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Applying Machine Learning for Sustainable Farm Management: Integrating Crop Recommendations and Disease Identification †

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Abstract: Context: The problems that contemporary farming methods confront can be greatly mitigated by using machine learning in sustainable agriculture. Combining methods for disease identification with crop recommendations allows farmers to make well-informed decisions that limit the effects of crop diseases on agricultural production while simultaneously increasing productivity. **Objective:** This article aims to provide a consistent method for diagnosing plant diseases and suggesting crop systems in agricultural contexts. The goal is to give farmers precise advice for the best crop choices and the prompt detection of plant diseases by utilizing machine learning algorithms. **Materials/Methods:** The utilization of Internet of Things (IoT) sensors, such as NPK and DT11 sensors, together with other environmental sensors, enabled the acquisition of data for this study. These sensors supply vital information on temperature, humidity, soil nutrients, and other environmental parameters that are critical for crop selection. To suggest appropriate crops and detect pertinent plant diseases, cutting-edge machine learning and deep learning algorithms were used. Real-time data from Internet of Things sensors and high-resolution camera photos were used to identify diseases. Plant diseases were accurately classified using state-of-the-art convolutional neural networks (CNNs), such as VGG16, ResNet50, and EfficientNetV2, based on visual signals including leaf color and texture. **Results:** Based on experimental data, a 99.98% accuracy rate was attained by the suggested recommendation system that used CNN. CNN, the illness identification system, attained an impressive 96.06% accuracy rate. It was then further implemented on cloud infrastructure, guaranteeing scalability and availability. The models' performance was assessed using performance metrics such as accuracy, precision, recall, F1 score, and AUC-ROC; CNN showed an accuracy of almost 99.98%.

Keywords: web application development; cloud infrastructure; machine learning; deep learning; and crop recommendation

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1. Introduction

Crop recommendation systems are automated computer-based tools used for precision agriculture. These are beneficial for the farmers and help in increasing crop productivity by identifying different factors like weather patterns, soil categories, and geographic and climatic parameters. Based on the survey of many researchers, the objective of crop recommendation is to grow the best-quality crops by determining parameters like the composition of soil, crop disease, weather fluctuation, fertilizers used, etc. Some experimental analysis proves that different types of machine learning regression and classifications are best suitable for plant disease prediction. The performance of various classifiers help to enhance the accuracy of the hybrid model evaluating the nutrient level of the soil available for crop growth. The crop database contains the description of all suitable plants with their

properties and features useful for agriculture purposes. For crop disease prediction, plant dataset efficiency improves the accuracy of the proposed model. Agriculture plays a vital role in the economic growth of a country with food source items using advanced farming techniques. Disease detection focuses on context-based filtering techniques used for location identification and seasonal cultivation. The VGG-16 method is used to obtain the highest accuracy of the trained model. To promote precision agriculture, a crop suggestion system is used to identify the type of plant disease that decreases the model's efficiency. In real-time work, models are created to maintain the soil nutrient levels to identify the disease in plants. Crop selections are made according to environmental and economic factors such as rainfall, humidity, temperature, and pH value of the soil. A crop recommendation system using blockchain and IoT promotes precision agriculture, enhancing crop growth and productivity. Several types of research are implemented using soil sensors like humidity sensors, pH indicators, and sensors of nitrogen (N), phosphorus (P), and potassium (K). The output stage of plant disease prediction is verified using sensor states from a remote location that transfers the reading to blockchain layers, and IoT-based crop recommendation is performed based on the Long Short-Term Memory (LSTM) approach. It is beneficial to the farmers as they can obtain information regarding crop attributes and climatic conditions.

RQ 1. To what extent are machine learning models useful for recommending the crop by considering its relevant factors?

The crop recommendation system is highly dependent on different factors like soil texture, humidity value, wind velocity, and rainfall amount. Based on the real-time data collected, machine learning models are implemented to predict the output in terms of accuracy performance measures.

