supply chains and negatively impacted both these industries, contributing to a rise in hunger and malnutrition as noted by the FAO. Nevertheless, the integration of artificial intelligence (AI) and machine learning (ML) into agricultural management and automated production systems offers solutions to major challenges, enabling improvements in both crop yield and the quality of food ingredients (Zhou et al., 2023). Figure 3 illustrates the transformative influence of AI on the FMCG and related industries. This section reviews significant ML innovations applied in agriculture that have contributed to more effective crop management and productivity.

7.2. Grain grading and sorting

Manual methods for grain inspection are time-consuming, labor-intensive, and susceptible to human error, potentially leading to the selection of substandard grain batches. Various factors—including worker fatigue, physical obstacles, and suboptimal lighting—can further impair the accuracy of manual sorting. Consequently, computer vision-based solutions are increasingly being adopted in the agricultural sector. These systems leverage advanced imaging technologies and machine learning (ML) algorithms to analyze grain samples, effectively detecting flaws such as cracked kernels, contamination, and fungal presence (Taneja et al., 2023).

Key computer vision techniques commonly deployed in agriculture include Artificial Neural Networks (ANN), Dense Scale Invariant Feature Transform (DSIFT), and Support Vector Machines (SVM). For instance, ANNs classify wheat grains by attributes like size, shape, and color, while DSIFT recognizes various features such as texture and type. SVM is utilized to analyze germinated wheat and milled rice grains (Zhou et al., 2023). The integration of Convolutional Neural Networks (CNN) and deep learning models in robotic systems has enabled automated grading of agricultural products, such as the root-trimmed garlic grading system described by Huyet et al. (2020).

AI-powered sorting encompasses various stages, including the determination of product maturity, decay, and physical damage. At the foundational input stage, advanced technologies—ranging from lasers, X-rays, and high-resolution cameras to infrared (IR) spectroscopy—enable precise detection of contaminants and product defects, thereby supporting more informed decision-making and enhancing overall product quality (Taneja et al., 2023). Machine vision is also proving effective in tasks such as fruit sorting, maturity assessment, and damage identification for produce including apples, coconuts, and blueberries. By enabling automated, non-destructive field sorting, machine vision bolsters harvest efficiency and offers a viable alternative to traditional manual methods. Additionally, computer-controlled hydraulic systems have delivered significant operational savings and better compliance with production requirements (Abbas et al., 2019).

The advancements in machine learning, deep learning, and machine vision have facilitated the integration of AI into on-farm sorting processes. ANN models are particularly successful in pattern recognition tasks and are increasingly employed for hyperspectral imaging-based chemical analyses, such as quantification of mineral nutrients, dry matter, size, external defects, and visual attributes. CNN architectures are widely used for determining fruit quality metrics—including weight, size, color, visual flaws, and bruising—thus providing a robust, automated alternative to manual fruit inspection (Masakowski, 2020).

7.3. Support vector machines in sorting and associated bottlenecks

Support Vector Machines (SVMs) represent a robust machine learning methodology frequently utilized to optimize crop management decisions via binary and multiclass classification tasks (Kok et al., 2021). Due to high accuracy and resilience when working with limited sample sizes, SVMs have been extensively implemented for agricultural sorting applications. For instance, Patel et al. (2021) demonstrated the effectiveness of SVM algorithms in discriminating mangoes based on ripeness by extracting and analyzing visual indices, such as chromaticity and surface texture, thus achieving superior classification precision.

Bharadwaj et al. (2012) revealed that applying SVM models to discretized agricultural datasets yields enhanced classification accuracy, providing a scalable solution for managing high-dimensional and complex field data to support informed agronomic decision-making. In plant pathology, Pooja et al. (2017) successfully leveraged SVMs for automated leaf image recognition and disease diagnostics, utilizing colorimetric and texture parameters to differentiate symptoms such as mildew, rust, and blight from healthy foliage with high reliability.

Further advancements in pedological mapping have been demonstrated by Barman and Choudhury (2020), where multiclass SVM frameworks classified soil texture based on key physicochemical parameters—including pH, nitrogen, potassium, and moisture levels—achieving an overall categorization reliability of 91.37 percent. Xu et al. (2021) integrated Genetic Algorithms (GA) with SVMs to develop an autonomous grading system for apples, employing feature extraction from RGB image data (color intensity, morphological characteristics, and ripeness indicators). GA-optimized feature selection significantly improved SVM model performance, resulting in a grading accuracy of 92.3 percent.

