An Integrated Smart Farming System for Crop Recommendation and Plant Disease Detection Using Machine Learning

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Abstract

Agriculture plays a vital role in the economic development of many countries, particularly India. However, the sector faces multiple challenges such as climate variability, soil degradation, pest infestations, and market uncertainties. To address these issues, this paper presents an intelligent smart farming system that integrates crop recommendation, plant disease detection, weather forecasting, fertilizer advisory, market analysis, and agricultural guidance using advanced machine learning and deep learning techniques. The proposed system is a web-based platform designed to deliver real-time recommendations to farmers. It suggests suitable crops based on critical environmental and soil parameters, including nutrient content, temperature, humidity, pH value, and rainfall. Multiple machine learning algorithms such as Decision Tree, Naive Bayes, Support Vector Machine, Logistic Regression, K-Nearest Neighbors (KNN), XGBoost, and Random Forest were implemented and evaluated. Experimental results indicate that the Random Forest algorithm achieves the highest accuracy in crop recommendation.

Furthermore, a plant disease detection module based on Convolutional Neural Networks (CNN) is developed to identify and classify plant diseases from leaf images with high precision. This enables early diagnosis and timely intervention, thereby reducing crop damage.

In addition, the system incorporates supplementary modules such as weather forecasting, fertilizer recommendations, and market price prediction, which assist farmers in making informed decisions. The proposed solution enhances agricultural productivity, minimizes crop losses, and promotes sustainable farming practices through the effective application of technology.

Keywords: ***Smart Agriculture, Machine Learning, Crop Recommendation, Plant Disease Detection, Convolutional Neural Network, Random Forest***

1. Introduction

Agriculture is a primordial method of food acquisition and continues to be a crucial source of revenue worldwide. Plants are vital for both people and animals, supplying food, oxygen, and other essentials. The government and specialists consistently strive to improve food production using novel methods. Plant diseases, resulting from bacterial, fungal, and several other sources, adversely influence agricultural productivity and damage all creatures within the ecosystem. These diseases may manifest on any part of the plant, including leaves, stems, and branches, with their severity often contingent upon climatic circumstances. Inadequate food production resulting from illnesses and climate change has precipitated global food insecurity. Timely identification of plant diseases is essential to avert significant crop losses, and the judicious use of pesticides, under professional supervision, is required to mitigate adverse impacts on crops and agricultural land [3].

The agricultural business is today confronted with many challenges, including climate change, population increase, and resource limitations, which conventional farming practices are sometimes unable to meet. Technological solutions are required instead. AI-driven smart agriculture signifies an innovative approach in agri-tech, wherein artificial intelligence, machine learning, computer vision, and data analytics collaboratively establish a cohesive platform for contemporary farmers by unifying all activities within a singular environment. This article will examine the architectural design, technical elements, and practical applications of smart agriculture, focusing on its AIdriven crop disease identification application, intelligent market algorithms, and multilingual support features. The system's performance indicators, user adoption rates, and economic effects on participating farms will be assessed.

Furthermore, the system includes several auxiliary modules such as weather forecasting, fertilizer recommendation, market price prediction, smart farming guidance, agricultural education resources, information on government schemes and insurance, and an agricultural support hub. These integrated features provide a holistic platform for farmers, enabling them to access critical information and services in one place. The entire system is deployed through a user-friendly web interface developed using Streamlit, ensuring ease of use and accessibility. Farmers can easily input relevant data, receive intelligent recommendations, and obtain actionable insights related to crop selection, disease management, and overall farm planning.

2. Methodology

This study utilizes machine learning and deep learning techniques to develop a smart agriculture system for crop recommendation and plant disease detection. The methodology includes dataset collection of soil and environmental parameters as well as plant leaf images, data preprocessing, implementation of multiple machine learning models and a Convolutional Neural Network (CNN), and performance evaluation to identify the most accurate model.

