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A DATA-DRIVEN APPROACH TO VERTICAL HARVESTING: ARTIFICIAL INTELLIGENCE AND INTERNET OF THINGS-BASED AUTOMATION IN AGRICULTURE

Hemlathadhevi **Annadhurai**[1], Lakshmikanth **Paleti**[2],
Ramesh Kumar **Chinnakunnu**[3], Surendran **Rajendran**[4*]

[1]Panimalar Engineering College. Department of Computer Science and Engineering. Poonamallee, Chennai, Tamil Nadu 600123, India.
[2]RVRJC College of Engineering. Department of Computer Science and Business Systems. Chowdavaram, Guntur, Andhra Pradesh 522019, India. lakshmikanthpaleti@gmail.com.
[3]Galgotias University. School of Computer Science and Engineering. Greater Noida, Uttar Pradhesh 203201, India.
[4]Saveetha School of Engineering. Saveetha Institute of Medical and Technical Sciences, Department of Computer Science and Engineering. Chennai, Tamil Nadu 602105, India.
* Author for correspondence: surendranr.sse@saveetha.com

ABSTRACT

Smallholder farmers cultivating limited landholdings often experience low yields and reduced returns, as restricted plot sizes limit crop rotation and expansion. Vertical farming provides a practical alternative by enabling intensive production in compact and densely populated areas, supporting year-round cultivation and increased food output. Artificial Intelligence (AI) and the Internet of Things (IoT) play a central role in modern agriculture by enabling precision farming and data-driven decision-making. The proposed system integrated soil-based, hydroponic, and aeroponic techniques within a unified vertical framework. Advanced irrigation and monitoring technologies, including moisture sensors and image-based crop analysis, optimized water usage, nutrient delivery, and crop health management. The approach automated irrigation and nutrient control and achieved a disease detection accuracy of 96 %, demonstrating improved performance compared to conventional machine learning models. Real-time monitoring through sensors and imaging devices reduced manual intervention, improved resource utilization, and supported sustainable agricultural practices. Overall, the system enhanced productivity across diverse farming conditions while promoting resource efficiency, sustainability, and climate resilience.

Keywords: automatic drip irrigation system, sustainable agriculture, crop growth, disease prediction.

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INTRODUCTION

Agriculture involves the cultivation of crops and the rearing of animals to supply food and fiber, which is essential for human needs and economic development. These activities depend on effective management of soil, water, and biodiversity to maintain productivity. This sector plays a central role in the globalized food system, generating value for rural communities worldwide. However, rising population growth continues to reduce arable land per capita. Developing horticultural areas face labor shortages due to rural-to-urban migration, alongside persistent inefficiencies and economic constraints. At the same time, rapid urbanization, climate variability, environmental contamination, and freshwater depletion intensify pressure on natural resources and global food security (Gürsu, 2024).

Farmers operating on restricted agricultural land face significant limitations in maximizing production efficiency. Constrained space restricts expansion and proper crop rotation, negatively affecting soil productivity, yields, and economic stability. Limited land availability also reduces the feasibility of adopting contemporary farming technologies that require additional space, such as precision agriculture and automated systems, thereby limiting improvements in yield and efficiency. Consequently, smallholders struggle to remain competitive compared to larger-scale producers.

Vertical farming has emerged as an innovative food production method that enhances productivity while reducing resource consumption and environmental impact. By arranging crops in vertically stacked layers, it maximizes land use efficiency and is particularly suitable for urban environments and land-limited regions. Vertical farming supports continuous year-round production, strengthens food security, and reduces transportation-related costs associated with conventional agriculture (Deepa *et al*., 2024a), while addressing land scarcity through controlled environment cultivation.

In practical applications, vertical farming systems operate within controlled environments where crops are grown in stacked layers equipped with advanced monitoring technologies. Sensors positioned across layers continuously measure moisture, nutrient concentration, temperature, humidity, and light exposure. Internet of Things (IoT) platforms transmit these data in real time to centralized processing systems for analysis, while Artificial Intelligence (AI) processes sensor-generated data to optimize irrigation scheduling, regulate nutrient delivery, and detect early signs of disease or stress through image-based monitoring.

The integration of IoT and AI enables precise vertical crop management and data-driven automation (Abraham *et al*., 2025). AI-based predictive analytics combined with continuous sensor monitoring allow early identification of pests and diseases, minimizing crop damage while preserving resources and improving yield performance. AI-supported monitoring incorporates computer vision and image recognition to assess plant growth, detect abnormalities, and implement prompt corrective actions. Automated irrigation systems integrated with AI analytics deliver precise quantities of water and nutrients according to plant developmental stages and environmental conditions, reducing manual labor and enhancing resource efficiency.

Harvesting strategies in vertical farming are designed to maximize efficiency and productivity within limited space. Manual harvesting remains appropriate for delicate or high-value crops requiring careful handling, whereas automated systems integrating robotics and AI reduce labor costs and increase operational speed. Precision harvesting uses sensors and data analytics to determine optimal harvest timing, ensuring maximum yield and quality. Mechanical harvesting supports large-scale operations, while continuous and selective harvesting techniques maintain steady production by collecting mature crops and allowing immature plants to reach full development. These approaches strengthen production capacity and environmental sustainability in compact growing environments.

Recent studies have advanced vertical farming technologies across multiple dimensions. Erekath *et al*. (2024) explored AI-enabled IoT technology for sustainable environmental management, demonstrating how advanced AI supports precise environmental regulation, early pest prevention, automated operations, and data-driven agricultural decision-making. Xie *et al*. (2024) designed a vertical farming prototype to examine wind energy opportunities in urban environments, conducting parametric analyses of turbine placement along building envelopes and ventilation corridor widths, and investigating the feasibility of integrating micro wind turbines into façade and roof structures. Gürsu (2024) presented a system aimed at improving productivity for small growers working on restricted agricultural areas, including the "PETREE" vertical planting system that converts durable fifth LT-PET packages into plant pots and recycled plastic frames to create mobile sustainable agriculture units.