Despite the pronounced utility of SVMs within precision agriculture and IoT-enabled smart farming infrastructures, several operational bottlenecks persist. The computational cost and scalability of SVM training can become prohibitive when processing voluminous datasets generated by sensor arrays, UAV imaging, and remote sensing platforms. Paoletti et al. (2020) proposed GPU-accelerated training architectures to mitigate memory constraints and expedite model convergence. Additionally, challenges such as imbalanced datasets and reduced prediction throughput can adversely affect classification outcomes within heterogeneous sensor networks and automated decision-support systems (Anguita et al., 2010). Addressing these limitations is vital for enhancing SVM deployment in data-driven, IoT-integrated agricultural environments.

7.4. AI-assisted food packaging solutions and transportation

Intelligent packaging represents a cutting-edge technology within the agri-food sector, designed to augment quality assurance, safety, and real-time decision support across supply chains. Current advancements in smart packaging incorporate digital features such as barcode encoding, RFID (Radio Frequency Identification) tags, biosensors monitoring biophysical properties, and dynamic indicators for time, temperature, and gas composition (Yam et al., 2005). Through AI and Internet of Things (IoT) integration, packaging systems are now increasingly optimized for sustainability, efficiency, and material safety, with machine learning (ML) algorithms deployed to select cost-effective, eco-friendly substrates for food and beverage applications. Nevertheless, certain packaging materials may present risks of chemical migration, particularly with fatty foods—such as adverse interactions from unsuitable printing inks—necessitating algorithmically driven material compatibility analysis (Taneja et al., 2023)

The deployment of neural networks, fuzzy inference systems, and genetic algorithms allows for adaptive modification of packaging processes, optimizing both operational costs and regulatory compliance in accordance with food safety guidelines. Visual sensing modality, leveraging computer vision and image processing, is used to minimize polymer usage by accurately conforming packaging around irregularly shaped produce (Masakowski, 2020). Novel battery-free, AI-enhanced packaging architectures—such as the one engineered by Douaki et al. (2025)—demonstrate the capability to actively monitor freshness biomarkers and automatically dispense preservation agents, extending the shelf life of perishable commodities like fish by up to 14 days. In automated food packaging and filling operations, robotic platforms have achieved near-perfect accuracies (99.8% for packaging and 100% for container filling), significantly surpassing conventional manual methodologies (Drijver et al., 2023).

On-farm sorting and intralogistics are integral to minimizing pre-processing losses and optimizing downstream traceability. This involves IoT-enabled systems for real-time removal of compromised, contaminated, or physiologically degraded produce, followed by high-resolution sorting based on hyperspectral and RGB image analyses to classify outputs by size, chromatic attributes, maturity indices, and ripeness gradients (Majeed & Waseem, 2022; Zhou et al., 2023). Large-scale agro-industries deploy automated conveyors, robotic actuators, and integrated data acquisition networks for warehouse-bound handling, whereas smallholders rely on local mechanized or semi-automated solutions for in-field sorting prior to marketplace aggregation (Bader & Rahimifard, 2020)

