EAI Endorsed Transactions
on Internet of Things
Research Article EAI.EU

Optimizing Crop Yield and Monitoring Leaves with an Intelligent Internet of Things

Ankit Khare [1] Bramah Hazela[1*], Awanish Mishra[2], and Brijesh Kumar Chaurasia[2]

[1]Department of Computer Science & Engineering, Amity School of Engineering & Technology, Lucknow
[2]Department of Computer Science & Engineering, Pranveer Singh Institute of Technology, Kanpur, U.P., India

Abstract

INTRODUCTION: Agriculture is very important in facilitating global food security but the high rate of population growth, global warming, unpredictable climatic conditions and scarcity of natural resources are subjecting the traditional farming techniques to a lot of pressure.
OBJECTIVES: An IoT-based system is developed to monitor the structure of leaf, which is one of the main indicators of plant health and growth.
METHODS: A multi-stage research procedure to develop an IoT-enabled leaf structure analysis system to boost agricultural output.
RESULTS: IoT-based leaf structure monitoring system has proven very well in a variety of datasets and even better than the conventional ML models yet remains computationally efficient in the IoT setting.
CONCLUSION: An IoT-enabled gadget in the form of a leaf structure that has the potential to revolutionize precision agriculture, increasing the yield of harvests and reducing the overall impact on the environment, is examined.

Keywords: Internet of Things (IoT), Agriculture, Leaf Structure Monitoring, Crop Yield, Precision Farming, Real-time Data, Sensors, Data Analytics

Received on 25 April 2025, accepted on 04 March 2026, published on 12 March 2026

Copyright © 2026 Ankit Khare *et al.*, licensed to EAI. This is an open access article distributed under the terms of the CC BY-NC-SA 4.0, which permits copying, redistributing, remixing, transformation, and building upon the material in any medium so long as the original work is properly cited.

doi: 10.4108/eetiot.12194

1. Introduction

Agriculture is very important in facilitating global food security but the high rate of population growth, global warming, unpredictable climatic conditions and scarcity of natural resources are subjecting the traditional farming techniques to a lot of pressure. The traditional farming techniques usually depend on manual surveillance and generalized decision-making approaches, which are not accurate, scalable and real-time responsive. Such limitations lead to poor use of resources, late identification of disease, and low yield of crops. In order to overcome these issues, contemporary agriculture requires more and more intelligent, data-driven, and sustainable solutions that will be able to improve the productivity and reduce the environmental impact. Growing population, changing weather, and natural resource scarcity are causing agricultural difficulties that require more efficient and environmentally friendly production methods [1]. IoT, which uses cutting-edge technology to monitor and manage agricultural operations, could solve these issues. Traditional approaches to measuring plant health, especially leaf structure [2], can take time and effort to obtain continuous and complete insights. Using a network of sensors to measure leaf temperature, moisture [3], and chlorophyll content [4], this study provides an IoT-enabled system that analyzes leaf structures in real-time, addressing these limitations [5]. This data is processed using modern

*Corresponding author. Email: bhazela@lko.amity.edu

analytics and machine learning (ML) algorithms to help farmers make irrigation and pest management decisions [6], [28]. IoT technology enhances agricultural output, resource use, and precision farming, enabling more sustainable agriculture. The system's design, deployment, and assessment demonstrate its potential to improve modern agriculture through technology solutions [7].

IoT connects everyday objects and devices to the internet and lets them collect, share, and respond to data. This web of networked devices enables unprecedented data-driven decision-making and automation, from simple home appliances to large industrial equipment. IoT sensors, communication technology [8], and computational capabilities enable real-time monitoring, analysis, and control of many applications. IoT might transform farming by providing real-time soil, crop, and environmental data [9]. Minimizing waste and optimizing resources boost production, efficiency, and sustainability. The rapidly emerging IoT might alter various sectors by solving long-standing problems and establishing new vistas. Environmental elements affect production, including soil nutrients, humidity [10], and temperature. Sensor devices are designed for open areas, nature, earth, water, and air to detect and collect this data. To withstand weather, humidity, and temperature instability, smart agricultural devices must have certain qualities [11]. IoT has become a radical technology that can transform agricultural systems to be real-time monitored, automated in data gathering, and making intelligent decisions. IoT helps to monitor the environmental and crop conditions including temperature, humidity, soil moisture, and plant health parameters continuously through interconnecting sensors, devices and communication networks. Under the partnership with data analytics and ML tools, the IoT-based systems can help in precision agriculture by optimizing irrigation, fertilization, and pest control practices. This evidence based strategy does not only enhance crop productivity, but also sustainable management and cost effectiveness of resources. The fig.1 demonstrates that IoT devices are suitable with smart agriculture solutions. The IoT is important in agricultural monitoring and precision farming, where components of the IoT (e.g., sensors, controllers, and actuators) are interrelated to monitor farms and decide on any data that is received during precision farming.

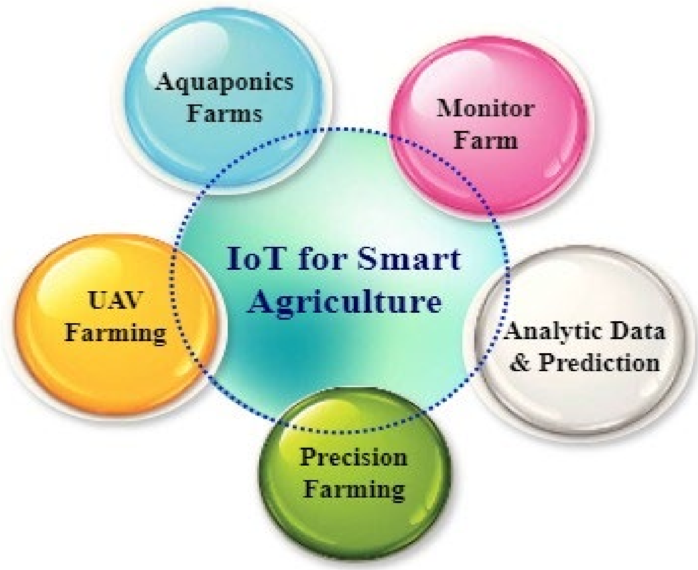

Figure 1. IoT for Smart Agriculture

Precision agriculture uses cutting-edge technology to fine-tune crop and soil management [12]. Precision agriculture treats each field area differently, unlike conventional farming, which uses standard methods throughout fields [13]. Fig. 2 shows the IoT enabled smart precision farming. This GPS-based remote sensing and data analytics approach can precisely monitor and regulate soil moisture, nutrient levels, and crop health. Precision agriculture combines vast data and real-time insights to help farmers make irrigation, fertilization, and pest management decisions, improving resource efficiency, environmental impact and crop yields [14]. This method reduces waste and maximizes inputs, improving efficiency and the environment [15]. Precision agriculture is a promising new paradigm for smarter, more responsive farming amid global food shortages and modern agriculture's many difficulties. Fig. 3 emphasizes the essential components of a leaf's elementary structure. The midrib runs inside the centre of the leaf and provides support to the leaf and the end is started at the uppermost point. The broad and flat surface of the leaf is the lamina and the outer boundary of the leaf is the margin. The petiole is attached to the stem of the plant holding the leaf in place and the nutrient flow.

