

# A Review of Integrated CNN and ML Models for Crop Disease Diagnosis, Soil-Nutrient-Based Crop Selection, and Yield Forecasting

Deshmukh Harshal Dattatraya<sup>1</sup>, Prof. Jagruti R. Mahajan<sup>2</sup>, Dr. Hemantkumar B. Jadhav<sup>3</sup>,  
Prof. Pragati B. Chandane<sup>4</sup>, Dr. Pradeep M. Patil<sup>5</sup>

<sup>1</sup>Student, Department of Computer Engineering

<sup>2,3,4</sup>Assistant Professor, Department of Computer Engineering

<sup>5</sup>Principal, Adsul Technical Campus, Chas, Ahilyanagar (MS) India  
Adsul Technical Campus, Chas, Ahilyanagar (MS) India

**Abstract:** *Recent advancements in artificial intelligence have led to significant progress in agricultural automation, particularly in the areas of crop disease detection, crop recommendation, and yield prediction. This review paper examines the development of integrated systems that combine deep learning and machine learning to support data-driven decision-making in farming. A detailed analysis is presented on Convolutional Neural Networks (CNNs) used for identifying diseases from leaf images, as well as machine learning models that utilize soil nutrient values—specifically nitrogen, phosphorus, and potassium (NPK)—along with climatic factors to recommend suitable crops. The study also reviews current regression-based approaches for estimating crop yield using environmental, soil, and plant-related parameters. Existing research, methodologies, datasets, performance trends, strengths, and limitations of these approaches are summarized to provide a unified understanding of the field. The review highlights the increasing need for integrated frameworks that combine image-based diagnostics and soil-nutrient analysis to improve crop productivity. Future directions emphasize robustness in real-world conditions, localized datasets, and scalable intelligent systems for precision agriculture.*

**Keywords:** Deep Learning, Machine Learning, Crop Disease Detection, CNN, NPK Analysis, Crop Recommendation, Yield Prediction, Smart Agriculture, Precision Farming, Agricultural Decision Support Systems

## I. INTRODUCTION

Agriculture plays a central role in sustaining the global population, and its efficiency directly influences food security, rural development, and economic stability. With the growing demand for agricultural output and the increasing pressures of climate change, traditional farming practices are no longer sufficient to ensure consistent productivity [1]. In recent years, artificial intelligence (AI), deep learning (DL), and machine learning (ML) have emerged as transformative technologies capable of addressing long-standing challenges in agriculture. These technologies assist farmers in identifying crop diseases early, selecting suitable crops based on soil conditions, and predicting yield outcomes with improved accuracy. The integration of digital tools with field-level data has opened new pathways for creating intelligent decision-support systems that reduce crop losses, optimize resource utilization, and enhance overall farm management efficiency [2], [3].

Plant diseases continue to be a major cause of crop loss worldwide, affecting both small-scale and commercial farmers. Early identification and treatment of these diseases play a crucial role in minimizing economic damage and protecting food quality [4]. Traditional disease detection methods rely heavily on manual field inspection, which requires domain expertise and is often time-consuming, subjective, and prone to human error [5]. Deep learning models, particularly Convolutional Neural Networks (CNNs), have proven highly effective in analyzing plant leaf images and distinguishing between healthy and diseased crops [6]. These models automatically extract features from images, eliminating the need



for handcrafted feature engineering and enabling reliable disease classification across various crop types and environmental conditions [7], [8].

In addition to plant health, soil quality remains a fundamental determinant of crop performance. Soil nutrient levels—especially Nitrogen (N), Phosphorus (P), and Potassium (K)—are essential for plant growth, energy transfer, and disease resistance [9]. Farmers traditionally rely on local experience or general guidelines for selecting crops suitable for their land, which may lead to suboptimal outcomes [10]. ML-based crop recommendation systems offer a data-driven approach by analyzing NPK values along with environmental factors such as temperature, humidity, pH, and rainfall to suggest the most compatible crop for cultivation [11], [12]. Random Forest classifiers and other ensemble techniques are widely used due to their robustness and ability to handle nonlinear feature interactions [13].