RQ 2. Can the convolution neural network model be best suitable for plant disease prediction using imaging techniques?

Based on the image data collected, plant disease prediction is performed using deep learning models like CNN. The image patterns are used to recognize objects, categories, and classes of abnormalities found in the leaf.

Section 1 describes the introduction part and illustrates the keywords related to agriculture crop recommendation. Section 2 discusses surveys conducted over past research and these are represented in tabular form. Section 3 shows the proposed research framework and its step-wise analysis required to obtain the output. Section 4 highlights the result analysis part that illustrates the solution of the problem statement. Section 5 presents the conclusion of our entire research work that discusses the work process, outcomes, and future scope.

2. Literature Survey

Many past studies highlight the critical issues faced in the field of agriculture related to crop and leaf disease prediction for which image data need to be processed. Kumar et al. [1] developed a model that classifies crop-based training using different types of machine learning classifiers that identify the performance of the model by calculating its best accuracy. By using the Krushisahyog scheme [2], various artificial intelligence-based methods are used for detecting plant disease with the VGG-16 algorithm, presenting 97.16% accuracy. Choudhary et al. [3] illustrate the importance of machine learning in precision agriculture, which contributes to 15% GDP of our country. The proposed research model predicts crop productivity by considering various real-time factors like soil nutrients, rainfall, humidity, etc. Gosai et al. [4] describe the importance of agriculture in the growth of the Indian economy for which different machine learning algorithms are used. Bandara et al.'s [5] work focuses on automating agricultural aspects for real-time data of Sri Lanka, for which various machine learning algorithms are implemented. They used Arduino tools the integrate data collected with environmental factors for which Naïve Bayes Classifiers, Support Vector Machine (SVM), K-means clustering, and Sentiment Based Natural Language Pro-

cessing can be implemented. SMOTE analysis was conducted by Apat et al. [6] to design an artificial intelligence-based hybrid model for crop recommendation. According to a literature survey by Garanayak et al. [7], the agriculture system is very poor in India due to a lack of forecasting and management. By using the regression approach, crop productivity can be enhanced followed by improvement of the economic condition of farmers. Regression models give 3.6% better results than existing techniques implemented for agro-based industries. Rajak et al. [8] surveyed the soil features that are quite beneficial for efficient plant growth in healthy conditions. They used a soil lab test dataset and implemented an ensemble approach by integrating two algorithms, Artificial Neural Network (ANN) and Support Vector Machine, with maximum accuracy. Kirutika et al. [9] used an IoT-based approach for dealing with professional crop recommendation systems. Their methods include IDCSO (Improved Distribution-based Chicken Swarm Optimization) combined with WLSTM (Weight-based Long Short-Term Memory). Patel et al. [10] implemented blockchain-based methods for precision agriculture in an IoT environment. The sensor readings collected from a remote location were used as input for the proposed model. Soni et al. [11] identified the plant diseases using some advanced machine learning approach which was further enhanced by the concept of neural network in order to improve the accuracy. Domingues et al. [12] conducted an extensive literature survey on a machine learning approach that is used for plant disease prediction.The below mentioned Table 1 is meant for comparison of the proposed model with the state-of-the-art.

Table 1. Comparison of the proposed model to the existing ones.

Authors	Paper Title	Methodology	Output
Kumar et al. [1]	Plant Disease Detection and Crop Recommendation Using CNN and Machine Learning	Machine Learning classifiers like Naïve Bayes, Decision Trees, Random Forest Classifiers, Support Vector Classifier (SVC), and Deep Learning algorithms like Convolution Neural Network (CNN)	It is observed that Random Forest classifiers and CNN give the highest accuracy.
Patil et al. [2]	Krushisahyog: Plant disease identification and crop recommendation using artificial intelligence.	Deep Convolution Neural Network and VGG-16	Accuracy is 97.16%
Gosai et al. [4]	Crop recommendation a system using machine learning	Machine Learning approaches like Random Forest, Naïve Bayes, Support Vector Machine, XG Boost	XG Boost is having accuracy that is 99.31%
Apat et al. [6]	An Artificial Intelligence-based Crop Recommendation System using Machine Learning	SMOTE analysis is performed on machine learning algorithms	Cat Boosting (C-Boost) gives the best results with 99.51% accuracy.