Strategic and resource-oriented evaluations have also been conducted. Akbari *et al*. (2024) applied the Quantitative Strategic Planning Matrix (QSPM) together with SWOT analysis to assess the feasibility of vertical farming in Gilan Province, Iran. Walia *et al*. (2024) proposed a comprehensive rainwater harvesting system incorporating catchments, mesh filters, gutters, conduits, first-flush devices, and storage tanks, and described *in situ* techniques such as contour farming, strip cropping, vegetative hedges, tied ridging, bunds, terracing, and runoff harvesting for arid and semi-arid regions. Talbot and Monfet (2024) developed a simulation framework for evaluating building performance that concurrently assesses energy demand and crop productivity in compact vertical farming systems, incorporating a dynamic crop model. Fasciolo *et al*. (2024) categorized and analyzed Key Performance Indicators (KPIs) in vertical farming, compiling a structured set of 78 KPIs from the literature.

Technological advancements in automation and robotics have further strengthened vertical farming systems. Fei and Vougioukas (2024) introduced a real-time optimization system to adjust platform travel speed and lift height for improved harvest efficiency, validated through simulations and field trials in a commercial apple orchard. Wang *et al*. (2023) proposed a biomimetic robotic harvesting system for strawberries in vertical cultivation environments, employing deep neural networks and conditional Generative Adversarial Networks to detect ripe fruit using synthetic data. Kabir *et al*. (2023) reviewed developments in sensor technologies, monitoring and control systems, unmanned aerial systems, and the growing influence of AI in optimizing vertical farming operations. Carotti *et al*. (2023) examined water use efficiency in lettuce (*Lactuca sativa* L.) under ebb-and-flow substrate culture and high-pressure aeroponic systems in an experimental vertical farm at the University of Bologna. Ciriello *et al*. (2023) investigated light quality, quantity, and photoperiod effects for energy-efficient basil cultivation. Vandewetering *et al*. (2023) developed an innovative wood-based photovoltaic racking solution using an open-source hinge system to reduce mechanical pressure.

Advances in data analytics and intelligent modeling also contribute to agricultural innovation. Sivasubramanian *et al*. (2025) proposed an Al-Biruni Earth Radius Optimization-based deep transfer learning framework for remote sensing scene image classification, integrating SqueezeNet for feature extraction and a deep autoencoder neural network optimized through the Al-Biruni strategy to address high dimensionality and limited labeled data. Deepa *et al*. (2024b) introduced Agri-Ontology, an ontology-driven framework for organizing heterogeneous agricultural data using natural language processing techniques, employing BERT for semantic representation, Jaccard similarity for relationship extraction, and a BiGAN-based model for evaluation, achieving 94.64 % accuracy.

While these studies greatly improve vertical farming technologies, many only look at specific parts like energy systems, water management, structural design, robotics, or data representation, without bringing together AI-driven disease detection and real-time IoT-based automation into a complete vertical harvesting system. Some approaches present scalability challenges for small or urban farms, while others involve high operational costs or complex infrastructure. Limited real-time decision-making and delayed disease identification further reduce system effectiveness.

The present study positions vertical farming as a strategic response to contemporary agricultural challenges. The primary aim was to develop an intelligent vertical harvesting system by integrating AI-based crop monitoring with IoT-enabled automation to enhance productivity and resource efficiency. The objectives were to design a vertical farming framework combining soil-based, hydroponic, and aeroponic techniques; to monitor environmental and crop conditions using IoT sensors and imaging devices; to apply machine learning models for early crop disease detection; and to automate irrigation and nutrient delivery based on real-time data. Motivated by increasing land scarcity, climate variability, and the need for sustainable food production that reduces water usage, labor dependency, and crop losses, this work focused on controlled vertical farming environments with sensor-based monitoring, AI-driven disease detection, and automated decision-making for efficient crop management.

MATERIALS AND METHODS

An advanced vertical harvesting system was implemented to combine multiple technologies for enhancing agricultural yield (Figure 1). The system integrates three cultivation methods (aeroponics, hydroponics, and traditional soil-based farming) arranged in vertically stacked tiers. Crops grown under aeroponic conditions were