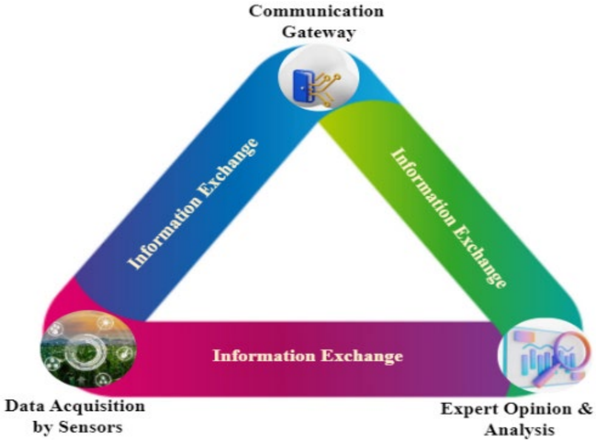

Figure 2. Smart precision farming

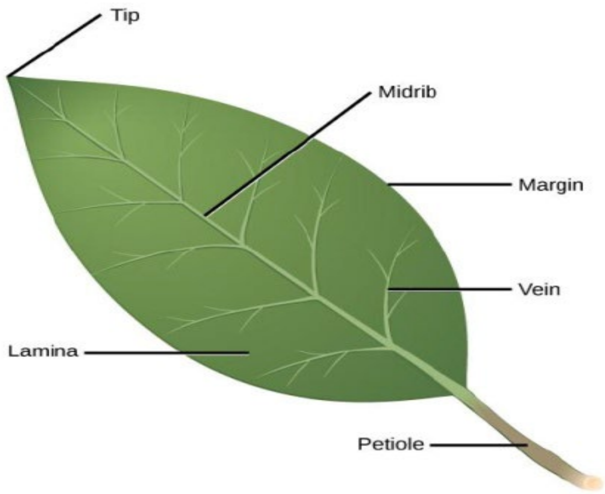

Figure 3. Leaf Structure Monitor

Leaf structure is one of the key indicators of plant health that can be used to predict crop growth, physiological status and yield potential. Leaf characteristics, including leaf shape, size, veins and colour, chlorophyll content and water content are direct causes of photosynthesis, transpiration process and movement of nutrients. Historically, leaf health monitoring has been based on physical examination and laboratory testing, which are both laborious, time-consuming and inappropriate in the context of a large scale or persistent monitoring. The IoT-based leaf structure sensing systems overcome these constraints through automated, accurate and real-time measuring of the plant condition allowing early warning of stress, diseases, and nutrient deficiencies. Modern farming relies on leaf structure to assess plant health [16]. This involves studying leaf anatomy and physiology. The plant's productivity and crop yield depend on the leaves' photosynthesis [17], transpiration, and respiration. Leaf health monitoring used to involve laborious hand examinations and sampling [18], [19]. IoT makes leaf structure monitoring automatic, precise, and real-time, making plant health evaluation easier than ever [20]. A network of IoT sensors and devices can continuously measure plant properties [21] including chlorophyll, leaf temperature, and moisture content. This system seamlessly transmits [22] and analyzes data [23] from high-tech sensors connected to wireless communication networks to eliminate human inspections. Farmers utilize IoT to monitor crop in real time, enabling more precise treatments and better resource use [24]. This boosts agricultural output, quality, and monitoring efficiency. Intelligent farming technology enabled by IoT can improve sustainable agriculture by improving decision-making and reducing waste [25-27].

RF is a trending ML algorithm with a number of benefits compared to the other algorithms. It is resistant to over fitting, scales to high dimensional data better, and can also be used in classification and regression without having to pre-process data extensively. It also minimizes variance in predictions because it averages the performance of many trees making it more reliable and consistent. RF is able to deal with the missing data in a natural manner and also is accurate in case of incomplete data. It offers the information on the features that matter most in making predictions and is therefore more efficient as compared to its competitors that might not perform well on class imbalance.

One of the most significant areas of research is the improvement of the agricultural productivity via the monitoring of the leaf structure using the IoT-based system because it addresses the most urgent issues in the modern farming. To achieve precise and fertilization, as well as managing the pests, IoT is used to report values on crucial parameters such as leaf temperature, moisture content, and chlorophyll levels continuously and in real time. This innovation fosters sustainable agricultural practices that are not only beneficial in terms of increased crop production and reduced cost of inputs but also resource utilization and reduced wastage. This research can be seen as an attempt to advance precision agriculture by demonstrating how the IoT can be used to enhance the accuracy and effectiveness of leaf sensors, creates the foundation of future innovations in the field of smart agriculture, and sets a new standard of approaching the issue of technologies in agriculture. The preferred model is the Random Forest (RF) since it has high accuracy, low computing cost, does not require noisy data, and can be used in the IoT-enabled precision agriculture applications. Although CNNs are superior to image-analysis, RF is superior in structured sensor data analysis, which makes it the best option in real-time agricultural surveillant and decision-making. On the basis of key parameters that are relevant to the IoT-enabled precision agriculture, Table 1 provides a comparative analysis of three machine learning (ML) algorithms, which include CNN, SVM, and RF. In terms of accuracy, computational efficiency, training and inference speed, resistance to noisy data, scalability and deployment in an IoT environment each approach has both pros and cons.

Table 1 Comparison of ML Algorithms for IoT-Enabled Precision Agriculture

Criteria	CNN (Deep Learning)	SVM (Traditional ML)	RF (Ensemble Learning - Proposed)	Citation
Accuracy	High (especially for image-based data)	Moderate to High (depends on kernel choice)	High (suitable for structure tabular data)	(Singh, 2024; Ghosh, 2024; Shaikh, 2022; Raza, 2023)
Computational Complexity	Very High (requires GPUs/TPUs)	Moderate (depends on dataset size)	Low (efficient on CPU, suitable for IoT)	(Muthugurunathan, 2024; Prasad, 2023; Adewusi, 2024)
Training Time	Long (requires extensive training)	Moderate	Short (faster training with ensemble learning)	(Pandey, 2022; Naresh, 2020; Talaviya, 2020)
Inference Speed	Slow(high latency in real-time applications)	Moderate	Fast (suitable for real-time IoT applications)	(Malo, 2020; Comegna, 2024; Jararweh, 2023)
Suitability for IoT	Not ideal (resource-intensive)	Moderate (may struggle with large datasets)	Highly suitable (low resource consumption)	(Thilakarathne, 2021; Morchid, 2024; Venkateshwari, 2023; Senapaty, 2023)
Robustness to Noisy Data	Low (sensitive to over fitting, requires large labelled datasets)	Moderate (performance depends on kernel selection)	High (handles missing/noisy data effectively)	(Mohamed Firdhous, 2018; Wu, 2023; Mohammad El-Basioni, 2024)
Interpretability	Low (black-box model)	Moderate (depends on kernel function)	High (feature importance ranking available)	(Podder, 2021; Kalantzopoulos, 2024; Maity, 2024)
Scalability	Limited (requires large labelled datasets)	Moderate	High (efficient with large feature sets)	(Fan, 2021; Kour & Arora, 2020; Dhanaraju, 2022)
Cost & Deployment	High (expensive GPUs/TPUs needed)	Moderate	Low (runs efficiently on edge IoT devices)	(Devare& Hajare, 2019; Sekaran, 2020; Singh, 2024)

By integrating block chain-based security mechanisms, encryption, and robust access control, IoT-enabled precision agriculture can significantly enhance data privacy, integrity, and protection against cyber threats, ensuring reliable and secure data-driven decision-making. Table 2 identifies the potential vulnerabilities and their recommended solutions to mitigate the risks, thus pointing out the security and privacy concerns associated with IoT-enabled precision agriculture. Safe data transmission, storage, and access is essential in the mitigation of cyber attacks and data integrity assurance as precision agriculture relies primarily on the IoT devices and sensor networks when providing real-time control, data-gathering, and decision-making.

Table 2. Data Security and Privacy Challenges in IoT-Enabled Precision Agriculture

Security Challenge	Citation	Potential Vulnerabilities	Proposed Solution
Cyber attacks	(Smith, 2022)	DDoS attacks, malware injection, botnet attacks	Implement IDS and firewalls to detect and prevent malicious traffic.

