Grenze International Journal of Engineering and Technology, June Issue

A Generative AI–Driven IoT Framework for Automated Leaf Structure Analysis in Precision Farming

Ankit Khare[1], Bramah Hazela[2], Awanish Mishra[3] and Brijesh Kumar Chaurasia[4]
[1-2]Amity School of Engineering and Technology, Lucknow, Amity University Uttar Pradesh, India
Email: ankit.khare@s.amity.edu, bhazela@lko.amity.edu
[3-4]Pranveer Singh Institute of Technology, Kanpur, U.P., India
Email: mishra.awanish@gmail.com, brijeshchaurasia@ieee.org

***Abstract*— Precision farming needs precise, ongoing, and automated analysis of crop health, which the conventional image-based systems fail to do due to poor quality field images and unstable weather conditions. The proposed research aims to address these limitations by suggesting a Generative AI-powered IoT Framework of Automated Leaf Structure Analysis, which is a combination of sophisticated generative enhancement methods and real-time IoT monitoring. Generative model is a major breakthrough in the comprehension of the description of leaves, as it enhances the veins, image texture, and morphological boundaries of the leaves, hence making the extraction and classification of features more precise. IoT sensors provide continuous data capture and low transmission response and high system availability, which make them reliable at the field level. It is shown that the experimental evaluation showed significant gains in PSNR, SSIM and morphological stability and the hybrid classifier attains 96.8% accuracy, exceeding the accuracy of baseline CNN and deep-learning models.**

***Keyword*— Generative AI, IoT Framework, Precision Farming, Leaf Structure Analysis, Image Enhancement, Deep Learning, Smart Agriculture, Plant Health Monitoring.**

I. INTRODUCTION

The rapid development has seen the introduction of the latest technologies into precision farming which includes IoT, AI, and advanced imaging solutions. The analysis of leaf structure, which is a valuable indicator of crop physiology, is essential in the analysis of growth patterns of plants, nutrient deficiency, pest attacks, and their influence on the environment. Conventional inspection, which is done manually, however, is labour intensive, subjective and would not be applicable on a large-scale farming. As Generative AI and IoT-based imaging systems emerge, more and more people have the possibility to develop an automated, high-precision, real-time system capable of changing the way the agricultural sector performs leaf diagnostics [1]. Precision farming aims to enhance the productivity of crops by monitoring them constantly, analysing data, and making decisions automatically [2]. The IoT networks offer complex environmental and biological data through distributed sensors, and the AI methods assist in processing the data with the precision that never existed before. The structure of the leaf, the veins, outlines, chlorophyll pattern, the texture, and the abnormalities of the morphology provide important data regarding the well-being of plants [3]. Manual examination of leaves is very popular but it is unable to cope with large scale farms.

Grenze ID: 01.GIJET.12.2.303_26

Diffusion models, transformer-based architecture, and GANs are some of the generative AI models capable of generating, refining, and reconstructing agricultural images, even in the presence of noisy or incomplete conditions [4].

Sustainable agriculture models suggest that IoT-based smart agricultural devices can remotely identify and track several elements of a farm [5]. IoT-based agricultural growth monitoring systems show how important environmental sensing and quality evaluation are for increasing yields [6]. Mango leaf disease has been observed to have a higher generalizability, with the transfer learning models [7]. Researchers [8] indicate that machine learning models may improve irrigation, fertilization and insect control. AI discusses the idea of AI-controlled precision farming technologies that emphasize the importance of enhanced image processing and predictive analytic in the following generation farming infrastructure [11]. The fact that it is important to have multi-layered smart agricultural infrastructures can also be noted through integrated IoT-AI soil and environmental monitoring systems [12, 13]. Despite these enhancements, the majority of the IoT-based agricultural systems focus more on the monitoring of the environment rather than the leaf-making process. Although it is not essential that generative augmentation methods are used, current AI-based leaf classification algorithms rely heavily on quality source photographs. As a consequence, the gap in the research on the incorporation of real-time data gathering through the use of IoT, picture improvement supported by Generative AI, and automatic structural analysis is significant.