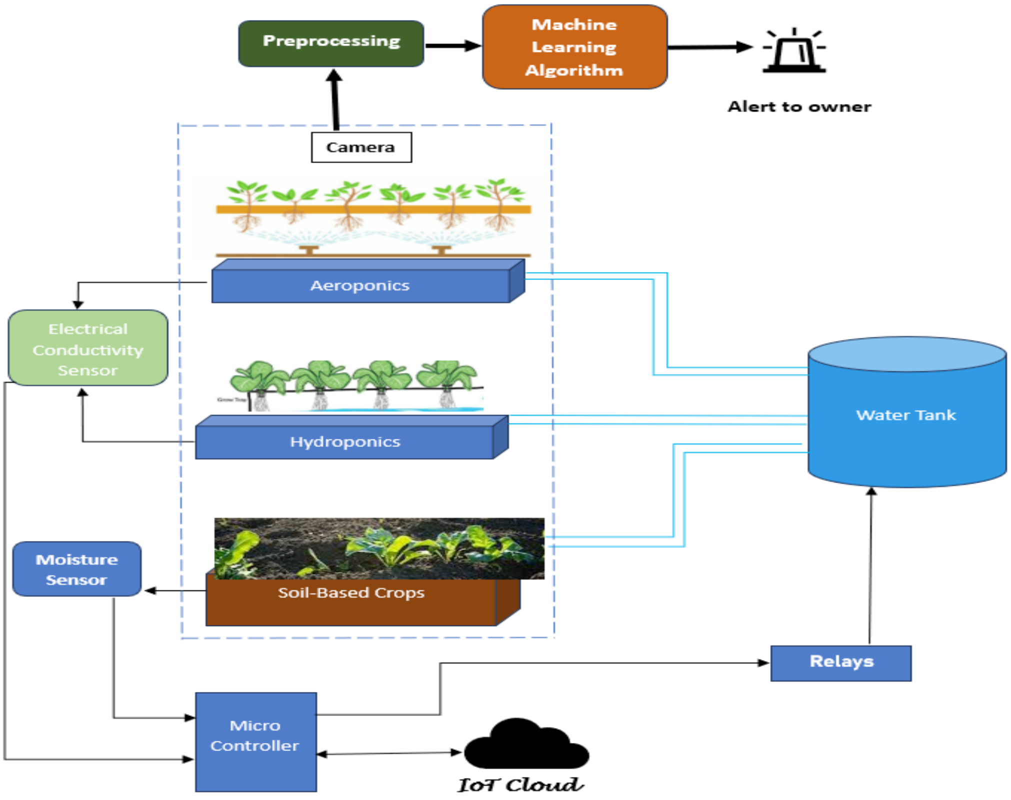

Figure 1. Integrated Artificial Intelligence (AI) and Internet of Things (IoT)-based vertical harvesting system architecture combining aeroponic, hydroponic, and soil-based cultivation.

monitored using video cameras, hydroponic crops were equipped with electrical conductivity sensors to verify nutrient solution adequacy, and soil-based crops utilized moisture sensors to regulate water levels.

The hydroponic and soil-based units were supplied by a central water tank containing nutrient-enriched water, with relays allowing selective distribution according to crop type. Sensor data were collected by a microcontroller that preprocessed the information using machine learning algorithms and generated alerts when anomalies were detected. Mahaveerakannan and Gade (2025) explained that this integration of AI and IoT technologies supports real-time monitoring, management, and optimization across diverse farming systems.

The problem addressed in this work is formulated as a quantitative optimization task aimed at maximizing crop disease detection accuracy and resource utilization efficiency under constrained farming conditions. Let the sensor data vector be defined as

$$S = \{m, t, h, ec\}$$

where m denotes soil moisture, t represents temperature, h indicates humidity, and ec corresponds to electrical conductivity. The objective was to maintain these parameters within predefined threshold ranges while minimizing water and nutrient waste.

Soil based crops

Soil-based farming relies on plant production in natural soil systems, where crop performance depends on nutrient availability and soil-borne microorganisms that support healthy growth. Major crops cultivated under this model include rice (*Oryza sativa* L.), maize (*Zea mays* L.), vegetables such as tomato (*Solanum lycopersicum* L.), root crops including potato (*Solanum tuberosum* L.) and carrot (*Daucus carota* L.), and legumes such as soybean (*Glycine max* (L.) Merr.). Rice requires flooded fields and specific soil conditions to achieve maximum yield. Maize depends on fertile, well-drained soils with consistent moisture availability. Tomatoes are sensitive to soil pH and nutrient balance, requiring well-conditioned soils for optimal fruit development. Potatoes and carrots require loose, well-aerated soils to facilitate proper tuber and root formation. Soybeans enhance soil fertility by fixing nitrogen through symbiotic relationships with soil bacteria, benefiting subsequent crops in rotation systems.

Moisture sensors are used for continuous monitoring of soil water content. These sensors collect soil condition data and transmit it to the IoT cloud for storage and analysis. When moisture levels fall below defined thresholds, a relay mechanism activates an automated drip irrigation system to supply the required amount of water. Optimal soil moisture ranges vary by crop: wheat performs best at 50–75 % of field capacity, rice at 80–100 % with periodic flooding, tomatoes at 60–80 %, carrots at 50–70 %, potatoes at 60–80 %, and lettuce at 70–90 % of field capacity. These thresholds guide irrigation management by defining the moisture levels necessary to support optimal crop growth while avoiding over- or under-irrigation.

Hydroponics

Hydroponics is a soil-less cultivation method in which plants receive nutrients from a circulating solution delivered directly to their roots. This system is suitable for urban agriculture and controlled environment systems such as greenhouses. Crops commonly grown using hydroponics include leafy vegetables such as lettuce, spinach (*Spinacia oleracea* L.), and kale (*Brassica oleracea* L.), which require nutrient-rich solutions supplied consistently through the system. Herbs such as basil (*Ocimum basilicum* L.) and cilantro (*Coriandrum sativum* L.) also perform well due to continuous nutrient availability and regulated environmental conditions. Vine crops, including tomato and cucumber (*Cucumis sativus* L.), are frequently cultivated in hydroponic systems, often supported by trellising structures during growth and fruiting. Hydroponics enables precise control over nutrient delivery and environmental conditions, improving production efficiency.

The operational parameters and threshold values for hydroponic crops (Table 1) include essential nutrients such as nitrogen, potassium, calcium, and magnesium, as well as

Table 1. Water pH, electrical conductivity (EC), and nutrient solution ranges used for the selected hydroponic crops.

Crop	Water pH Range	Electric conductivity ($mS\ cm^{-1}$) range	Nutrient solution ($mg\ L^{-1}$)
Basil (*Ocimum basilicum* L.)	5.5–6.5	1.5–2.5	18–22
Tomatoes (*Solanum lycopersicum* L.)	5.5–6.5	2.0–2.5	20–24
Strawberries (*Fragaria* × *ananassa* Duchesne)	5.5–6.5	1.8–2.5	18–24
Cucumbers (*Cucumis sativus* L.)	5.8–6.2	2.0–2.5	22–26
Lettuce (*Lactuca sativa* L.)	5.5–6.5	1.2–2.0	18–22

water quality indicators that influence crop growth and productivity. Monitoring and optimizing these factors according to crop type are necessary to maintain system stability and achieve optimal yield under hydroponic cultivation.

