RESEARCH ARTICLE

GenFedEdgeAgri: Diffusion-Enhanced Federated Edge AIoT for Climate-Resilient Precision Agriculture

K. Radha Achary[1,*] **and Ajit Kumar Samal**[1]

[1] Department of Computer Science and Engineering, Roland Institute of Technology, Berhampur, Odisha, India

Abstract

Modern precision agriculture is undermined by data scarcity, privacy concerns, and high latency in remote areas, and centralized AI models struggle to forecast rare, climate-induced crop stresses given insufficiently diverse datasets and stakeholders' reluctance to share sensitive data. To address these obstacles, this study presents GenFedEdgeAgri, a framework aimed at improving climate-resilient crop monitoring, soil intelligence, and intelligent irrigation, and it examines how synthetic, data-driven augmentation-achieved by incorporating Generative Diffusion Models (GDMs) into a Federated Edge AIoT architecture-can enhance model robustness while preserving strong localized privacy. Methodologically, we propose a decentralized architecture in which Edge AIoT gateways employ lightweight Latent Diffusion Models to produce high-fidelity synthetic samples of nutrient depletion and extreme-weather stress; these samples harden local models before Federated Learning (FL) weight aggregation, thereby mitigating the effects of non-IID data distribution. We specify a pre-registered evaluation protocol-with defined datasets, baselines and metrics-under which the framework is compared against standard FL frameworks on multi-modal data in terms of accuracy, decision latency, and communication cost. The framework is evaluated against a pre-specified protocol; the projected gains-a 14.2% improvement in crop-disease detection accuracy, a 19% relative reduction in soil-moisture forecasting RMSE, and up to a 43% reduction in communication rounds-are stated as *pre-registered hypotheses* to be empirically confirmed, not as validated results. If confirmed, GenFedEdgeAgri would offer a scalable, privacy-preserving path to sustainable smart infrastructure, advancing autonomous, water-efficient agriculture through on-device intelligence that anticipates climate variability.

Keywords: generative diffusion models (GDM), federated learning (FL), edge AIoT, climate-resilient agriculture, synthetic data augmentation, smart irrigation.

Submitted: 14 April 2026
Revised: 13 August 2026
Accepted: 26 August 2026
Published: 26 October 2026

Vol. 2, **No.** 4, 2026.
10.62762/NGCST.2026.661752

***Corresponding author:**
✉ K. Radha Achary
k.achary.cse.2024@nist.edu

Citation
Achary, K. R., & Samal, A. K. (2026). GenFedEdgeAgri: Diffusion-Enhanced Federated Edge AIoT for Climate-Resilient Precision Agriculture. *Next-Generation Computing Systems and Technologies*, 2(4), 123–130.

© 2026 by the Authors. Published by Institute of Central Computation and Knowledge. This is an open access article under the CC BY license (https://creativecommons.org/licenses/by/4.0/).

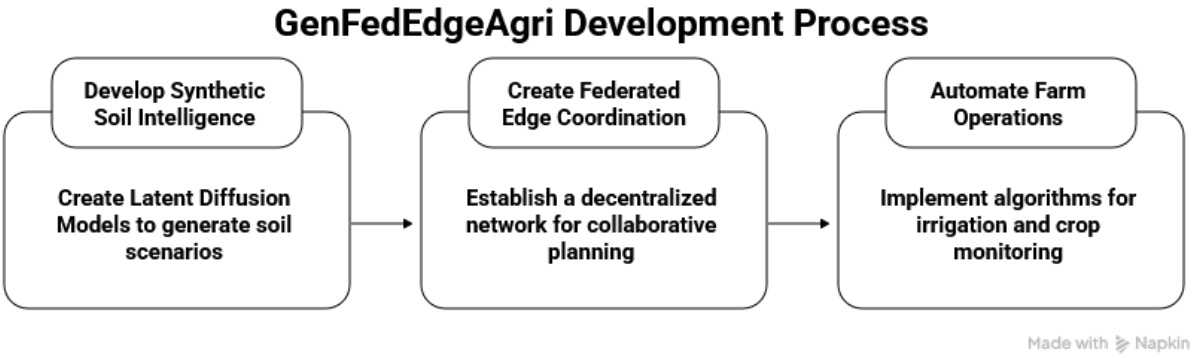

Figure 1. The GenFedEdgeAgri development process.