Crop yield prediction is another critical area where AI-driven approaches have shown substantial promise. Yield estimation depends on numerous factors, including soil fertility, climate patterns, crop type, and the presence of diseases [14]. ML regression models such as Random Forest Regressor, Gradient Boosting, and neural network-based regressors have demonstrated strong predictive capabilities when trained on historical and environmental datasets [15], [16]. These predictive tools enable farmers and policymakers to plan agricultural activities more effectively, estimate production levels, and mitigate risks arising from unexpected climatic variations or disease outbreaks [17].

Recent research highlights the importance of integrating multiple AI components into a unified framework to address the full cycle of agricultural decision-making [18]. Systems that combine disease detection, crop recommendation, and yield prediction provide farmers with a comprehensive solution that minimizes uncertainty at various stages of crop production. A multi-component approach also improves the reliability of predictions, as the insights from one module—such as disease diagnosis—can influence yield estimation or crop selection [19]. Such integrated frameworks are becoming increasingly feasible due to advancements in sensor technology, availability of agricultural datasets, and cloud-based AI deployment models [20].

Despite promising developments, several challenges persist that limit large-scale adoption of AI in agriculture. Variability in soil composition, plant species, geographic conditions, and farming practices significantly affects model performance across regions [21]. Image-based disease detection models often struggle when exposed to real-world conditions involving varying lighting, background noise, or leaf occlusion [22]. Similarly, yield prediction systems face difficulties due to inconsistent or incomplete datasets, especially in rural areas where historical data is scarce [23]. Addressing these limitations requires region-specific datasets, scalable architectures, and continual model retraining to adapt to local environmental dynamics [24]. The need for cost-effective, user-friendly tools further emphasizes the importance of developing intelligent agricultural systems that can be accessed by farmers with minimal technical expertise [25].

### **Motivation**

The growing challenges of modern agriculture—such as rising crop diseases, declining soil fertility, unpredictable climate conditions, and the need for higher productivity—highlight the necessity for intelligent, data-driven solutions. Farmers often rely on manual observation and traditional knowledge, which may lead to delayed disease detection, improper crop selection, and inaccurate yield estimation. By integrating deep learning and machine learning techniques, it becomes possible to automate disease diagnosis, analyze soil nutrients effectively, and predict yield with greater accuracy. This motivates the development of a unified AI-based framework that can empower farmers to make timely, informed decisions, reduce crop losses, optimize resource use, and ultimately improve agricultural sustainability and profitability.

### **Goals and Objectives**

- To classify plant diseases accurately using CNN-based image analysis.
- To recommend the most suitable crop based on NPK and environmental parameters.
- To predict crop yield using machine learning regression models.
- To integrate disease detection, crop selection, and yield prediction into one framework.



- To support timely and data-driven agricultural decision-making

### Scope

The scope of this review focuses on analyzing deep learning and machine learning techniques applied to crop disease detection, soil-nutrient-based crop recommendation, and crop yield prediction. It covers CNN-based image classification methods, NPK-driven recommendation models, and regression approaches for yield forecasting. The study evaluates existing frameworks, datasets, methodologies, advantages, and limitations, and outlines how these components can be integrated into a unified intelligent agricultural system. The scope is limited to digital, data-driven approaches and does not include traditional agronomic or manual diagnostic practices.

## II. EXISTING SYSTEM

Deep learning has become one of the most widely adopted techniques for crop disease diagnosis, and numerous studies have explored its potential for image-based plant health assessment. Mohanty et al. [1] conducted one of the earliest large-scale investigations using deep CNN architectures on the PlantVillage dataset and demonstrated that deep learning models can outperform traditional machine learning approaches in identifying plant diseases. Their work established a solid baseline for image-driven diagnosis and inspired subsequent research into multi-crop disease classification. Following this, Sladojevic et al. [2] presented a practical system using a custom CNN architecture to recognize diseases from leaf images and achieved promising results across multiple crop categories. The study highlighted the importance of robust feature extraction for disease classification and showed that CNNs could reliably distinguish subtle visual differences among disease classes.