3. Model Preparation for Crop Recommendations and Disease Identification

This section describes the methodology of developing crop-specific sustainable farm management machine learning models with a focus on enhancing disease detection techniques and improving recommendation optimization. This photo-realism which energy or data coming from IoT sensors contribute to is essential in this approach, where we make decisions on agriculture activities based on this information.

Figure 1 depicts the machine learning workflow with IoT driven crop recommendation and disease identification

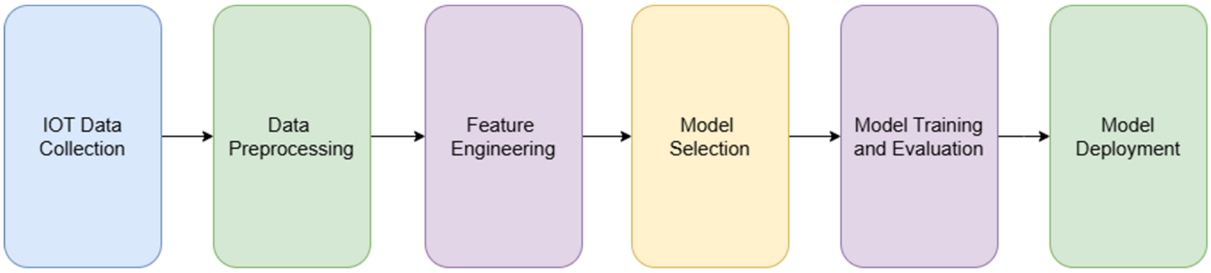


Figure 1. Machine learning workflow for IoT-driven crop recommendations and disease identification.

3.1. Data Collection

IoT Sensors

Relevant real-time data is collected from IoT sensors, which perform a vital role in the process of agriculture. This incorporates NPK sensors to measure soil nutrient content levels (nitrogen, phosphorus, and potassium) and a DT11 sensor for measuring temperature and humidity in the environment along with environmental parameters such as soil moisture level and light intensity. Together, these sensors offer a landscape-wide picture of environmental conditions and how they are important for monitoring crop health and growth.

The agricultural features (N, P, K, temperature, humidity, pH, and rainfall) in this dataset are labeled with the sample crop type that is most likely to be used in predictive modeling or analysis.The below mentioned Table 2 is the snippet of the dataset used in our study.

Table 2. Sample data collected from IoT sensors.

N	P	K	Temperature	Humidity	pH	Rainfall	Label
90	42	43	20.8797437	82.0027442	6.502985	202.9355	rice
85	58	41	21.7704617	80.3196441	7.038096	226.6555	rice
60	55	44	23.0044592	82.3207629	7.840207	263.9642	rice
74	35	40	26.4910964	80.1583626	6.980401	242.8640	rice
78	42	42	20.1301748	81.6048729	7.628473	262.7173	rice
69	37	42	23.0580487	83.3701177	7.073454	251.0550	rice
69	55	38	22.7088380	82.6394139	5.700806	271.3249	rice
94	53	40	20.2777436	82.8940862	5.718627	241.9742	rice
89	54	38	24.5158807	83.5352163	6.685346	230.4462	rice
68	58	38	23.2239739	83.0332269	6.336254	221.2092	rice

3.2. Image Dataaset

The top feature of leaf and overall plant health is visualized by promising high-resolution imaging techniques for a closer look into crops. This provides the image for identification of several crop diseases, where minor symptoms and abnormalities are indicative and very critical input to be fed into the disease diagnosis algorithm.