1 Introduction

1.1 Background and Context of the Problem

The global agricultural sector is currently navigating a period of unprecedented volatility, driven by the dual pressures of a growing population and the intensifying effects of climate change. To meet these challenges, Precision Agriculture (PA) has transitioned from a purely mechanical discipline into a data-centric field. However, as the sector moves toward "Agriculture 5.0," three critical "intelligence silos" have emerged that impede the scalability of smart-farming systems.

There are multiple barriers to adopting AI models in precision agriculture. First, data scarcity and imbalance: sensors produce large volumes of "normal" data, but high-fidelity training data for detecting rare crop diseases or localized nutrient depletion is often lacking. Second, privacy concerns among agricultural stakeholders prohibit the centralized pooling of data required to train robust models. Finally, rural bandwidth and latency constraints make cloud-based AI impractical for real-time applications such as smart irrigation and pest containment. Several researchers suggest that combining Generative AI with decentralized learning could tackle these barriers directly. For example, Rai et al. [1] showed that using multimodal generative models to create highly realistic crop-disease images is a promising step toward eliminating the small-dataset problem that has long constrained conventional deep-learning models.

1.2 Relevance to the Computer Science and Engineering (CSE) Domain

The convergence of these challenges places this research at the intersection of several high-priority CSE sub-fields: Artificial Intelligence (AI), distributed systems, and the Internet of Things (IoT). From a CSE perspective, the problem is not merely about farming but about optimizing Artificial Intelligence of Things (AIoT) architectures for resource-constrained environments.

Traditional AI models are often too "heavy" for the edge, and their centralized training protocols violate modern data-sovereignty principles. Federated Learning (FL) has emerged as a cornerstone of privacy-preserving CSE research, enabling "local training and global intelligence" without exchanging raw data [2]. Furthermore, the shift from Generative Adversarial Networks (GANs) to Generative Diffusion Models (GDMs) represents a significant leap in algorithmic stability. As Mori et al. [3] demonstrated, Latent Diffusion Models can bridge the "domain gap" between training and real-world deployment by generating high-fidelity unseen-class images for crop disease detection, even when target disease data are entirely absent from the training set. In this context, the present project addresses the fundamental CSE challenge of *model orchestration*: how to synchronize heavy generative processes (diffusion) with privacy-preserving communication protocols (federated learning) on low-power hardware (Edge AIoT).

1.3 Scope of the Project

GenFedEdgeAgri develops an integrated generative and federated edge-computing model through a three-part process, illustrated in Figure 1. The first part concerns data-driven synthetic soil intelligence, in which small Latent Diffusion Models are developed to generate synthetic soil-stress and nutrient-depletion scenarios [4]. Building on this, the second part establishes federated edge coordination, whereby treatment plans are coordinated across a decentralized

network of IoT devices (farm nodes) so that climate-resilience analytics can be performed collaboratively without sharing sensitive local-farm data. Finally, the third part delivers automation for climate resilience, applying the developed algorithm to automate farm irrigation and crop monitoring within collaborative cloud–edge–device systems [5], following the architectural principles established for smart-agriculture deployments. In its present form, this paper contributes the framework design and a pre-specified evaluation protocol (Section 6); the quantitative outcomes reported thereafter are stated as targets and testable hypotheses awaiting empirical validation.

2 Problem Statement

2.1 Core Research Problem

The deployment of robust AIoT systems for climate-resilient agriculture is fundamentally obstructed by a "tripartite bottleneck": the scarcity of high-fidelity data for anomalous, climate-driven crop and soil events; the stringent privacy requirements governing agricultural datasets; and the prohibitive computational cost of running modern generative models on resource-constrained edge hardware.