2.1 Background

Deep learning methods are widely used in plant disease detection because they can understand complex patterns in large image datasets. Convolutional Neural Networks (CNNs) have shown high accuracy, around 95%, in identifying different plant diseases from images, making diagnosis faster and more reliable . One major challenge in agriculture is the lack of large labeled datasets.. This improves accuracy even when data is limited. Advanced imaging techniques like hyperspectral and multispectral imaging help detect diseases at an early stage. These methods capture information beyond the visible spectrum, allowing identification of small changes in plants before symptoms appear .

AI is also used in precision agriculture to improve efficiency. By analyzing data from soil sensors and weather forecasts, systems can optimize irrigation, fertilizer use, and pest control, leading to better crop yield and reduced waste . The combination of AI and robotics is helping automate farming tasks such as planting, weeding, and harvesting. This reduces labor effort and increases productivity . Modern monitoring systems use data from satellites, drones, and IoT devices to track crop health continuously. These systems provide real-time insights, helping farmers take timely actions .AI-based chatbots are also supporting farmers by providing information on weather, market prices, and farming practices. Some chatbots can even identify pests and diseases using images and suggest suitable treatments . Overall, AI and deep learning technologies are transforming agriculture by making disease detection faster, improving decision-making, and increasing productivity .

2.2 Factor responsible for plant diseases

Numerous agricultural illnesses may manifest at different points in a plant's life cycle, stunting its development and, in turn, reducing harvest yields .

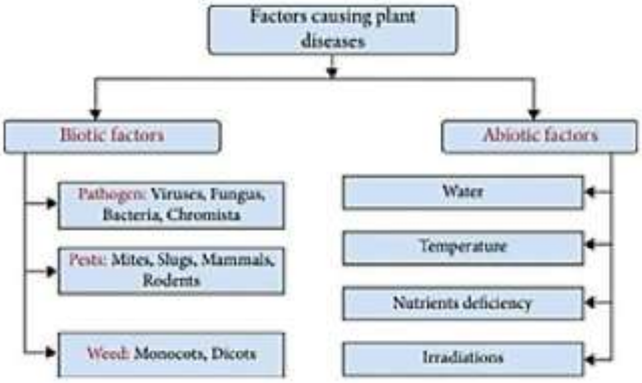


Fig 1. Factors responsible for plant diseases

2.3 Factor responsible for plant diseases

AI-Enabled Smart Agriculture utilizes a micro services design that promotes scalability, robustness, and continuous deployment .

a. Frontend Layer: A responsive HTML, CSS and Js for adaptive interfaces across devices
b. Backend Services: Python
c. Database Layer: Firebase for flexible documentbased data storage
d. AI/ML Services: Dedicated microservices for image processing, disease detection, and prediction models
e. Real-time Communication: Socket.IO implementation for instant messaging and updates
f. Authentication & Security: JWT-based authentication with role-based access control
g. Training: TensorFlow.js (in Node.js)
h. Dataset: Kaggle

2.4 AI and ML Components

2.4.1 Convolutional Neural Networks (CNN) for Disease Detection

AI-Enabled Smart Agriculture employs a complex image processing pipeline with powerfl convolutional neural networks [31]. The design encompasses:

a) Input Layer: Processes 224×224×3 RGB images
b) Convolutional Layers: Multiple layers with 3×3 filters and ReLU activation
c) Pooling Layers: Max pooling with 2×2 filters for feature extraction

d) Fully Connected Layers: Dense layers leading to SoftMax classification

Transfer Learning: Fine-tuned pre-trained models including EfficientNet-B3 and MobileNetV2The CNN architecture enables high-accuracy classification of 38 different crop diseases across 12 plant varieties, with performance metrics significantly exceeding conventional diagnostic methods