Several researchers extended these efforts by incorporating deeper and more complex neural networks. Too et al. [3] evaluated various deep CNN models, including VGG, ResNet, and DenseNet, for plant disease classification and demonstrated that transfer learning significantly improves model performance. Their comparative study concluded that deeper architectures, particularly DenseNet, yield superior results due to enhanced feature propagation. Similarly, Ferentinos [4] implemented deep neural networks for real-time plant disease identification across 58 classes and reported high classification accuracy, thus showcasing the potential of scalable CNN-based systems for agricultural applications. These studies collectively emphasize that CNN models have become the standard backbone for crop disease detection due to their high accuracy and robustness.

In addition to pure image-based systems, researchers have also integrated environmental and soil-related data for improved agricultural decision-making. Pantazi et al. [5] introduced a system that combines machine learning with precision agriculture sensors to predict crop status and detect potential issues early. Their findings showed that integrating environmental variables can enhance the reliability of predictions. Likewise, Liakos et al. [6] provided an extensive review of machine learning applications in agriculture, including crop recommendation and yield prediction. Their work highlighted that algorithms such as Random Forest, Support Vector Machines (SVM), and regression models play an important role in analyzing soil nutrients and environmental parameters.

Another important contribution to the field is the work by Chlingaryan et al. [7], who examined advanced predictive analytics techniques for precision agriculture. Their study emphasized the importance of data fusion, especially when combining soil nutrient values with climatic data for crop-related predictions. Similarly, Jeong et al. [8] proposed a yield prediction framework using climatic variables, soil characteristics, and machine learning regression models. Their research demonstrated that models such as Random Forest Regressor can effectively capture nonlinear relationships in multi-factor agricultural datasets.

Deep learning-based yield prediction has also gained interest in recent years. Khaki and Wang [9] introduced a deep neural network model for corn yield prediction and demonstrated that deep learning substantially outperforms traditional statistical methods. Their results indicate that yield forecasting improves significantly when models incorporate multiple environmental parameters. Further, Sun et al. [10] developed a hybrid approach that integrates CNNs and LSTMs to capture both spatial and temporal features for crop yield estimation, reporting increased prediction accuracy across multiple datasets.



Collectively, these existing systems demonstrate immense progress in crop disease detection, crop recommendation, and yield prediction. However, most studies remain limited to single-objective tasks, such as disease diagnosis alone or yield prediction alone, without providing an integrated solution. This gap highlights the need for a unified framework that combines CNN-based disease classification, nutrient-driven crop recommendation, and machine learning-based yield prediction into a single intelligent decision-support system for agriculture..

### III. PROPOSED SYSTEM

The proposed system introduces an integrated deep learning and machine learning framework that combines crop disease classification, crop recommendation, and crop yield prediction within a unified architecture. Unlike existing systems that address these tasks independently, the proposed design allows simultaneous analysis of leaf images, soil nutrient values, and environmental parameters to support comprehensive agricultural decision-making. The framework aims to assist farmers in identifying diseases early, selecting appropriate crops based on soil fertility, and estimating potential crop yield before cultivation, thereby reducing risk and improving productivity.

The system architecture is composed of three major modules: CNN-based disease classification, NPK-driven crop recommendation, and regression-based yield prediction. In the first module, the system processes leaf images using a Convolutional Neural Network trained on multi-crop datasets consisting of wheat, corn, citrus, tomato, and other crops. The CNN performs feature extraction through convolution, pooling, and dense layers to identify visual patterns associated with diseases. The output layer classifies the leaf image into healthy or diseased categories, and in case of disease presence, specifies the type and severity. This module provides immediate diagnostic insight and reduces dependency on manual inspection.

In the second module, the system analyzes soil nutrient values (N, P, K), alongside temperature, humidity, rainfall, pH, and land area. These parameters are fed into a Random Forest Classifier trained on multi-crop agricultural datasets. The model evaluates the suitability of various crops by learning patterns between soil fertility and successful cultivation outcomes. The recommendation module outputs the most suitable crop options ranked by probability, enabling farmers to choose crops that best match the current soil and climatic conditions. This approach improves resource planning and reduces the risk of poor crop selection.

