Smart Farming AI Powered Assistant

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Abstract

Agriculture is the backbone of India's economy, with 60% of the land used for agricultural purposes. However, farmers face challenges such as undetectable crop disease and in enhancing the yield. To address these issues, this project proposes a smart farm assistant that incorporates Machine Learning to optimize farming activities. The system detects plant disease based on plant leaf image and detect soil type based on soil image. Once it predicts the disease, it will recommend fertilizer to treat that disease. Likewise, it will recommend the best plants for the detected soil type. This system enables farmers to take quick and informed decisions and enhance productivity. The solution, which is scalable, affordable, and suitable for actual field conditions, bridges the gap between traditional farming and intelligent agriculture.

I. INTRODUCTION

Agriculture provides a strong economics for many countries and nourishing billions of people. But in recent years, farmers facing major issues like: plant diseases, can't identify proper fertilizer recommendation, wastage of water use, timely guidance for plant growth. These issues lower the crop yields and also broke farmers income. Traditional farming techniques often fails to meet these challenges due to reliance on manual methods and lack of advanced farming tools.

So, we need a smart, intelligent, productive and easy-to-use farming application. This project aims to provide a solution for these issues by the power of Machine Learning (ML). Our goal is to make an all-in-one smart farming application that is efficient, user-friendly and designed to make farming more productive and sustainable.

In [1], a system for automatic identification of plant species was implemented through computer vision and machine learning algorithms. The methodology entailed feature extraction of texture and

colour features from leaf images of plants and classification with a multiclass SVM, obtaining 93.26% classification accuracy on the Swedish Leaf Dataset. The model was able to successfully identify 15 species, showcasing the potential of statistical feature-based classification. The model is, however, subject to various limitations. It is based on a region-specific and limited dataset that lacks generalizability to different plant species worldwide. The images were taken in controlled environments, diminishing the effectiveness of the model in real-world conditions with varying backgrounds and lighting. Moreover, the system doesn't include deep learning methodologies such as CNNs, which have demonstrated better performance in image recognition tasks.

In [2], a soil type detection approach was suggested involving Gabor wavelet-based feature extraction with subsequent use of Teager-Kaiser Energy Operator (TKO), and classification was carried out with Polynomial Neural Networks (PNN). The system efficiently enhanced feature extraction accuracy through texture-based energy patterns in soil images to the level of 98–100% detection accuracy, better than existing SVM-based approaches. Nevertheless, the method was validated on only a small test set of six soils, had no real-time application validation, and was not implemented in any end-user platform or mobile user interface for farming use.

In [3], an extensive systematic literature review (SLR) was performed to identify the state of plant disease detection (PDD) with the help of image-based artificial intelligence techniques. The study screened 176 out of a total of 1349 studies that focused on machine learning (ML), deep learning (DL), and image processing (IP) based techniques for detecting diseases in crops like rice, grapes, tomatoes, and maize grown globally. The review picked out achievements like attention-based CNNs, transfer learning, and light models. There was much progress made, but considerable shortcomings were recorded, such as no standardized data sets, no real-time and in-field tests, and limited examination of localization methods and multilingual or farmer-friendly systems.

In [4], a plant leaf disease detection system based on deep learning was proposed, concentrating mainly on oilseed crops grown in Tamil Nadu. The proposed model employed CNN architecture to diagnose plant diseases with significant accuracy, aiding in early disease diagnosis and better crop management. The research is limited in scope, targeting only a limited set of crops and regional use. It is deficient in greater crop diversity and applicability in varying geographic and linguistic environments, which are essential for scalable agricultural applications.

In [5], a smart agriculture system that was IoT integrated was proposed using machine learning algorithms for crop prediction and plant disease identification. The system employed sensors to track real-time field conditions such as temperature, humidity, and soil moisture and integrated it with weather and soil data to forecast appropriate crops using a Random Forest algorithm. Plant diseases were also identified through image processing based on the SIFT algorithm. Although the model was highly accurate, its limitations are that it is internet-dependent, does not support multilingualism for greater adoption by a diverse group of farming communities, and is limited in scalability beyond controlled settings.

In [6], a detailed review on conventional and contemporary plant disease detection methods from visual examination and laboratory testing to remote sensing and artificial intelligence was done. The

research highlighted the need for early detection in sustainable agriculture and outlined recent developments, such as CNN-based models, IoT incorporation, and fuzzy logic systems. Nonetheless, the review identified some limitations like the reliance on high-quality image datasets, unavailability of models for real-time or outdoor field deployment, and limited integration of multilingual or farmer-friendly interfaces. Additionally, most models specialize in paddy diseases, with their generalizability across crop types being limited.