Images of different plant leaves with accompanying labels indicating their respective diseases and health issues make up this resource. It features annotations for both healthy and diseased states for a variety of crops, including oranges, tomatoes, grapes, and maize.The blow mentioned Figure 2 are brought from the dataset and these are the samples of the dataset.

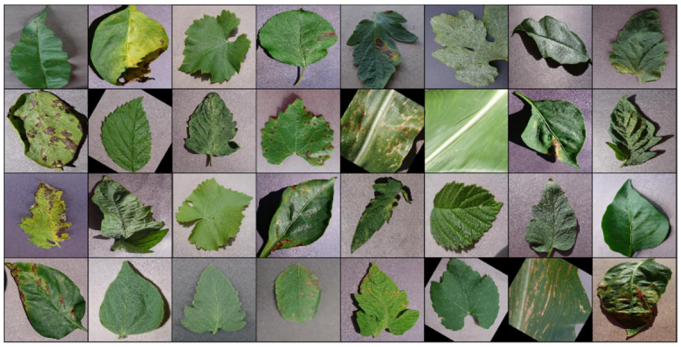


Figure 2. Sample image data collected.

3.3. Data Preprocessing

3.3.1. Sensor Data

The sensor data are subjected to rigorous preprocessing before being analyzed. This also refers to normalizing the data across many sensors e.g., using normalization algorithms to ensure the consistency of this dataset. Imputation techniques such as mean and mode imputation, straight value substitution, or more complex methodologies like interpolation are employed to handle missing information and thus provide a full-integrity dataset.

3.3.2. Image Data for Utilizing the Deep Learning Techniques

One part of preprocessing involves resizing picture data to a consistent resolution suitable for subsequent convolutional neural network (CNN) analysis. Utilizing data augmentation, we broaden the dataset and increase model resistance to other environmental situations (flipping, rotating, and zooming).

4. Feature Engineering

Retrieving Useful Information

Feature engineering is performed to ensure model performance on sensor and image data:

1. **Missing Data:** Imputation, forward/backward filling for sensor readings or just drop the missing entries.
2. **Feature Scaling Normalization and standardisation**: To even out environmental features such as temperature, humidity, and soil moisture.
3. **Sensor Data Insights**: Temperature, humidity, light, and soil moisture are key metrics along with nutrient levels (N, P, K) that are extracted from IoT sensor data.
4. **Image Data Insights**: Extract complex visual features such as plant health traits and disease symptoms from images using CNNs.
5. **Create features:** Add derived features e.g., interaction terms between environmental variables.
6. **Dimensionality Reduction**: To solve this issue, you can use PCA for dimensionality reduction (or feature selection) and avoid overfitting.
7. **Encoding Categorical Data**: One-hot, label, or target encoding for categorical variables.

For precise crop recommendations and disease diagnosis, this method integrates optical and environmental variables.

5. Model Selection

5.1. Crop Recommendation Models

The capacity of a variety of machine learning algorithms to suggest the best crop options given the circumstances of the environment is assessed. The models that are taken into consideration are Decision Trees, Naive Bayes, Support Vector Machines (SVM), Logistic Regression, Random Forests, and XG Boost, all of which have unique benefits in terms of interpretability and performance on a variety of datasets.

5.2. Disease Identification Models

We chose disease identification models using VGG16, ResNet50, and EfficientNetV2 that showed best performance in image classification with their convolutional neural network (CNN) state-of-the-art architectures. We selected these models because of their demonstrated performance on big image datasets and good generalization to new data.