Aeroponics

Aeroponics is a form of hydroponics that does not involve the use of soil or any substrate. Plants are placed in growing pods and intermittently sprayed with a nutrient-saturated mist. This method allows precise control over the amount of oxygen, nutrients, and water vapor supplied to the root system. Aeroponic systems use approximately 80 % less water compared to soil-based farming and even conventional hydroponic systems. One advantage of aeroponics is that nutrients are delivered to the roots as fine moist particles, promoting faster growth and reducing material requirements compared to soil-based cultivation. This approach is particularly suitable in regions with limited arable land or infertile soils. Because there is no soil contact, the risk of soil-borne diseases is minimized, and plant health monitoring is more straightforward. Despite their advanced technology and high initial investment costs, aeroponic systems are sustainable and support year-round production in controlled environments such as greenhouses.

Sensor operation and application

Electrical conductivity (EC) sensors operate by measuring the ability of a solution to conduct electric current, which is directly proportional to the concentration of dissolved ions, particularly salts and nutrients. These sensors consist of electrodes, typically made of stainless steel or graphite, placed in the solution of interest. A small electrical current is passed between the two electrodes, and the resulting conductivity is measured. Higher ion concentrations correspond to increased conductivity of the solution. EC sensors are widely applied in hydroponic systems and soil-based farming to assess nutrient availability. They allow farmers to adjust nutrient solutions or soil amendments to ensure that appropriate levels of essential nutrients are supplied to crops. Real-time EC monitoring supports precise control of irrigation and fertilization practices, and prevents nutrient imbalances.

Sensors measure parameters and generate raw data. The measurement process involves calibration and conversion procedures to translate raw readings into meaningful units, such as converting voltage outputs from an EC sensor into conductivity values:

$$EC\left(\frac{mS}{cm}\right) = \frac{Voltage_{out}}{K * R}$$

where $Voltage_{out}$ is the sensor output voltage, K is the cell constant of the sensor, and R is the reference resistance.

Similar to moisture sensors connected to the cloud, EC sensors monitor ion concentration in nutrient solutions. When nutrient levels fall below optimal thresholds, the sensors trigger automated drip systems. This function ensures that plants receive appropriate nutrient supplementation, thereby optimizing agricultural productivity and resource efficiency.

Dataset preparation and image preprocessing

Image dataset

A camera was used for real-time plant monitoring, and the captured images were transmitted for preprocessing and subsequent analysis. To train and validate the disease detection model, a publicly available dataset sourced from Kaggle was utilized. This dataset comprises approximately 87 000 Red-Green-Blue (RGB) images of healthy and diseased crop leaves distributed across 38 distinct classes. It was used to train the model to discriminate features associated with different plant diseases and healthy conditions. The dataset was partitioned into training and validation sets in a 70:30 ratio while preserving the original directory structure. In addition, a separate directory containing 33 test images was created to evaluate the model's predictive performance.

Preprocessing

The images were preprocessed to improve the performance and accuracy of the machine learning model. Image dimensions and pixel values were standardized to ensure uniformity across the dataset. Feature representation was enhanced through normalization and augmentation techniques, and noise was reduced to enable clearer data interpretation. This preprocessing procedure improved robustness and generalization capability in the computer vision task.

Image resizing

The images were resized to a uniform spatial resolution using bilinear interpolation to preserve spatial continuity and reduce distortion. Specifically, the bilinear interpolation equation was applied to compute the intensity value of each resized pixel as a weighted average of its four nearest neighboring pixels:

$$I'(x', y') = (1-\Delta x), (1-\Delta y) I(x_1, y_1) + \Delta x (1-\Delta y) I(x_2, y_1) \\ + (1-\Delta x) \Delta y I(x_1, y_2) + \Delta x \Delta y I(x_2, y_2)$$

where $I'\ (x', y')$ is the interpolated pixel value; $I\ (x_1, y_1)$, $I\ (x_2, y_1)$, $I\ (x_2, y_2)$ and $I\ (x_1, y_2)$are the pixel values of the four nearest neighbors; and $\Delta x\ \Delta y$ correspond to the fractional offsets in the horizontal and vertical directions, respectively.

Normalization

Normalization scales pixel values to a specified range, commonly [0, 1]. This was achieved by directly applying the normalization equation to each pixel in the dataset:

$$I_{norm}(x, y) = \frac{I(x, y) - I_{min}}{I_{max} - I_{min}}$$

where $I\ (x, y)$ represents original pixel value, and I_{max} and I_{min} represent the maximum and minimum pixel intensities within the image, respectively.

The preprocessed dataset was split into training (70 %), validation (15 %), and testing (15 %) sets. The training set was used to learn model parameters by minimizing the loss function. The validation set was used to tune hyperparameters and monitor overfitting, with early stopping applied when validation performance declined. The testing set was used after training to evaluate the model's generalization on unseen data. This split ensured reliable performance assessment and model robustness.

Machine learning model

Crop disease detection was implemented using You Only Look Once version 6 (YOLOv6). The optimized backbone network and anchor-free design enhanced feature extraction and improved detection of disease symptoms in crops. Model performance was strengthened through training techniques such as mosaic augmentation and label smoothing. In field deployment, YOLOv6 processes images captured by cameras in real time. Enhanced Non-Maximum Suppression (NMS) further improves detection by pruning overlapping bounding boxes. This integrated system supports continuous field monitoring, reduces manual inspection effort, and promotes precise treatment application to improve crop health and yield.

The process for detecting crop diseases using YOLOv6 is carried out in sequential stages. First, a convolutional neural network backbone, such as CSPDarknet53, extracts discriminative features from input images. These features enable identification of disease symptoms, including lesions and discoloration on leaves or stems. YOLOv6 utilizes an anchor-free mechanism that directly predicts bounding box coordinates relative to reference points within the image. During training, mosaic augmentation and label smoothing improve the model's ability to distinguish between healthy crops and various disease classes. In post-processing, non-maximum suppression eliminates overlapping detections to ensure precise localization of affected regions. When deployed in real time, this integrated pipeline allows immediate intervention, helping farmers protect crops and minimize damage efficiently.