The third module focuses on yield prediction using machine learning regression models such as Random Forest Regression or Gradient Boosting Regression. The model receives input features including soil nutrients, weather variables, historical yield records, irrigation availability, and recommended crop type. By capturing complex nonlinear relationships among these variables, the regression model estimates the expected yield for the selected crop. This prediction supports farmers in planning harvesting, assessing profitability, and making informed decisions regarding fertilizer use and irrigation scheduling.

To ensure seamless integration, a unified data pipeline is implemented, where each module communicates with the others using a structured feature-sharing mechanism. Leaf image classification results contribute to the final decision-making framework by identifying whether the crop is fit for cultivation or if alternative crops should be recommended. Similarly, the crop recommendation module provides input to the yield prediction model, ensuring that prediction is aligned with the suggested crop type. A user-friendly interface allows farmers to upload leaf images, enter soil and environmental parameters, and receive outputs in the form of disease status, recommended crops, and estimated yield. The system can be deployed on mobile or web platforms for broad accessibility.

Overall, the proposed integrated system enhances agricultural intelligence by combining visual diagnostics with soil analysis and predictive modeling. It addresses gaps in existing works by offering a multi-functional solution that supports disease detection, crop selection, and yield forecasting within a single framework. This unified approach improves efficiency, reduces manual effort, and contributes toward developing scalable smart farming technologies that can be adopted in real-world agricultural environments.

### IV. SYSTEM DESIGN

The Atithi Accommodation Booking Platform is designed as a modular, scalable, and secure full-stack web application to automate accommodation management efficiently. The system design focuses on separating concerns through



layered architecture, ensuring maintainability, reusability, and ease of future expansion. The architecture follows a Model–View–Controller (MVC) pattern, which allows clear separation between presentation, business logic, and data management layers. The proposed system is designed as an integrated computational framework that combines plant disease classification, soil-nutrient-based crop recommendation, and machine-learning–driven yield prediction. The overall system design ensures a unified workflow where image data, soil attributes, and environmental parameters are processed together to generate intelligent and actionable insights for farmers. The system design is organized into multiple structured components, each responsible for a specific analytical task, yet capable of interacting seamlessly with others to support end-to-end agricultural decision-making.

