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AI POWERED SOLUTIONS FOR FARMING SUCCESS

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I. ABSTRACT

Abstract— In the evolving domain of precision agriculture, machine learning is reshaping how agricultural challenges are approached in modern precision farming. This research introduces an integrated system addressing the three key domains essential for optimizing agricultural performance: leaf disease detection, crop yield prediction, and remedies recommendation. Leveraging advanced algorithms like Random Forest, XGBoost, Decision Tree, KNN, LSTM, and InceptionResNetV2, are employed across various modules, the system not only achieves exceptional prediction accuracy but also promotes sustainable, data-driven farming practices. Experimental results showcased high accuracy, with random forest achieving 99.89% in yield prediction, dysentery 99.04% in soil moisture monitoring, and InceptionResNet V2 excelling

in plant classification. Through smart predictions and actionable recommendations, our framework achieves high prediction accuracy while supporting sustainable and intelligent farming decisions, ultimately boosting crop adaptability in the face of shifting climatic patterns.

Through careful model selection and experimental validation, our framework empowers farmers with actionable insights, ensuring enhanced crop productivity and resource optimization. The experimental validation across datasets sourced from Kaggle reflects the robustness and versatility of the approach. It delivers live predictions, supports irrigation planning, advises on optimal crop selection, and identifies early signs of disease.

Keywords: crop yield prediction, leaf disease detection, random forest, XGBoost, machine learning, deep learning, remedies recommendation, precision agriculture,

II. INTRODUCTION

Agriculture remains one of the foundational pillars of India's economy, with its roots extending back to the Indus Valley civilization. Despite technological advancements in other sectors, agriculture often struggles with inconsistent productivity due to unpredictable weather patterns, soil degradation, and pest outbreaks. The agriculture sector continues to employ a significant portion of the population, contributing around 15.4% to the national GDP. In recent years, machine learning (ML) has opened new doors for revolutionizing farming practices by providing predictive insights and data-driven decision-making support. Integrating ML into agriculture offers an opportunity to tackle major challenges such as fluctuating crop yields, water resources mismanagement, and crop diseases.

The integration of machine learning into agricultural practices offers promising pathways to predictive models that can analyze historical patterns, real-time environmental data, and biological indicators to assist farmers in making informed decisions. This research focuses on building a comprehensive system using ML techniques to predict crop yields, monitor soil moisture, detect plant diseases, and recommend remedial actions, thereby enhancing farming outcomes sustainably.
Many pieces of literature are available for classifying plant diseases using machine learning. The majority were done in laboratory conditions, natural backgrounds with sunlight eliminations, and shadows. Furthermore, some literature had images taken in the natural environment but was conducted with limited data. Through this work we seek to contribute towards the modernization of farming by equipping farmers with intelligent tools that foster resilience, efficiency, and sustainability.
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This paper is organized as follows. Section II reviews related work, followed by Section III & Section IV, which present the objectives and detailed methodology used. Section V describes the experiments and results, and finally, Section VI concludes with future work.

III. LITERATURE REVIEW

In recent years, the integration of machine learning (ML) and deep learning (DL) in precision agriculture has led to significant advancements in crop monitoring, yield forecasting, and disease detection. The growing availability of agricultural datasets has allowed researchers to experiment with various supervised and unsupervised learning techniques across multiple domains of farming technology. Several studies have addressed drought prediction and sustainable farming.

In their study Suvetha et al. [1] Presented framework utilising IoT sensors and ML algorithms for early drought warnings their system collected real-time soil and atmospheric data which was then processed using support vector machines (SVM) and Random Forest models while effective in predicting moisture shortage the solution did not extend to disease management or crop recommendation.This work informs our system design by highlighting the limitations of single-function models

In their study Farooqui et al. [2] Explored the use of predictive analytics for crop yield estimation ML models like decision trees and gradient boosting were used to forecast wheat and rice yields. Although promising, the study lacked generalizability to other crops and failed to incorporate external parameters such as plant disease conditions or soil moisture levels. This work informs our system design by highlighting the limitations of single-function models

In their study Getahun et al. [3] conducted a systematic review on Precision Agriculture Technologies (PATs). The review highlighted how PATs can optimize fertilizer application, monitor soil health and reduce environmental stress on crops. However, most studies analyzed were modular in nature, each focusing only on one functionality, such as moisture sensing or pest prediction, rather than integrating multiple functionalities into one system.This work informs our system design by highlighting the limitations of single-function models