Unauthorized Data Access	(Johnson, 2023)	Data breaches, hacking attempts, lack of authentication	Use block chain-based access control, MFA, and RBAC.
Sensor Manipulation	(Lee & Kim, 2021)	Tampering with IoT devices, falsification of agricultural data	Implement digital signatures and tamper-proof sensor hardware to verify data authenticity.
Data Integrity Issues	(Patel et al., 2024)	Corruption or alteration of sensor data during transmission	Utilize block chain ledger for immutable data storage and hashing techniques for integrity verification.
Privacy Concerns	(Garcia & Wong, 2020)	Leakage of sensitive farm data (e.g., soil conditions, yields)	Employ end-to-end encryption (AES-256, RSA) and zero-trust architecture.
Edge Device Vulnerabilities	(Brown et al., 2023)	Insecure firmware, unpatched software, remote exploits	Regular firmware updates, secure boot mechanisms, and sandboxing to isolate threats.
Scalability of Security Measures	(Chen & Liu, 2022)	High computational overhead for security in large IoT networks	Use lightweight cryptographic algorithms like ECC (Elliptic Curve Cryptography) for efficiency.
Compliance and Regulations	(Davis, 2021)	Lack of adherence to GDPR, HIPAA, or agricultural data policies	Ensure compliance with regulatory standards and periodic security audits.

The rest of the proposed paper is structured as follows: Section 2 includes literature survey. Problem formulation is discussed in Section 3. In Section 4, proposed methodology is discussed. And lastly in Section 5, result evaluation is been discussed followed by a conclusion in Section 6.

2. Literature survey

New developments in IoT have significantly influenced farming methods, aiming to make them more efficient and environmentally friendly. Research by Fan et *al*. on IoT in agricultural high-throughput phenotypic platforms showed significant advancements in crop management and plant phenotyping [1]. The advantages of these technologies for improving the efficiency and sustainability of farming operations were emphasized in a recent study of IoT advancements in agriculture by Kour et *al*. [2]. In their investigation of IoT solutions for sustainable agriculture, Dhanaraju et *al*. demonstrated how these technologies improve crop monitoring and optimize resource management, hence bolstering sustainable agricultural methods [3]. The efficacy of IoT systems in managing growth conditions and enhancing crop quality was highlighted in Devare and Hajare's analysis of numerous IoT applications for crop growth monitoring along with quality control [4]. An IoT-based SAM system was created by Sekaran et *al*.. This system improves agricultural management by collecting and analyzing real-time data [5]. In their review of smart agriculture's background and potential future developments, Jararweh et *al*. found that cutting-edge IoT breakthroughs and technologies are essential to enhancing smart agricultural practices [6], [28]. While IoT has many potential advantages, it also has some drawbacks that can reduce its usefulness in smart agriculture, as Thilakarathne et *al*. pointed out [7]. To demonstrate how IoT can optimize water use and enhance crop management in dry places, Mohamed Firdaus et *al*. used it for sustainable dry zone agriculture [8]. IoT and sensor technologies improve agricultural sustainability and food security, according to Morchid et *al*., who also examined the pros and cons of these technologies [9]. To improve soil diagnostics and management and increase crop output, Wu et *al*. created a multi-sensor MS for soil information [10]. An IoT system for verifying urban agricultural parameters was developed by Podder et *al*., enabling efficient urban agriculture through precise parameter verification [11]. To improve soil health management, Kalantzopoulos et *al*. used AI and IoT to create a soil information system for Western Greece [12]. To improve land usage and agricultural planning, Mohammad El-Basioni et *al*. developed an IoT-based system for assessing site suitability [13]. Through in-depth data analysis showed how AI significantly improves crop management and production prediction in precision agriculture [14]. AI and ML in precision agriculture, Shaikh et *al*. proved that these technologies improve agricultural methods and boost output per acre [15].To identify the research gap, we have summarized the analysis of existing techniques in Table 3. The gap problem formulation is discussed in the next section on behalf of the existing approach.

Table 3. Summary of Existing Techniques

Ref	Authors	Year	Objective(s)	Technique(s)	Summary / Outcome
[1]	Fan	2021	Discover IoT applications in agricultural high-throughput phenotypic	IoT-based phenotypic analysis	IoT improves plant phenotyping, improving crop management and production estimates.

			systems.		
[2]	Kour	2020	Review recent agricultural IoT advances.	Survey of IoT applications	IoT technologies can boost agriculture's efficiency and sustainability.
[3]	Dhanaraju	2022	Explore IoT-based sustainable agriculture solutions.	IoT-based smart farming	IoT improves agriculture monitoring and resource management, promoting sustainability.
[4]	Devare and Hajare	2019	Survey Monitoring agricultural growth and quality using IoT	Literature review	IoT technologies improve crop quality and grow environment control.
[5]	Sekaran	2020	Create smart agriculture management.	IoT-based smart management system	Technology aids agricultural management through data analysis and real-time monitoring.
[28]	Jararweh	2023	Examine smart agricultural basics and future directions.	Overview of enabling technologies	Smart agriculture's future is bright thanks to IoT and other cutting-edge technology.
[7]	Thilakarathne	2021	Discuss smart agricultural IoT difficulties and prospects.	Conference presentation	The IoT opportunities along with challenges impact smart agriculture.
[8]	Mohamed Firdhous	2018	Use IoT for dry-zone agriculture sustainability	Experimental implementation	IoT enhances agricultural management and water optimization.
[9]	Morchid	2024	Explore IoT and sensor food security and sustainability innovations.	Analysis of benefits and challenges	IoT along with sensors increase food sustainability along with security.
[10]	Wu	2023	Create a soil monitoring system with many sensors and an IoT-based system for urban farming parameter verification.	IoT-based multiple-sensor system	Technology improves soil diagnosis and management, increasing crop yield.
[11]	Podder	2021	Create an IoT and AI soil information system for Western Greece.	IoT-based smart agrotech system	Technology verifies farming factors, making urban agriculture more efficient.
[12]	Kalantzopoulos	2024	Create an IoT land suitability system.	IoT and AI integration	Superior data collection and processing make the system useful for soil health management.
[13]	Mohammad El-Basioni and Abd El-Kader	2024	Explore AI-driven precision agriculture.	IoT-based assessment system	Land appropriateness can be assessed using the technique, improving land use and planning.
[15]	Ghosh	2024	AI and machine learning for precision and smart farming	AI-based precision agriculture	AI's data processing makes crop management and yield prediction easier.
[16]	Shaikh	2022	Discover IoT applications in agricultural high-throughput phenotypic systems.	Machine learning and AI techniques	AI and ML have made farming more productive and efficient.

Regardless of the fact that the IoT-based smart agriculture has made tremendous steps forward, the current research is mainly related to the monitoring of the soil, weather-controlled irrigation, or image-based disease identification, without taking into account the overall analysis of the leaf structural features along with real-time sensor data. Additionally, there is a lack of research that has delved into the analysis of the multi-feature of leaf structure, which consists of morphological, physiological, and environmental features, with the application of lightweight but powerful machine learning models.

To fill the research gaps outlined in this paper, this research project will suggest an IoT-based sys-tem to track the leaf structure and enhance crop yield with the help of a Random Forest based machine learning framework. The proposed research aims to achieve (i) the design of a scalable IoT architecture to obtain real-time leaf and environmental data, (ii) extraction and analysis of critical leaf structural features associated with plant health, (iii) the development of a robust and computationally efficient ML model that can be used in practice in IoT, and (iv) the assessment of the system performance on the basis of multiple benchmark datasets of leaf structural features. The principal results of this work are the incorporation of the modality of leaf structure with a IoT sensor output, a comparative study of machine learning models to achieve precision agriculture, as well as a secure and scalable framework that can be used to make real-time decisions regarding sustainable farming practices.