Feature extraction with convolutional neural network (CNN) backbone

YOLOv6 employs a CNN backbone (e.g., CSPDarknet53) to extract feature representations *F* from input images *I*:

$$F = CNN_{backbone}(I)$$

The convolutional layers apply filtering operations followed by Rectified Linear Unit (ReLU) activation, batch normalization, and other nonlinear activation functions to generate feature maps that capture patterns indicative of crop diseases.

Anchor-free bounding box prediction

YOLOv6 predicts bounding boxes $B = (\, b_x, b_y, b_h, b_w)$ directly relative to reference points within the image:

$$b_x, b_y, b_h, b_w \; = CNN_{head}(F)$$

Here, b_x and b_y represent the center coordinates, while b_h and b_w are the width and height of the bounding box, predicted based on features extracted by the backbone network.

Training with augmentation and label smoothing

During training, mosaic augmentation combines four images into one to improve robustness:

$$I_{mosaic} = MosaicAugmentation(I_1, I_2, I_3, I_4)$$

Label smoothing modifies ground-truth labels Y to reduce overfitting and enhance generalization:

$$Y_{smooth} = \; LabelSmoothing(Y)$$

Loss function calculation

YOLOv6 minimizes a combined loss function *L* consisting of bounding box regression, confidence, and classification losses:

Bounding box regression loss (L_{box}),

$$L_{box} = \lambda_{coord} \sum_{i=0}^{S^2} \sum_{j=0}^{B} 1_{ij}^{obj} [(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2]$$

Confidence loss (L_{conf}),

$$L_{conf} = \sum_{i=0}^{S^2} \sum_{j=0}^{B} 1_{ij}^{obj} [\sigma(b_i) - b_i{}^{true}]^2$$

Classification loss (L_{class})

$$L_{class} = \sum_{i=0}^{S^2} \sum_{j=0}^{B} 1_{ij}^{obj} \sum_{c \in classes} [\sigma(c/b_i) - c^{true}]^2$$

Here, λ_{coord} balances the importance of coordinate predictions, 1^{ij}_{obj} indicates if an object is present in grid cell i and bounding box j, σ represents the sigmoid function, and b_i^{true} and c^{true} are ground-truth values.

Post-processing with non-maximum suppression (NMS)
After prediction, NMS removes redundant overlapping bounding boxes:

$$NMS(B) = \{b \in B | IoU(b, b') < threshold\}$$

where IoU denotes the Intersection over Union between predicted boxes b and b', and the threshold defines the allowable overlap.

Real-time deployment
In real-time operation, YOLOv6 processes input images I from field cameras using trained parameters θ and produces disease detection outputs:

$$Detection_{disease} = YOLOv6(I, \theta)$$

This pipeline enables timely detection and intervention to mitigate crop disease spread and improve agricultural productivity. Following detection, the system sends alerts directly to the farm owner through a dedicated mobile application. When symptoms such as lesions or discoloration are identified, the model processes the captured images in real time and evaluates them against predefined detection thresholds. Upon confirming disease presence, the application generates and transmits an alert message to the owner's phone. This immediate notification enables prompt intervention, limiting disease spread and protecting crop yield. The integration of automated alerts strengthens responsiveness and supports informed, data-driven agricultural management.

Experimental setup

The framework of the proposed AI-IoT-based vertical harvesting system (Figure 2) utilized an EC sensor to measure nutrient concentrations in aeroponic and hydroponic systems. This sensor was calibrated to detect variations that are critical for optimal plant growth. A moisture sensor was deployed to monitor soil water content in soil-based crops. Both sensors were interfaced with a microcontroller (Arduino Mega 2560), which processed analog inputs and controlled digital outputs. The microcontroller

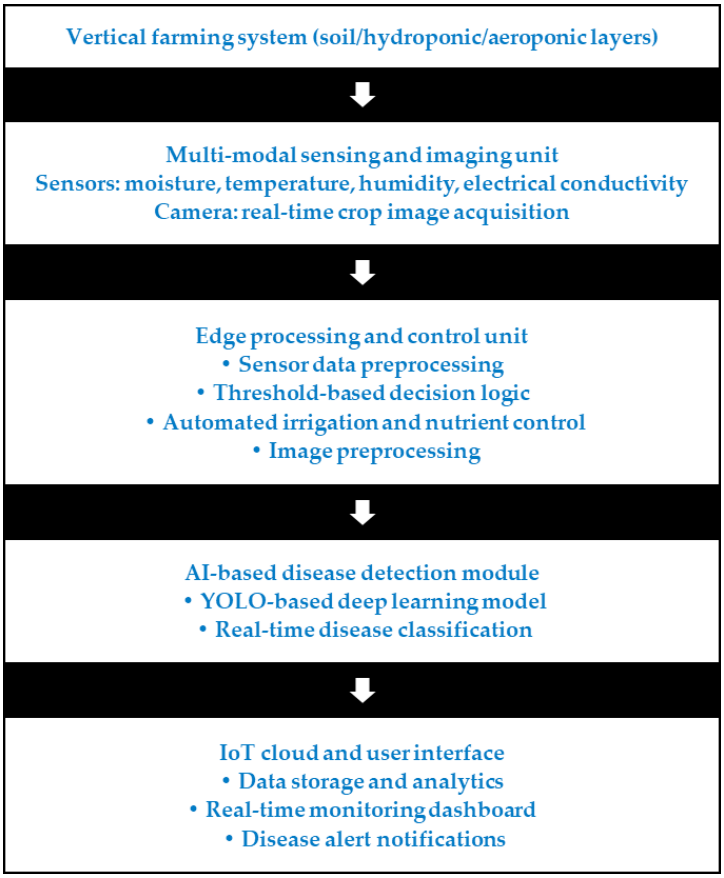

Figure 2. System architecture of the proposed Artificial Intelligence-Internet of Things (AI-IoT)-based vertical harvesting and monitoring system.

transmitted data to the cloud via Amazon Web Services Internet of Things (AWS IoT), where incoming data streams were stored and analyzed in real time. Cloud-based algorithms evaluated predefined thresholds, such as low nutrient levels, and triggered automated alerts when necessary.