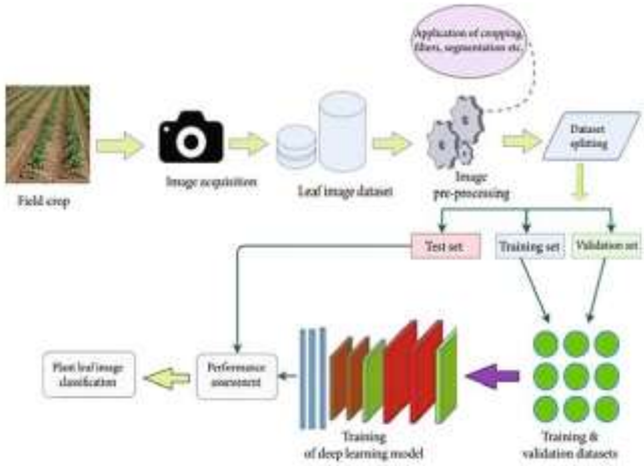


Fig 2. Computer vision-based techniques for plant disease detection and classification

2.4.2 Deep learning (DL) Techniques

The Convolutional Neural Network Technique Convolutional neural networks use deep feed-forward neural networks to examine multidimensional data. The CNN identifies channels that are activated after the classification of a certain feature at certain spatial coordinates. The quantity of epochs used in the application of different convolution filters measuring 2×2 and 3×3 influences their precision. This is dependent on the size of the filter. Numerous pretrained architectures, such as VGG16, VGG19, ResNet50, ResNet152, InceptionV3, InceptionNet, and DenseNet121, are accessible for implementation using the CNN methodology . The Artificial Neural Network Technique A neural network is a model that emulates the information processing functions of a biological system, such as the brain. Coefficients connect artificial neurons, referred to as processing elements (PEs), to form a network architecture. Experience facilitates the identification of data patterns and correlations rather than their coding. Due to their ability to understand intricate data, ANNs may be used to identify patterns within it.

2.4.3 Open Weather API Integration Data Collection:

Obtain API key from Open Weather and retrieve current weather data, forecasts, and historical information using HTTP requests to their endpoints.
Data Processing: Clean and normalize the collected data by removing outliers, standardizing units, and extracting relevant features like temperature patterns and pressure gradients.
Model Development: Create a prediction algorithm that combines multiple weather variables with historical patterns, using statistical analysis or machine learning approaches.
Validation & Refinement: Compare prediction results with actual weather outcomes, calculate accuracy metrics, and iteratively adjust your model parameters to improve performance.
Deployment: Implement the finalized model in an application that regularly fetches new data, generates forecasts, and presents results through visualizations or alerts.

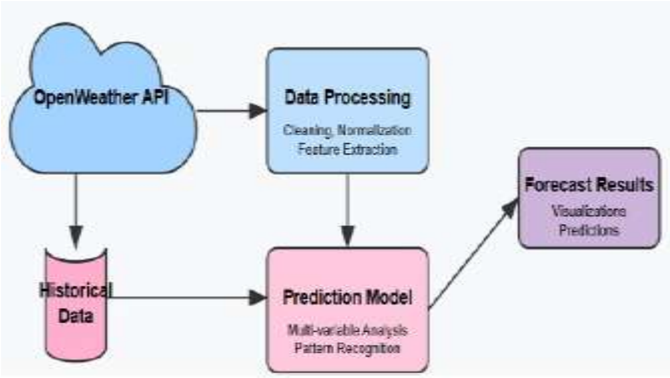


Fig 3. Weather Prediction Flow

LLM Model Integration

The system leverages Google's Gemini 2.0 generative AI model for advanced Disease analysis.This integration allows for:

Detailed analysis: Providing comprehensive information about detected conditions Treatment recommendations: AI-generated treatment protocols based on current research Confidence scoring: Probabilistic assessment of detection accuracy