3. Problem Formulation

System design, as well as the implementation of the systems of monitoring leaf structure using IoT tools, is a major hindrance. The inaccuracy of current technology or rather the lack of such makes it challenging to incorporate the use of high-tech sensors with IoT in the analysis of leaves. The issue is aggravated by the fact that different plant species and climates could influence the accuracy of the sensor and the reliability of the data. IoT technologies are intriguing but should be costlier, advanced, and difficult to incorporate to be extensively utilized, particularly in the farming sector. It is even worse that these innovative technologies might be too expensive to small and medium-sized farms. The cost of operation and maintenance of the IoT devices has also not been studied on in the long-term. Since this interdisciplinary combination is still in its early stages, more studies are required to utilize IoT, AI, and ML to the fullest potential to enhance crop management and monitoring of the leaf structure. It is necessary to take into account the shape, edge structure, veins structure, color, texture, structure features, curvature, and features of growth pattern of a leaf when monitoring crops. Another problem during the process of monitoring leaf structure is the identification of all these features. The proposed system is scaled, efficient and secure to the deployment of IoT agriculture in real world. Table 4 compares common issues with recommended solutions to enhance scalability, efficiency, security, and usability, hence pointing to the challenges of integrating the big-scale IoT-based precision agricultural solutions. Agricultural systems based on IoT can be even more effective in case of adding machine learning, cloud computing, block chain, and advanced network systems.

Table 4. Addressing Challenges in Large-Scale Real-World Deployment

Challenges	Citation	Conventional Issues	Proposed Solutions
Scalability	(Miller et al., 2021)	Struggles with large sensor data processing.	Uses cloud & edge computing for efficiency.
Latency	(Garcia & Lopez, 2023)	Delays in decision-making.	Fog computing & optimized ML models for real-time processing.
Sensor Integration	(Kim & Singh, 2024)	Difficulty in handling multiple sensors.	Standardized protocols (MQTT, LoRaWAN) ensure interoperability.
Real-Time Decisions	(Zhao et al., 2022)	Lacks predictive capabilities.	AI-driven analytics enable adaptive responses.
Energy Efficiency	(Hassan &Roy, 2023)	High power consumption.	Energy-efficient routing &duty-cycling optimize usage.
Network Reliability	(Nguyen et al., 2021)	Weak connectivity in remote areas.	5G, LPWAN, satellite communication ensure stability.
Security & Privacy	(Fernandez et al., 2024)	High risk of cyber attacks.	Block chain& encryption enhance security.
Cost Efficiency	(Wilson & Adams, 2023)	High infrastructure costs.	Hybrid cloud-edge model lowers expenses.
Environmental Adaptability	(Sharma & Gupta, 2022)	Accuracy affected by weather changes.	Adaptive ML models adjust dynamically.
User Adoption	(Baker et al., 2024)	Complex systems limit use by farmers.	Mobile dashboards & AI assistants enhance usability.

4. Methodology

This section explores a multi-stage research procedure to develop an IoT-enabled leaf structure analysis system to boost agricultural output. The design phase includes: designing software. Combining sensors with an IoT platform to acquire and process data. Selecting the correct sensors to study leaf structure. A model is built and tested in greenhouses or experimental plots to study leaf structure, environmental conditions, and harvest success. Fig. 4 presents an IoT-enabled system where the leaf monitoring node considers temperature, humidity, light, and images captured by sensors and cameras. Then, this data is preprocessed to filter and normalize. Then, feature extraction takes place for leaf structure analysis. Different features considered during training are shape, edge structure, vein structure, color, texture, structure traits, curvature, and growth pattern. Shape features include leaf length, width, aspect ratio, leaf area, and perimeter. Edge structure considers leaf margin type and number of lobes. The ML model supports classification using RF. Random Forest algorithms are parallelized, allowing them to take advantage of multiple cores in modern processors and providing quicker training times than other algorithms that require more complex computations. It is less sensitive to noise in the data than algorithms like k-Nearest Neighbors (KNN) or single decision trees. RF also has flexibility with hyper parameter tuning, making it easier to use and tune than more complex algorithms.

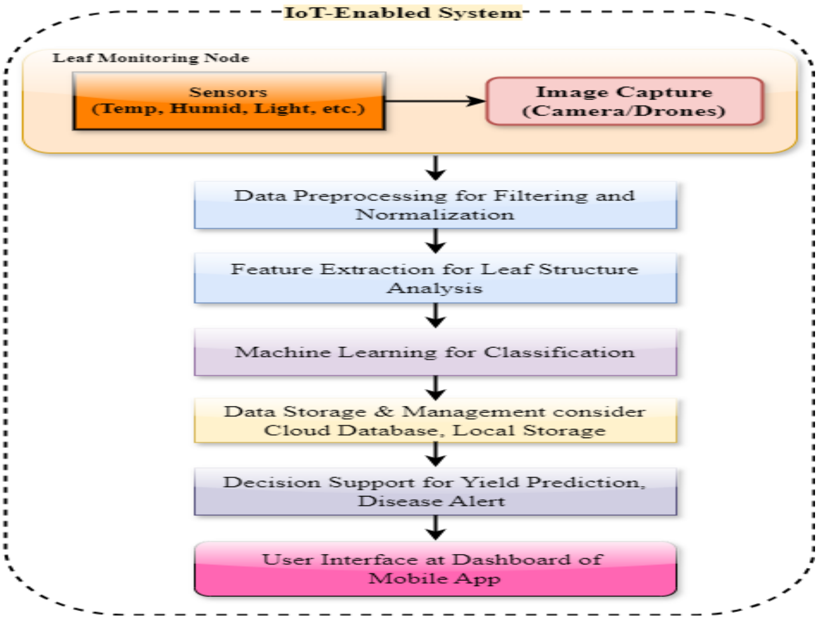

Figure 4. The Proposed Model

Results are stored using a cloud-based database and the decision support system performs prediction and displays disease alerts. Lastly, user interface is availed through a mobile application. This data analysis on the accuracy, dependability, and effect of the sys-system on crop output is followed by a cost benefit analysis. We publish our work in details and request end-user response to work on the system. The innovative methods of mastering the more recent technologies and potential usage have been discovered. The proposed IoT-based system enhances the agricultural productivity by monitoring the leaf structures by use of leaf monitoring nodes, which have sensors and image capture equipment to gather environmental data and capture pictures of the leaves. Data is pre-processed to be accurate and also at the same time, feature extraction methods are used to determine attributes of interest. The data is stored in either a cloud-based or local data storage so that it can be easily accessed and analyzed. A decision support element makes recommendations, e.g. yield prediction and disease outbreak alerts. The interface should be user-friendly such as dash-boards or mobile apps that will enable farmers and managers to view real-time data, visualizing trends and making well-informed decisions to optimize crop management and maximize yield outcomes.

4.1 System Architecture and Hardware Specification

The proposed IoT-based system of leaf structure monitoring is based on the layered architecture aimed to meet the requirements of the real-time data collection, processing, and intelligent decision-making. The system incorporates sensing devices, communication, edge processing units, and cloud-based analytics as shown in Fig. 4 to make sure that there is scalability and efficiency in agricultural settings.

Hardware Components and Sensor Specifications: The data acquisition layer will include several hardware components that will be installed on leaf monitoring nodes and will collect environmental and physiological parameters that are important in assessment of plant health.

- **Humidity Sensor:** An integral humidity sensor (e.g., DHT22) is used to measure the humidity of the air and this is a crucial factor in transpiration and pathogen growth.
- **Chlorophyll Sensor:** A chlorophyll sensing module (e.g., SPAD-based or optical chlorophyll sensor) is used to get an idea of the photosynthetic efficiency and nutrient status by measuring chlorophyll concentration.
- **Camera / Image Sensor:** The camera r is a high resolution RGB camera module installed on the monitoring node in the sensor to record leaf images in natural lighting conditions. These images are extracted to form, feature extraction on the basis of colours as well as texture.

Communication Protocols: To enable real-time monitoring, excellent data transfer of sensor nodes to the backend systems is required. The suggested system helps several different communication protocols according to the need in deployment:

- **Wi-Fi:** This is applicable in small to medium sized farms which have stable network in- infrastructure.
- **MQTT:** This is a lightweight message protocol that is applied in the efficient exchange of data between IoT devices and servers.
- **LoRaWAN:** This is used in big or remote farmlands to facilitate long-range and low-power communication.