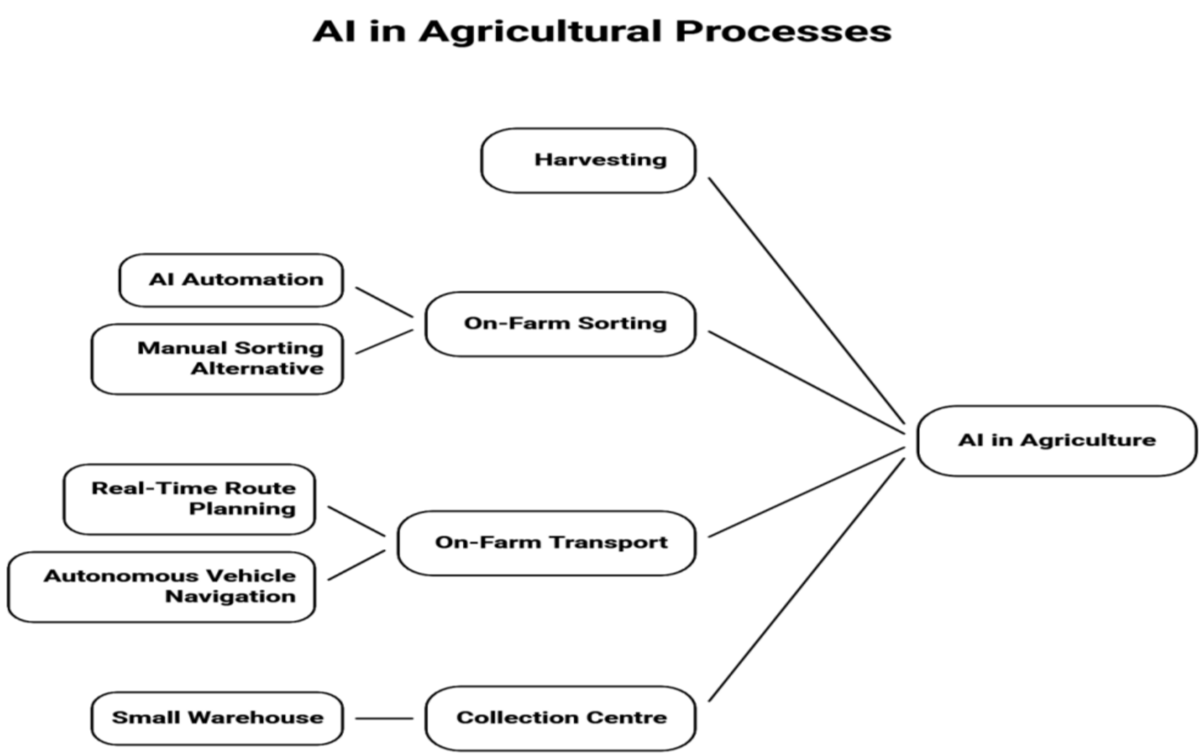

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Fig. 4. AI and transportation.

The use of computer vision and ML algorithms in on-farm sorting and transportation systems improves both spatial and temporal precision, reducing post-harvest losses and expediting throughput (Zhou et al., 2023). Predictive analytics and route optimization—facilitated by AI-driven inventory forecasting and IoT-based tracking platforms—yield measurable reductions in logistics costs and delivery intervals (Fashina et al., 2024). The implementation of Artificial Neural Networks (ANNs) also enables seamless IoT-integrated asset tracking, thus addressing on-farm inventory and resource allocation inefficiencies. Additionally, collaborative robotic systems—co-robots—have been introduced for assisted harvesting and deterrence of hazardous labor conditions, particularly in high-value horticultural crops like grapes, apples, and strawberries (Zhou et al., 2023).

VIII. MACHINE LEARNING IN PLANT BREEDING

Plant breeding is widely recognized as a pivotal strategy for eradicating global hunger and constitutes one of the most efficacious approaches to ensuring future food security. Recent advancements in plant breeding have focused on the development of novel cultivars exhibiting enhanced productivity and augmented resistance to abiotic stresses, pathogens, and pest pressures (Yoosefzadeh-Najafabadi et al., 2022). The integration of artificial intelligence (AI), machine learning (ML), bioinformatics, and high-performance computing facilitates breeders' ability to decipher the complex genetic architecture underlying agronomic traits, design optimized breeding methodologies, and extract actionable insights from multidimensional datasets (Zhang, 2021)