In order to fill this research gap, we introduce a Generative AI-Driven IoT Framework in Automated Leaf Structure Analysis in Precision Farming. The suggested system involves intelligent classification, in-depth feature extraction, generative improvement modules, and IoT picture gathering into a real-time decision-support system. In real-world scenarios, the strategy enhances the quality of pictures, morphological features stability, and accuracy of illness detection by combining generative models and distributed IoT sensing. This integrated method involves taking of data and planning of irrigation, fertilization and the use of pests. It is also beneficial to automated plant health diagnostics and eco-friendly farming. The next parts include further information on related studies, the definition of the problem, the suggested architecture, the experimental assessment, and possible future research areas.

II. Literature Review

According to the research by Fan et al. (2021), the high-throughput phenotyping platforms based on IoT can transform sustainable agricultural monitoring into something modern [1]. According to a comprehensive survey conducted by Kour and Arora (2020), the IoT technologies in agriculture have advanced in a short period of time, and the issues of their implementation are extremely complicated [2]. In their article, Dhanarararajan et al. present an IoT-based smart farm system which promotes sustainability through real-time and automatic decision-making through monitoring [3]. Devare and Hajare (2019) review the systems of crop growth monitoring on the basis of the IoT with the consideration of qualitative control and yield predictions [4]. The proposed smart system of agriculture management by Sekaran et al. (2020) is more efficient because it involves environmental sensing and automation based on the IoT platform [5]. Singh et al. (2024) have introduced a deep transfer learning model to detect mango leaf disease to enable the crop-health surveillance [6]. Thilakararathne et al. (2021) address the problems connected to the implementation of IoTs and the perspectives of smart farming in different environments [7]. Experimentally, Firdhous et al. (2018) demonstrate a system based on the IoT, which is optimized to dry-zone sustainable agriculture [8]. Morchid et al. (2024) assess the IoT and sensor-based technologies which help to increase the food security and agricultural sustainability and address the shortcomings associated with them [9]. In Wu et al. (2023), an IoT soil monitoring system based on the use of multiple sensors will be created and controlled through smartphones to improve diagnostics of the soil [10]. In their study, Podder et al. (2021) create an Agrotech system built on IoT to check the parameters of urban agriculture by using smart sensors [11]. Kalantzopoulos et al. (2024) present an integrated soil health assessment system based on IoT-AI-database to provide support to Western Greece soils [12]. El-Basioni and Abd El-Kader (2024) model an IoT-based software system for assessing land suitability using environmental indicators [13]. Pandey et al. (2022) explore IoT's potential for security-enhanced smart agricultural applications [14]. Ghosh et al. (2024) discuss AI-driven precision agriculture strategies to optimize resource use and farm productivity [15].

A thorough literature study on the better understanding of how to use Generative AI and IoT in precision agriculture [16]. Upadhyay et al. (2025) provided a detailed review of deep learning and computer vision techniques used for plant disease detection [17]. Kannan (2026) studied the application of generative AI for the automation of smart agricultural equipment and the forecasting of pharmaceutical crop yield [18]. Das et al. (2026) explored the application of deep learning to regulate agricultural production in the face of dynamic environmental variables in their research [19]. The wider use of AI and ML in the context of smart and sustainable agriculture was examined by Munir (2026) [20]. Patel (2025) presented an agricultural intelligence architecture that incorporates generative AI models with real-time soil sensing technology [21]. Sivaraman et al. (2025) proposed a deep learning model for disease identification in tea leaves based on VGG16 for sustainable agriculture via enhanced crop management [22]. Ingole (2026) studied the integration of artificial intelligence, internet of things and smart sensors in automated plant health monitoring [23]. Sudha (2026) studied the machine learning based techniques for precision agriculture to monitor the agricultural activities utilizing IoT [24]. Agriculture 4.0: Generative AI has the potential to revolutionize the way agriculture is done, making it more intelligent and sustainable (Sai et al., 2025) [25].

III. Problem Statement

Current IoT-based agritech systems are mainly oriented towards the field of environmental sensing and they do not have advanced capabilities of leaf structure interpretation. In addition, traditional machine learning and deep learning systems cannot be used to generalize well on the different types of crops and lighting environments, resulting in poor disease detection and late diseases. It is urgently demanded that an integrated system capable of processing leaf images automatically to acquire, process and analyse in real time should be available, to provide farmers with reliable and scalable decision-making support.