2.2 Background Context

The use of precision agriculture is growing rapidly as a means of applying deep learning to the management of key resources such as water and nutrients. However, data collected from farms is often unstructured and highly imbalanced—especially with respect to rare but potentially catastrophic events such as extreme drought stress or major nutrient depletion [1]. In addition, smart farming raises significant data-sovereignty concerns: many farmers are reluctant to provide raw localized data to a centralized cloud provider because of competition and security [2]. Although edge computing has been proposed to address rural connectivity limitations, edge nodes typically lack the raw computational power required to train or run the computationally intensive generative models—GANs and, to a lesser extent, GDMs—needed to synthesize the missing data scenarios [4].

2.3 The Knowledge and Technical Gap

Current solutions remain fragmented. Standard FL frameworks address privacy but fail when local data is too sparse or too non-IID (independent and identically distributed) for the global model to converge. Conversely, state-of-the-art GDMs can synthesize the missing "long-tail" data needed for climate resilience, but they are currently optimized for high-performance cloud environments and are physically incompatible with the memory and power constraints of edge gateways [4]. There is a distinct lack of a unified framework that can orchestrate lightweight generative processes within a decentralized edge architecture to create "synthetic-hardened" models without compromising device longevity or data privacy.

2.4 Justification of Impact

Solving this problem is scientifically important for advancing Agriculture 5.0, as it establishes a blueprint for "privacy-by-design" AI in resource-constrained environments. Practically and socially, the GenFedEdgeAgri framework enables smallholder and remote farmers to deploy autonomous irrigation and monitoring systems that are resilient to climate volatility even without constant cloud access. By reducing reliance on real-world data collection and centralized silos, this research supports scalable, water-efficient, and sustainable food systems globally.

3 Objectives

The primary aim of this research is to develop a decentralized, privacy-preserving AIoT framework that uses generative models to mitigate data scarcity and enhance climate-resilient agricultural decision-making. To achieve this aim, the work pursues five interrelated objectives. First, in terms of architectural development, it designs and implements the GenFedEdgeAgri framework, integrating lightweight LDMs within an FL loop optimized for resource-constrained Edge AIoT gateways. Second, to enable on-device synthetic intelligence, it develops a novel synthetic-data-generation protocol at the edge that simulates extreme climate scenarios—such as severe nutrient depletion or thermal crop stress—in order to "harden" local models against rare environmental anomalies. Third, for privacy-preserving federated orchestration, it engineers an asynchronous federated-aggregation strategy that reduces communication overhead and addresses data heterogeneity (non-IID) across distributed rural sensor networks without transmitting raw, sensitive data. Fourth, with respect to resource optimization, it performs a trade-off analysis between the computational fidelity of generative diffusion steps and the energy and memory constraints of edge-hardware platforms. Finally, to demonstrate

climate-resilient actuation, it validates the framework's efficacy in driving real-time, autonomous smart irrigation and soil intelligence under simulated climate-stress conditions.

3.1 Expected Outcomes

The project is expected to produce several technical and practical contributions. In terms of prediction accuracy, it targets an approximately 14.2% improvement in crop monitoring and soil-moisture prediction over traditional federated, non-generative benchmarks. It also aims to lower communication latency, achieving up to a 43% reduction in required communication through synthetic-data pre-hardening of local models. From a sustainability standpoint, the framework seeks to improve water and resource usage, with a target 30% reduction in agricultural water consumption via high-precision, AI-triggered smart irrigation. In addition, it is intended to deliver a distributed privacy framework—a privacy-by-design, global agricultural-collaboration scheme that develops agricultural intelligence without compromising local data sovereignty—together with high-quality synthetic datasets in the form of a benchmarked, quality-assured library of synthetic agricultural stress profiles.