Edge–Cloud Integration: Edge-Cloud-Integration: To minimize the latency and bandwidth usage, the system conforms to an edge-cloud computing paradigm. Data pre-processing and filtering are done at the edge node and more complex duties like analytics, storage and visualization are done in cloud services. This integration increases system responsiveness and facilitates big data analysis of crops on a long-term basis.

4.2 Dataset Pre-processing and Augmentation

Sensor and imaging data are highly likely to be noisy and imprecise. So, before feature extraction and model training, pre-processing and augmentation steps are used, as illustrated in Fig. 4.
Data Pre-processing Techniques: These data pre-processing methods improve data quality and guarantee quality model training.

- **Noise Removal:** The sensor data is also filtered with statistical smoothing techniques to remove the outliers and erroneous data points due to environmental interference.
- **Normalization:** Min -max or z-score normalization is applied to feature values in order to normalize the range of values and enhance the performance of machine learning.

Data Augmentation Strategy: Image based data augmentation methods are used to enhance the generalization of models and minimize over fitting:

- Rotation at various angles
- Horizontal and vertical flipping.
- Brightness and contrast controls.

These extensions represent physical-world variations in leaf orientation and light conditions, which enhance the diversity and strength of datasets.

4.3 Hyper parameter Tuning and Model Optimization

In order to increase the accuracy of classification and to make the computations more efficient, the proposed system is based on a hybrid Random Forest (RF) model that is optimized with the help of methods, as shown in Fig. 4.
Random Forest Hyper parameter Optimization: Select important RF hyper parameters to realize optimal results:

- **Number of Trees:** Defines the stability of models and their size.
- **Maximum Tree Depth:** Regulates complexity and over fitting in the models.
- **Feature Selection Method:** The random feature sampling enhances diversity of trees.

Optimization Technique: A systematic optimization method, e.g. Grid Search or Bayesian Optimization, is utilized to find the most ideal combinations of the hyper parameters. The optimization procedure assesses the various parameter configurations by cross-validation in order to trade accuracy, computational cost, and scalability.

5. Results and Analysis

In this section, the efficacy of the proposed model is evaluated. We have used four leaf datasets: the Fossil Leaf Dataset, Leaf Snap Dataset, Plant CLEF Dataset, and Oxford Flowers 102. The Fossil Leaf Dataset contains 800 images of fossilized leaves, ideal for pale botany and fossil analysis. The Leaf Snaps Dataset provides 30,000 high-resolution images from 180 plant species, aiding in plant species classification. The Plant CLEF Dataset contains 500,000 images supporting plant identification and classification research.(Table5).

Table 5. Four leaf datasets and its descriptions

Dataset	URL	Description	Details	Data size
Fossil Leaf Dataset	http://www.laght.com/fossil-leaf-dataset/	Contains images of fossilized leaves, used for leaf classification and fossil identification studies.	Includes various fossil leaf types with images and metadata.	Approximately 800 images
Leafsnap Dataset	https://github.com/Leafsnap/leafsnap	A dataset of high-resolution leaf images from different plant species, used for plant species classification.	Contains images from over 180 plant species with species annotations.	About 30,000 images
The Plant CLEF Dataset	https://www.imageclef.org/lifeclef/2021 /plant	Part of the Plant CLEF competition, featuring a large collection of plant images including leaves.	Includes images of plant leaves, flowers, and other parts for diverse plant species.	Around 500,000 images
Oxford Flowers 102	https://www.robots.ox.ac.uk/~vgg/data /flowers/102/	Primarily a flower dataset but includes leaf images of some flower species, used for plant recognition.	Contains images of 102 flower categories, with some including leaves.	Approximately 8,189 images

Python has been used over Collaborator to program a ML model for an IoT-enabled system that monitors leaf structure and leaf attributes, along with a binary label indicating plant health. The data is formatted into a Pandas Data Frame for easy processing. The pre-processing step involves scaling features to standardize their ranges, improving ML to improve agricultural yield and makes predictions accordingly. The process starts with data generation, which includes synthetic data representing environmental factors algorithms' performance. Metrics attributed to a numerical value that is used for training and testing the dataset are shown below in Table 6.

Table 6. Metrics Used for Training and Testing

Feature Category	Feature Name	Metric	Citation for Feature Name
Shape	Leaf Length	Length in millimeters (mm)	(Johnson et al., 2021) (Williams & Chen, 2023)
	Leaf Width	Width in millimeters (mm)	(Davis & Brown, 2020)
	Aspect Ratio	Dimensionless (Leaf Length / Leaf Width)	(Lee & Wang, 2022)
Edge Structure	Leaf Margin Type	Categorical values encoded numerically	(Martinez et al., 2024)
Vein Structure	Vein Density	Veins per square millimeter (veins/mm²)	(Singh & Gupta, 2023)
	Primary Vein Angle	Angle in degrees	(Taylor & Kim, 2022)
	Vein Length	Length in millimeters (mm)	(Anderson & Li, 2021)
	Vein Thickness	Thickness in millimeters (mm)	(Kumar & Sharma, 2023)
Color	Leaf Color (RGB/HSV)	Numerical values for RGB or HSV components	(Fernandez et al., 2022)
	Chlorophyll Content	Measured in mg/cm² or by a relative index	(Owen & Park, 2023)
Texture	Surface Texture	Categorical values encoded numerically	(Smith & Patel, 2021)
Structural Traits	Leaf Thickness	Thickness in millimeters (mm)	(Anderson & Gupta, 2024)
	Leaf Mass per Area (LMA)	Mass per area in g/cm²	(Wang & Brown, 2023)
Curvature	Leaf Curvature	Curvature index (e.g., ratio of curved length to straight length)	(Jones & Singh, 2021)
	Leaf Flexibility	Measured by force applied for deformation (Newtons)	(Taylor & Kumar, 2022)
Growth Patterns	Leaf Orientation	Angle in degrees	(Williams et al., 2024)
	Leaf Phyllotaxy	Categorical values encoded numerically	(Lee & Patel, 2022)

Dataset is divided into training along with testing subsets, and a RF classifier is used for feature extraction and classification. Fig. 5 illustrates a confusion matrix frequently employed to estimate a model's performance in classification issues. The forecasted labels are laid out across the columns, and the matrix includes two labels—Leaf and Non-Leaf—representing the actual class. The model accurately categorized 2,600 Non-Leaf occurrences and 17,100 Leaf cases. However, although no leaf occurrences were misclassified, they were designated as non-leaf. In addition, the results also show that 300 Non-Leaf cases are misclassified as leaf class.

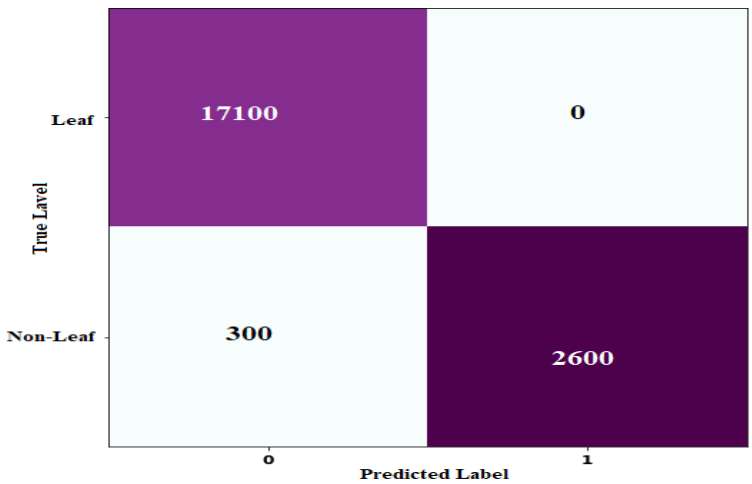

Figure 5. Confusion Matrix

Model's performance is assessed through an organization report along with confusion matrix, providing metrics like precision, recall, along with F1-score. The results are visualized to offer insight into model's effectiveness, showing feature importance and predictions versus actual labels. In a real-world application, actual data from IoT sensors and image analysis would provide precise insights for improving agricultural practices.