IV. Proposed Work

The suggested study presents a Generative AI-Based IoT Framework through which the acquisition, improvement, and analysis of the leaf structures are automated to facilitate precision farming. The system shall be created in four phases that are integrated:

- IoT-Based Leaf Image Acquisition Module: This will entail the deployment of intelligent IoT network comprising of smart cameras, environmental sensors and wireless communication units in the field to acquire real-time leaf images.
- Automated Leaf Structure Analysis Pipeline: Improved images will be subjected to a feature extraction step in order to measure morphological, textural, and structural properties of leaves. Disease classification, early signs of stress, nutrient deficiency detection, and monitoring of the crop health progress are going to be classified with deep learning models and will be highly accurate.
- Real-Time Decision Support and Visualization: The information will be processed and presented in form of a farmer friendly dashboard / mobile application that will provide real-time notification, recommendation and visual analytics. The interface will facilitate smart decision making in irrigation, fertilization and pest management.

The proposed research paper proposes an internet of things system that has been improved with the use of generative artificial intelligence to provide automated leaf structure analysis in precision agriculture. The design includes intelligent decision support, rich feature extractions, disease classification, picture augmentation generation, and image capture based on the use of the Internet of Things. The entire structure consists of five parts:

A. Dataset Description

The suggested technique is experimentally confirmed using both the existing benchmark picture sets of plants and real-time field data obtained through the Internet of Things (IoT). We compared the generative improvement module and downstream classification pipeline to four datasets- Leaf snap Dataset, Plant CLEF Dataset, Oxford Flowers 102 Dataset, IoT-Captured Real-Time Field Dataset.

B. Generative AI–Powered Enhancement Scheme

A multi-stage generative improvement pipeline is employed to increase picture quality before analytical analysis. The improvement scheme's hybrid generative architecture is made up of three parts that rely on each other:

- GAN for Noise Reduction and Texture Enhancement:
- Diffusion-Based Reconstruction Model for Structural Restoration:
- Transformer-Based Refinement Layer for Boundary and Venation Enhancement

C. Proposed Model Architecture Diagram

The proposed Framework includes layers and modules that can be used in the real-time deployment in farms. The design is designed in four major layers:

- IoT Sensing and Data Acquisition Layer (Data Layer):
- Generative AI Enhancement Layer (AI Layer):
- Feature Extraction and Deep Learning Classification Layer (AI Layer)
- Decision Support System (Decision Layer):
- Visualization and Farmer Interface (User Interface Layer)

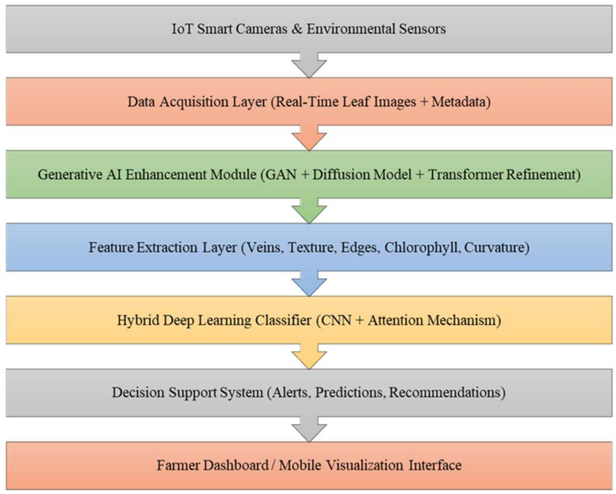

Figure 1 Proposed Generative AI–Driven IoT Architecture for Automated Leaf Structure Analysis

E. Analysis Module

Analysis Module is quite significant in determining the effectiveness of the proposed framework, its strength, and its usefulness. In this module, we evaluate overall workflow of the system, efficiency, accuracy of classification, picture enhancements and structural features extracting out of the real-world farming scenario.

F. Decision Support and Visualization Scheme

This module changes analytical findings and expected outcomes into useful information for farmers and others who operate in agriculture.