In [7], a deep learning method was discussed for plant disease detection and classification. The article brought out the ability of sophisticated CNN architectures such as AlexNet, VGG, ResNet, and tailored models to enhance accuracy for image-based plant disease recognition. It underlined the employment of visualization methods such as saliency maps and heatmaps for localizing symptoms of disease with classification accuracies of up to 99% in certain instances. Nonetheless, the research was mainly based on datasets with simple backgrounds and did not comprehensively treat real-field conditions or incorporate new imaging technologies such as hyperspectral sensing, which may further improve robustness in actual agricultural environments.

In [8], a machine learning system for plant disease classification and detection was suggested to aid the agricultural industry, which is crucial to India's economy and provides employment to approximately 80% of the population. The research solves important problems like crop loss due to disease, climate change, and farmer indebtedness. By using a deep learning model based on ResNet architecture, the system was trained on more than 54,000 images to identify 26 plant diseases on 14 crops. The approach involves image pre-processing, segmentation, feature extraction, and classification using convolutional neural networks. The suggested model obtained a high accuracy of 99.35%, providing a robust solution to automate disease identification and enable farmers to take timely measures for better crop yield and financial security.

In [9], the research is cantered on the vital problem of plant disease on crop yields, a key issue in a nation such as India where agriculture accounts for 17% of the GDP and provides employment for approximately 60% of the population. Though climate change is out of human control, plant disease detection is a controllable factor that can greatly enhance yield. The study highlights that most farmers cannot afford expert consultation or lab-based testing, making traditional methods impractical for early disease diagnosis. To address this challenge, the paper explores advanced deep learning models—including CNNs, transfer learning using InceptionV3, and visual transformer networks—to automate plant disease detection. The suggested Large Transformer Network (LTN) performed a 97.98% validation accuracy superior to classic CNN approaches, and with lower numbers of model parameters, with an inexpensive and efficient high-performance model for realistic farming applications.

In [10], the research paper shows an extensive review of soil identification and classification based on state-of-the-art machine learning methods to aid agricultural processes including crop selection and yield enhancement. The paper shows that soil properties such as texture, colour, and particle constitution are affected by variables extending from geological and biological attributes at regional scales to topography and human influence at local scales. Manual or laboratory-based traditional classification processes are time-consuming and inefficient. Therefore, the study promotes automated image processing and deep learning techniques—like CNN and clustering-based segmentation—to

effectively classify soil types. These AI-based solutions facilitate quick, low-cost, and scalable means of soil analysis, which are crucial for precision agriculture and enhanced monitoring of soil health[11].

This paper proposes a technique to increase the productivity of agriculture and sustainability of farming. It uses ML models to handle major challenges faced by farmers. The project has these main goals: the first is to detect plant diseases and suggest fertilizers to treat those diseases. The second is to detect the soil type and recommend the best crops to grow in that soil to achieve high yield.