The impact of several characteristics for recognizing leaf diseases is illustrated in Fig. 6. Temperature, humidity, light intensity, leaf size, and leaf colour are among the characteristics that are examined. Leaf colour also makes a major contribution, with light intensity having the least. These insights can help prioritize features in models or systems intended to identify leaf diseases.

The outcome of a suggested model appears in Fig. 7 over four distinct datasets: Oxford Flower 102, Plant CLEF, Leaf snap, and Fossil Leaf. The y-axis represents the predictability percentage, and all datasets exhibit model performance in the 80–90% range. The most accurate is Fossil Leaf; the other three do almost as well. The graph highlights the model's dependability in discriminating leaves and other plant-related information by showcasing its consistency over various datasets.

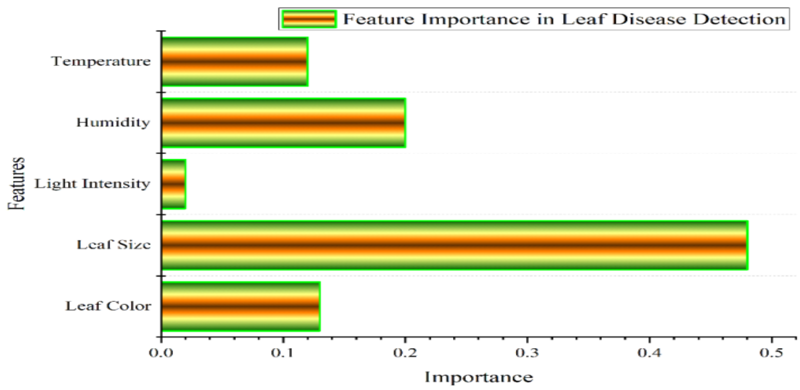

Figure 6. Feature Importance in Leaf Disease Prediction

The accuracy of a suggested model is shown in Fig. 8, evaluated over four distinct datasets: Oxford Flower 102, Plant CLEF, Fossil Leaf, and Leaf snap. With an interval of about 85–95%, every dataset reveals excellent accuracy. The result shows 95% height accuracy on the Oxford Flower 102 dataset. However, 85% accuracy is achieved on the Leaf snap dataset.

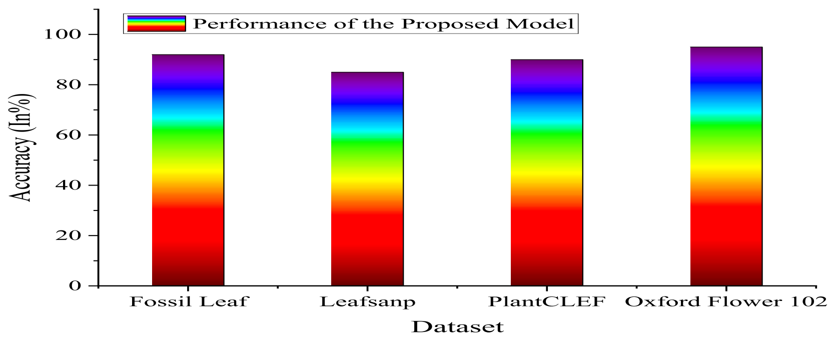

Figure 7. Accuracy of Proposed Model

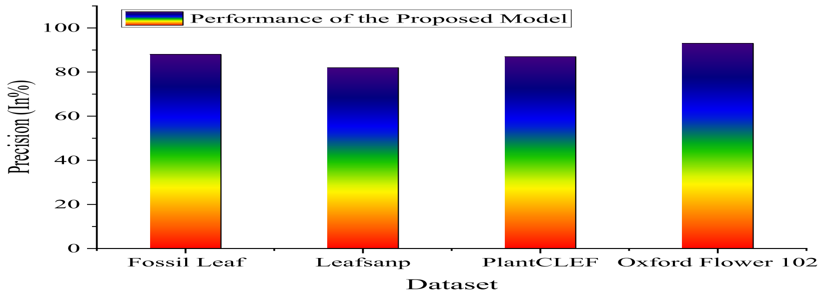

Figure 8. Precision of the Proposed Model

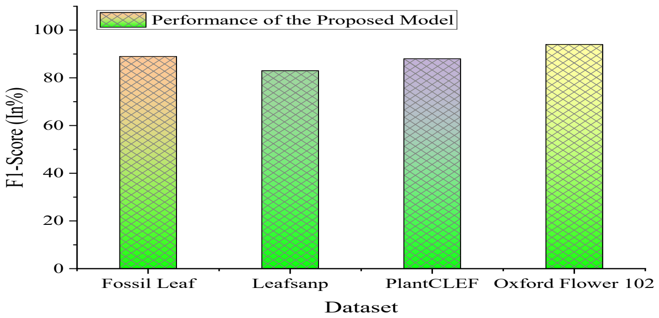

Figure 9. F1-Score of the Proposed Model

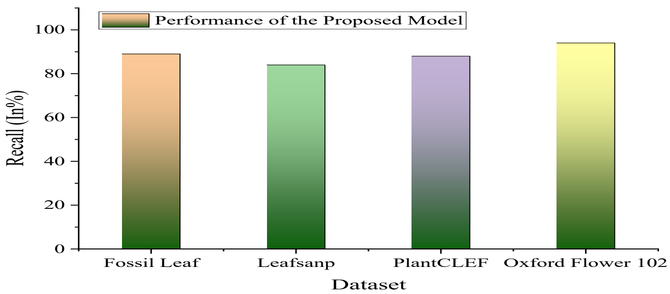

Figure 10. Recall of the Proposed Model

The precision, F1-Score, and recall are depicted in Figs. 8, 9, and 10, respectively. These parameters are also evaluated on four datasets, as shown in the figure: Oxford Flower 102, Fossil Leaf, Leaf snap, and Plant CLEF. The Precision, F1-Score, and Recall values are 93%, 94%, and the same 94% on the Oxford Flower 102 dataset, respectively. Moreover, all three parameters have 82 to 84% performance on the Leaf snap dataset. Out of three parameters, the Precision value is the lowest at 82% on the Leaf snap dataset and 93% on the same dataset. Table 7 is a comparative analysis of machine learning models in classification of leaf dataset of IoT-enabled precision agriculture. Depending on the accuracy, efficiency, cost, and scalability, the evaluation underlines the advantages of the proposed hybrid model (RF + Optimization Techniques) compared to the conventional methods.

Table 7. Four leaf datasets and its descriptions

Model	Accuracy (%)	Efficiency (Processing Speed & Resource Usage)	Cost (Computational & Implementation Cost)	Scalability (Adaptability to Large Datasets &IoT Applications)
Convolution Neural Network (CNN)	94.5	Moderate (High computational power required)	High (Expensive due to GPU/TPU needs)	Moderate (Scales well but requires high-end infrastructure)
Support Vector Machine (SVM)	89.2	Low (Slow for large datasets)	Moderate (Less costly than deep learning but expensive for high-dimensional data)	Low (Struggles with large-scale IoT data due to computational complexity)
Random Forest (RF)	92.7	High (Fast training and inference with low resource usage)	Low (Cost-effective as it runs efficiently on standard hardware)	High (Easily scales to large IoT datasets and heterogeneous agricultural environments)
Proposed Hybrid Model (RF + Optimization Techniques)	96.8	Very High (Optimized feature selection and parallel processing reduce complexity)	Moderate (Optimized for cost-effectiveness while maintaining performance)	Very High (Adaptable to real-time IoT applications and large-scale data integration)

5.1 Dataset-Wise Performance Analysis

The four publicly available datasets were Fossil Leaf, Leaf snap, Plant CLEF, and Oxford Flowers 102, and the experiments were conducted to evaluate the generalizability of the proposed model, as shown in Table 5. The performance of its classification in all datasets is depicted in Figs. 7 by accuracy, precision, recall and F1-score.