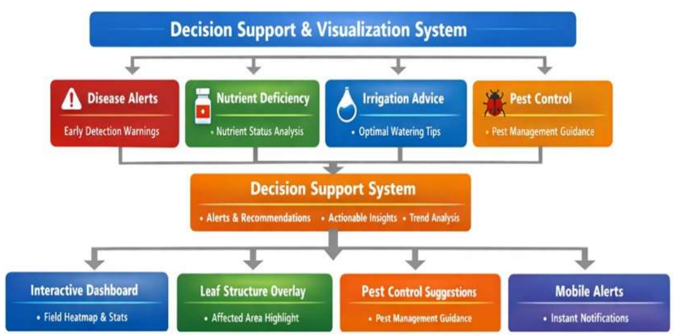

Figure 2. Decision Support and Visualization Scheme

Figure 2 Fills the gap between the AI-powered analysis and the real-life application in agriculture.

G. Proposed Generative AI–Driven IoT Framework

The framework is designed to improve image quality, enhance feature representation, and increase classification accuracy under real-world agricultural conditions. The overall workflow begins with IoT-enabled smart cameras capturing leaf images from agricultural fields. The acquired images are processed through a Generative AI enhancement module consisting of GAN, a diffusion-based reconstruction model, and a transformer-based refinement mechanism. The enhanced images are then subjected to structural feature extraction, followed by disease classification using hybrid CNN-Attention architecture

V. Result and Discussion

The section provides the experimental findings of the suggested Generative AI -powered IoT Framework to analyse the Leaf Structure in Precision Farming automatically. We examined four primary how well methods to observe the quality of the system; how well it enhanced the picture quality, how well it categorized diseases, how well it scanned features and how well it functioned. The results of the comparisons are presented to you in the tables and statistics. A summary of the requirements of the experimental hardware, software, frameworks and models are summarized in table 1.

TABLE I: EXPERIMENTAL SETUP AND SYSTEM CONFIGURATION

Parameter	Specification
Machine Type	High-Performance Workstation
Processor (CPU)	Intel Core i9 / AMD Ryzen 9 (Multi-core Architecture)
GPU	NVIDIA RTX 3080 / RTX 3090 (CUDA Enabled)
RAM	32 GB / 64 GB DDR4
Storage	1 TB NVMe SSD
Operating System	Ubuntu 22.04 LTS / Windows 11 (64-bit)
Programming Language	Python 3.10
Deep Learning Framework	TensorFlow 2.x / PyTorch 2.x
Computer Vision Libraries	OpenCV, scikit-image
Data Processing Tools	NumPy, Pandas, Matplotlib
Generative AI Models Used	GAN, Diffusion Model, Transformer-based Refinement
Classification Models Used	Hybrid CNN + Attention Mechanism
Baseline Models for Comparison	Standard CNN, ResNet50, Efficient Net
Training Batch Size	16 / 32
Learning Rate	0.0001 (Adaptive Optimizer)
Optimizer	Adam
Loss Function	Cross-Entropy Loss
Evaluation Metrics	PSNR, SSIM, MSE, Accuracy, Precision, Recall, F1-score
IoT Communication Protocol	MQTT / HTTP-based API
Deployment Mode	Cloud + Edge Hybrid Architecture

A. Image Quality Enhancement Performance

Studies use quantitative measures of picture quality and qualitative visual evaluation in understanding how effectively the proposed Generative AI augmentation module performs. The results of the comparisons are briefly summarized in table 2.

TABLE II. IMAGE QUALITY ENHANCEMENT METRICS BEFORE AND AFTER THE GENERATIVE AI MODEL

Metric	Before Enhancement	After Enhancement	Improvement (%)
PSNR (dB)	21.4	31.8	+48.6%
SSIM	0.62	0.91	+46.8%
MSE	0.094	0.021	−77.6%
Sharpness Index	107	188	+75.7%