A Raspberry Pi high-quality camera module captured real-time images of crop conditions. These images were preprocessed and analyzed using the YOLOv5 machine learning model to enable accurate disease detection and classification. Upon detection of disease symptoms, alerts were sent via email and Short Message Service (SMS) through Amazon Web Services Simple Notification Service (AWS SNS), ensuring timely notification for intervention.

The proposed system was implemented using a multi-layer vertical structure comprising soil-based, hydroponic, and aeroponic units. Moisture sensors were installed within soil layers, while EC sensors were positioned in hydroponic nutrient tanks to continuously monitor nutrient concentration. The camera module was mounted to capture real-time crop images for disease detection. All sensing devices were connected to a central microcontroller responsible for data acquisition, preprocessing, and transmission to the cloud platform. Relay modules interfaced with irrigation pumps and nutrient valves allowed automated control actions based on predefined threshold values and AI-based analysis.

A water tank was constructed to provide a continuous water supply to the crops. The system automatically activated the water tank and irrigation mechanism to deliver the required water when it detected inefficient nutrient levels or inadequate moisture conditions. If disease presence was predicted, the system generated immediate alerts to notify the owner, enabling prompt corrective action.

Performance metrics

These metrics quantitatively evaluate the accuracy and effectiveness of machine learning and image processing models. They measure accuracy, precision, recall, and overall performance by comparing predicted outputs with ground-truth labels and determine whether the model is reliable and suitable for tasks such as crop monitoring and disease prediction.

Accuracy (A): Measures the proportion of correctly classified instances among all instances.

$$A = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision (P): Quantifies the correctness of positive predictions.

$$P = \frac{TP}{TP + FP}$$

Recall (R): Measures the ability to correctly identify positive instances.

$$R = \frac{TP}{TP + FN}$$

F1-Score (F1): Represents the harmonic mean of precision and recall, providing a balanced metric.

$$F1 = 2 * \frac{Precision. Recall}{Precision + Recall}$$

Here, TP and TN denote True Positive and True Negative, while FP and FN represent False Positive and False Negative, respectively.

RESULTS AND DISCUSSION

The vertical harvesting system optimized land use through vertically stacked crop layers, increasing production per unit area compared to conventional cultivation. The integration of hydroponic and aeroponic techniques reduced water consumption and nutrient loss while improving growth rates and yield consistency. Continuous real-time monitoring using camera systems and machine learning enabled timely disease detection and intervention. The system also reduced reliance on pesticides and herbicides, lowered transportation-related carbon emissions due to proximity to urban areas, and supported year-round cultivation, contributing to improved food security and environmental sustainability.

The performance of the real-time crop condition classification model was evaluated using a confusion matrix (Figure 3). The results showed difficulty in distinguishing between the four classes: Poor, Average, Good, and Excellent. A substantial proportion of “Excellent” instances (67 %) were misclassified as “Poor,” while 57 % of “Poor” instances were incorrectly predicted as “Excellent.” The “Good” category achieved 41 % correct classification with notable dispersion into other classes. Similarly, only 27 % of “Average” instances were correctly identified, with frequent misclassification into “Poor” and “Good.” These findings indicate that the model particularly struggled with extreme categories, meaning it requires further refinement to improve classification reliability.

Hydroponic nutrient dynamics were analyzed over time (Figure 4), evaluating nutrient concentration (mg L^{-1}) variations for potassium, phosphorus, calcium, magnesium, and nitrogen. The model compared observed nutrient levels with predefined threshold values to regulate automated nutrient supply. Phosphorus and magnesium remained relatively stable over time, while potassium and nitrogen showed slight variations. Calcium fluctuated within shorter intervals, reflecting dynamic nutrient adjustments. The EC of the hydroponic solution (Figure 5) initially measured 2.6 mS cm^{-1} and

Figure 3. Confusion matrix for real-time crop condition classification.

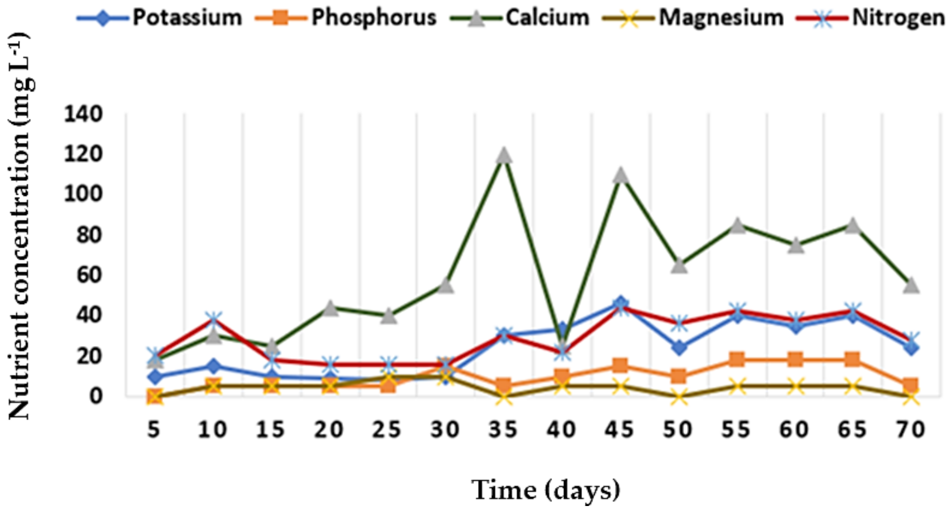

Figure 4. Temporal variation of hydroponic nutrient concentrations.