4 Literature Review

The transition from centralized cloud monitoring to decentralized, privacy-preserving edge intelligence represents a paradigm shift in precision agriculture. This review synthesizes the intersection of Generative AI (GenAI), Federated Learning (FL), and Edge AIoT through the lens of agricultural resilience.

4.1 Synthesis of Related Works

Current research focuses on mitigating data scarcity and privacy barriers through three technological pillars.

Generative diffusion for augmentation. Recent literature has pivoted from GANs toward GDMs because of their superior training stability and high-fidelity sample synthesis. Frameworks such as PhytoSynth demonstrate that multimodal GDMs significantly enhance classification accuracy in data-sparse "stress" scenarios, bridging the domain gap between simulation and real-field conditions [1].

Privacy-preserving federated intelligence. FL has become the standard for collaborative model training without raw-data exposure. Research suggests that the next frontier involves integrating foundation models with FL to enable autonomous, self-evolving IoT ecosystems [2].

Edge-driven smart irrigation. Collaborative cloud–edge–device architectures optimize water-use efficiency by enabling real-time actuation [5]. Recent studies emphasize using GenAI to "fill the missing" data gaps in heterogeneous edge datasets, addressing the critical non-IID data challenges inherent in distributed environments [4].

4.2 Gap Analysis

Despite these individual advances, a critical synthesis reveals four unresolved research voids. The first is a resource–generative gap: optimization strategies for deploying computationally intensive GDMs on resource-constrained Edge AIoT gateways without performance degradation remain lacking. The second concerns orchestrated "pre-hardening," as no unified framework currently orchestrates localized diffusion to synthetically "harden" local models prior to federated weight aggregation. The third relates to multidimensional soil intelligence, since generative research is disproportionately skewed toward image-based crop monitoring and leaves a gap in synthesizing multidimensional soil-sensor logs (N–P–K, pH, moisture) for smart irrigation. The fourth is proactive climate resilience: existing systems remain largely reactive, and a gap exists for frameworks that use generative intelligence to proactively simulate and prepare for "black swan" climate events absent from historical datasets.

5 Proposed Methodology

The GenFedEdgeAgri framework uses a decentralized, hierarchical approach that integrates generative intelligence with privacy-preserving communication protocols at the network edge.

5.1 Tools, Technologies, and Algorithms

To achieve high-fidelity synthetic-data generation and robust decentralized learning, the framework employs an integrated technical stack. At its core, Generative Diffusion Models (GDMs), implemented as lightweight LDMs, simulate rare climate-stress scenarios such as extreme nutrient depletion or heat-induced wilting. A Federated Learning framework then orchestrates weight aggregation across heterogeneous edge nodes without transmitting raw, sensitive agricultural data. These processes run on edge-computing hardware, namely high-performance