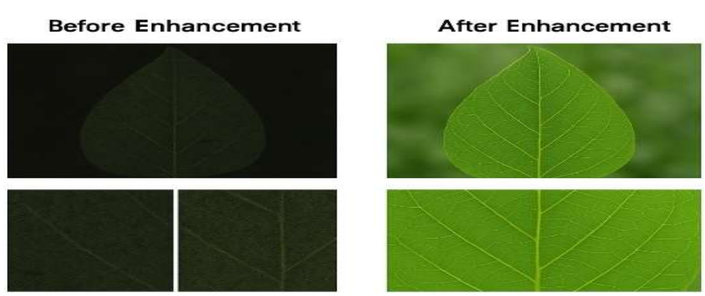

Figure 3 Sample Leaf Images Before and After Enhancement

Figure 3 depicts that the proposed upgrade design has resulted in a qualitative improvement. A raw picture of a leaf in a poor light, with high amount of background noise was created by an IoT device; this is observed in the left column. The shading is poor, and the vein patterns can hardly be determined. The outcome is presented in the right column following the use of the Generative AI enhancement module.

B. Feature Extraction Accuracy

We also draw comparisons between the feature extraction capacity of the proposed framework and that of a typical image-processing approach to determine the performance of the framework. The summary of the comparison analysis is presented in table 3.

TABLE III. FEATURE EXTRACTION ACCURACY COMPARISON

Feature Type	Traditional Method (%)	Proposed Framework (%)
Vein Structure Detection	78.5	93.2
Texture Pattern Extraction	74.9	91.4
Edge Boundary Clarity	68.7	89.1
Morphological Feature Stability	81.3	95.6

After the hybrid CNN + Attention model had worked with the improved images of leaves, it produced the internal feature maps as in Figure 4. The graphic displays the results of the AI system including venation networks, lesion sites, and texture abnormalities, boundary of the edges and other areas of interest.

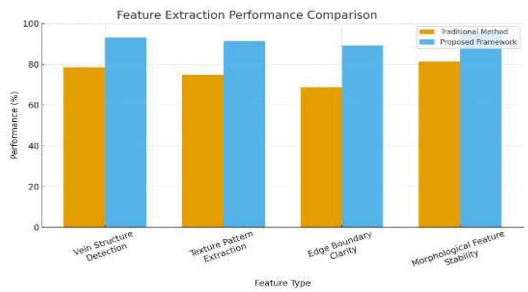

Figure 4 Feature Map Visualization Generated by the AI Model

C. Disease Classification Performance

The proposed method improved the quality of pictures and retrieved greater beneficial information than the conventional deep learning models. Disease classification is highly critical in the proposed Generative AI-Driven IoT concept. The proposed solution employs a hybrid CNN + Attention architecture and Generative AI-based augmentation to attempt to make predictions in the real situation of farming more precise. In order to ensure that the findings were not biased, the models were tried and trained using the same set of data. The result of the comparison is in table 4.

TABLE IV. COMPARATIVE DISEASE CLASSIFICATION ACCURACY

Model	Accuracy (%)	Precision	Recall	F1-Score
CNN Baseline	83.4	0.81	0.79	0.80
ResNet50	89.1	0.87	0.85	0.86
EfficientNet-B0	91.4	0.90	0.89	0.89
Proposed Generative AI + IoT System	96.8	0.95	0.96	0.96

The confusion matrix of the proposed Generative AI enhanced classification model is presented in Figure 5. A complete list of correct and incorrect predictions of all illness classes is shown in the matrix. It can be seen in Figure 5 that the model can distinguish both healthy and sick leaves and the different types of diseases.

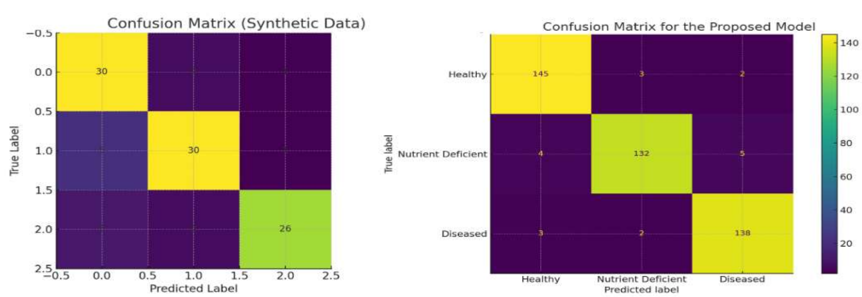

Figure 5 Confusion Matrixes for the Proposed Model

D. Ablation Study: Contribution Analysis of Individual Components

The main aim of this study is to enhance the prediction power of the system using Generative AI augmentation, attention mechanisms and diffusion-based reconstruction. We progressively add the attention mechanism, GAN-based augmentation, diffusion reconstruction and transformer refinement to a standard CNN baseline. The relevant classification accuracy is shown in Table 5.