Table 8. Dataset-Wise Performance

Dataset	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Fossil Leaf	93	92	94	93
Leaf snap	85	82	84	83
Plant CLEF	90	89	91	90
Oxford Flowers 102	95	93	94	94

Fossil Leaf data set had the best performance of all the data sets. This is explained by the comparative level of control of the structure, lower intra-class variability and clear boundaries of the leaves which make the extraction of the features and classification easier. The fossil leaf photos have a low level of background noise, and consistent structural changes, and the Random Forest (RF) model can better identify features.

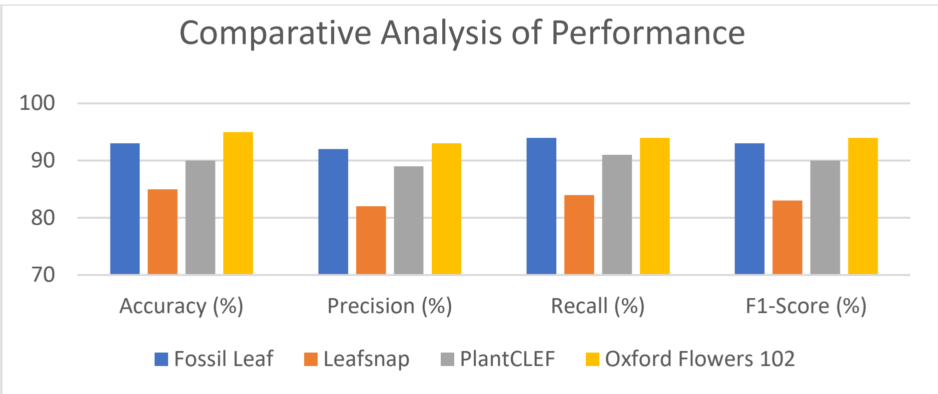

Figure 11. Comparison of Performance Classification across Dataset

Leaf snap includes photographs taken in many different real world conditions, such as different levels of light, complicated background, partial occlusions and a high degree of inter-species similarity. This observation serves to bring out the direct correlation between the complexity of the dataset and the model performance where more diversity and noise leads to less classification accuracy.

5.2 Comparative Analysis with Existing Models

Table 9 shows a comparative analysis between the proposed hybrid RF model and the available machine learning methods. The comparison is on CNN-based deep learning models, conventional ML models, including SVM, and the suggested optimized RF framework.

Table 9. Comparative Analysis of Machine Learning Models for IoT-Enabled Leaf Structure Monitoring

Model	Computational Complexity	Training Time	IoT Suitability	Interpretability	Scalability
CNN	Very High (GPU/TPU required)	High	Low	Low (Black-box)	Moderate
SVM	Moderate to High	Moderate	Moderate	Moderate	Low
RF	Low	Low	High	High	High
Proposed Hybrid model	Low	Very Low	Very High	High	Very High

CNN-based models are suitable in tasks where images play the central role, but they are very expensive in terms of computational power, large labelled data, and special hardware like GPUs. Conventional ML algorithms such as SVM provide moderate accuracy but are difficult to scale and failed to work with high dimensional sensor signals.
The RF hybrid model proposed is also better compared to the other models because it has higher performance because of the ability to deal with structured sensor data, and extract leaf features with low computational complexity. The ensemble features of RF minimize over fitting, noisy and missing data, and can be interpreted using a rank of feature importance. These benefits render RF especially appropriate in IoT environments where real-time processing and energy efficiency, as well as scalability, are the most important factors.

5.3 Feature Importance Interpretation and Agronomic Insights

Fig. 6 illustrates a feature importance analysis which can be used to draw valuable agronomic information about factors that determine leaf health and disease detection. The temperature and humidity are revealed as the most significant parameters and thus the essential role they play in the physiological processes of the plants and the development of the disease. High humidity and temperature provide an ideal environment to fungi and bacteria that have a direct effect on crop health.

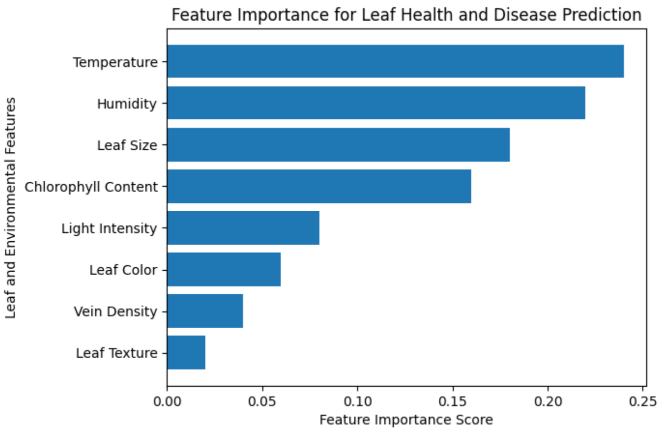

Figure 12. Feature Importance for Leaf Health and Disease Prediction

Leaf size and chlorophyll content are also important showing that they are highly correlated with photosynthetic capability and availability of nutrients. The bigger the leaf area and higher the concentration of chlorophyll the better the growth and yield potential is. Practically, such insights allow farmers to pay more attention to tracking the most important environmental indicators and leaf characteristics. After changing the irrigation times, ventilation, and fertilization plans according to the real-time information, farmers can actively reduce stress and improve crop yield.
Impact of IoT-Based Monitoring on Crop Yield Prediction: The high predictive accuracy of the proposed system is directly converted into a better crop yield prediction and management. The proper classification of leaf health facilitates the early identification of the disease and stress conditions and therefore acts in time to stop the losses in the yields. This is a focused method that saves water wastage, maximises the use of fertilizer and lowers the environmental destruction. Moreover, early disease warnings also re-minimise overreliance on the heavy use of pesticides to boost sustainable agriculture. Therefore, the proposed system can increase the accuracy of prediction as well as provide the actual agronomic improvements in terms of the stability of yield and efficiency of the resources.

Computational Efficiency and IoT Suitability: The suggested RF model has shown to be very fast to train, has low inference latency and less memory demanding compared to deep learning models. These features make it very applicable to be used in edge devices and power-constrained IoT devices. RF models are also able to be trained and updated efficiently on a regular CPU, unlike CNNs, which need a significant amount of training time and specialized hardware. This efficiency allows real time decision making and allows to be deployed across distributed agricultural environments on a large scale.

Robustness and Scalability Analysis: The fact that the proposed model has been shown to remain stable when faced with noisy data conditions as well as its capacity to support missing sensor values without experiencing a major drop in accuracy. The use of the ensemble learning technique in RF inherently reduces the effects of outliers and in-complete data. Scalability analysis shows that the system can be used in small-scale farms and in large commercial farms that carry out agriculture activities. The cloud-edge and modular IoT architecture can be expanded by smoothly incorporating more sensor nodes without impacting the system performance.

5.4 Discussion

Reliable agriculture of precision, based on the IoT, can only be guaranteed by security and data integrity. Data tampering and unauthorized access are cyber threats to the IoT systems as indicated in Table 8. Combination of encryption mechanisms, safe authentication, and storage of the data via block chain promotes confidence and data immutability. The block chain technology can offer clear and non-modifiable records of the sensor information enhancing accountability and traceability. Such security controls are essential to establishing confidence in the farmers and inspiring a large-scale use of IoT-based agricultural solutions.