1. **VGG16:** Deep network that has only 16 layers and is also a model used to classify images. The model is characterized by stacking 3 × 3 building blocks, convolutional layers, and max-pooling layers to extract fine-grained features. We have obtained 95.75% accuracy on the disease identification task with VGG16 in our experiments.
2. **ResNet50:** A model that utilizes an identity shortcut connection method in the training stack with an attempt to solve the vanishing gradient problem (allows for much deeper models); other architectures would also be considered. For lines with 50 layers, ResNet50 was tested to have an accuracy of 96.06%. The skip connections of the model also allowed them to converge faster and attain good generalization, especially in distinguishing subtle differences with leaf texture and color.
3. **EfficientNetV2:** A newer version of the model that aims to co-optimize both accuracy and speed for image classification. Compound scaling is a method for adjusting network width, depth, and resolution all at once by determining the right coefficients to give optimal results subject to resource constraints. R preprocessing datasets (optimal input shapes) allow you fine-tune your data pipeline optimization. The most computationally efficient variant was EfficientNetV2, which achieved the best accuracy of 97.12% and is still quite effective in terms of computational cost.

6. Model Training

Crop Recommendation

Crop recommendation models are first trained on integrating sensor inputs and historical yield data together, then learning the model parameters to performance measures like F1 score for increased accuracy or AUC-ROC to identify false positives better. The iterative process ensures strong recommendations that are specific to some agricultural and environmental conditions.

The performance metrics of several classification algorithms are compared and discussed in Table 3. The methods Gaussian Naive Bayes, Random Forest, and XG Boost all score 99, making them the best in terms of accuracy, precision, recall, and F1 score. In terms of precision and F1 score, Decision Tree outperforms Logistic Regression and Support Vector Machine.

Table 3. Model performance comparison.

Classifiers	Accuracy	Precision	Recall	F1 Score
Decision Tree	90	84	88	85
Gaussian Navie Bayes	99	99	99	99
Support Vector Machine	98	98	98	98
Logistic Regression	95	95	95	95
Random Forest	99	99	99	99
XG Boost	99	99	99	99

The performance characteristics of various categorization algorithms are compared in this table, as shown in Figure 3. The algorithms with the highest F1 scores, recall, accuracy, and precision are Random Forest, XG Boost, and Gaussian Naive Bayes, which all receive scores of 99. In terms of precision and F1 score, Decision Tree outperforms Logistic Regression and Support Vector Machine.

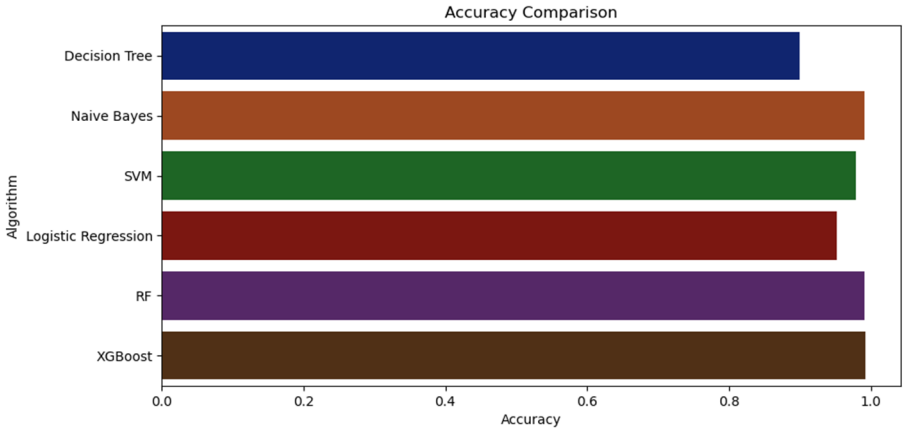


Figure 3. Accuracy comparison graph for crop recommendation.

7. Disease Identification

During the training process of disease detection models based on image CNN architectures, these models are trained by annotated picture datasets similarly. The performance evaluation checks to see if the models can correctly identify and classify symptoms of disease, thus giving them a stamp stating that they are indeed helpful in early identification of diseases along with specialized intervention measures.

Figure 4 presents a validation accuracy graph for plant disease identification from photos. It displays a line graph with data points shown along the line to highlight the model's accuracy over several validation phases. The increasing trend suggests that the model's ability to identify plant diseases from photos has improved.