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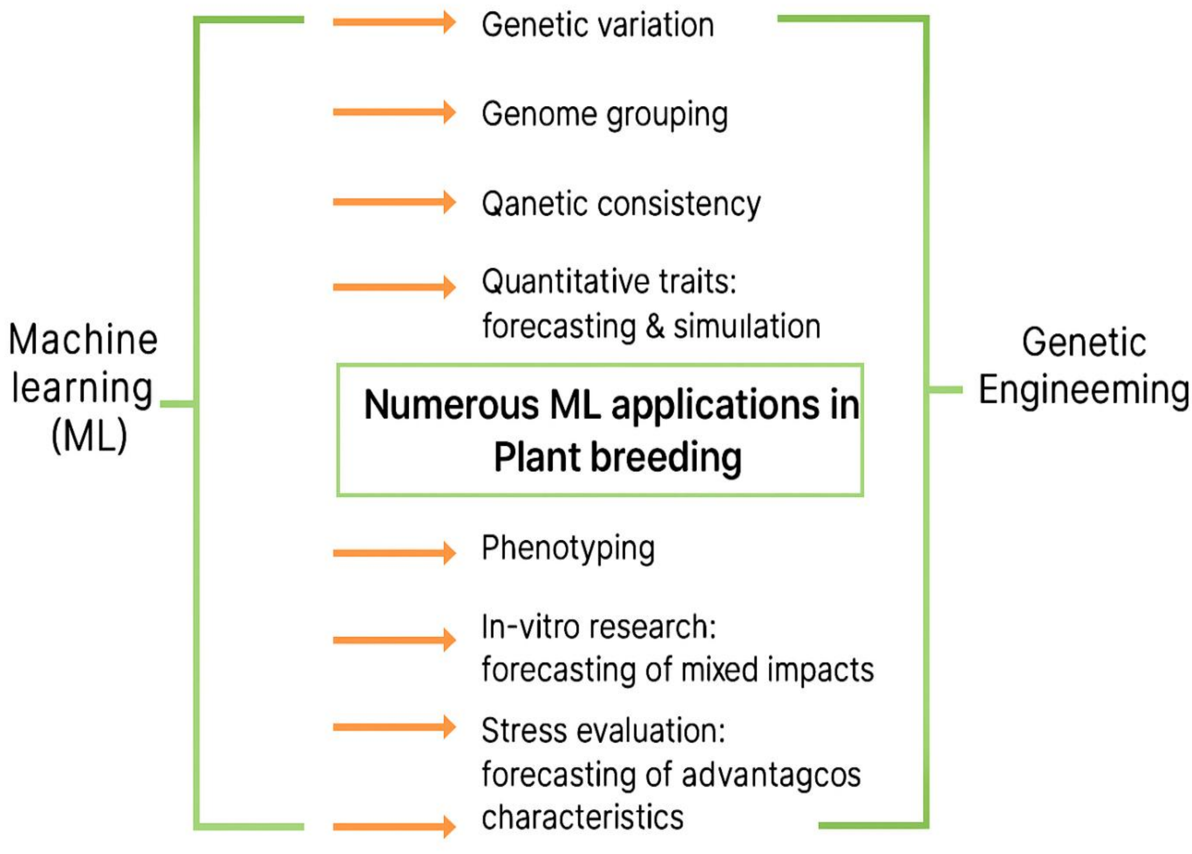

Figure 5 illustrates the deployment of ML techniques within modern breeding pipelines.

Despite the transformative potential of ML in breeding programs, implementation challenges persist, chiefly related to the requirement for extensive, high-fidelity phenotypic and genotypic datasets along with significant computational capacity (Yoosefzadeh-Najafabadi et al., 2023). The traditional breeding paradigm has undergone a paradigm shift with the adoption of AI-enhanced computational tools that enable precise marker-assisted selection, accelerated breeding cycles, enhanced disease diagnostics, comprehensive data management, and cost mitigation (Farooq et al., 2024). Nonlinear ML algorithms provide superior capacity for modeling complex genotype-phenotype relationships and yield component interactions.

A suite of advanced DL architectures and ensemble learning techniques—including Support Vector Machines (SVM), Random Forests (RF), Artificial Neural Networks (ANN), Gradient Boosting Machines, and Convolutional Neural Networks (CNNs)—are extensively applied for phenotypic trait prediction, genomic selection, and decision support within breeding programs. Montesinos-López et al. (2018) highlighted the efficacy of SVM, RF, and Gradient Boosting algorithms in predicting polygenic traits across heterogeneous breeding populations. Singh et al. (2016) demonstrated the application of SVM leveraging thermal, light, and fluorescence imaging spectra, Spectral Angle Mapper (SAM) algorithms for remote sensing analyses, and ANN-based processing of RGB imagery for accurate plant disease detection.