In their study Teshome et al. [4] improve soil moisture prediction by comparing various deep learning models like LSTM and GRU. Their findings suggested that hybrid models outperform traditional techniques in dynamic soil monitoring. Nevertheless, their model did not consider real-time farmer recommendations or visual plant health assessments .This work informs our system design by highlighting the limitations of single-function models

In their study Mohanty et al. [5] made a significant contribution in plant disease detection using CNN architectures like AlexNet and GoogleNet, training on a massive dataset of 54,306 images. They achieved 99.35% classification accuracy. However, their results dropped significantly, as low as 31%, when tested in non ideal Real world lighting and background conditions, releasing a gap in practical deployment.This work informs our system design by highlighting the limitations of single-function models

The intersection of agriculture and machine learning has been extensively explored over the past decade. Many studies have employed Random Forest, SVM and ensemble learning methods for specific tasks like crop yield prediction or soil health monitoring. Other research has leveraged deep learning models like CNNs for accurate plant disease classification. CNNs and architectures such as InceptionResNetV2 have proven effective in classifying plant diseases from image datasets, particularly for tomato, apple and other economically important crops. Notably ensemble methods like Voting classifiers have shown promising results in tasks involving environmental prediction where multiple parameters interact in complex ways.

However, most prior works focus on isolated aspects rather than delivering a unified, practical solution covering multiple agricultural needs simultaneously. Furthermore, the application of integrated ML models for real-time prediction and Recommendation in actual farm conditions remains limited. Our study bridges this gap by proposing an all in one precision farming system for real world applicability.

IV. OBJECTIVES

- To develop machine learning models capable of accurately predicting crop yield based on historical and environmental parameters
- To develop a robust ML-based system capable of Crop yield prediction with high accuracy.
- To design a soil moisture monitoring model that can optimize irrigation planning.
- To create a dynamic crop recommendation engine based on soil and environmental factors.
- To enable early detection of plant diseases through deep learning-based classification models.
- To build a farmer-friendly modular platform that integrates all prediction models seamlessly.
- To validate model performance using real world datasets and established practical viability for smart agriculture applications

V. METHODOLOGY

The methodology adopted for developing the platform involves multiple stages, from data acquisition to model evolution the complete workflow is illustrated and described below.

The development of this platform involved structured and sequential methodology comprising data collection, preprocessing, model development, model evolution, system integration, and results generation. Each step was carefully designed to ensure robustness, scalability, and applicability of the system in real-world agricultural scenarios.

Workflow Diagram for Image-Based Plant Disease Detection

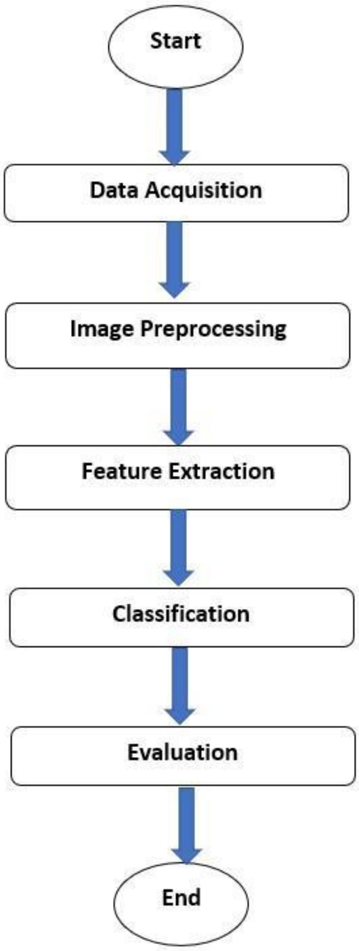


Figure 1 : Workflow Diagram for Image-Based Plant Disease Detection

This flowchart represents the sequential process of detecting plant diseases using image-based analysis. It begins with data acquisition, where leaf images are collected either from public datasets or user uploads. These images are then preprocessed — resized, normalized, and augmented — to improve quality and reduce model overfitting. The feature extraction step is carried out by a deep convolutional neural network (CNN), which automatically learns spatial patterns from image pixels. The extracted features are passed to a classification layer, which predicts the disease class. The final evaluation step computes model performance using metrics such as accuracy and the confusion matrix.

Random Forest (RF): Random Forest is effective in handling high-dimensional agricultural datasets such as multivariate soil features, enabling better prediction of non-linear crop yield trends. Each tree is built using a random subset of features and a bootstrap sample of the data, ensuring diversity among the trees. The final prediction is made through majority voting (for classification tasks), which enhances the robustness of the model. Its ability to rank features based on their importance also aids in refining the dataset during preprocessing.