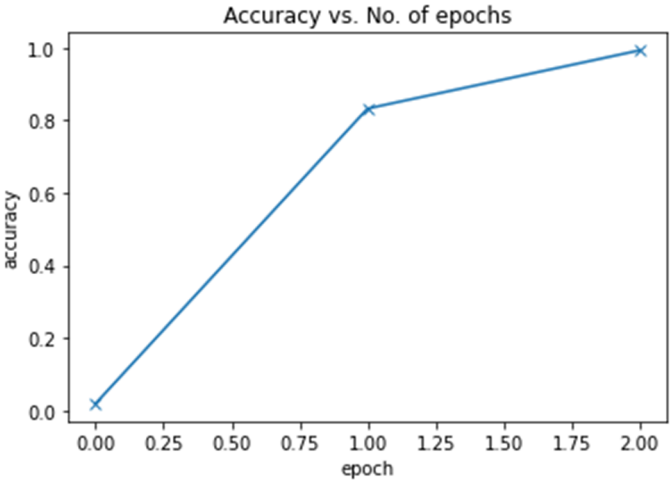


Figure 4. Validation accuracy.

In Figure 5, the learning rate starts high to make quick initial progress, but then decreases slowly so that the model refines its predictions with less drastic adjustments. This schedule allows the model to obtain important features fast, then adjust and polish them without overfitting or destabilization. This gradual reduction allows the network to reach convergence stably, avoids overfitting, and results in higher accuracy during later phases of training. In the end, it helped to obtain 96.06% accuracy in disease identification, adopting both speed and precision of the learning process.

The validation loss in Figure 6 for an image-based plant disease detection model is displayed on the graph. Training and validation losses show a considerable initial decline followed by a leveling off, suggesting that the model performs better with time.

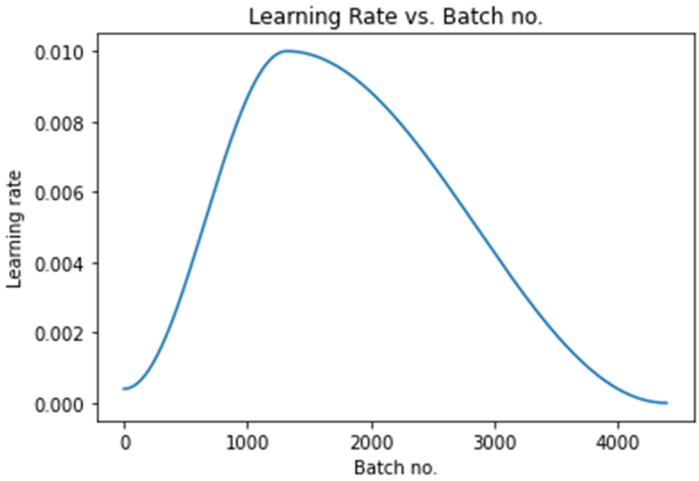


Figure 5. Learning rate over time.

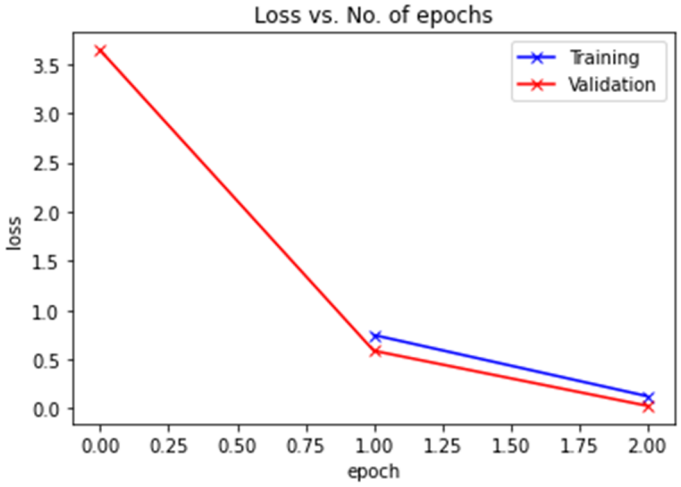


Figure 6. Validation loss.