AI-driven Decision Support Systems (DSS) further optimize breeding scheme design and hybrid performance forecasting. The Genomic Selection Decision Support Tool (GS-DST) exemplifies such platforms, providing quantitative breeding value estimations with precision (Crossa et al., 2017). Branstad-Spates et al. (2023) utilized Gradient Boosting Machines to predict aflatoxin concentrations in corn grown in Iowa, attaining 90.32% prediction accuracy. In addition, Gradient Boosting models outperformed conventional approaches in optimizing corn seeding rates, resulting in yield increments of approximately 6.2% through spatially variable seeding strategies (Du et al., 2022).

Further advances underscore AI's role in enhancing climate resilience traits by deploying RF, SVM, and neural network algorithms across multi-omics datasets, encompassing genomics, transcriptomics, proteomics, and phenomics. These integrative data layers empower the selection of breeding lines with robust tolerance to climate-induced stressors and environmental fluctuations (Khan et al., 2022). The synergetic use of IoT-enabled high-throughput phenotyping platforms and AI analytics is poised to accelerate the generation of climate-adaptive cultivars for future agro ecosystems.

8.1. Several applications of ML and plant breeding

Throughout their lifecycle, plants encounter diverse biotic and abiotic stressors that significantly affect their vigor and productivity. To identify elite genotypes and accurately assess stress tolerance and resistance, advanced methodologies have been integrated into breeding and monitoring pipelines. Conventional machine learning (ML) techniques, when combined with deep convolutional neural networks (CNNs), enable precise identification of crop stressors and plant diseases, achieving diagnostic accuracies as high as 95%. These integrated approaches, enhanced through imaging technologies, facilitate simulation and predictive modeling of genotype responses under various stress regimes, allowing for optimized selection of stress-resilient variants under both challenged and optimal growing conditions (Van Dijk et al., 2021).

Artificial neural networks (ANNs)—particularly multilayer perceptron models (MLP-ANNs)—have proven highly effective for modeling the effects of key environmental variables, including atmospheric pressure, precipitation, temperature, and disease incidence, on crop performance (Niedbała et al., 2020). Accurately quantifying genetic control over phenological, morphological, and yield-determining traits is critical for assessing heritability and optimizing parental selection in hybridization programs. ML-driven ANN algorithms provide advanced tools for evaluating cross-parental combinations and ultimately identifying optimal breeding configurations (Gakhar, 2021).

Biotic and Abiotic Stress Characterization

The growth and yield potential of many horticultural crops are substantially impacted by pathogenic invasions and suboptimal abiotic factors such as soil salinity or water scarcity. Early and accurate detection of these stressors enables timely management interventions, such as targeted irrigation modifications or strategic disease containment, thus preventing extensive crop losses (Savary et al., 2012). State-of-the-art imaging sensors—including hyperspectral cameras—detect initial signs of physiological deterioration before visual symptoms manifest. Hyperspectral imaging is especially valuable, capturing high-resolution reflectance profiles across broad spectral bands, far exceeding conventional RGB imaging and allowing for sensitive detection and classification of stress-induced plant responses from laboratory to field scale (Navarro et al., 2022). Integrative analysis combining phenomic, genomic, and metabolomic data streams further enhances the reliability of stress assessments across molecular, physiological, and phenotypic domains.

Genetic Diversity Assessment and Yield Prediction

Genetic diversity forms a fundamental criterion in breeding programs and is traditionally evaluated using physiological, biochemical, and morphological markers, as well as molecular genetic profiles. Multivariate analytical frameworks—such as Principal Component Analysis (PCA), Discriminant Function Analysis, K-NOVA, Support Vector Machine (SVM), and cluster-based methods—are routinely employed for population structure and diversity studies. While these methods are computationally intensive and often require rigorous feature engineering, ANNs offer object-oriented, high-fidelity detection for genetic diversity analysis (Van Dijk et al., 2021).

Enhancing crop yield remains the primary breeding objective, complicated by low trait heritability and pronounced environmental influences. Traditional linear models for trait correlation and prediction—including multiple regression, PCA, correlation coefficients, and path analysis—are limited by their inability to capture nonlinear genotype-phenotype interactions, which often reduces prediction accuracy. In contrast, advanced nonlinear ML algorithms—specifically ANNs—demonstrate improved accuracy in modeling yield determinants, allowing for robust projection of yield outcomes in response to complex biophysical stimuli (Niedbała et al., 2020).

