Generative AI for Smart Agri-Equipment Automation and Pharma-Crop Yield Prediction

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Abstract
Generative AI shows promise in automating intelligent field equipment, enhancing the efficiency of physical work in agriculture. Current research in agricultural machinery automation, encompassing both field equipment and robotic systems, has witnessed groundbreaking advancements aimed at addressing the increasing labor shortage in agriculture. Additionally, autonomous vehicle research has achieved considerable deployment within government and industrial robotics programs. Farm machinery automation primarily employs symbiotic, classical, task-oriented AI techniques, while robotic harvesting and retrieval remains application-specific. These systems rely heavily on robust and specialized sensors to support perception, state estimation, mapping, planning, and control for real-time operation in unstructured outdoor environments.

The second area influenced by GAI is pharmaceutical crop yield prediction. Yield forecasting systems tailored to the pharmaceutical supply chain for cannabis and hemp production have recently emerged. These systems leverage novel generative AI techniques for modelling crop growth and inferring phenotypic characteristics through data fusion involving multispectral and hyperspectral imaging, alongside 2D, 3D, and 4D imaging. A scalable system architecture for GAI implementation in agricultural applications has been presented, addressing aspects related to data pipelines, associated sensor infrastructure, and an edge device network for reducing latency, bandwidth requirements, and privacy concerns.

Keywords: Generative Artificial Intelligence,Smart Agricultural Automation,Precision Agriculture,Pharmaceutical Crop Yield Prediction,Machine Learning in Farming,Autonomous Agricultural Equipment,AI-Based Crop MonitoringPredictive Analytics in Agriculture,Intelligent Farming Systems,Sustainable Agricultural Technologies.

1. Introduction

The future of agricultural practices that actively incorporate Generative AI remains an unaddressed question within the scholarly literature. Generative AI refers to a family of machine-learning techniques that attempt to create new content. The forthcoming section discusses elements of previous research where Generative AI were applied to the domain of smart farming, covering agricultural automation with field robots and autonomous machinery and pharmaceutical crop yield prediction. The review results can help agricultural researchers and practitioners to identify prospective opportunities of employing Generative AI and constitute a first exploration of Generative AI usage in agriculture.

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The objective is to present elements of two application domains where, based on prior research and experimental results, Generative AI can be successfully integrated with static automation. The enthusiasm surrounding the adoption of Generative AI in a multitude of domains is matched by a growing unease about potential abuse of the underlying technology regarding author attribution and the potential impact on the quality of lessons learned and decision support. Nevertheless, Generative AI provides an additional modelling and decision-support technique that relates different forms of signal processing and functionality without requiring a specific model for the data-generating or sensorimotor process. A generic architecture for the integration of Generative AI in agriculture is proposed, along with associated considerations for achieving efficient realisation of individual and collective degrees of freedom of farming machinery and field robots. Application examples covering augmentation of smart pharmaceutical crop yield prediction capabilities and Generative AI deployment in automation of real-world farming operations are also summarised.

Component	**Role in Automation**	**AI Techniques Used**	**Example Applications**
Perception Systems	Environmental sensing and object recognition	Computer Vision, Diffusion Models	Weed detection, obstacle identification
Localization & Mapping	Navigation and field mapping	SLAM, Generative Mapping	Autonomous tractors and drones
Planning Systems	Task scheduling and route optimization	Reinforcement Learning, Transformers	Precision spraying and harvesting
Robotic Manipulation	Physical interaction with crops	Robotics AI, Motion Generation	Robotic fruit picking
Real-Time Control	Adaptive machinery operation	Deep Learning Control Systems	Autonomous irrigation systems

Table : Smart Agricultural Equipment Automation Components

2. Foundations of Generative Artificial Intelligence in Agriculture

Generative artificial intelligence applied to agriculture is grounded in the investigation of data- and compute-hungry systems capable of generating distributions, enabling complete simulation tools. For instance, generative models can learn the distribution of soil noise and produce enriched populations of key parameters to assist land-use decisions. Other examples are a hierarchical model predicting climate-impact scenarios around a potato