K-Nearest Neighbors (KNN): KNN is a simple yet powerful instance-based learning algorithm. KNN predicts crop type or disease category by comparing new samples to their closest matches in the training data, using similarity measures like Euclidean distance or Manhattan distance. Its simplicity makes it highly interpretable, while its non-parametric nature allows it to adapt to the underlying data distribution without assuming specific forms.KNN is useful in detecting localized data clusters such as specific disease patterns in a crop region

Logistic Regression (LR): Logistic Regression is a statistical method used for binary classification tasks. Its interpretability and computational efficiency make it a preferred choice for large datasets. The inclusion of regularization techniques like L1 (Lasso) or L2 (Ridge) helps prevent overfitting, especially when dealing with a large number of features.

Data acquisition :

Dataset : The datasets for yield prediction,soil condition monitoring, and leaf disease detection were sourced from Kaggle. The datasets were preprocessed to remove anomalies, normalize features, and improve model learning efficiency.

Crop yield dataset : Containing records of crop production, soil parameters, rainfall statistics, temperature patterns and other climatic factors for

different regions over several years.
Soil moisture dataset : Comprising features like soil pH, soil temperature, moisture percentage and surrounding atmospheric parameters.
Plant disease image dataset : Tomato and Apple leaf datasets labelled as healthy or infected with specific diseases like bacterial spot, late blight, leaf mold etc .

Data preprocessing :

Before entering the datasets into machine learning, rigorous preprocessing was performed to clean, standardize, and enhance the data quality.

Numerical dataset preprocessing :

Handling missing values : Missing soil pH, rainfall, or temperature values were filled using mean or median imputation techniques.
Normalization : features were scaled between 0 and 1ing Min-Max normalization to ensure faster convergence during model training.
Feature engineering : New features were derived such as "soil moisture index" rainfall deviation index to improve prediction accuracy.

Image dataset preprocessing :

Image resizing : All leaf images were resized uniformly to 256 x 256 pixels to match model input requirements.
Data augmentation : Only applied to the training dataset to improve generalization techniques.
Techniques involved :
random rotations
horizontal and vertical flips
zoom range
brightness adjustments
Label encoding : Each disease category was encoded into numeric labels for model understanding.

Model development :

After preprocessing, separate models were developed for each major function.

- **Crop yield prediction:** implemented using Random Forest regressor, XGBoost regressor, Linear regression, KNN simple RNN and LSTM. Comparative performance analysis revealed that Random Forest and XGboost achieved the highest (~99.2-100%) while deep learning models like LSTM and RNN struggled slightly due to the sequential nature of input data.
  - **Process :**
  - We considered key agricultural factors such as soil pH levels, rainfall data, temperature readings, and past crop production records as inputs for the model
  - Input features included soil pH, rainfall, temperature and previous crop yields.
  - The output was the predicted yield in kilograms per hectare.
  - Feature importance was extracted to identify the most influential factors affecting yield.

- **Soil Moisture Monitoring:** Deployed Random Forest Classifier, Decision Tree Classifier, KNN, Naive Bayes classifier and Voting Classifier(ensemble).
  Soil moisture levels were predicted using classification models like Random Forest classifier and decision tree with voting classifiers enhancing accuracy through ensemble learning.
  - **Process :**
  - Input features included soil temperature, humidity , atmospheric pressure and previous moisture readings.
  - The model categorized the soil moisture levels into three distinct classes: high, moderate, and low, based on the input parameters

- **Crop Recommendation:** Achieved through Random Forest KNN, Naive Bayes and Voting Classifier algorithms.
  Using supervised classification algorithms, optimal crop choices were suggested based on input features like soil type, PH value, rainfall patterns and temperature .
  - **Process :**
  - To recommend the most suitable crop for the next growing season, the system analyzed environmental inputs like soil pH, rainfall trends, and temperature patterns.
  - Multi output models were trained to recommend two or three alternative crops based on environment and conditions.
- **Leaf Disease Detection:** Deep Learning models like InceptionReSNetV2 and AlexNet were trained for identifying various plant diseases.
  Process :
  - Transfer learning was employed : pretrained models on ImageNet were adapted to our agriculture dataset.
  - The last few layers were customized (the softmax layer was adjusted to the number of disease classes).

  Evaluation Matrix :
  - Accuracy.

- Precision, recall, and F1 score per class.
- ROC-AUC curve.

Model Training & Evaluation:

Each model's performance was carefully tested using a thorough validation process to ensure reliability and accuracy.