gradually increased to a peak of 4.5 mS cm^{-1}, indicating higher dissolved salt concentration, and later decreased to 2.9 mS cm^{-1}. The pH variation of the hydroponic solution (Figure 6) through time showed an increase from 5.5 to a maximum of 6.5, and then decreased to 5.6. This pattern indicated a gradual shift from acidic to near-neutral conditions before returning toward slightly acidic levels. Such variations were

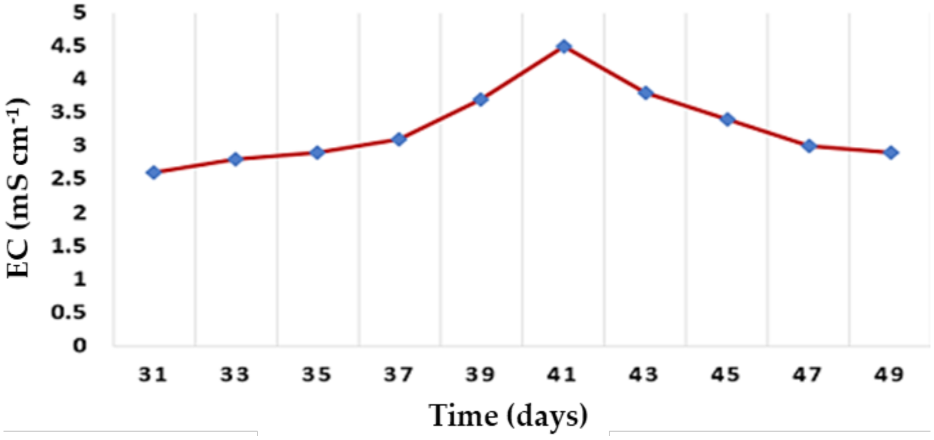

Figure 5. Temporal variation of electrical conductivity (EC) in hydroponic solution.

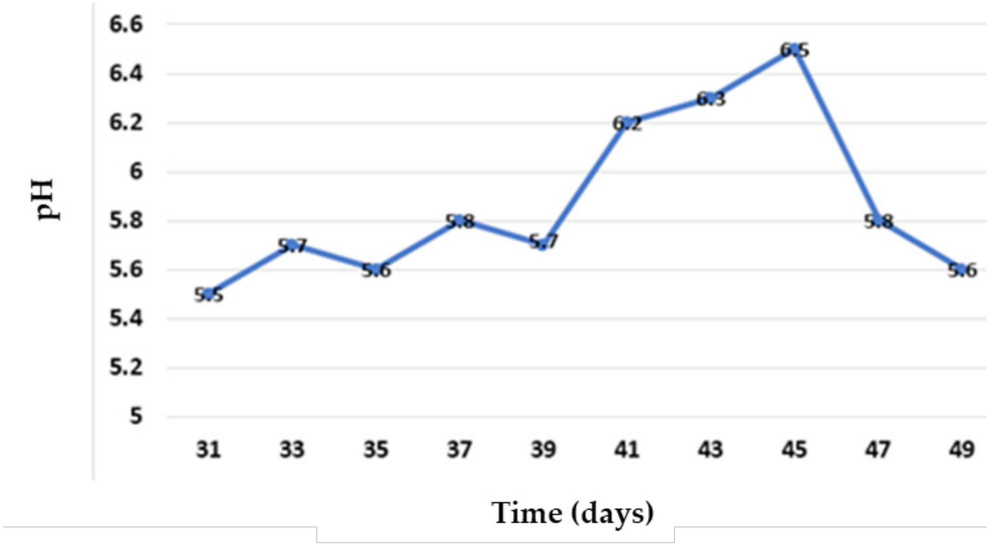

Figure 6. Temporal variation of pH Levels in hydroponic nutrient solution

likely influenced by factors including water source changes and nutrient adjustments. Quantitative evaluation demonstrated strong disease detection performance. The proposed method achieved an accuracy of 96 %, with 95.5 % precision, 96 % recall, and an F1-score of 94 %. These results confirmed balanced precision and recall, indicating robust and reliable performance in real-time crop monitoring.

Comparative analysis with baseline models further validated the effectiveness of the proposed approach. The Convolutional Neural Network (CNN) achieved 94 %

accuracy, the Support Vector Machine (SVM) achieved 95.8%, Extreme Gradient Boosting (XGBoost) achieved 88 %, Long Short-Term Memory (LSTM) achieved 90 %, and Long Short-Term Memory-Recurrent Neural Network (LSTM-RNN) achieved 95 %. The proposed YOLOv5 model outperformed all comparison models with 96 % accuracy. In addition to superior accuracy, it maintained strong precision (95.5 %) and recall (96 %), demonstrating consistent and balanced performance across evaluation metrics.

Sensor-based automation further reduced unnecessary irrigation events by maintaining moisture and EC levels within optimal thresholds, confirming the effectiveness of the quantitative optimization framework. Overall, the integrated system demonstrated reliable monitoring, accurate disease detection, efficient nutrient regulation, and improved agricultural resource management.

CONCLUSION

The proposed system is well suited for controlled vertical farming environments and has the potential to improve productivity under land and resource constraints. Despite its strong performance, certain limitations remain. The evaluation was conducted under controlled environmental conditions, and large-scale deployment may require further calibration to accommodate diverse climatic variations. The framework depends on continuous sensor connectivity and camera availability, which may increase initial setup costs for small-scale farmers. In addition, disease detection performance relies on dataset diversity; rare diseases or previously unseen crop varieties may reduce prediction accuracy.

