

# Smart Green House Automated System

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**Abstract** - Agriculture is undergoing a major technological transformation with the integration of intelligent automation systems aimed at improving productivity, sustainability, and resource efficiency. Traditional farming methods often rely on manual monitoring and fixed operational practices, which can lead to inefficient resource utilization, reduced crop yields, and increased vulnerability to environmental changes. To address these challenges, advanced technologies such as climate-controlled greenhouses, smart irrigation systems, and automated pest detection mechanisms are being increasingly adopted in modern agriculture.

**Keywords:** Smart Agriculture, Climate-Controlled Greenhouse, Smart Irrigation System, Internet of Things (IoT), Precision Agriculture, Automated Farming, Soil Moisture Sensors, Environmental Monitoring, Machine Learning in Agriculture, Water Resource Management, Sustainable Agriculture, Greenhouse Automation.

## Introduction

Climate-controlled greenhouses represent a significant advancement in protected cultivation by enabling continuous regulation of environmental parameters such as temperature, humidity, CO<sub>2</sub> concentration, and lighting. Unlike conventional greenhouses that depend on manual ventilation and natural shading, these intelligent systems provide optimal growing conditions while protecting crops from extreme weather variations, unseasonal rainfall, and excessive solar radiation.

Similarly, smart irrigation systems enhance water management by using real-time data from soil moisture sensors, environmental monitoring devices, and weather forecasting services. Traditional irrigation methods often result in over-irrigation or under-irrigation due to fixed schedules that fail to consider changing crop and environmental conditions. Through IoT integration, automation, and machine learning algorithms, smart irrigation systems deliver water precisely when and where it is required, reducing wastage and improving crop productivity.

In addition to environmental and water management, automated pest detection and control systems help mitigate one of the major threats to agriculture—pest infestations. Conventional pest control methods involve periodic inspections and excessive pesticide application, leading to delayed responses, higher costs, and environmental harm. Modern automated systems utilize image processing, sensors, drones, robotics, and AI-based algorithms to continuously monitor crops and identify pests at an early stage. This enables targeted pesticide application, minimizes chemical usage, and promotes sustainable farming practices.

The integration of these intelligent technologies demonstrates the growing role of Artificial Intelligence (AI), Machine Learning (ML), Internet of Things (IoT), and automation in agriculture. Together, they contribute to the development of smart farming systems capable of increasing efficiency, conserving natural resources, reducing human intervention, and ensuring sustainable food production in the face of climate change and rising global food demands.

## Literature survey

A.Morchid and H. Tairi's Study says that a systematic review of smart irrigation systems that integrate Internet of Things (IoT) and machine learning (ML) technologies to optimize agricultural water use. Using PRISMA methodology, the authors analyze over 100 relevant studies to highlight how real-time data from IoT sensors—such as soil moisture and environmental conditions—combined with ML decision models can enhance irrigation efficiency, reduce water waste, and improve crop productivity. The review also identifies key benefits of these integrated systems, including improved sustainability and profitability, while discussing challenges related to technical complexity, adoption barriers, and future integration with renewable energy and advanced predictive frameworks.[1]

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

S.Gupta and et al. study says that the research by S. Gupta, R. Tripathi, A. K. Singh, and N. Gupta investigates the application of IoT technologies in smart agriculture to develop an automated irrigation system that improves water resource management and crop yield. The paper emphasizes the integration of wireless sensor networks (WSNs), soil moisture and environmental sensors, and cloud-based IoT platforms to monitor field conditions in real time and automate irrigation decisions. The study also explores machine learning approaches for predicting irrigation needs based on historical and sensor data, demonstrating that IoT-enabled irrigation systems can significantly reduce water wastage and improve precision farming outcomes. Available data and field implementations show that such systems enhance operational efficiency while minimizing human intervention.[2]

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

S.Puajpanda and D. Mahapatra’s Study say the use of advanced machine learning models to improve prediction accuracy within IoT-based smart irrigation systems. By comparing ensemble learning approaches (e.g., hybrid combinations of linear regression and random forest) with traditional machine learning algorithms such as SVM and decision trees, the research demonstrates that ensemble techniques provide superior predictive performance using soil moisture and environmental sensor data. The results highlight that integrating robust predictive models with IoT frameworks can enhance water usage forecasting and decision-making in precision agriculture, contributing to more efficient and sustainable irrigation management.[3]

$$MSE = \frac{1}{n} \sum (Y_i - \hat{Y}_i)^2 \quad (3)$$

J.Liu and et al.’s Study says that an intelligent irrigation scheduling method that integrates a high-fidelity crop growth model (DSSAT) with an improved deep reinforcement learning (DRL) agent to optimize water use efficiency and crop yield. By constructing a temporal state representation using a BiLSTM network with attention mechanisms, and enhancing the Soft Actor–Critic algorithm with agronomic priors through a dynamic reward function, the authors demonstrate significant improvements—achieving up to 39% higher water use efficiency compared to fixed-schedule irrigation strategies. This research highlights the potential of combining crop simulation models with advanced DRL techniques to support sustainable and adaptive irrigation decision-making in precision agriculture environments. [4]