- **5-fold cross validation :**
  Ensured model generalization and avoided overfitting.
- **Confusion matrices and ROC Curves :**
  Provided insight into misclassification trends.
- **Feature importance ranking :**
  Helped interpret which environmental factors most influence yield and moisture.
- **Hyper parameter tuning :**
  Grid search and Randomized search employed for models like Random Forest and XGBoost to optimize performance.

Each model underwent hyperparameter tuning using Grid Search and Random Search techniques where feasible.
Performance metrics recorded included:

- **Accuracy:** For classification models.
- **R² Score:** For regression models (yield prediction).
- **Confusion Matrix and Precision-Recall curves:** For disease detection models.

Cross-validation techniques (5-fold) were adopted to ensure reliability and prevent model overfitting.

System integration and data flow :

All independently trained models were orchestrated into a modular platform.

System data flow

- **User input: The farmer** provides environmental data on rainfall, soil pH, temperature, and leaf images via web or mobile app.
- **Data preprocessing :** Inputs are normalized images, and features are extracted automatically in real -time.
- **Model selection :** The back and system roots inputs to appropriate trained models.
  - Crop yield model → Predicts production quantity.
  - Soil moisture model → Classifies irrigated needs.
  - Disease detection model → Identify plant health status.
  - Crop recommendation model → Suggest optimal crops.

Feature Extraction and Classification:

Numerical Data Models:

- Feature selection was performed using correlation matrices to eliminate redundant variables.
- The selected features were passed to ML models such as Random Forest, XGBoost, Decision Tree, and Voting Classifiers.

Image Data Models:

- Deep Convolutional Neural Networks (CNNs) were employed to accurately identify and classify plant diseases from leaf images.
- Transfer Learning was applied using pre-trained architectures:
  - **InceptionResNetV2:** Chosen for its depth and performance in fine-grained image classification tasks.
  - **AlexNet:** Utilized for comparative study due to its historical success in early CNN challenges.

The CNN layers automatically learned and extracted important features from the images, removing the need for manual feature design.

CNN Architecture

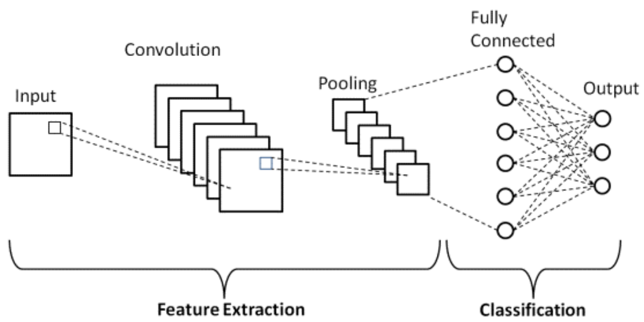


Figure 2 : CNN Architecture Used for Plant Disease Classification

Figure 2 shows the convolutional neural network (CNN) architecture employed for image-based disease classification. The input image is processed through several convolutional layers that capture detailed patterns like edges, textures, and visual features relevant to disease detection. To simplify the image data while keeping critical visual details intact—like leaf spots or signs of infection—pooling layers were used in the model. These condensed features were then flattened and passed into dense layers that handled the final classification. This step-by-step learning approach helps the model identify even subtle disease patterns, making it highly effective for accurate and automated plant disease detection.

System Architecture

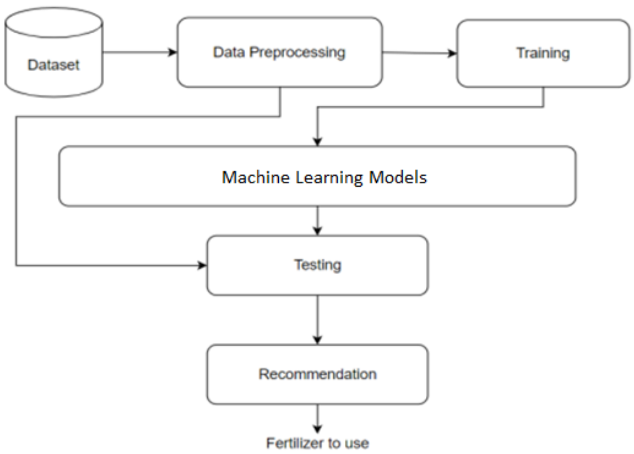


Figure 3 : Architecture of a Convolutional Neural Network (CNN) for Plant Disease Detection