With a unified solution, cost-effectiveness is achieved, and dependency on external specialist consultations is minimized. The smart farming application can further be updated from time to time to accommodate more crops and local agricultural practices, hence being scalable and adaptable regionally and climatically. Apart from focusing on the common difficulties that farmers undergo, our project also emphasizes ease of use and accessibility. Most farmers, particularly those residing in rural communities, might lack familiarity with intricate digital systems. We thus developed an application that is straightforward and intuitive, so even individuals with low technical expertise may utilize sophisticated technology. Fig. 1. shows the plant disease app
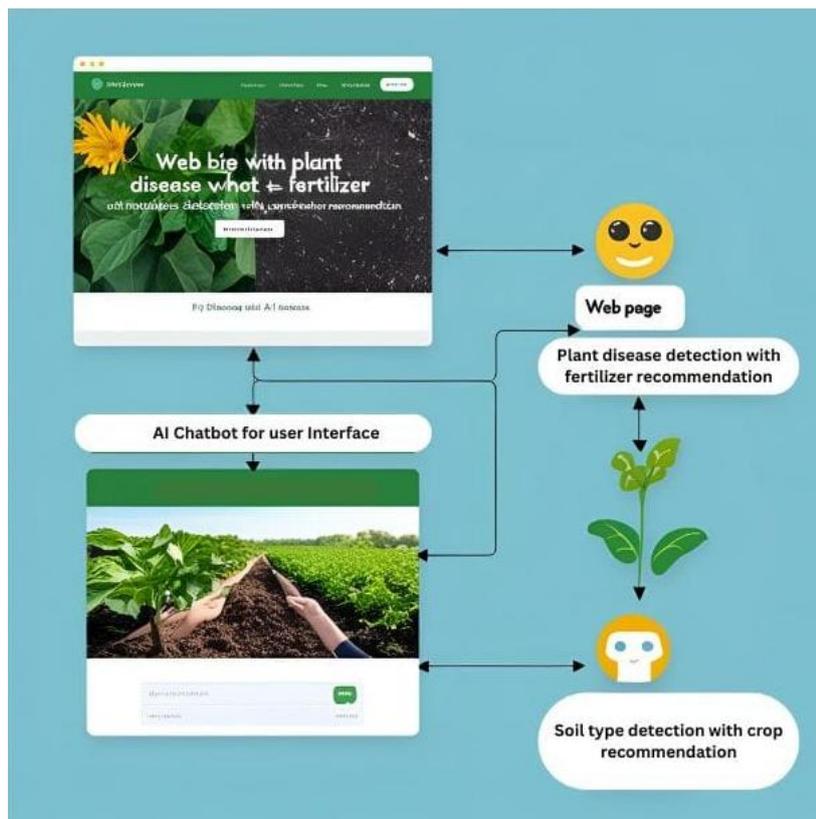
I.   SYSTEM DESCRIPTION

Fig. 1: Plant Disease App

Fig. 2. IoT Soil Moisture Analysis

The block diagram depicted in Fig.1 illustrates an intellectual agricultural system designed specially to assist farmers with plant health monitoring, fertilizer recommendations, soil analysis and crop recommendations using AI and IoT technologies. The system incorporates multiple module including plant disease detection, soil type classification, a multilingual AI chatbot for user interaction and an Iot-based soil moisture monitoring system. Fig. 2. shows the IoT Soil Moisture Analysis.

The plant disease detection module employs a trained deep learning model to classify diseases from image of diseased plant leaves. After identifying the disease, the system provides fertilizer recommendation from the knowledge base, help farmers to treat the plant at time and improve the yield of crops.

The soil type detection module identifies soil type based on input image using a separate trained model. From the detection, it recommends the suitable crops that grow well in that soil. Both models are implemented through an interactive streamlit-based web interface, which allow users to easily upload images and view results. The system also features a multilingual AI chatbot, developed using open source NLP models, knowledge base and voice tools. The chatbot supports multiple languages in both text and voice, responds to queries related to plants, soil, fertilizers, etc., It improves interactions with users by responding in the same language as the user. Furthermore, an IoT-based soil moisture monitoring system is implemented using an ESP32 microcontroller and a capacitive soil moisture sensor. It Measure soil moisture level continuously and activates a buzzer alert whenever the moisture level falls below the threshold, helping farmers to water plants correctly and maintain healthy soil conditions. This integrated smart farming system uses AI and IoT to support the farmers by improving crop health, optimizing soil use, and offering recommendations, user friendly interaction.

I. PLANT DISEASE DETECTION USING ML

MobilenetV2:

MobileNetV2 is a lightweight and efficient deep learning model designed for mobile and low-power devices. It is commonly used for image recognition tasks, including classification and object detection, because it is fast, accurate, and requires less computational power compared to larger models.
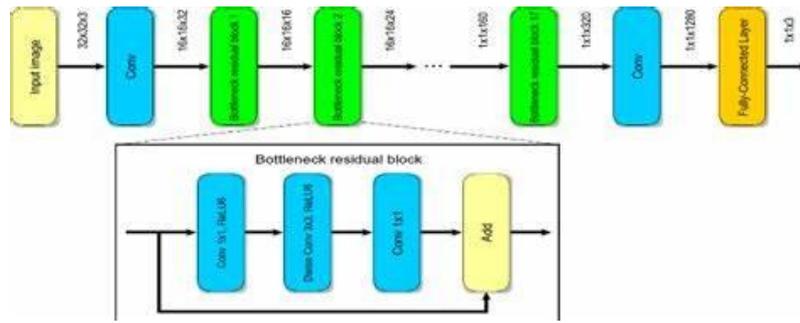
Fig.3 a. Architecture of MobilenetV2