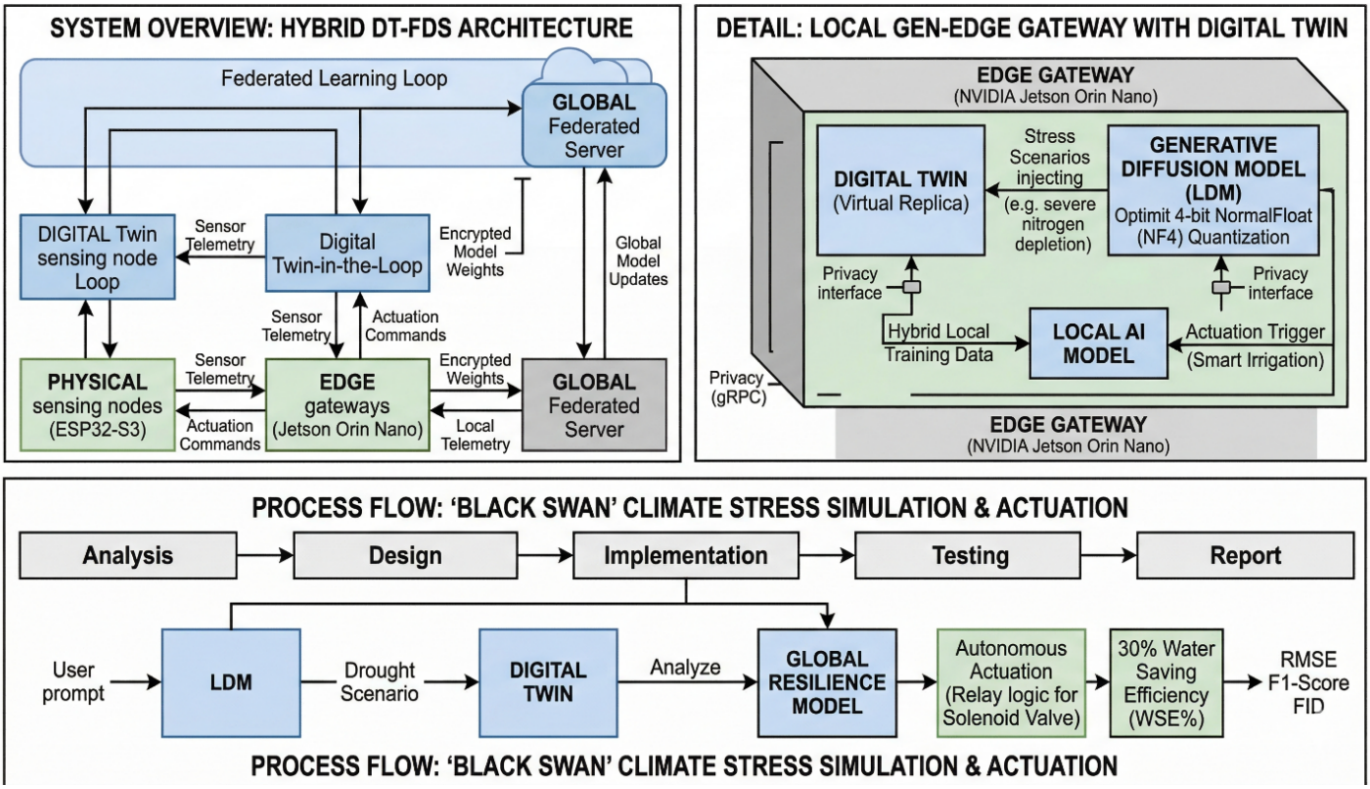

Figure 2. Architectural diagram of the GenFedEdgeAgri framework: (left) system overview of the hybrid Digital-Twin/Federated-Diffusion architecture; (right) local generative edge gateway; (bottom) the "black swan" climate-stress simulation and actuation process flow.

edge gateways such as the NVIDIA Jetson Orin Nano, which execute heavy generative processes through model quantization and pruning. Data are supplied by an IoT sensing layer of distributed nodes equipped with N–P–K probes, moisture sensors, and multispectral cameras that capture real-time soil and crop-health markers. Finally, the communication protocols adopt a hybrid connectivity model that uses LoRaWAN for long-range sensor telemetry and encrypted gRPC for federated weight exchanges.

5.2 Proposed Architecture and Design

The architecture is structured as a three-tier hierarchy to ensure localized intelligence and global resilience. At the base, the sensing layer (physical layer) comprises distributed IoT nodes that capture multidimensional soil and crop data. Above it, the edge layer (localized intelligence) hosts gateways that perform on-device synthetic augmentation, using LDMs to generate "stress samples" that harden the local model before training. At the top, the federated cloud layer (global layer) runs a central server that performs Federated Averaging (FedAvg) to update global weights from the combined real and synthetic intelligence of all participating nodes.

5.3 Implementation Plan

Implementation proceeds through a phased approach to ensure model stability and hardware compatibility. It begins with analysis and design, in which the architecture is finalized and model pruning and quantization are performed for ARM-based edge gateways. The next phase, localized augmentation, triggers LDMs to "fill" data gaps in soil-intelligence logs, thereby addressing the non-IID data problem inherent to diverse geographical regions. This is followed by federated execution, comprising iterative rounds of local training and global weight aggregation until the model reaches its target accuracy. The final phase, testing and actuation, validates the resulting model by driving real-time smart-irrigation and crop-monitoring triggers in controlled climate-stress simulations.