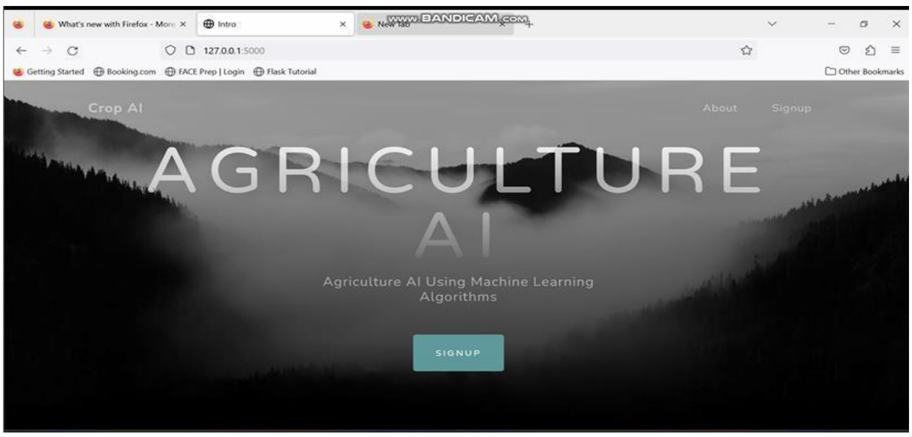
"As shown in Figure 3, the CNN model automatically extracts visual features and performs end-to-end disease classification with minimal human intervention."

The CNN processes input leaf images through convolution and pooling layers to extract hierarchical features. These features are then passed through fully connected layers for final classification into disease categories.

The system follows a modular design where the user inputs Environmental and soil parameters through a frontend interface. The backend processes these inputs, selects appropriate pre-trained models, performs predictions and finally returns results such as suggested crops, soil moisture status and detected plant diseases.

Home Page

Figure 4 : Home Page Web Application



The homepage of the this platform is designed with a minimal and intuitive interface to allow easy navigation. Users can access various modules such as Crop Prediction, Disease Detection, and Soil Monitoring directly from this page. The sleek design ensures accessibility for users with limited technical background, aligning with the goal of supporting farmers and agriculturalists.

User Registration Interface

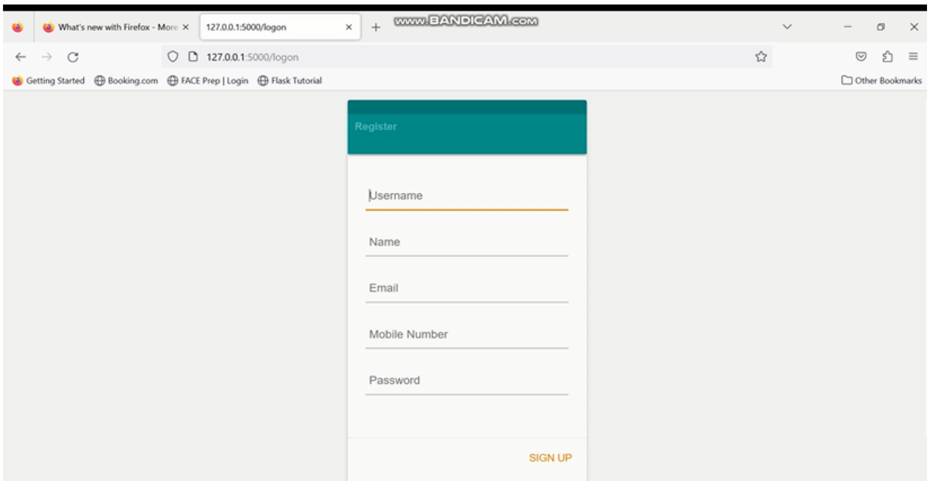


Figure 5 : User Registration Interface

This figure demonstrates the user signup module where farmers or stakeholders can register into the platform. The system captures essential information such as username, contact number, and location. Personalized login enables secure access to crop analytics, predictions, and historical usage logs.