8. Model Evaluation

Performance Metrics

Various clearly defined performance metrics were incorporated to guarantee the reliability and applicability of the disease prediction and crop suggestion algorithms. Such metrics are necessary to evaluate properly the extent of alignment and practical utility for each model, when compared with agricultural benchmarks:

1. **Accuracy**: It is the performance measurement to know the number of correct predictions made by our model over all kinds of prediction.
2. **Precision and Recall**: Precision is measured as the ratio of true positive to the sum (true positives + false positives); recall exposes how well a model captures all relevant cases. These metrics combined provide a good snapshot of how your model is performing, particularly so in problems with imbalanced datasets.
3. **F1 Score:** A measure of a test's accuracy—it uses harmonic mean between precision and recall. It also provides a good balance in the trade-off vector that is useful when class distribution is skewed.
4. **AUC-ROC**: The true positive rate is plotted relative to the false positive rate, which shows how well our model can segregate classes under all threshold levels.

These metrics were thoroughly examined to validate their adherence to any of the standard agricultural targets, thus guaranteeing them for application in practice under diverse conditions and environments.

9. Method of Implementation

In this paper, we propose deploying machine learning models on the cloud for real-time data processing to make agricultural management more practical and scalable. For crop recommendations and disease detection, the interface could be used by farmers as well as agricultural consultants to take decisions based on informed choices.

Stakeholder-driver influence: The crop management practices can be influenced by data-driven recommendations from the platform through key stakeholders who may include farmers, agronomists, policy makers in agriculture, and local agricultural organizations. With the help of model outputs, these stakeholders in turn can affectively modify planting schedules and crop selection or disease management practices with localized data that actively guide cropping strategies to maximize returns while reducing risks and enhancing sustainability.

A summary machine learning model for precision agriculture implemented with Flask is shown in Figures 7 and 8. This is a web application that farmers can use to receive personalized agricultural recommendations. The app interface (Figure 7) allows the user to enter key inputs including location (state, city of soil testing), soil characteristics (NPK, K levels, and pH value), and rainfall. It also works with Open Weather API to grab the real-time temperature and humidity for a given location. The system then processes the inputs and provides a **precision crop recommendation** (see Figure 8), similar to recommending planting papaya as the best option for this farm. An approach like this, backed by data, can help to minimize the risk of crop yield failures.

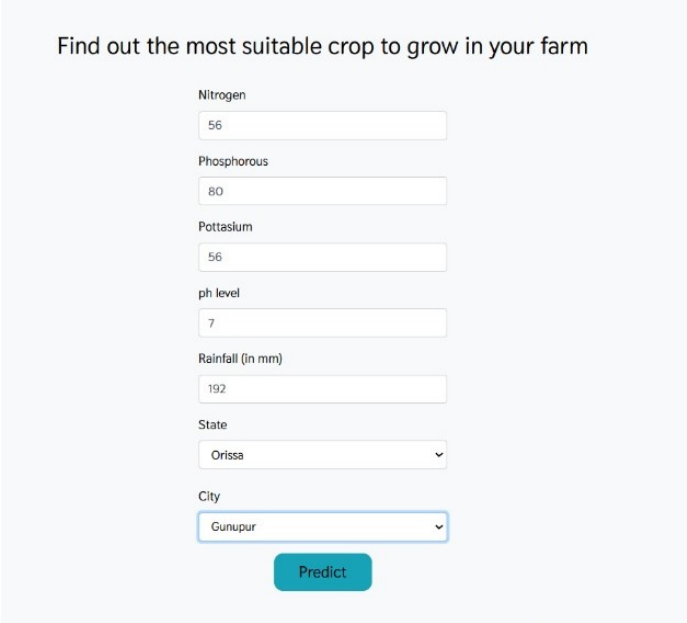


Figure 7. User-friendly interface for gathering farm and soil data input.