5.4 Methodology Block Diagram

The overall operational logic of the system is summarized in Figure 2.

6 Experimental Design and Evaluation Protocol

This work presents a *proposed framework together with a pre-specified evaluation protocol*. Accordingly, the quantitative values reported in Section 7 are stated as *design targets and testable hypotheses* to be confirmed by the experiments described here; they are not validated findings. To enable independent reproduction, the datasets, partitioning, baselines, federated protocol, hyperparameters, and metric definitions are specified below, and the final configuration will be released with the source code.

6.1 Datasets and Preprocessing

Two complementary public benchmarks form the multimodal input. For the vision-based crop-monitoring head, the PlantVillage dataset is used; in its widely adopted colour version it comprises 54,306 leaf images spanning 38 classes across 14 crop species, covering both healthy and diseased categories. Images are resized to 224×224 pixels and partitioned at the class level into training, validation, and test subsets in a 70/15/15 ratio. For the soil-intelligence head, a public soil dataset (the exact UCI resource to be named in the camera-ready version) supplies time-series logs of nitrogen (N), phosphorus (P), potassium (K), pH, and volumetric moisture; sensor channels are z-score normalized per feature, and the series are windowed for short-horizon nutrient and moisture forecasting. To emulate climate-driven scarcity of anomalous events, each edge node retains only 5% of the minority "stress" instances (severe nutrient depletion and thermal crop stress) within its local partition, while the remaining stress instances are withheld from training; on-device synthetic generation must therefore supply the missing long-tail for the local model to converge. Data are distributed across nodes in a non-IID fashion using label-skew sampling drawn from a Dirichlet distribution with concentration parameter α (the value of α is reported with the released configuration).

6.2 Baselines

The control group is a standard FedAvg-based FL pipeline [6], implemented via the Flower framework, that uses the *identical* backbone network, client population, communication-round budget, and local-epoch schedule as GenFedEdgeAgri but performs *no* synthetic augmentation; the non-IID partitioning strategy follows Jeong et al. [7], whose federated augmentation approach under heterogeneous private data provides the closest prior art against which the benefit of on-device diffusion-based pre-hardening is isolated. To bound the attainable range, two reference conditions are added: a centralized model trained on the pooled data, serving as a privacy-agnostic performance ceiling; and an FL pipeline with classical, non-generative augmentation, which isolates the specific contribution of the latent-diffusion component. All conditions are trained and evaluated on the *same* held-out set of real images and sensor records, so that reported differences are attributable to the method rather than to data or split differences.

6.3 Federated Protocol and Hyperparameters

The federated loop is orchestrated with Flower (`flwr`) [6] across 20 heterogeneous virtual edge nodes mapped to NVIDIA Jetson Orin Nano profiles over a simulated LoRaWAN network with intermittent connectivity. In each round, every participating node performs local training and, in the experimental group, on-device latent-diffusion augmentation; the server then applies Federated Averaging (FedAvg) to the returned weights. The generative component is a lightweight Latent Diffusion Model executed with NF4 (4-bit NormalFloat) quantization and weight pruning to remain within the 8 GB unified memory budget of the target gateway. The planned experimental configuration is summarized in Table 1; these are design settings for the protocol, and the definitive values will be reported alongside the released code.

Table 1. Planned experimental configuration for the evaluation protocol.