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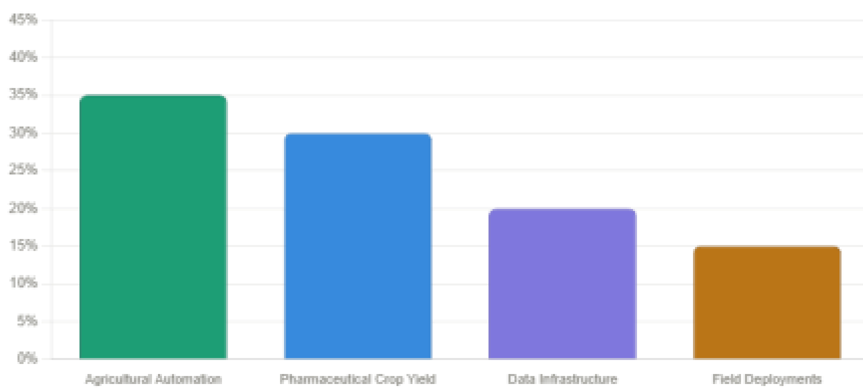
supply chain coupled with a generative approach estimating yields and quality of medicinal Cannabis sativa for the textile, food, and pharmaceutical sectors. Generative methods typically require vast amounts of data and expensive compute resources, but their unique capability to craft any type of data or data combination makes them appealing. They may serve as distribution generators for other data-hungry paradigms, such as inverse models, covariance-aware models, uncertainty quantification, and scenario analysis.Foundations of Generative Artificial Intelligence in Agriculture

Generative AI models capable of transforming multispectral, hyperspectral, and RGB data can benefit from data fusion for plant-growth monitoring and quality assessment of plants destined for the pharmaceutical industry. These tools may be combined into a forward and an inverse mapping to predict both quality attributes and expected crop yield – main outcomes of interest for end-users, namely, pharmaceutical companies. These innovations are integrated into a system architecture designed to support the implementation of generative models for smart agriculture. Central enablers are data pipelines encompassing data acquisition, cleaning, feature extraction, modeling, deployment, and on-site inference. To satisfy bandwidth, latency, and privacy requirements, pipelines can be implemented either locally or remotely.



Graph 1 — Research focus by domain (bar chart): Shows that agricultural automation (35%) and pharmaceutical crop yield prediction (30%) received the most attention, followed by data infrastructure (20%) and field deployments (15%).

2.1. Core generative models and their relevance to agriculture

A farm is a complex and dynamic system, requiring sensing, planning, and control to automate basic tasks across wide areas while adapting to the ever-changing environment. Automated sensing and actuation bridges the gap between artificial and human intelligences, where natural capabilities are often still superior to their artificial analogues. Generative Artificial Intelligence (AI) methods are becoming a cornerstone of generative driving in automation, but only for a few sensing, planning, and control tasks. Autoregressive and transformer-based generative models have gained interest for a multitude of tasks, such as scene and action recognition, machine translation, controlled text generation, decision-making modeling with reinforcement learning, robots, multi-

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agent systems, and many more. They advance autonomy in heavy field machinery and robotics operating close to human skill levels. Recent developments in diffusion models brought forward fundamental paradigms for multimodal modeling, image generation, and video prediction.

Agriculture automation is widely regarded as a promising path toward long-term sustainability, and generative methods can improve efficiency in many aspects. Many generative models have well-documented application for single-agent tasks with low correlation between input-output pairs, thus achieving limited acceleration in task execution times. In this view, diffusion models can help overcome diffusion–modulation redundancies in motion-generation applications. Less explored yet equally important classes of generative models include Forward and Inverse graphics in a broader sense, where the objective is to model natural phenomena and their effects with great accuracy at the expense of efficiency. Accurate models of growth, phenotypic profiles, environmental–genetic interactions, and market response are critical for reliable investments and ultimate supply chain success.