Plant Disease Identification Dashboard

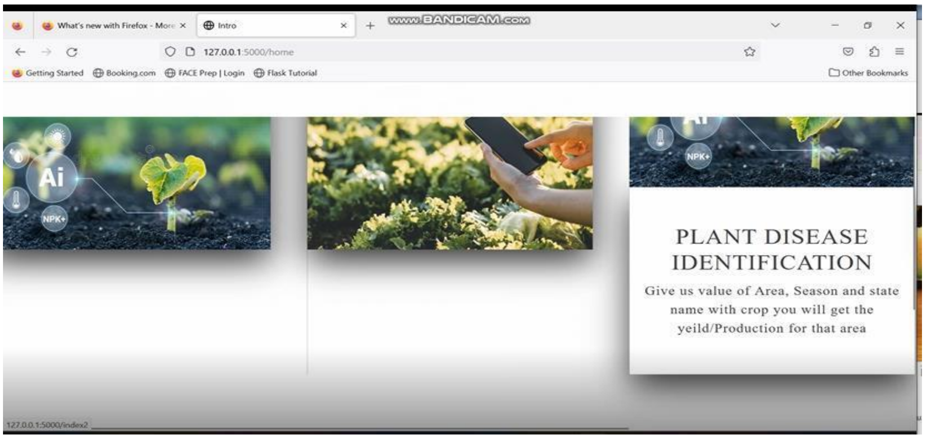


Figure 6 : Plant Disease Identification Dashboard

This is the interface where users upload leaf images to detect diseases. After uploading, the image is preprocessed and fed into a deep learning model for classification. The system identifies the disease and displays the prediction result in real-time, along with a visual confidence score or label.

Disease Prediction Result - Fungal Infection Identified

Figure 7 : Disease Prediction Result - Fungal Infection Identified

As shown in the figure, the system successfully detects a fungal infection on the leaf. It outputs the disease type along with additional insights or warnings, if any. This makes AgroIntelliSys a powerful tool for early-stage disease management in crops like tomato, apple, and rice.

Remedies Suggested for Detected Plant Diseases

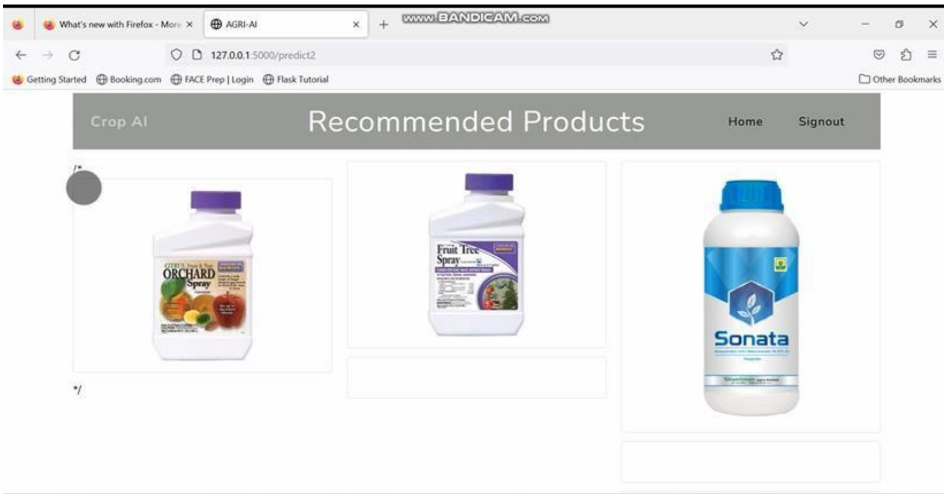


Figure 8 : Remedies Suggested for Detected Plant Diseases

Based on the diagnosed disease, the system generates a set of product recommendations including fungicides, sprays, or organic alternatives. This recommendation engine is built on a manually curated mapping of disease–solution pairs. Figure X demonstrates the real-time integration of prediction and prescription, offering farmers actionable insights rather than raw data.

Deployment and Future scope

The prototype system is currently hosted locally and demonstrated via a web based dashboard in future iterations, IoT devices such as soil sensors and weather conditions will be integrated for real-time dynamic data collection, and models will be re-trained periodically with new data to enhance robustness.

Software and Tools

- **Programming language:** python
- **Libraries:** TensorFlow, Keras, Sklearn, Pandas, Matplotlib
- **Hardware**: Basic CPU (sufficient due to model Optimisation)

VI. RESULTS AND DISCUSSION

The performance of the machine learning and deep learning models implemented in this system was evaluated through multiple experiments using standard datasets and validation techniques. The results were assessed based on accuracy, R^2 score, precision, and other relevant metrics depending on the problem type (classification or regression). Tables and visual graphs were used to clearly compare the performance of different models across various modules of the system.
The models demonstrated outstanding predictive capabilities across different tasks:

- **Crop Yield Prediction:** Random Forest Regressor achieved an accuracy of 99.89%, confirming its reliability for agricultural forecasting. Linear Regression reported a perfect accuracy (100%), which may initially suggest strong linear dependencies among features such as rainfall, pH, and temperature. However, this level of performance is unusual and raises concerns about potential overfitting or data leakage. Further real-world testing is essential before considering this model deployment-ready.