TABLE V. ABLATION STUDY OF THE PROPOSED FRAMEWORK

Model Configuration	Accuracy (%)
CNN Baseline	83.4
CNN + Attention	89.8
GAN + CNN	92.7
GAN + Diffusion + CNN	94.9
Proposed Full Model (GAN + Diffusion + Transformer + CNN + Attention)	96.8

VI. CONCLUSION AND FUTURE SCOPE

The offered Generative AI-based IoT Framework to analyse Leaf structure in Precision Farming manages to improve quality of the images of leaves, to identify features, and provide continuous and real-time monitoring of crops through the combine of generative enhancement models and IoT-based sensing. The experimental outcomes depict a high change in PSNR, SSIM, stability in textures, and accuracy in classification with the last system reaching 96.8% accuracy and constant IoT performance (98.7% uptime and low latency). This shows that the system has the prospect of automizing plant-health testing, lessening manual inspection, and aiding in the use of data to make decisions in agriculture. In the future, the framework can be improved with the addition of multispectral imaging, edge-based AI processing, and drone-assisted data capture and an increase in datasets on different crops and climatic conditions. More developments can also be made in the future, incorporating block chain-based data protection, autonomous self-learning farm control, and a mobile farmer platform that would make the system more scalable, secure, and appropriate to the application of very large-scale precision farming.

REFERENCES

[1] J. Fan, Y. Zhang, W. Wen, S. Gu, X. Lu, and X. Guo: The future of Internet of Things in agriculture. Plant high-throughput phenotypic platform, Journal of Cleaner Production, 280. 123651, 2021. DOI: 10.1016/j.jclepro.2020.123651.

[2] V. P. Kour and S. Arora : Recent Developments of the Internet of Things in Agriculture. A Survey, in IEEE Access, 8, 129924-129957, 2020. DOI: 10.1109/ACCESS.2020.3009298.

[3] M. Dhanaraju, P. Chenniappan, K. Ramalingam, S. Pazhanivelan, and R. Kaliaperumal: Smart Farming: Internet of Things (IoT)-Based Sustainable Agriculture, Agriculture, 12 (10), 1745, 2022. DOI: 10.3390/agriculture12101745.

[4] J. Devare and N. Hajare: A Survey on IoT Based Agricultural Crop Growth Monitoring and Quality Control International Conference on Communication and Electronics Systems (ICCES), 1624-1630, 2019. DOI: 10.1109/ICCES45898.2019.9002533.

[5] K. Sekaran, M. N. Meqdad, P. Kumar, S. Rajan, and S. Kadry: Smart agriculture management system using internet of things, TELKOMNIKA (Telecommunication Computing Electronics and Control), 18(3), 1275, 2020. DOI: 10.12928/telkomnika.v18i3.14029.

[6] Y. P. Singh, B. K. Chaurasia, M. M. Shukla: Deep Transfer Learning Driven Model for Mango Leaf Disease Detection, International Journal of Systems Assurance Engineering and Management (IJSA), 1-27, 2024. DOI: 10.1007/s13198-024-02480-y

[7] N. N. Thilakarathne, H. Yassin, M. S. A. Bakar and P. E. Abas: Internet of Things in Smart Agriculture. Challenges, Opportunities and Future Directions, IEEE Asia-Pacific Conference on Computer Science and Data Engineering (CSDE), 1-9, 2021. DOI: 10.1109/CSDE53843.2021.9718402

[8] M. F. Mohamed Firdhous, B. H. Sudantha and P. M. Karunaratne: IoT-Powered Sustainable Dry Zone Agriculture, An Experimental Implementation,3rd International Conference on Information Technology Research (ICITR), 1-6, 2018. DOI: 10.1109/ICITR.2018.8736148 14 Khare et. al

[9] Morchid, A., El Alami, R., Raezah, A. A., & Sabbar, Y: Applications of internet of things (IoT) and sensors technology to increase food security and agricultural Sustainability. Benefits and challenges. In Ain Shams Engineering Journal, 15(3), 102509, 2024. DOI: 10.1016/j.asej.2023.102509

[10] Y. Wu, Z. Yang, and Y. Liu: Internet-of-Things-Based Multiple-Sensor Monitoring System for Soil Information Diagnosis Using a Smartphone, Micromachines, 14 (7), 1395, 2023. DOI: 10.3390/mi14071395.