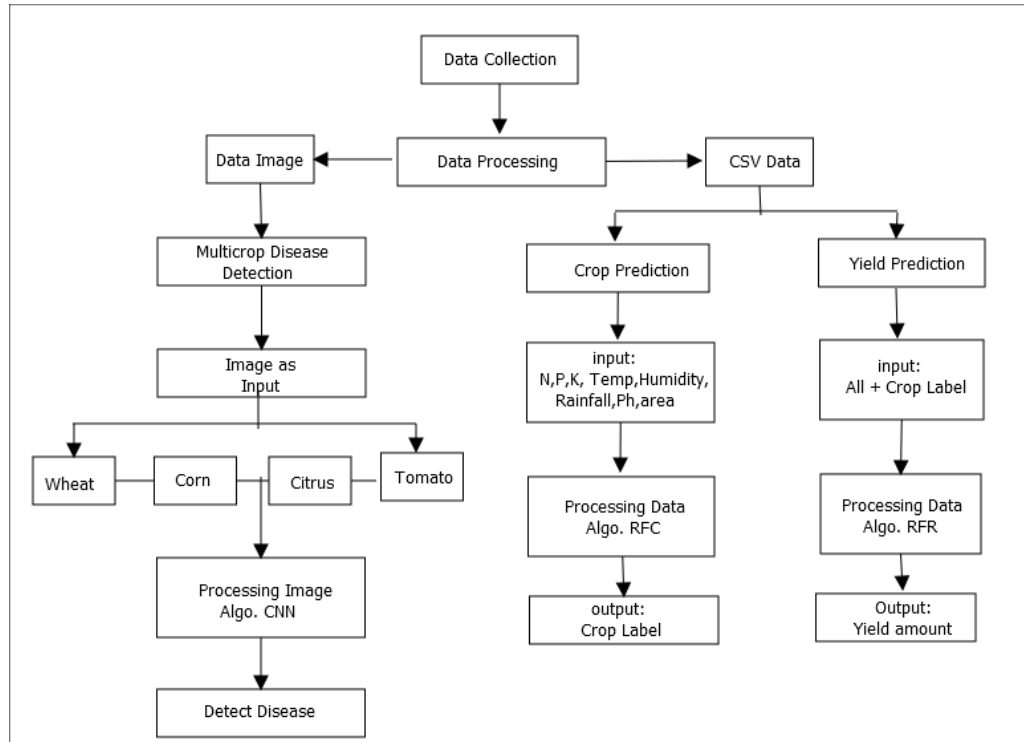


Figure 1: System Architecture Diagram

### A. Overall Design Concept

The design philosophy of the system is based on creating a unified, data-centric agricultural intelligence platform. Instead of handling disease detection, crop recommendation, and yield prediction separately, the system integrates all modules into a single decision-support pipeline.

It emphasizes the following principles:

#### Multi-Input Integration

The system accepts two forms of input:

Leaf images for disease detection

Soil NPK values and environmental parameters for recommendation and yield prediction

#### Modular Processing

Each analytical task is handled by an independent module, ensuring scalability, maintainability, and clarity.

#### Inter-Module Communication

Output from one module (e.g., disease classification) can influence downstream modules (e.g., yield estimation).

#### Human-Centered Output Delivery

Results are presented in simple, actionable terms so that farmers or extension workers can make informed decisions quickly.



## **B. Major System Components**

### **1. Plant Disease Classification Module**

This module is responsible for analyzing leaf images and identifying disease conditions.

#### **a. Image Pre-Processing**

Normalization and resizing to ensure uniform dimensions

Noise filtering to improve model clarity

Background reduction to focus on the leaf region

#### **b. Feature Extraction and Classification**

A Convolutional Neural Network (CNN) extracts spatial patterns from images

The model identifies symptoms such as discoloration, spots, fungal growth, lesions, or wilt

The system outputs:

Disease name

Confidence level

Health status (Healthy/Unhealthy)

#### **c. Decision Contribution**

If a disease is detected, the module flags plant health as compromised

This information is forwarded to the yield prediction module to adjust expected productivity

### **2. Soil-Nutrient-Based Crop Recommendation Module**

This component predicts the most suitable crop based on soil chemistry and environmental conditions.

#### **a. Input Parameters**

Nitrogen (N)

Phosphorus (P)

Potassium (K)

pH level

Temperature

Humidity

Rainfall

Farm area

#### **b. Data Modeling**

A Random Forest Classifier analyzes soil nutrient patterns and environmental factors

The model evaluates crop suitability based on historical relationships between soil features and successful cultivation outcomes

#### **c. Output Generation**

Ranks crops according to suitability

Provides a probability score for each recommended crop

Ensures alignment between soil properties and crop nutrient requirements

### **3. Crop Yield Prediction Module**

This module estimates the potential yield for the recommended crop.

#### **a. Feature Inputs**

Soil NPK values

Weather and climatic factors

Historical yield data

Recommended crop type

Disease status from the first module

#### **b. Regression-Based Estimation**

Machine learning regression models (Random Forest Regression or Gradient Boosting Regression) learn the relationship between multiple variables and yield quantity

**Copyright to IJARSCT**

**[www.ijarsct.co.in](http://www.ijarsct.co.in)**

**DOI: 10.48175/568**



The model accounts for non-linear interactions between soil fertility, crop type, and environmental conditions

**c. Predicted Output**

Expected yield (kg/ha or quintals/acre)

Confidence estimate

Yield variation range based on environmental uncertainty

**C. Integrated Workflow Design**

The system follows a sequential yet interconnected workflow:

**Leaf Image Classification**

User uploads an image → processed through CNN → disease label generated.

**Soil and Climate Data Evaluation**

Farmer inputs NPK and environmental parameters → analyzed for crop suitability.