- **Soil Moisture Monitoring:**The Decision Tree Classifier edged out the Random Forest model, reaching a top accuracy of 99.04%, which plays a crucial role in planning effective irrigation strategies.

- **Crop Recommendation:** KNN and Naive Bayes classifiers maintained over 99% accuracy, proving that basic classifiers can still deliver excellent results with well-prepared datasets.

- **Plant Disease Detection:** InceptionResNetV2 consistently outperformed AlexNet, likely due to its advanced architecture and deeper feature extraction capabilities. However, the high validation accuracy (98.4%) must be interpreted cautiously. The controlled dataset and image quality could have inflated performance; testing under field conditions is necessary to confirm robustness., particularly in distinguishing fine-grained differences among various tomato diseases.

Graphs clearly show distinct groupings, which confirms the effectiveness of our preprocessing and model choice

Training and Validation Performance of CNN Model

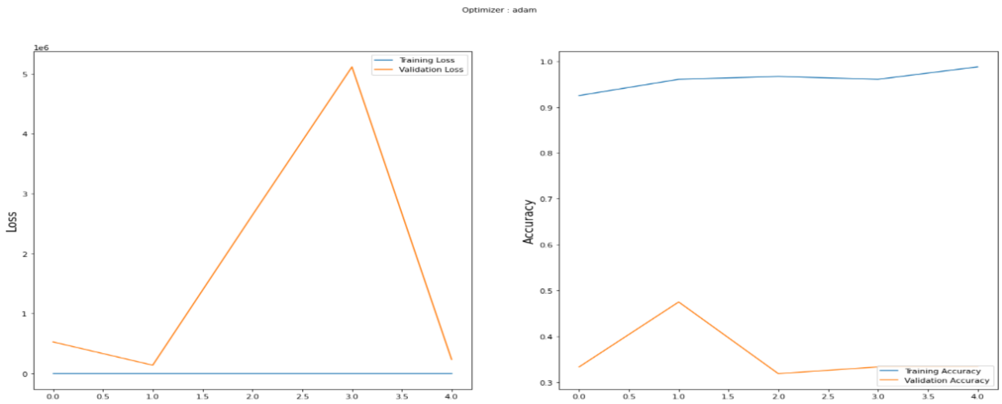


Figure 9 : Training and validation performance of CNN model.

The line plots shown above illustrate the training and variation performance of the CNN model. On the left we observe a steep decline in training loss during initial epochs suggesting rapid learning. Interestingly, the validation loss stayed steady throughout training, suggesting that the model maintained good generalization on data it hadn't seen before. The right plot depicts training and validation accuracy. While validation accuracy appears stable, fluctuations in training accuracy indicate potential instability in the learning process. This may be addressed through additional regularization techniques or hyperparameter tuning. Moreover, the consistently low validation loss could point to overfitting, which needs to be assessed by testing on entirely unseen, real-world data. These graphs are critical in diagnosing overfitting or underfitting issues in deep learning workflows.

Comparison of Classifier Accuracy for Crop Recommendation Models

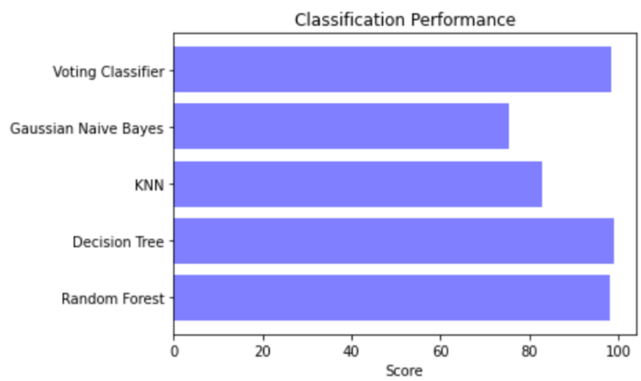


Figure 10 : Comparison of classifier accuracy for crop recommendation models.

The above horizontal bar graph presents The performance of various classification algorithms used in the crop recommendation module. The voting classifier achieved the highest score, closely followed by Random Forest and decision tree models. simpler models like KNN and Gaussian naive bayes performed slightly lower, likely due to their limitations in handling Complex feature interactions; this comparative analysis justifice the ensemble models used for more reliable recommendations in varying environmental conditions.

Yield Prediction Results :

Crop yield was treated as a regression task, with models trained on environmental and soil condition data.