IX. AI-DRIVEN SOLUTIONS FOR SOIL AND PEST MANAGEMENT IN AGRICULTURE

The soil foundation underpins agriculture, with crop growth boosted by soil nutrients. Soil moisture, temperature, pH, and other physical and chemical properties greatly influence yields. Open-source field sensors can monitor these soil traits (Bhatnagar & Chandra, 2020). Modern agriculture, agronomy, and soil analysis increasingly rely on digital technologies such as sensors, IoT, machine learning, AI, and big data, along with drones and GPS satellites (Ramesh & Rajeshkumar, 2021). Whether using deep learning tools or image-capture with visual recognition, AI and ML enable monitoring of soil attributes like quality, fertility, microorganisms, and nutrient deficiencies, as well as plant patterns. Image-based perception allows AI to rapidly collect and interpret data beyond human capacity, aiding in tracking crop health, predicting yields more accurately, and detecting crop malnutrition (Chella swamy et al., 2020). Crop diseases and insect infestations pose major threats to farmers by reducing yields and profits. Manual early diagnosis requires substantial expertise and can be imprecise. Advances in ML and AI have made disease and pest detection faster and easier. Artificial neural networks trained on extensive image datasets of plant diseases and pests develop predictive models that learn to identify these issues with high accuracy (Shet & Shekar, 2020).

Pests remain a primary danger to agriculture. AI platforms leverage satellite imagery and historic data with AI algorithms to determine whether an insect has landed, identify the pest type (e.g., locust, grasshopper), and push alerts to farmers' phones for timely pest management, supporting agricultural pest control (Singh et al., 2022).

Overuse of pesticides can contaminate soil, water, vegetation, and other crops and may harm birds, fish, beneficial insects like bees, and non-target species. AI and robotics innovations enable more precise application of herbicides and insecticides, targeting only harmful pests while sparing crops and beneficial organisms. Drones are now used for spraying, offering automation that can reduce labor requirements (Balaska et al., 2023). Equipped with sensors, GPS, and laser guidance, drones adjust position and spray rate according to field height, wind speed, geography, and terrain. Robotic rovers fitted with cameras and image sensors navigate agricultural fields autonomously, capturing crop images. A deep learning model then analyzes these images to identify pests and dangerous insects, triggering actuators to apply pesticides precisely where needed (Shet & Shekar, 2020).

X. CHALLENGES AND LIMITATIONS OF AI IN AGRICULTURE

Agriculture precision farming faces security risks that can harm stakeholders, including unauthorized data access and financial losses. Protecting data is essential when AI and cloud platforms are integrated into farming, since privacy worries can deter farmer participation in AI-driven data collection. Amiri-Zarandi et al. (2022) discuss privacy concerns in smart farming and advocate privacy assurances along the data lifecycle, such as safeguarding data from collection to deletion on cloud services to prevent misuse. Table 3 offers a broad view of AI applications in farming, covering yield prediction, irrigation optimization, post-harvest management, cold-chain logistics, transportation, plant breeding, and soil health monitoring. AI concepts include multilayer perceptrons, artificial neural networks, support vector regression, machine learning, and deep learning models. Benefits noted include precise yield estimation, enhanced water-saving irrigation, accurate ripeness and quality assessment, improved load planning and routing, accelerated sorting and transport on farms, and enriched breeding programs through sensor- and ML-driven analyses of oil content, moisture, temperature, and light. Adhaileh et al. (2022), Tace et al. (2022), Kutyauripo et al. (2023), Liu (2020), Zhou et al. (2023), Khan et al. (2022), Wadoux (2025) are cited for various data collection and analysis methods, including sensor and drone data stored securely in password-protected clouds with secure deletion to prevent threats. To enhance privacy in smart agriculture, Taji and Ghani mi (2024) proposed a homomorphic signcryption scheme based on hyper-elliptic curves to protect data during transmission and storage on the cloud. Farm systems may be vulnerable if devices have weak security, so farmers should verify security with suppliers and demand encryption for data both in transit and at rest (Hazrati et al., 2022). Multi-factor authentication, such as one-time passwords, facial recognition, or fingerprints, can mitigate security risks from open networks (Yang, Shu, et al., 2021). Despite limited awareness of advanced ML applications in farming, AI remains highly promising for agricultural programs. Barriers include low digital literacy, which can be addressed through training, AI-powered chatbots, and local-language digital literacy efforts. Multilingual NLP-enabled chatbots and voice interfaces can support dialectal farmers, even with low connectivity; IVR and SMS can deliver weather, market alerts, and farming tips in local languages (Mittal & Mehar, 2016; Singh, Wang'ombe, et al., 2024). ICT interventions, including messaging, videos, voice calls, and training guidelines, have been shown to raise farmer awareness and promote good agricultural practices (Mulungu et al., 2025; Meera et al., 2004). Data quality and high costs remain major obstacles; cloud- and open-source platforms (e.g., TensorFlow, PyTorch) can reduce costs and accelerate adoption (Lohith et al., 2022; Pechuho et al., 2020; Talaviya et al., 2020). IoT hardware is often physically exposed and vulnerable; protective measures include blocker tags, encrypted data, and strict deletion policies. Location-based services can be targeted by device capture attacks, enabling attackers to retrieve encrypted algorithms and gain data access. To broaden adoption, governments can offer affordable web-enabled devices and ongoing training to farmers (Eli-Chukwu, 2019)