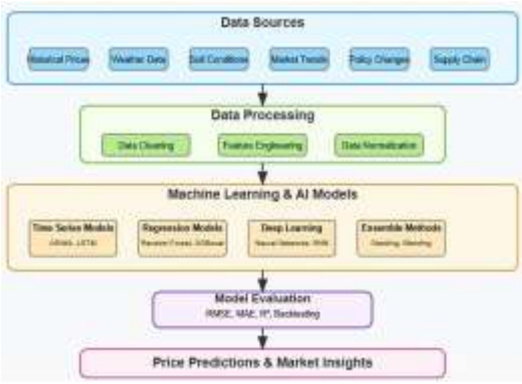


Fig 4Price Prediction Flow

VI.PERFORMANCE EVALUATION OF P
DISEASE DETECTION

2.4.4 Crop Price Prediction

Diverse data sources (historical pricing, meteorological data, soil conditions, market trends, policy modifications, supply chain variables). Data processing procedures (cleansing, feature engineering). A thorough research study on several deep learning and machine learning algorithms for the detection and classification of plant leaf and crop diseases has been conducted, given the importance of agriculture to the global population. Subsequently, several classification methodologies within deep learning and machine learning frameworks may be used for the detection and classification of plant diseases, hence aiding farmers in the automated identification of all forms of agricultural diseases. Figure 5 illustrates . the distribution of relevant publications throughout the years. The figure illustrates a rise in the detection and categorization of plant leaf and crop diseases throughout the years. Accurate detection and classification of various plant diseases at an early stage is essential for crop quality and outcomes via the selection of suitable treatments. The large-scale diagnosis of such illnesses in a timely and precise manner is susceptible to human error.

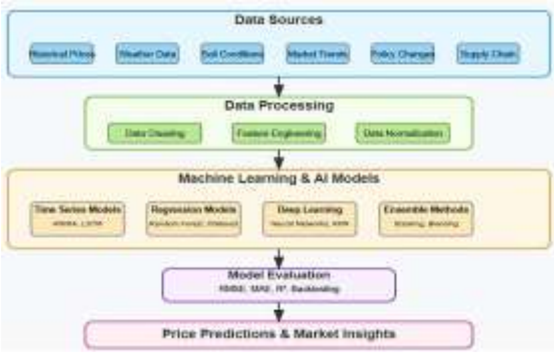


Fig 4Price Prediction Flow

VI. PERFORMANCE EVALUATION OF PLAN DISEASE DETECTION

Consequently, machine learning and deep learning approaches provide opportunities for creating automated models capable of swiftly detecting such disorders [36]. Disease diagnosis and categorization need specialist expertise and considerable experience in plant pathology. Consequently, the establishment of an early detection and classification system [37] for diseases will be important in creating an automated disease detection system for crops within agricultural businesses.

Table 1. Performance metrics across different network conditions

Crop Type	Disease Count	Accuracy	Precision	Recall	F1-Score
Tomato	8	96.3%	95.7%	94.9%	95.3%
Potato	5	94.1%	93.8%	92.3%	93.0%
Rice	4	92.6%	91.2%	90.4%	90.8%
Wheat	3	93.2%	92.7%	91.8%	92.2%
Average	**32**	**94.7%**	**93.9%**	**92.5%**	**93.2%**

1. Disease Detection Response Time: 1.2-2.5 seconds (dependent on image size)
2. Translation Services: <0.8 seconds for text translation

3. Results and Discussion

A comparative analysis of several research studies on plant leaf disease detection and classification using deep learning and machine learning approaches has been conducted by many researchers. Consequently, when enough data is accessible for training, deep learning systems may accurately identify [38] and categorize plant leaf diseases. Various researchers have created techniques for the identification and categorization