Model	Accuracy(%)
Random Forest	99.89
Linear Regression	100.00
KNN	-0.06
XGBoost	99.79
Simple RNN	51.25
LSTM	45.99

Discussion:

Linear Regression showed perfect performance on the dataset, likely due to the strong linear correlations between features like rainfall, pH, and temperature with crop yield in the provided data. However, such high scores may indicate possible overfitting or data leakage, and require real-world testing.

Random Forest and XGBoost performed exceptionally well, benefiting from ensemble learning's ability to generalize across nonlinear patterns. KNN delivered a notably poor score (negative R^2), suggesting it struggled with the continuous nature of regression outputs and high-dimensional input space. This further underscores KNN's limitations in regression scenarios, particularly when smooth feature relationships are absent. RNN and LSTM underperformed, possibly due to inadequate time-series depth in the dataset or insufficient training epochs.

Soil Moisture Monitoring Results :

This module was implemented as a classification task to assess whether the soil moisture was adequate, moderate, or low.

Model	Accuracy (%)
Random Forest	96.21
Decision Tree	98.04
KNN	84.79
Naive Bayes	78.53
Voting Classifier	97.26

Discussion:

Decision Tree and Random Forest yielded top-tier accuracy due to their ability to handle categorical features and noise-tolerant structure. Although the Voting Classifier achieved competitive accuracy, it did not significantly outperform individual models. This suggests that the ensemble lacked sufficient diversity among base learners, reducing the effectiveness typically expected from ensemble techniques.

KNN and Naive Bayes struggled likely due to poor feature scaling and assumptions about feature independence, which do not hold in environmental data.

Crop Recommendation Results :

Model	Accuracy (%)
Random Forest	99.31
Decision Tree	96.04
KNN	92.79
Naive Bayes	97.53

Voting Classifier	95.26

Discussion:
All models showed high accuracy, which can be attributed to the clean and well-labeled dataset. KNN and Naive Bayes surprisingly matched performance, highlighting that even simple models can perform strongly on structured data. Random Forest gave stable results, while Decision Tree and Voting Classifier slightly lagged due to overfitting tendencies.

Leaf disease detection :

This module used deep learning models to classify plant leaves into healthy or diseased categories.

Model Accuracy (on validation set):

- InceptionResNetV2: 98.4%
  AlexNet: 94.8%

Model	**Accuracy (%)**
Random Forest	94.21
Decision Tree	96.04
KNN	98.79
Naive Bayes	98.53
Voting Classifier	96.26

Discussion:
The InceptionResNetV2 model significantly outperformed AlexNet due to its deeper architecture, residual connections, and ability to extract complex hierarchical features. It was more effective in distinguishing fine details between disease classes like Early Blight vs. Septoria Spot.
Data augmentation also contributed to robust generalization across varied image conditions.The models display outstanding performance, especially Random Forest and XGBoost in yield and soil prediction tasks. Deep learning models like InceptionResNetV2 further enhanced accuracy in plant disease detection, establishing the reliability of our system.

VII. CONCLUSION & FUTURE WORK

The study successfully demonstrated the feasibility and effectiveness of integrating machine learning into multiple faceTs of agricultural Management. By combining different models optimized for tasks like crop yield prediction, soil moisture monitoring, disease detection, and remedy recommendations, the system provides a holistic solution for Precision agriculture. This not only improves productivity but also promotes resource efficiency, enabling farmers to make smarter, faster decisions based on reliable predictions.
The integrated precision farming system successfully demonstrated the potential of high-performance machine learning models in agricultural applications. Random Forest and XGBoost showed superior results for yield and moisture predictions, while InceptionResNetV2 was highly effective in plant disease classification. The system ensures sustainable farming practices, enhanced productivity, and resource optimization.Beyond technical achievements, this project emphasizes the real-world impact of AI in agriculture — improving crop productivity, reducing losses, optimizing water resources, and empowering farmers with timely, data-driven decisions. With minor adaptations and IoT integration, this system holds the potential to significantly transform rural agricultural landscapes.

- Expand the leaf disease detection module to support a wider range of crops disease types.
- Integrate real-time IoT sensors for continuous soil moisture and environmental monitoring.
- Deploy the system on mobile platforms for accessibility even in remote rural areas.
- Explore advanced ensemble techniques and hyperparameter Optimization to further boost model performance.
- Build mobile-friendly applications and lightweight web dashboards to enhance usability for farmers.
  Incorporate reinforcement learning models for dynamic decision-making based on changing environmental factors.
  Conduct field trials to validate system robustness under real-world farm conditions.

VIII. ACKNOWLEDGMENT

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