$$G_t = \sum_{k=0}^{\infty} \gamma^k R_{t+k+1} \text{ where } \gamma \in [0, 1) \quad (4)$$

$$R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} \dots$$

E.Torres-Quezada and E.Geijo’s Study says that the integration of remote sensing data and in-situ soil moisture sensors to optimize irrigation scheduling and water use efficiency in agricultural systems. The research evaluates various machine learning regression models—such as random forest, support vector regression (SVR), and gradient boosting—to predict soil moisture content using combined satellite imagery and ground sensor inputs. Results indicate that machine learning methods can significantly enhance soil moisture estimation accuracy, enabling more precise irrigation decisions compared to traditional sensor-only approaches. This work highlights the value of fusing remote sensing with ground-based sensing and data-driven models to improve irrigation management and promote sustainable agriculture.[5]

$$NDWI = \frac{(NIR - SWIR)}{(NIR + SWIR)} \quad (5)$$

S. Chakrabarty et al.’s Study says that the application of artificial intelligence techniques in insect pest identification for agriculture. The study highlights the limitations of traditional manual pest identification methods and emphasizes the effectiveness of AI approaches such as machine learning, deep learning, and computer vision. In particular, convolutional neural networks (CNNs) are shown to provide high accuracy in classifying insect pests using image-based data. The authors also discuss challenges such as limited labelled datasets and practical deployment issues. Overall, the study concludes that AI-based pest identification systems significantly improve detection accuracy and support sustainable and precision agriculture.[6]

$$L = - \sum_{k=1}^K y_k \log(p_k) \quad (6)$$

S. Puajpanda et al.’s Study says that the literature reviewed in the article from Uttar Pradesh Journal of Zoology shows that traditional manual pest detection is inefficient and error-prone, leading to the adoption of AI-based methods such as CNNs and object detection models (e.g., YOLO and Faster R-CNN) for automated and real-time identification. Studies highlight the use of computer vision, multispectral imaging, drones, and IoT systems to improve early detection and enable precision pesticide application, while also identifying challenges like limited datasets, environmental variability,

high computational costs, and the need for more scalable and explainable models.[7]

$$s(x_i) = \frac{e^{x_i}}{\sum_{j=1}^n e^{x_j}} \tag{7}$$

Y. Wu et al.'s Study says that advances in artificial intelligence and deep learning techniques for agricultural pest detection and control. It highlights the effectiveness of deep learning models, particularly CNN-based image recognition systems, in improving detection accuracy and early warning capabilities. The review also discusses challenges such as dataset limitations and deployment on resource-constrained devices, emphasizing the need for scalable and efficient AI-based pest management solutions.[8]

$$(f * h)(x, y) = \sum_{i=-k}^k \sum_{j=-k}^k f(x-i, y-j) \times h(i, j) \tag{8}$$

D. Kapetas et al.'s Study says that an AI-driven system for insect detection, real-time monitoring, and population forecasting in greenhouse environments. The study employs a YOLOv10 deep learning model to detect black aphids from sticky paper trap images with high accuracy, and evaluates multiple machine learning and time-series prediction methods—including random forests and ARIMAX—for forecasting insect counts. The integration of detection and prediction into a mobile application demonstrates the potential for early intervention and sustainable pest management by providing actionable insights and scalable solutions for precision agriculture.[9]

$$MSE = \frac{1}{n} \sum (Y_i - \hat{Y}_i)^2 \tag{9}$$

P. Hu, W. Fang, and J. Li's Study says that an enhanced deep learning model for agricultural pest detection by improving the standard Faster R-CNN framework. The authors introduce modifications including DIOU-NMS optimization and an attention mechanism with SE modules to strengthen feature extraction and object localization. Through ablation studies and benchmark comparisons, the enhanced model demonstrated higher detection accuracy for various pest categories than traditional detection methods. The results highlight the potential of advanced deep learning architectures to support accurate and efficient pest recognition, which is essential for timely pest management in precision agriculture.[10]

$$f(x) = \frac{1}{m} \sum_{i=1}^m f_i(x). \tag{10}$$

The study by S. D. Bhagwat, A. I. Hulloli, and A. S. Kamble T says that a comprehensive look at how Cloud-IoT integration can revolutionize traditional farming. The authors convey that by using a NodeMCU-based architecture, farmers can achieve a "borderless" monitoring system where data is accessible regardless of physical distance. They emphasize that the primary benefit is the reduction of human labor through automated irrigation triggered by real-time sensor thresholds. However, they highlight a critical challenge: the system's total reliance on internet stability, noting that any network downtime can lead to a failure in the automated control cycle.[11]

$$S(t) = \begin{cases} 1 & \text{if } M(t) < T_{min} \\ 0 & \text{if } M(t) \geq T_{max} \end{cases} \tag{11}$$