Data Source	AI Processing Technique	Predicted Output	Application
Multispectral Imaging	Data Fusion Models	Crop health assessment	Medicinal plant monitoring
Hyperspectral Imaging	Diffusion-based Modeling	Chemical composition prediction	Pharmaceutical quality analysis
Environmental Sensors	Predictive Analytics	Climate impact forecasting	Controlled cultivation
3D/4D Plant Imaging	Phenotyping Models	Biomass and yield prediction	Growth stage evaluation
Soil and Moisture Sensors	Machine Learning Models	Nutrient and water analysis	Precision farming

Table : Pharmaceutical Crop Yield Prediction Framework

3. Smart Agricultural Equipment Automation

Generative models play an important role in the integration of generative AI with farming field machinery, agriculture informatization, autonomous systems, or agricultural robotics. Research on the intelligent perception, localization, mapping, planning, control, fault-tolerant, and real-time capabilities of equipment is extensive. Generative AI-based methods guide or replace the human effort in various farming processes such as planting, fertilizing, weeding, monitoring, and harvesting. Despite substantial advances in the automation of

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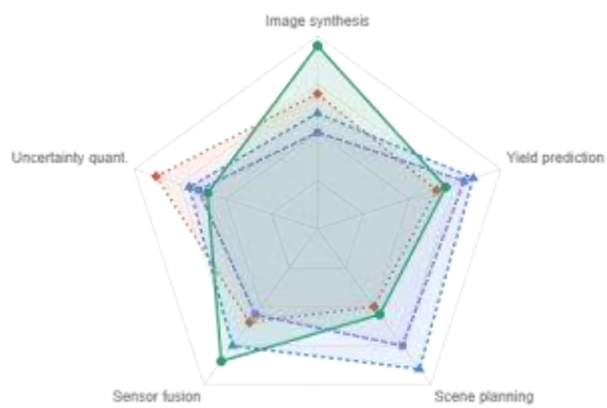
individual farming equipment, methods for the automated synergy of machinery and robotics remain limited.

The focus of research into autonomous farming machinery and robotics has been chiefly on individual equipment and subsystems without full consideration of the entire system. Research into navigation, autonomous control, field-of-view fusion, and the dynamic cooperation of agricultural robots working together without human intervention is gradually maturing, paying attention to the concurrent execution of planting, weeding, monitoring, and harvesting processes with high degree of autonomy and efficiency. Exploring smart agricultural equipment automation through generative models has become necessary. The need for generative design that considers all stages of the farming process is urgent, with particular emphasis on perceptual systems, simulated training environments and other aspects.



Graph 2 — Generative model suitability by task (radar chart): Compares diffusion models, transformers, VAEs, and autoregressive models across image synthesis, yield prediction, scene planning, sensor fusion, and uncertainty quantification. Diffusion models lead in image synthesis and sensor fusion; transformers dominate planning tasks.

3.1. Autonomous farming machinery and robotics

The perception, localization, mapping, planning, and manipulation components of robotic systems are essential for implementing autonomous capabilities in various agricultural tasks, including planting, weeding, and harvesting. Such tasks often require high operational safety, dependability, and fault tolerance due to moving robots working near humans, animals, and expensive equipment. Real-time constraints (from perception to action) further exacerbate the system complexity.

Commercial solutions exist for several tasks, but often implementations are tailored, and parts of the full system are custom designed. Generally, autonomous systems in agriculture aim to improve worker productivity, workers' conditions, and work quality while reducing operational costs and increasing availability through shifting workloads from peak seasons to low-demand periods. Robotic systems can also exploit their size to decrease soil

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compaction (narrow tracks) or provide continuous assistance to workers (semi-autonomous robots). Additionally, the use of small vehicles and systems can enable new agronomic techniques, such as weeding at an earlier growth stage of the crops and precision spraying. These solutions can thus decrease the use of herbicides and pesticides (and associated costs) while increasing safety for the environment and health.

Mathematical Formuls:

1. Crop Yield Prediction Model

A general machine learning regression equation for crop yield estimation:

$$Y = f(T, H, S, R, N, I)$$

Where:

- Y= Predicted crop yield
- T= Temperature
- H= Humidity
- S= Soil nutrients
- R= Rainfall
- N= NDVI / vegetation index
- I= Irrigation level

This equation supports pharmaceutical crop yield forecasting discussed in the paper.