**Synchronized Decision Flow**

Disease status influences the interpretation of yield and feasibility of recommended crops.

**Final Decision Synthesis**

The system combines:

Disease detection result

Best crop recommendation

Expected yield value

**User-Ready Output**

A consolidated result is presented, enabling farmers to choose the correct crop, prevent disease spread, and plan harvest cycles.

**D. Key Design Features****1. Multi-Crop Support**

The system can classify diseases across multiple crops such as wheat, tomato, maize, and citrus, ensuring broad usability.

**2. Unified Decision Support**

All outputs—disease status, recommended crop, expected yield—are integrated to avoid conflicting or isolated decisions.

**3. Scalability**

Modular design allows adding new crops, diseases, and soil parameters without redesigning the entire architecture.

**4. Explainability**

Each module produces interpretable results, essential for agricultural practitioners.

**5. Automation and User Convenience**

Minimal manual intervention is required; users only upload one image and enter soil attributes.

**E. Benefits of the Proposed Design**

**Early Disease Identification** prevents crop loss and supports timely treatment.

**Scientifically Informed Crop Recommendation** reduces uncertainty in cultivation decisions.

**Predictive Yield Estimation** improves planning, resource allocation, and market readiness.

**All-in-one System** avoids the need for separate tools and ensures consistent results across modules.

**Supports Precision Agriculture** through data-driven farming insights.

**V. EXPECTED OUTCOMES**

The proposed integrated framework is expected to deliver accurate and reliable results across all major components of the system. The CNN-based disease classification module is anticipated to provide high precision in identifying multi-crop diseases from leaf images, helping farmers take timely corrective actions. The NPK-driven crop recommendation module is expected to suggest the most suitable crop based on soil nutrients and environmental conditions, improving land utilization and reducing the risk of crop failure. Additionally, the machine learning-based yield prediction component is projected to forecast crop output with improved accuracy, enabling better planning and resource



management. Overall, the system is expected to enhance agricultural decision-making through automation, reduce manual dependency, and support sustainable farming practices.

## VI. CONCLUSION

The proposed integrated framework effectively combines deep learning and machine learning to address major agricultural challenges such as disease diagnosis, crop selection, and yield prediction. By unifying image-based disease classification with NPK-based crop recommendation and regression-driven yield forecasting, the system provides farmers with a reliable, automated decision-support tool. This contributes to improved productivity, reduced losses, and more efficient agricultural planning.

## VII. FUTURE WORK

Future advancements may include expanding the model to support additional crop varieties, integrating real-time sensor networks, incorporating satellite-based remote sensing data, and developing a mobile application for field-level deployment. The system can also be enhanced by adopting advanced deep learning architectures and IoT-enabled automation for continuous monitoring and precision farming.