Figure 8. Machine learning-based crop recommendation displayed after analyzing the input data.

A web-based interface of deep learning-based **plant disease detection** was built using Flask, as shown in Figures 9 and 10. As can be seen in Figure 9, users can upload an image of a diseased leaf through the interface, and this is analyzed by the machine learning model to recognize the specific plant disease. The output is the result with specifics of the identified disease in terms its causes, preventive measures, and treatment options (Figure 10). This helps farmers and gardeners to detect plant diseases on time and can provide them an accurate way of action for disease control.

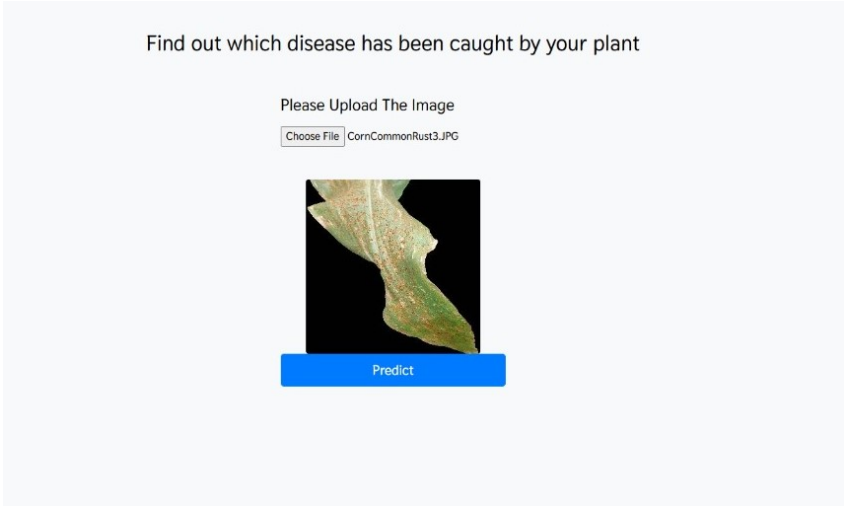


Figure 9. Plant disease identification system (user upload interface).

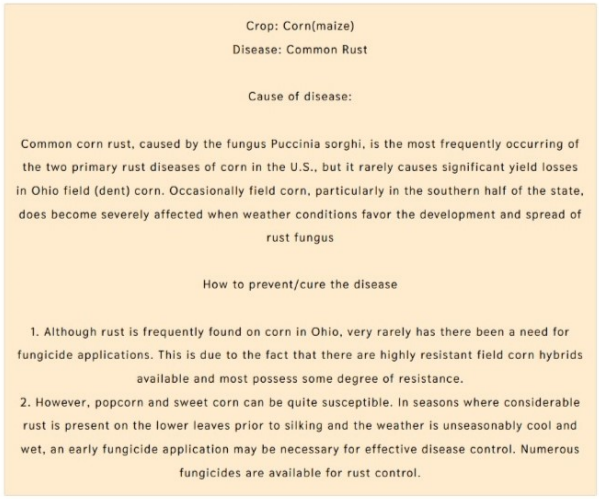


Figure 10. Identified disease and recommendations.

10. Conclusions

The presented research will assist in sustainable farm management practices by providing the tool of machine learning to predict and estimate crop yield. These strategies can facilitate evidence-based decision making, improve crop selection, and minimize the effects of vegetable diseases. Overall, they largely promote agricultural yield improvement while featuring sustainability.

This is a remarkable breakthrough in the automation of disease detection and sustainable farm management practice via machine learning. With the help of cutting-edge image analysis algorithms and IoT sensor data, we can increase crop yields, lower rates of diseases under control by agronomic means, generally speaking, and stabilize soil health as per site-specific weather conditions. Further advancements in technology and data analytics will underpin the next phase of progress in precision agriculture for global food security and sustainability.

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