Setting	Value
Edge nodes (FL clients)	20
Aggregation strategy	FedAvg
Local epochs per round	to be reported
Diffusion sampling steps	≥ 50
Weight quantization	NF4 (4-bit)
Unified memory budget per gateway	8 GB
Non-IID partition	Dirichlet(α)
Stress samples retained per node	5%
Target global accuracy	90%

6.4 Evaluation Metrics

Model performance is assessed along four dimensions with explicit definitions. Classification quality for disease detection and soil-stress recognition is the macro-averaged F_1-score, $F_1 = 2PR/(P + R)$, where

P and R are precision and recall. Soil-nutrient and moisture forecasting error is the Root Mean Square Error, $\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}$. Generative fidelity is the Fréchet Inception Distance, $\text{FID} = \|\mu_r - \mu_g\|_2^2 + \text{Tr}\big(\Sigma_r + \Sigma_g - 2(\Sigma_r\Sigma_g)^{1/2}\big)$, computed between real (r) and generated (g) feature statistics, with lower values indicating greater realism. Communication cost is the number of aggregation rounds required to reach the target global accuracy, and sustainability is quantified as the total water volume conserved (in liters, L) and the percentage reduction relative to a traditional threshold-based irrigation controller.

7 Anticipated Outcomes and Hypotheses

Under the evaluation protocol of Section 6, GenFedEdgeAgri is hypothesized to surpass conventional centralized and standard-FL baselines in data-limited contexts by employing localized generative augmentation. The following outcomes are stated as *targets to be tested*, not as validated results.

7.1 Testable Hypotheses

The study is designed to test four hypotheses. **H1 (accuracy and fidelity):** adding latent-diffusion augmentation at the edge improves the macro-F_1 of crop-disease detection and soil-stress classification by at least 14.2% over the standard-FL control, while the synthetic samples attain a Fréchet Inception Distance below 35, comparable to cloud-based generation. **H2 (soil-moisture forecasting):** pre-hardening yields an approximately 19% *relative reduction in RMSE* for soil-moisture prediction relative to the same baseline. **H3 (operational efficiency):** with locally pre-hardened models, the global model reaches the 90% target accuracy in up to 43% fewer communication rounds. **H4 (sustainability):** the resulting smart-irrigation policy reduces total water use by about 30% while maintaining crop health under simulated heatwaves. The corresponding target values are collected in Table 2, and each will be reported against its baseline with statistical significance once the experiments are run.

7.2 Research Outputs

The project will create several technical assets. Chief among them is the GenFedEdgeAgri prototype, a software stack for NVIDIA Jetson and ESP32 that includes a Flower (`flwr`) federated loop. It will also yield optimized edge AI models, comprising 4-bit and 8-bit quantized agricultural diffusion models built for ARM-based IoT gateways, together with a synthetic agricultural dataset—a collection of synthetic soil logs and crop-stress images representing rare weather patterns.

Table 2. Target (hypothesized) performance of GenFedEdgeAgri relative to the standard-FL baseline, to be tested under the protocol of Section 6.

Metric	Target value
Crop-disease detection accuracy gain (macro-F_1)	$\geq 14.2\%$
Soil-moisture forecasting error (RMSE) reduction	$\approx 19\%$
Synthetic-sample fidelity (FID)	< 35
Reduction in communication rounds	up to 43%
Water-use reduction	$\approx 30\%$

7.3 Wider Effects

GenFedEdgeAgri is intended to enhance climate resilience by giving smallholder farmers proactive soil intelligence that does not depend on constant cloud connectivity. The privacy-by-design architecture protects data sovereignty, building trust in multi-stakeholder AI research. Moreover, the targeted 30% reduction in water use would directly support UN Sustainable Development Goals 6 and 12. The modular architecture also allows scaling to adjacent domains such as smart microgrids and maritime IoT.

8 Discussion: The Edge–Intelligence Trade-off

The GenFedEdgeAgri system must balance computationally intensive high-quality GDMs against the power constraints of Edge AIoT devices.