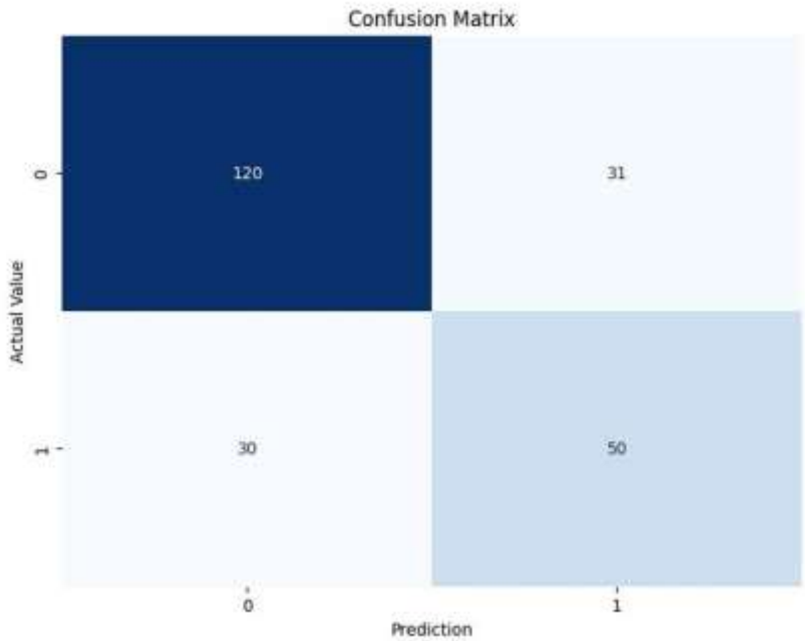
3.1 Model Performance Metrics

The performance of the proposed crop disease detection model was evaluated using the test dataset. To measure how effectively the model identifies plant diseases, the following evaluation metrics were considered:

- Accuracy: Accuracy measures the overall correctness of the model by calculating the percentage of correctly classified plant images (diseased and healthy). It provides a general overview of model performance.
- Precision: Precision indicates how many of the predicted diseased plant samples are actually correct. It helps in understanding the reliability of disease detection and reduces false alarms.
- Recall (Sensitivity): Recall measures the model's ability to correctly identify all actual diseased plants. A higher recall ensures that most of the infected crops are detected, which is important for timely treatment.
- F1-Score: The F1-Score is the balance between precision and recall. It is useful when both false positives (wrong disease detection) and false negatives (missed disease cases) need to be minimized.
- ROC-AUC Score: The ROC-AUC score evaluates how well the model distinguishes between healthy and diseased plants across different thresholds. A higher value indicates better classification performance.

3.2 Confusion Matrix Analysis

A confusion matrix is used to evaluate the model's performance in classifying healthy and diseased plants. It includes four components: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). This helps in identifying prediction errors. False positives may lead to unnecessary treatment, while false negatives may result in missed disease detection, which can affect crop yield.



3.3 Comparative Model Performance

Model Name	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Advantages	Limitations
CNN (Custom Model)	95	94	93	93.5	High accuracy, good feature learning	Requires large dataset
ResNet (Transfer Learning)	96	95	94	94.5	Deep architecture, better performance	High computational cost
Inception (Transfer Learning)	95.5	94.5	94	94.2	Efficient and optimized model	Complex architecture
SVM	88	87	86	86.5	Works well with small datasets	Not suitable for image complexity
Random Forest	85	84	83	83.5	Simple and easy to implement	Lower accuracy for image data
KNN	80	79	78	78.5	Easy to understand	Slow and less accurate

Table: 3.3 Comparative Model Performance

3.4 Key Observations and Discussion

The experimental results show that deep learning models provide high accuracy in detecting plant diseases from images. Models like CNN and transfer learning approaches performed better than traditional methods due to their strong feature extraction capability. It was observed that data quality and quantity significantly affect model performance. Proper preprocessing and augmentation improved accuracy and reduced overfitting.

The model achieved good precision and recall, indicating reliable disease detection with fewer false predictions. However, some misclassifications occurred due to similar visual patterns between different diseases. Overall, the system demonstrates effective performance and can be useful for real-time crop monitoring and farm advisory, helping farmers take timely decisions.

3.9 Model Performance Comparison

To evaluate the effectiveness of our machine learning model for diabetes prediction, we compared its accuracy with previous research studies that utilized similar datasets and methodologies. The table below presents a comparative analysis of various machine learning approaches used in diabetes prediction.