Research conducted by M. Azaza, C. Tanougast, and E. Fabrizio investigates the application of "intelligent" control algorithms in agriculture. The authors convey that traditional "on-off" controllers are inefficient because they cause rapid fluctuations in the greenhouse environment. By implementing Fuzzy Logic, they demonstrate a more nuanced approach that mimics human reasoning to maintain a steady micro-climate. While they highlight the advantage of high precision in temperature regulation, they also discuss the disadvantage of technical complexity, noting that the system requires extensive expert tuning to be effective. [12]

$$u^* = \frac{\int \mu_C(z) \cdot z \, dz}{\int \mu_C(z) \, dz} \tag{12}$$

The study by S. Singh and C. Vishwa examines the transition from reactive to predictive greenhouse management. The authors convey that by applying Machine Learning algorithms, specifically Linear Regression, the system can "learn" from past environmental patterns to predict future moisture needs. They argue that this predictive capability is the key to maximizing crop yield while minimizing water waste. However, the research also identifies a significant adoption barrier: the "data dependency" challenge, where the system's accuracy is only as good as the volume of historical data provided.[13]

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n + \epsilon \tag{13}$$

The research by MD Jiabul Hoque, Md Razu Ahmed, and Saif Hannan explores the sustainability aspect of modern farming. The authors convey that for smart greenhouses to be truly viable in developing regions, they must be decoupled from the national power grid. Their work demonstrates that a solar-powered system can run autonomously for 24 hours using stored battery energy. While they emphasize the long-term cost-effectiveness and carbon-neutral benefits, they also address the disadvantage of high initial investment, which often makes the technology inaccessible to small-scale, low-income farmers.[14]

$$E_{total} = \int_0^T [P_{solar}(t) - P_{load}(t)] dt \geq 0 \quad (14)$$

The study by B. J. Kang, D. H. Park, and J. W. Park focuses on the infrastructure required for large-scale agricultural monitoring. The authors convey that Wireless Sensor Networks (WSNs) are the most effective way to manage vast greenhouse complexes without the limitations of physical wiring. They highlight how a distributed network of nodes allows for localized "micro-management" of different sections of a farm. Despite these advantages, they point out technical challenges related to "node death" (battery depletion) and signal interference caused by the greenhouse's own physical structure and humidity levels.[15]

$$L = \frac{C_{batt}}{I_{sleep} \cdot (1 - D) + I_{active} \cdot D} \quad (15)$$

### Conclusion

The integration of intelligent technologies into agriculture is transforming traditional farming into a more efficient, sustainable, and data-driven system. This review highlights the importance of smart irrigation systems, automated pest detection and control, and climate-controlled greenhouses in improving agricultural productivity while conserving natural resources. Technologies such as IoT, Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL), and automation are enabling farmers to make precise decisions, reduce human effort, and improve overall crop management.

Smart irrigation systems powered by IoT and machine learning provide an effective solution to the limitations of conventional irrigation methods. By using real-time data from soil moisture sensors, environmental monitoring systems, and weather forecasting services, these systems ensure precise

water delivery based on crop requirements. The reviewed studies confirm that automated irrigation systems reduce water wastage, improve crop yield, and support sustainable agricultural practices. Continued advancements in sensors, cloud computing, and predictive analytics will further enhance their efficiency and adoption.

Automated pest detection and control systems also play a vital role in modern agriculture. Traditional pest management methods often involve excessive pesticide usage and delayed pest identification, resulting in environmental and economic losses. AI-, ML-, and DL-based systems use image processing, drones, robotics, and sensors to monitor crops continuously and detect pests at an early stage. These technologies improve pest management efficiency, reduce chemical usage, and promote environmentally friendly farming practices.

Climate-controlled greenhouses represent another major advancement in precision agriculture. These systems combine IoT networks, machine learning, and automated actuators to regulate temperature, humidity, lighting, and CO<sub>2</sub> concentration, creating optimal growing conditions for crops. The integration of aeronautical engineering concepts such as aerodynamic ventilation systems and lightweight structural designs further improves greenhouse efficiency and performance.

Although challenges such as high installation costs and internet dependency remain, the combination of intelligent technologies and interdisciplinary engineering provides a strong foundation for the future of sustainable agriculture. Overall, smart farming systems offer a promising solution for increasing food production, conserving resources, and ensuring global food security in the face of climate change and growing population demands.

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**Citation of this Article:**

Jeevan Varadharaji, Janaki Kandasamy, Harish, & Adwaitha A. (2026). Smart Green House Automated System. *International Research Journal of Innovations in Engineering and Technology - IRJIET*, 10(5), 218-222. Article DOI <https://doi.org/10.47001/IRJIET/2026.105030>

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