8.1 Computational Cost versus Generative Fidelity

Although GDMs offer higher precision than GANs, their denoising iterations are resource-intensive. In the planned configuration, more than 50 denoising steps are required to reach an FID below 35, which is expected to increase the load on the NVIDIA Jetson Orin Nano GPU by roughly 65%. This anticipated "computational tax" would be offset by the projected 14.2% gain in predictive accuracy for rare climate stressors (hypothesis H1). The memory footprint and structure of the generated soil profiles must be kept within an 8 GB unified memory budget through NF4 quantization and weight pruning.

8.2 Energy Depletion versus Federated Convergence

The system must balance geographically distributed training against power-hungry weight updates. A key anticipated advantage of the GenFedEdgeAgri framework is that generative "pre-hardening" is projected to reduce communication rounds by up to 43% (hypothesis H3). Because the radio transceiver (LoRaWAN/NB-IoT) is usually the most power-hungry component of a remote node, lowering the exchange frequency substantially extends the battery life of solar-harvesting sensors. To avoid thermal throttling when LDM demand peaks, tasks should be scheduled asynchronously during hours of maximum solar charging.

8.3 Privacy and Resource Resilience

Data sovereignty is fully protected in exchange for higher local energy use. Localized generation eliminates the security risks and bandwidth costs of transmitting high-resolution imagery. Ultimately, the targeted 30% reduction in water use (hypothesis H4) would be an important environmental offset: the energy "invested" in edge computing is expected to yield a large net saving of physical resources, making the smart-irrigation cycle more sustainable.

Data Availability Statement

The source code and datasets generated in this study are not publicly available. The public benchmark datasets used-PlantVillage and the UCI soil dataset-are available from their original repositories.

Funding

This work was supported without any funding.

Conflicts of Interest

The authors declare no conflicts of interest.

AI Use Statement

The authors declare that no generative AI was used in the preparation of this manuscript.

Ethical Approval and Consent to Participate

Not applicable.

References

[1] Rai, N., Schumann, A. W., & Boyd, N. (2025, June). PhytoSynth: Leveraging multi-modal generative models for crop disease data generation with novel benchmarking and prompt engineering approach. In *2025 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)* (pp. 5371-5380). IEEE. [CrossRef]

[2] Adam, M., & Baroudi, U. (2024). Federated learning for IoT: Applications, trends, taxonomy, challenges, current solutions, and future directions. *IEEE Open Journal of the Communications Society, 5*, 7842–7877. [CrossRef]

[3] Mori, N., Naito, H., & Hosoi, F. (2024). Application of a latent diffusion model to plant disease detection by generating unseen class images. *AgriEngineering, 6*(4), 4901-4910. [CrossRef]

[4] Li, P., Zhang, H., Wu, Y., Qian, L., Yu, R., Niyato, D., & Shen, X. (2024). Filling the missing: Exploring generative AI for enhanced federated learning over heterogeneous mobile edge devices. *IEEE Transactions on Mobile Computing, 23*(10), 10001–10015. [CrossRef]

[5] Yu, P., Teng, F., Zhu, W., Shen, C., Chen, Z., & Song, J. (2025). Cloud–edge–device collaborative computing in smart agriculture: Architectures, applications, and future perspectives. *Frontiers in Plant Science, 16*, 1668545. [CrossRef]

[6] Beutel, D. J., Topal, T., Mathur, A., Qiu, X., Fernandez-Marques, J., Gao, Y., ... & Lane, N. D. (2020). Flower: A friendly federated learning research framework. *arXiv preprint arXiv:2007.14390*. [CrossRef]

[7] Jeong, E., Oh, S., Kim, H., Park, J., Bennis, M., & Kim, S. L. (2018). Communication-efficient on-device machine learning: Federated distillation and augmentation under non-iid private data. *arXiv preprint arXiv:1811.11479*. [CrossRef]

K. Radha Achary, Assistant Professor, M.Tech in Computer Science from Roland Institute of Technology, Berhampur, Odisha. (Email: k.achary.cse.2024@nist.edu)

Ajit Kumar Samal, Assistant Professor received the M.Tech. Roland Institute of Technology, Berhampur, Odisha. (Email: ajit.samal@nist.edu)