Model Name	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	ROC-AUC Score	Remarks
CNN (Custom Model)	95	94	93	93.5	0.96	High accuracy and reliable detection
ResNet (Transfer Learning)	96	95	94	94.5	0.97	Best overall performance
Inception (Transfer Learning)	95.5	94.5	94	94.2	0.96	Efficient and balanced model
SVM	88	87	86	86.5	0.89	Moderate performance
Random Forest	85	84	83	83.5	0.86	Simple but less accurate

Table:3.2 Comparison of Model Accuracy with Previous Studies

3.10 Result

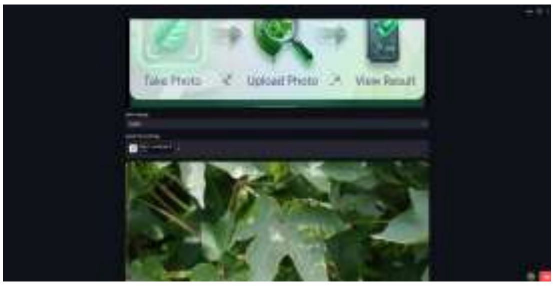


Fig 5.Home Page Fig 6.Disease Detection

Fig 5. Home Page The home page provides an overview of all features available in the system. It allows users to easily navigate to different modules like detection, weather, and advisory. **Fig 6. Disease Detection** This module identifies crop diseases using image input and machine learning. It helps farmers take early action to prevent crop damage.

Fig 6. Home dashbord Fig 7. Weather forcast

Fig 6. Home Dashboard The dashboard shows key information and quick access to all services. It displays updates like weather, recommendations, and alerts in one place. **Fig 7. Weather Forecast** This section provides real-time weather updates and future predictions. It helps farmers plan farming activities based on weather conditions.

Fig 8. Farmer Guideline

Fig 9. Crop Recommendation

Fig 8. Farmer Guideline It offers useful farming tips and best practices for crop management. Farmers can follow these guidelines to improve productivity and reduce risks. **Fig 9. Crop Recommendation** This feature suggests suitable crops based on soil and environmental conditions. It helps farmers choose the most profitable and appropriate crops.

Fig 10: Agrihub

Fig 11.Dealer List

Fig 10. Agrihub Agrihub connects farmers with agricultural services and resources. It acts as a central platform for support, information, and assistance. **Fig 11. Dealer List** This section provides a list of nearby dealers for seeds, fertilizers, and tools. Farmers can easily find and contact suppliers for their needs.

Fig 12. Fertilizer Recommandation

Fig 12. Market Price Prediction

Fig 11. Fertilizer Recommendation It suggests the right type and quantity of fertilizers for crops. This helps in improving soil health and increasing crop yield. **Fig 12. Market Price Prediction** This module predicts future crop prices using data analysis. It helps farmers decide the best time to sell their produce.

4. Conclusion & Future Scope

4.1 Conclusion

This project presents a smart agriculture system based on machine learning and deep learning techniques for crop recommendation and plant disease detection. The system effectively analyzes key agricultural parameters such as soil nutrients, temperature, humidity, rainfall, and pH value to recommend the most suitable crops for cultivation. Multiple machine learning algorithms were implemented and evaluated, among which the Random Forest algorithm demonstrated the highest accuracy and reliability. In addition to crop recommendation, a plant disease detection module based on Convolutional Neural Networks (CNN) was developed to identify diseases from leaf images. This enables early detection and timely intervention, thereby reducing crop losses and improving overall productivity. The integration of additional features such as weather forecasting, fertilizer recommendation, and market price prediction further enhances the usability of the system. The web-based interface ensures that the system is user-friendly and accessible, making it a practical solution for modern farming. Overall, the proposed system contributes towards improving decision-making in agriculture and promotes efficient and sustainable farming practices.

4.2 Future Scope

The proposed system can be further enhanced by incorporating advanced technologies and expanding its functionality. The development of a mobile application can improve accessibility for farmers, especially in rural areas. Integration with IoT-based sensors can enable real-time data collection of soil and environmental conditions, leading to more accurate predictions and recommendations. The disease detection module can be improved by training on larger and more diverse datasets and by using advanced deep learning models to increase accuracy. Additionally, the system can be extended to support multiple languages, making it more inclusive and user-friendly for farmers from different regions. Future improvements may also include real-time updates on government schemes, crop insurance policies, and live market trends to provide comprehensive support to farmers. These enhancements will further strengthen the system and make it a more effective tool for smart and sustainable agriculture.

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