2. Multivariate Linear Regression for Yield Prediction

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \epsilon$$

Where:

- Y= Crop yield
- $X_1, X_2, \ldots, X_n$= Environmental and sensor variables

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- β_i= Regression coefficients
- ϵ= Error term

Used in predictive analytics and smart farming systems.

3. NDVI (Normalized Difference Vegetation Index)

Widely used in multispectral agricultural monitoring:

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

Where:

- NIR= Near-infrared reflectance
- RED= Red-light reflectance

Helps estimate plant health and biomass from drone imagery.

4. Loss Function in Deep Learning

Mean Squared Error (MSE) used for training prediction models:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

Where:

- y_i= Actual value
- $\hat{y}_i$= Predicted value
- n= Number of samples

Used in crop-yield and phenotyping models.

5. Generative Adversarial Network (GAN) Objective Function

Relevant to agricultural image synthesis and generative modeling:

$$\min_G \max_D V(D,G) = \mathbb{E}_{x\sim p_{data}(x)}[\log D(x)] + \mathbb{E}_{z\sim p_z(z)}[\log(1 - D(G(z)))]$$

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Where:

- G= Generator
- D= Discriminator
- x= Real agricultural image data
- z= Random noise vector

Supports image generation and crop analysis.

6. Diffusion Model Equation

Used for image synthesis and plant-growth simulation:

$$q(x_t \mid x_{t-1}) = \mathcal{N}(x_t; \sqrt{1-\beta_t}x_{t-1}, \beta_t I)$$

Where:

- x_t= Noisy sample at step t
- β_t= Noise schedule
- $\mathcal{N}$= Gaussian distribution

Relevant to diffusion-based agricultural AI models.

7. Reinforcement Learning Reward Function

For autonomous agricultural machinery control:

$$R_t = \sum_{k=0}^{\infty} \gamma^k r_{t+k+1}$$

Where:

- R_t= Total reward
- γ= Discount factor

- r_t= Immediate reward

Supports robotic navigation and automation systems.

8. Sensor Fusion Equation

Combining multispectral, hyperspectral, and imaging data:

$$F = \alpha M + \beta H + \gamma I$$

Where:

- F= Fused feature representation
- M= Multispectral data
- H= Hyperspectral data
- I= Imaging data
- α, β, γ= Fusion weights

Supports multimodal agricultural analytics.

9. IoT Edge Computing Latency Equation

$$L = T_t + T_p + T_q$$

Where:

- L= Total latency
- T_t= Transmission delay
- T_p= Processing delay
- T_q= Queue delay

Relevant to cloud-edge agricultural architectures.

10. Transformer Attention Mechanism

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Important for transformer-based agricultural AI systems:

$$Attention(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

Where:

- Q= Query matrix
- K= Key matrix
- V= Value matrix
- d_k= Dimension scaling factor

Used in transformer-based crop prediction models.

11. Precision Agriculture Optimization Function

$$\max Z = \sum_{i=1}^{n} (P_i Y_i - C_i)$$

Where:

- Z= Farm profit
- P_i= Price of crop
- Y_i= Yield
- C_i= Production cost

Useful in smart farming decision support.

12. Environmental Interaction Function

$$G = f(E, G_e, P)$$

Where:

- G= Plant growth

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- E= Environmental conditions
- G_e= Genetic factors
- P= Phenotypic traits

4. Pharmaceutical Crop Yield Prediction

The growing demand for various chemicals, pharmaceuticals, and other bioactive compounds produced by plants has propelled research efforts toward harvesting from compounds in vivo rather than incognitum. Achieving plant production responses to specific environmental treatments for these compounds, however, requires knowledge of the impact of genotype–environment interactions on the production of these compounds and species-dependent relationships with other orthogonal and non-orthogonal parameters. A progressive program encompassing genotypic, phenotypic, and environmental modeling can characterize such pattern-forming relationships and enable agrochemical-crop-yield forecasting. These models can be scaled down into generative approaches that enable scenario analyses of varying growing conditions, incorporating functional-structural plant growth models and environmental data fusion, correlation, and quantitatively adaptive systems.