Application Area	AI-Based Concept / Method	Benefits	References
Yield Prediction	Multilayer Perceptron (MLP), Artificial Neural Networks (ANNs), Support Vector Regression (SVR), Machine Learning (ML)	Precise estimation of agricultural yield (Low RMSE, High R^2)	Adhaileh et al., 2022; Kutyauripo et al., 2023; Liu, 2020

Application Area	AI-Based Concept / Method	Benefits	References
Smart Irrigation	IoT, ML, ANNs	More sustainable and secure food production; Water-saving irrigation achieved; Addressing water scarcity	Tace et al., 2022; Zhou et al., 2023
Post-Harvest Management	IoT, Probabilistic Localization Algorithms, ANN, CNN	Accurate recognition rate (98.3%), Ripeness detection (Firmness RMSE = 0.539, R^2 = 0.724), Quality by color	Khan et al., 2022
Cold Chain Logistics	ML, Robotics	Real-time tracking of food product status; Resolving load and route planning challenges	Wadoux, 2025
Transportation	ML, Deep CNN	Accelerated, highly accurate sorting and transportation; Ripeness detection (RMSE = 1.08)	Liu, 2020; Zhou et al., 2023
Plant Breeding	ML, Sensors	Enriched breeding systems, leveraging past experience and knowledge	Kutyauripo et al., 2023
Soil Health Monitoring	ML, Sensors	Analysis of nutrient, moisture, temperature, sunlight using sensors; Improves soil health decisions	Dahileh et al., 2022

XI. CONCLUSION

Monitoring agriculture is crucial for reducing the need for daily human intervention. With the rising demand for food, it is becoming increasingly difficult to meet these needs without adopting advanced and modern agricultural technologies. Artificial intelligence has been harnessed to help farmers choose the right fertilizers and crops. Machines collaborate by sharing data provided by users, allowing them to determine the best crops for harvest and the most effective fertilizers to promote optimal growth. AI is transforming agriculture by improving the quality of farm products in significant ways. Deep learning is widely utilized, and its agricultural applications have progressed rapidly. The Internet of Things (IoT) also plays a key role by enabling real-time monitoring of agricultural data. AI-driven solutions—such as smart irrigation, yield prediction, post-harvest handling, and automated on-farm sorting—are helping to enhance productivity, cut down on waste, and increase crop yields. Additionally, AI facilitates detecting plant diseases and pests, applying pesticides more precisely, and monitoring soil health, all of which contribute to more sustainable and productive farming methods. As AI evolves, it has enormous potential to tackle challenges related to global food security and sustainability by boosting agricultural productivity, resilience, and efficiency. It is essential to embrace technological advancements throughout the agricultural supply chain. This includes automating farm machinery, utilizing sensors and satellite data for remote monitoring, and leveraging AI, machine learning, and water management to improve crop tracking. Major influencing factors include climate change, population growth, technology progress, and natural resource conditions

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