## REFERENCES

- [1] S. Sladojevic, M. Arsenovic, A. Anderla, D. Culibrk, and D. Stefanovic, "Deep Neural Networks Based Recognition of Plant Diseases by Leaf Image Classification," *Computational Intelligence and Neuroscience*, vol. 2016, pp. 1–11, 2016.
- [2] P. Mohanty, D. Hughes, and M. Salathé, "Using Deep Learning for Image-Based Plant Disease Detection," *Frontiers in Plant Science*, vol. 7, pp. 1–10, 2016.
- [3] A. Ferentinos, "Deep Learning Models for Plant Disease Detection and Diagnosis," *Computers and Electronics in Agriculture*, vol. 145, pp. 311–318, 2018.
- [4] X. Zhang, Y. Qiao, F. Meng, C. Fan, and M. Zhang, "Identification of Maize Leaf Diseases Based on Improved Deep Convolutional Neural Networks," *IEEE Access*, vol. 6, pp. 30370–30377, 2018.
- [5] N. Brahimi, K. Boukhalfa, and A. Moussaoui, "Deep Learning for Tomato Diseases: Classification and Symptoms Visualization," *Applied Artificial Intelligence*, vol. 32, pp. 1–13, 2018.
- [6] S. Too et al., "A Comparative Study of Fine-Tuning Deep Learning Models for Plant Disease Identification," *Computers and Electronics in Agriculture*, vol. 161, pp. 272–279, 2019.
- [7] Q. Wang, S. Li, X. Liu, and J. Liu, "Recognition of Apple Leaf Diseases Using Deep Convolutional Neural Networks," *Symmetry*, vol. 11, pp. 1–14, 2019.
- [8] J. Chen, J. Wang, and Z. Guo, "A Deep Transfer Learning Method for Plant Disease Detection," *Applied Sciences*, vol. 10, pp. 1–14, 2020.
- [9] G. Singh and S. Sharma, "Plant Disease Detection Using Machine Learning: A Review," *International Journal of Engineering Research & Technology*, vol. 8, no. 7, pp. 111–116, 2019.
- [10] K. Fuentes et al., "A Robust Plant Disease Recognition System Using Deep Learning," *Information Processing in Agriculture*, vol. 6, pp. 506–514, 2019.
- [11] R. Pustokhina et al., "Crop Recommendation Using Soil Nutrients and Environmental Data with Machine Learning," *Journal of Ambient Intelligence and Humanized Computing*, pp. 1–12, 2020.
- [12] A. Sharma and P. Ghosh, "Nutrient-Based Crop Recommendation System Using Random Forest Algorithm," *International Journal of Advanced Computer Science and Applications*, vol. 11, no. 5, pp. 210–215, 2020.
- [13] P. Patel and P. Pandya, "Soil Classification and Crop Suggestion Using Machine Learning Techniques," *Procedia Computer Science*, vol. 160, pp. 564–571, 2019.
- [14] S. Nayak and S. Misra, "Agricultural Crop Recommendation Using Soil and Weather Data," *IEEE Region 10 Conference (TENCON)*, pp. 1028–1033, 2019.
- [15] M. Reddy and S. Rani, "Precision Agriculture: Crop Recommendation and Yield Prediction Using Machine Learning," *International Journal of Engineering and Advanced Technology*, vol. 9, no. 1, pp. 58–63, 2019.



- [16] T. Tripathi and S. Mishra, "An Intelligent Crop Recommendation System Using KNN and Random Forest," *International Journal of Innovative Technology and Exploring Engineering*, vol. 8, no. 9, pp. 2361–2366, 2019.
- [17] H. Joshi and A. Patel, "Crop Yield Prediction Using Regression Techniques," *International Journal of Computer Applications*, vol. 183, no. 48, pp. 1–5, 2021.
- [18] R. Dubey and S. Gupta, "Machine Learning-Based Crop Yield Prediction: A Survey," *Journal of Agricultural Informatics*, vol. 11, pp. 23–35, 2020.
- [19] L. Sun et al., "Deep Learning for Crop Yield Prediction Using Remote Sensing Data," *Remote Sensing*, vol. 12, pp. 1–20, 2020.
- [20] B. Khaki and L. Wang, "Crop Yield Prediction Using Deep Neural Networks," *Frontiers in Plant Science*, vol. 10, pp. 1–10, 2019.
- [21] E. Chlingaryan, S. Sukkarieh, and B. Whelan, "Machine Learning Approaches for Crop Yield Prediction and Nitrogen Management," *Computers and Electronics in Agriculture*, vol. 151, pp. 61–69, 2018.
- [22] G. Jay, D. Sundaram, and R. Srinivasan, "A Review of CNN-Based Disease Classification for Precision Agriculture," *IEEE Access*, vol. 8, pp. 180402–180422, 2020.
- [23] M. Islam et al., "A Combined Deep Learning and Machine Learning Approach for Plant Disease Detection," *Plant Methods*, vol. 16, pp. 1–12, 2020.
- [24] A. Kamilaris and F. Prenafeta-Boldú, "Deep Learning in Agriculture: A Review," *Computers and Electronics in Agriculture*, vol. 147, pp. 70–90, 2018.
- [25] S. Ma, J. Jiang, and G. Liu, "A Unified Framework for Plant Disease Detection and Crop Yield Prediction Using AI," *IEEE Transactions on Automation Science and Engineering*, pp. 1–12, 2021