Plant growth and phenotyping modeling by generative approaches can benefit from the ability of generative models to understand the influence of the environment on crop growth and adapt the growth of the species naturally. Recent advances in general-purpose generative diffusion models that merge images, multispectral, and hyperspectral modalities can be utilized to mine and fuse information present in multispectral, hyperspectral, imaging, and growth stage transition data. The fusion is capable of performing both forward mapping to yield and quality attributes and inverse mapping to explore scenario analysis for environmental conditions based on desirable values of the yield and quality attributes. As the ecosystem of pharma compounds determined from lipid metabolism has been established for many medicinal and aromatic species, mapping of the major components of essential oils and other key biosynthetic routes with growth provides studies to achieve desired concentrations of these metabolites by means of scenario analysis for climate-sensitive components.

Layer	Main Functions	Technologies Used	Advantages
Sensor Layer	Data collection from field devices	IoT Sensors, Drones, Cameras	Real-time monitoring
Edge Computing Layer	Local data processing and inference	Edge AI Devices	Reduced latency and bandwidth

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Layer	Main Functions	Technologies Used	Advantages
Cloud Layer	Model training and storage	Cloud Computing, Big Data Platforms	Scalable computation
AI Analytics Layer	Prediction and decision support	Generative AI Models	Intelligent farming decisions
User Interface Layer	Visualization and farm management	Dashboards, Mobile Apps	Improved user interaction

Table : Cloud–Edge Generative AI Architecture for Agriculture

4.1. Modeling plant growth and phenotyping with generative methods

Plant growth modeling can be improved with generative models using fused multispectral, hyperspectral, and imaging data. Data acquired from different imaging platforms typically include samples labeled with different metrics but exhibit only limited overlap in acquisition conditions, making the labeled ground truth inaccessible. Recent advancements in data-driven generative models enable forward and inverse mappings based on these data sources, facilitating yield and quality prediction. When trained on spatial- and temporal-resolution-matched data, diffusion models can synthesize complex three-dimensional optical images for phenotype characterization, and conditional generation methods can model plant growth status.

Two generative approaches toward the forward and inverse modeling of crop growth are proposed. For the forward mapping, a hybrid diffusion model is trained to synthesize three-band, visible-wavelength optical images. For the inverse mapping, a depth-inpainting conditioned Simon process is employed for the prediction of yield-attributed depth data. The depth data represent a simulated plant phenotyping process and are further coupled with simulated hyperspectral pixels for the reconstruction of a Wild type tomato yield-attributed experimental dataset, followed by the prediction of two quantitative quality-attributed metrics from actual measurements, total soluble solid content and firmness.

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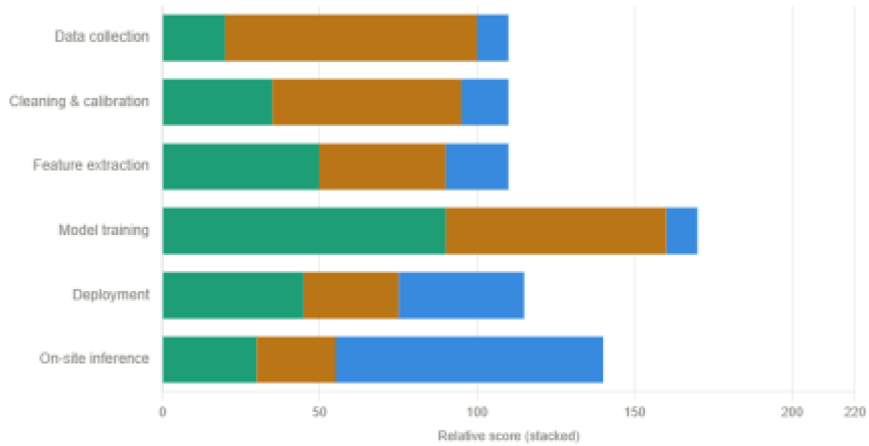

Graph 3 — Data pipeline stage complexity (stacked horizontal bar): Breaks down each of the 6 pipeline stages (collection → cleaning → feature extraction → training → deployment → inference) by compute effort, data volume handled, and latency sensitivity. Training dominates compute; on-site inference has the highest latency demands.