Table 10. Security and Data Integrity Mechanisms for IoT-Enabled Precision Agriculture

Security Aspect	Threat Description	Impact on Agriculture	Proposed Security Mechanism	Expected Benefit
Data Transmission Security	Eavesdropping, man-in-the-middle attacks	Leakage of sensitive crop and farm data	E2E encryption (AES-256, RSA)	Confidential and secure data communication
Data Integrity	Data tampering during transmission or storage	Incorrect decision-making and yield loss	Blockchain-based immutable ledger	Tamper-proof and verifiable data records
Authentication & Access Control	Unauthorized access to IoT devices and dashboards	Manipulation of sensor data	MFA and RBAC	Controlled and authorized system access
Device Security	Physical or remote manipulation of sensors	False data injection	Secure boot and digital signatures	Device authenticity and data reliability
Traceability	Lack of data provenance	Difficulty in auditing agricultural decisions	Block chain-enabled data traceability	Transparent and accountable data lifecycle
Privacy Protection	Exposure of farm operational data	Loss of farmer trust	Privacy-preserving encryption and access	Improved trust and user adoption

			policies	
System Availability	DoS attacks	System downtime and delayed decisions	IDS and firewalls	High system availability and resilience

To conclude, the suggested IoT-based leaf structure monitoring system has proven very well in a variety of datasets and even better than the conventional ML models yet remains computationally efficient in the IoT setting. The analysis of feature importance can provide valuable actionable agronomic information, and real-time monitoring can be used to detect diseases and manage resources in optimal ways. The findings directly respond to the research problem and objectives since they offer a scalable, precise and secure solution to precision agriculture. The results confirm the usefulness of IoT, ML, and decision support system integration in the effort to increase crop yield and sustainability in the farming processes.

6. Conclusion and Future Scope

In this paper, an IoT-enabled gadget in the form of a leaf structure that has the potential to revolutionize precision agriculture, increasing the yield of harvests and reducing the overall impact on the environment, is examined. The timely intervention is also precise and enabled by the work. The solution assisted farmers in the practice of sustainability since it minimized wastage and enhanced environmental management. The monitoring technology of agricultural leaf structure based on the IoT had great potential. Studies have established that the Random Forest model was more accurate than other models in handling large data sets, over fitting, and missing values. The rankings of feature significance also gave useful information. Random Forest was the superior model to use with complicated and noisy data due to the fact that it combined many trees in order to enhance resilience and predictive performance as compared to single decision trees or other less complex models. The algorithms of ML and AI would have improved the data processing, allowing predictive analytics and recommendations towards farming, to be more precise. The system might have connected to drones and autonomous vehicles and been adapted to work on dissimilar varieties of crops and agricultural contexts including small farms and large business ventures. The IoT required an upgrade of its infrastructure to safeguard the information of consumers.
Further developments in IoT and ML should be encouraging more farming inventions, enhance efficiency, durability, and adoptions to evolving environmental and climatic conditions. The suggested IoT-based leaf structure monitoring system opens a number of potential areas of research in the future. A further development of deep learning methods, including lightweight convolution neural networks and transformers, may be pursued in order to improve the appearance of features in complex leaf images and still be compatible with edge devices. Further accuracy in prediction of crop yields as well as in decision-making can be enhanced by incorporating other data sources such as soil nutrient sensors, weather stations and satellite imagery. The use of autonomous drones and robotic platforms to monitor the field and collect data on a large scale may also be examined in further research. Smart contracts that operate on block chain technology can be expanded into facilitating the secure sharing of data between: farmers, suppliers and policymakers which will guarantee transparency and traceability throughout the agricultural value chain. In addition, field experiments (in different crops and over different climatic conditions) over both short-term and long-term periods are necessary to confirm the robustness of the system and its economic viability. These innovations will lead to creation of smart, scalable and sustainable systems of precision farming.

Acknowledgements
This paper is an extended version of our previously published conference paper presented at the **AICON 2025** conference, organized by the ICST Institute for Computer Sciences, Social Informatics and Telecommunications Engineering. The original work was published in *S. Goel et al. (Eds.): AICON 2025, LNICST 672, pp. 22–39, 2026*, by Springer Nature Switzerland AG, 2026.

The extended version includes significant improvements such as additional experimental analysis, enhanced methodology, updated results, and expanded discussions beyond the scope of the original conference publication.

Original Paper DOI: https://doi.org/10.1007/978-3-032-14805-6_2

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-PacificConference 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
[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 farming 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. A. Shaikh, T. Rasool, and F. R. Lone: Towards leveraging the role of machine learning and artificial intelligence in precision agriculture and smart farming, Computers and Electronics in Agriculture, 198, 107119, 2022.
[17] G. Muthugurunathan, S. Padmapriya, L. Leelavathy, V. Talukdar, A. Gupta and M. Mittal: Smart Conversations: Enhancing User Engagement through NLP in IoT Environments , 11th International Conference on Reliability, Infocom Technologies and Optimization(Trends and Future Directions) (ICRITO), 1-6, 2024, DOI:10.1109/ICRITO61523.2024.10522332.
[18] R. K. Naresh, M. S. Chandra, G. R. Charankumar, J. Chaitanya, M. S. Alam, P. K. Singh, and P. Ahlawat: The prospect of artificial intelligence (AI) in precision agriculture for farming systems productivity in sub-tropical India: A review, Current Journal of Applied Science and Technology, 39(48), 96-110, 2020.
[19] T. Talaviya, D. Shah, N. Patel, H. Yagnik, and M. Shah: Implementation of artificialintelligence in agriculture for optimization of irrigation and application of pesticides and herbicides, Artificial Intelligence in Agriculture, 4, 58-73, 2020.
[20] M. Malo: Artificial intelligence in agriculture: strengthening the future of farming,Agriculture& Food e-Newsletter, 71, 2020.
[21] A. Comegna:S. B. M. Hassan, and A. Coppola: Development and Application of an IoT-Based System for Soil Water Status Monitoring in a Soil Profile, Sensors, 24(9), 2725, 2024. DOI: 10.3390/s24092725.
[22] R. Prasad, R. Tiwari, and A. K. Srivastava: Internet of Things-Based Fuzzy Logic Controller for Smart Soil Health Monitoring: A Case Study of Semi-Arid Regions of India, ECSA, 2023. DOI: 10.3390/ecsa-10-16208.
[23] P. Venkateshwari, V. Veeraiah, V. Talukdar, D. N. Gupta, R. Anand and A. Gupta: Smart City Technical Planning Based on Time Series Forecasting of IOT Data, 2023 International Conference on Sustainable Emerging Innovations in Engineering and Technology (ICSEIET), 646-651, 2023.DOI: 10.1109/ICSEIET58677.2023.10303480.
[24] M. K. Senapaty, A. Ray, and N. Padhy: IoT-Enabled Soil Nutrient Analysis and CropRecommendation Model for Precision Agriculture, Computers, 12(3), 61, 2023. DOI: 10.3390/computers12030061.
[25] T. Maity, A. Roy, O. Das, R. Kashyap, A. Mishra, and J. Samanta: Design and Development of IoT-Based Smart Health Monitoring System for Greenhouse Cultivation, Studies in Autonomic, Data-driven and Industrial Computing. Springer Nature Singapore, 173–185, 2024. DOI: 10.1007/978-981-99-5435-3_12.
[26] A. Raza, M. A. Shahid, M. Safdar, M. Zaman, M. Abdur, R. Tariq, and M. U. Hassan: Artificial Intelligence-Enabled Precision Agriculture: A Review of Applications andChallenges, presented at the 2nd International Electronic Conference on Agriculture, 1, 15, 2023.
[27] O. Adewusi, O. F. Asuzu, T. Olorunsogo, C. Iwuanyanwu, E. Adaga, and D. O. Daraojimba: AI in precision agriculture: A review of technologies for sustainable farming practices, World Journal of Advanced Research and Reviews, 21(1), pp. 2276-2285, 2024.
[28] Y. Jararweh, S. Fatima, M. Jarrah, and S. AlZu'bi: Smart and sustainable agriculture. Fundamentals, enabling technologies, and future directions, Computers and Electrical Engineering, 110, 108799, 2023. DOI: 10.1016/j.compeleceng.2023.108799.