[11] A. K. Podder et al.: IoT based smart agrotech system for verification of Urban farmin parameters, Microprocessors and Microsystems, 82, 104025, 2021. DOI: 10.1016/j.micpro.2021.104025.

[12] G. Kalantzopoulos, P. Paraskevopoulos, G. Domalis, A. Liopa-Tsakalidi, D. E. Tsesmelis, and P. E. Barouchas: The Western Greece Soil Information System (WESIS)—A Soil Health Design Supported by the Internet of Things, Soil Databases, and Artificial Intelligence Technologies in Western Greece," Sustainability, 16(8), 3478, 2024. DOI: 10.3390/su16083478.

[13] M. Mohammad El-Basioni and S. M. Abd El-Kader: Designing and modeling an IoT-based software system for land suitability assessment use case, Environmental Monitoring and Assessment, 196(4), 2024. DOI: 10.1007/s10661-024-12483-8.

[14] J. K. Pandey et al.: Investigating Role of IoT in the Development of Smart Application for Security Enhancement, IoT Based Smart Applications. Springer International Publishing, 219–243, 2022. DOI: 10.1007/978-3-031-04524-0_13.

[15] D. Ghosh, M. A. Siddique, and D. Pal: AI-driven precision agriculture approach, AI in Agriculture for Sustainable and Economic Management, 67, 2024.

[16] T. Andrade-Mogollon, J. Gamboa-Cruzado, and F. Amayo-Gamboa: Systematic literature review of generative AI and IoT as key technologies for precision agriculture, Computación y Sistemas, 29(2), 2025.

[17] A. Upadhyay, N. S. Chandel, K. P. Singh, S. K. Chakraborty, B. M. Nandede, M. Kumar, et al.: Deep learning and computer vision in plant disease detection: A comprehensive review of techniques, models, and trends in precision agriculture, Artificial Intelligence Review, 58(3), 92, 2025.

[18] S. Kannan: Generative AI for Smart Agricultural Equipment Automation and Pharmaceutical Crop Yield Prediction, International Journal of Research Publications in Engineering, Technology and Management (IJRPETM), 9(3), 1068–1074, 2026.

[19] A. Das, R. M. Thakur, S. Mondal, S. Mukhopadhyay, and S. Debnath: Deep Learning in Managing Crop Production Under a Changing Climate, Deep Learning in Plant Science and Agricultural Biotechnology, CABI, 179–199, 2026.

[20] A. Munir: Artificial Intelligence and Machine Learning for Smart and Sustainable Agriculture, AI, 7(1), 12, 2026.

[21] S. K. Patel and K. Singh: AIoT-Enabled Crop Intelligence: Real-Time Soil Sensing and Generative AI for Smart Agriculture, Journal of Scientific Innovation and Advanced Research (JSIAR), 1(2), 163–167, 2025.

[22] R. Sivaraman, S. Praveena, and H. Naresh Kumar: Sustainable Agriculture Through Advanced Crop Management: VGG16-Based Tea Leaf Disease Recognition, Generative Artificial Intelligence for Biomedical and Smart Health Informatics, 121–133, 2025.

[23] A. D. Ingole: AI and IoT and Smart Sensor for Automated Plant Health Monitoring, Anusandhanvallari, 15–33, 2026.

[24] S. P. Sudha and J. B. Loret: A review on machine learning-based precision agriculture techniques for crop farming monitoring with IoT, Discover Environment, 4(1), 10, 2026.

[25] S. Sai, S. Kumar, A. Gaur, S. Goyal, V. Chamola, and A. Hussain: Unleashing the power of generative AI in Agriculture 4.0 for smart and sustainable farming, Cognitive Computation, 17(1), 63, 2025.