Future work includes large-scale deployment across varied climatic and operational conditions to evaluate robustness and scalability. Integrating additional sensors, such as CO_2 and light intensity sensors, could further enhance precision farming capabilities. Extensions may also involve advanced deep learning architectures, expanded and more diverse datasets, and the incorporation of predictive analytics, cloud-edge computing, and drone-based monitoring to support fully autonomous and scalable smart farming systems.

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Dataset Source: https://www.kaggle.com/datasets/vipoooool/new-plant-diseases-dataset

REFERENCES

Abraham S, Thomas AJ, Ansleen S, Kumar D, Rishee PLG, Senthil K. 2025. Precision agriculture enhanced by spatio-temporal attention model for real-time crop monitoring and prediction. *In* 2025 7th International Conference on Intelligent Sustainable Systems. Institute of Electrical and Electronics Engineers: Tirunelveli, India, pp: 1123–1130. https://doi.org/10.1109/iciss63372.2025.11076290

Akbari Z, Yari Hesar A, Siamian N, Fürst C, Värnik R, Azadi H. 2024. Feasibility of using vertical farming in northern Iran: A multiple necessity. Journal of Environmental Management 354: 120232. https://doi.org/10.1016/j.jenvman.2024.120232

Carotti L, Pistillo A, Zauli I, Meneghello D, Martin M, Pennisi G, Gianquinto G, Orsini F. 2023. Improving water use efficiency in vertical farming: Effects of growing systems, far-red radiation and planting density on lettuce cultivation. Agricultural Water Management 285: 108365. https://doi.org/10.1016/j.agwat.2023.108365

Ciriello M, Formisano L, Rouphael Y, de Pascale S, Kacira M. 2023. Effects of daily light integral and photoperiod with successive harvests on basil yield, morpho-physiological characteristics, and mineral composition in vertical farming. Scientia Horticulturae 322: 112396. https://doi.org/10.1016/j.scienta.2023.112396

Deepa R, Das M, Thilakavathy P, Prabhu BA, Rajendran S. 2024b. Harvesting knowledge: An innovative ontology framework for agricultural advancement using NPL methodologies. *In* 2024 Third International Conference on Electrical, Electronics, Information and Communication Technologies. Institute of Electrical and Electronics Engineers: Trichirappalli, India. https://doi.org/10.1109/iceeict61591.2024.10718542

Deepa T, Maragathasundari S, Kameswari M, Swedheetha C. 2024a. Optimizing smart agriculture: Integrating queuing theory and IoT for enhanced resource management and efficiency. *In* 2024 International Conference on Communication, Computing, Smart Materials and Devices. Institute of Electrical and Electronics Engineers: Chennai, India. https://doi.org/10.1109/icccsmd63546.2024.11015216

Erekath S, Seidlitz H, Schreiner M, Dreyer C. 2024. Food for future: Exploring cutting-edge technology and practices in vertical farm. Sustainable Cities and Society 106: 105357. https://doi.org/10.1016/j.scs.2024.105357

Fasciolo B, Awouda AMM, Grasso N, Bruno G, Chiabert P, Lombardi F. 2024. An evaluation of research interests in vertical farming through the analysis of KPIs adopted in the literature. Sustainability 16 (4): 1371. https://doi.org/10.3390/su16041371

Fei Z, Vougioukas SG. 2024. A robotic orchard platform increases harvest throughput by controlling worker vertical positioning and platform speed. Computers and Electronics in Agriculture 218: 108735. https://doi.org/10.1016/j.compag.2024.108735

Gürsu H. 2024. Waste-based vertical planting system proposal to increase productivity in sustainable horticulture; "PETREE." Sustainability 16 (8): 3125. https://doi.org/10.3390/su16083125

Kabir MSN, Reza MN, Chowdhury M, Ali M, Samsuzzaman AMR, Lee KY, Chung SO. 2023. Technological trends and engineering issues on vertical farms: A review. Horticulturae 9 (11): 1229. https://doi.org/10.3390/horticulturae9111229

Mahaveerakannan R, Gade NVR. 2025. Smart agriculture comparative study of k-nearest neighbours and Random Forest for real-time crop monitoring and yield prediction. *In* 2025 International Conference on Digital Innovations for Sustainable Solutions. Institute of Electrical and Electronics Engineers: Faridabad, India. https://doi.org/10.1109/icdiss68238.2025.11320737

Sivasubramanian S, Kumar SGV, Thanarajan T, Rajendran S. 2025. Al-Biruni earth radius optimization for enhanced environmental data analysis in remote sensing imagery. Agrociencia 59 (5). https://doi.org/10.47163/agrociencia.v59i5.3380

Talbot MH, Monfet D. 2024. Analysing the influence of growing conditions on both energy load and crop yield of a controlled environment agriculture space. Applied Energy 368: 123406. https://doi.org/10.1016/j.apenergy.2024.123406

Vandewetering N, Hayibo K, Pearce J. 2023. Open-source vertical swinging wood-based solar photovoltaic racking systems. Designs 7 (2): 34. https://doi.org/10.3390/designs7020034

Walia SS, Kaur K, Kaur T. 2024. Water harvesting: Importance, its techniques. *In* Rainfed Agriculture and Watershed Management. Springer: Singapore, pp: 125–137. https://doi.org/10.1007/978-981-99-8425-1_16

Wang F, Urquizo RC, Roberts P, Mohan V, Newenham C, Ivanov A, Dowling R. 2023. Biologically inspired robotic perception-action for soft fruit harvesting in vertical growing environments. Precision Agriculture 24 (3): 1072–1096. https://doi.org/10.1007/s11119-023-10000-4

Xie S, Martínez-Vazquez P, Baniotopoulos C. 2024. Wind flow characteristics on a vertical farm with potential use of energy harvesting. Buildings 14 (5): 1278. https://doi.org/10.3390/buildings14051278