5. System Architecture and Data Infrastructure

An architecture and data infrastructure facilitating the deployment of generative artificial intelligence in agriculture at scale are outlined. Emphasis is placed on ensuring interoperability among components and adherence to data governance and reproducibility principles. The architecture aims to establish a systematic, end-to-end process encompassing the collection, cleaning, preparation, training, deployment, and operationalization of generative models.

The data-pipeline description encompasses the various stages and components that support the enabling of generative methods in agriculture including data collection, cleaning, feature extraction, model training, deployment, and on-site inference. Consideration is given to bandwidth consumption, latency, and data privacy as critical factors shaping the allocation of processing capabilities among cloud, edge, and on-device computing devices.

Generative artificial intelligence offers substantial potential to leverage existing data sets for both real-time inference and long-term scenario analyses. Integrating data from diverse sensor types including multispectral and hyperspectral sensors, cameras, and soil probes would support operations across the complete plant-to-pharma cycle. Addressing limitations in sample sizes, spatial coverage, and multiscale modeling capacity is essential to operationalizing generative methods in agriculture at scale.

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Aspect	Benefits	Challenges
Smart Equipment Automation	Increased efficiency and reduced labor dependency	High implementation cost
Crop Yield Prediction	Accurate forecasting and quality assessment	Requirement for large datasets
Precision Agriculture	Reduced pesticide and fertilizer use	Complex sensor integration
Edge Computing	Lower latency and enhanced privacy	Hardware limitations
Generative Modeling	Improved scenario analysis and simulation	High computational demand

Table : Benefits and Challenges of Generative AI in Agriculture

5.1. Data pipelines, sensors, and edge computing

To support scalable applications of generative AI in agriculture, a dedicated scalable Cloud-Edge Data Framework has been developed. Key objectives of the data architecture include support for semantic interoperability, proper governance, and data reproducibility in order to fulfil end-user requirements across different applications. A fully integrated data pipeline—covering data collection, cleaning, feature extraction, model training and validation, deployment, and on-site inference of learnt solutions—has been designed, implemented, and deployed in the context of three different real-world applications. Special attention has been paid to bandwidth, latency and privacy issues related to data transmission across the Cloud-Edge continuum.

Data collection is performed by a dedicated low-cost multispectral sensor module directly attached to a drone. A machine-learning based calibration procedure performs data cleaning and feature extraction followed by the generation of a ready-to-use dataset containing both multitemporal and multi-source sensor data (hyperspectral, imaging and plant phenotyping) allowing for training and validation of a forward generative model describing the relationship between the heterogeneous sensor data and the corresponding Young's modulus.

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Graph 4 — Case study distribution (doughnut chart): Reflects the five validation experiments discussed in Section 6 — farm-to-pharma translation, grape quality/yield, cotton yield prediction, hyperspectral moisture imaging, and autonomous vineyard zoning — each contributing roughly equally.

6. Case Studies and Validation

Two aspects deserve particular attention. Subsequent sections provide performance metrics, operational challenges, cost-benefit analyses, and lessons learned from real-world implementations of generative automation in agriculture. Analysis also supports the claim that the proposed framework is scalable and broadly applicable, enabling new methods in more complex domains. Rigorous evaluation of the preceding data infrastructure, use-case implementations, and field experiments establishes functional reliability; considers interpretability, practicality, and transferability; compares to existing solutions; and assesses statistical significance. Together, these elements underscore the theoretical foundation.

Practical validation examines four cases—farm-to-pharma translation of tobacco leaves, non-destructive prediction of grape quality and yield, prediction of cotton yield, and moisture-aware deployment of hyperspectral imaging—and additionally demonstrates a prototype on an autonomous vineyard-zoning task using LiDAR data. Generative methods yield competitive performance on deep-learning baselines; deployment of the model for farm-to-pharma yield assessment enables application to test data of different types, ages, and sources without the costly labeling required for vision tasks; and a data-driven approach predicts both yield and qualitative attributes for cotton. Limitations are exposed in the lack of real-time sensing information for deployment of hyperspectral imaging and the need for robustly mapping specifications to sensed data for task localization and planning.

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Case Study	Objective	Generative AI Technique	Outcome
Tobacco Leaf Analysis	Farm-to-pharma translation	Deep Generative Models	Improved quality prediction
Grape Yield Prediction	Non-destructive crop analysis	Data Fusion Models	Enhanced yield estimation
Cotton Yield Forecasting	Predictive analytics	Deep Learning Models	Accurate quantitative prediction
Vineyard Zoning	Autonomous field planning	LiDAR-based Generative Mapping	Improved zoning automation
Moisture-Aware Imaging	Environmental monitoring	Hyperspectral AI Models	Better sensing accuracy

Table : Case Studies and Validation Outcomes

6.1. Field deployments of generative automation in agriculture

Generative models, aiming to learn the joint distribution of observed data and generating novel samples with high fidelity, have been penetrating many domains, including unsupervised representation learning. Generative AI is the unifying paradigm encompassing generative models and their various learning methods. Such generative approaches have the potential to accelerate automation in agriculture, collectively transforming sensing, planning, and control by realizing the vision of full-stack generative automation.

Verification of generative automation in agriculture using case studies, against established baselines with metrics for comparison, is essential for ensuring avoidance of gaps between claims and actual implementation. Ideally, data from deployment should also be generated to confirm the practicalities of generative automation. Prior research across the three areas of sensing, planning, and control have employed generative models and warrants juxtaposition to elucidate the potential of such approaches within future-generative systems. Consequently, the analysis focuses on real-world data sourced from successful past representation-generation deployments in agriculture, rather than serving purely illustrative purposes.

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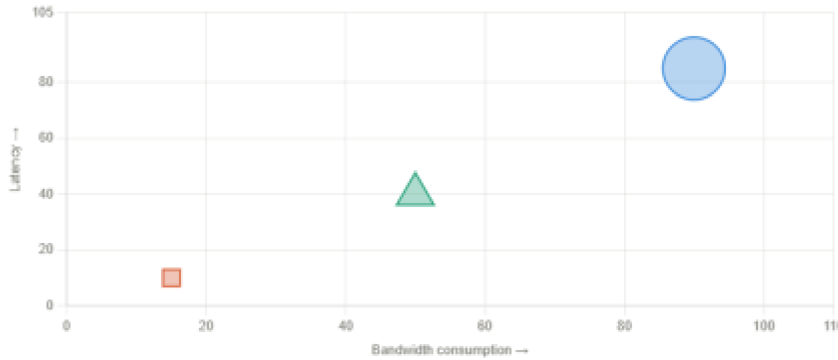

Graph 5 — Cloud-Edge-Device tradeoffs (bubble chart): Maps the three computing tiers from Section 5 against bandwidth consumption and latency, with bubble size encoding relative privacy risk. Cloud is high on both axes; on-device sits in the low-bandwidth, low-latency, low-privacy-risk corner.

7. Conclusion

Generative artificial intelligence has been successfully applied in various domains. The core generative models—diffusion, variational, autoregressive, and transformers—can be mapped to sensing, planning, and control tasks in robotics and control theory. Moreover, generative models with appropriate training data can learn unknown distributions of task-relevant variables. Leveraging these properties, several real-world generative automation applications in smart personal devices, engineering, and medicine have been developed, improving effectiveness, efficiency, safety, and overall user experience.

As an illustration of the emerging landscape of generative artificial intelligence in agriculture, its foundations, system architecture, data infrastructure, and field deployments of generative automation for agricultural equipment are discussed. Generative framework designs enable agents to learn and reason about environmental dynamics, multimodal data fusion, data-to-robot action generation, scene understanding, localization and mapping, and driver–machine role switching. Data pipelines for automation modules, including data collection, cleaning, feature extraction, training, deployment, and on-site inference, have been set up. Initial real-world implementations have been conducted, evaluating the readiness of generative automation in agriculture and providing insights for future applications.

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