The plant disease dataset has been trained using mobilenetV2 model and the dataset contains 10 types of plants (Apple, Corn, Grapes, Peach, Rice, Strawberry, Tomato, Potato, wheat, Pepper bell) and their diseases. Here we got the following results for apple model training. Fig, 3a shows the Architrecture of MobilenetV2. Fig, 3b, shows the test accuracy of Apple.

```
Found 7771 images belonging to 4 classes.
243/243 [==============================] – 49s 200ms/step – loss: 0.0328 – accuracy: 0.9889
Test Loss: 0.032753318548202515
Test Accuracy: 0.9889332056045532
```

Fig. 3b. Test Accuracy for Apple

The suggested model performed outstanding with 98.89% test accuracy and an incredibly minimal loss of 0.0328 on a dataset of 7,771 images in 4 classes. Evaluation completed successfully at 200ms per step, proving high precision and computational efficiency.Fig. 4. shows the Confusion Matrix for Apple.
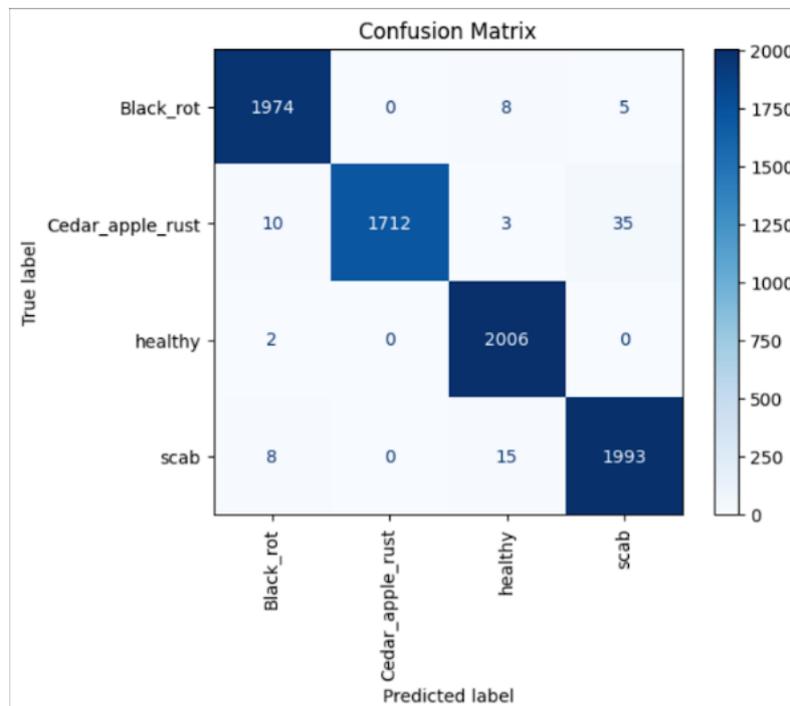

Fig. 4.: Confusion Matrix for Apple

The model has great ability to classify healthy leaves (2006 correct predictions) and Cedar_apple_rust (2006 correct) with very few misclassifications. Black_rot has high accuracy (1974 correct) but with some confusion with scab (35 misclassified). Although the majority of the classes are neatly separated, scab has minimal confusion with other diseases, indicating a scope for improvement in similar-appearing pathologies. Fig. 5. Shows the Classification report for Apple. Table 1. Shows the Test Accuracy of MobileNetV2 Model.

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Classification Report:

                 precision    recall  f1-score   support

      Black_rot       0.99      0.99      0.99      1987
Cedar_apple_rust      1.00      0.97      0.99      1760
        healthy       0.99      1.00      0.99      2008
           scab       0.98      0.99      0.98      2016

       accuracy                           0.99      7771
      macro avg       0.99      0.99      0.99      7771
   weighted avg       0.99      0.99      0.99      7771
```

Fig. 5. Classification report for Apple

Table 1. Test Accuracy of MobileNetV2 Model

MobnetV2
Apple - 98.89
Corn- 96.02
Grapes - 99.22
Peach-99.6
Pepper bell -98.13
Potato-98.42
Rice-79.81
Strawberry -100
Tomato-96.71
Wheat-98.19

II. SOIL CLASSIFICATION USING ML

CNN (Convolutional Neural Network) is a type of deep learning model specifically designed to process and analyse visual data like images. It mimics how the human brain processes visual patterns, making it excellent for tasks like image classification, object detection, and more. Fig. 6a. Shows the CNN Model Architecture.
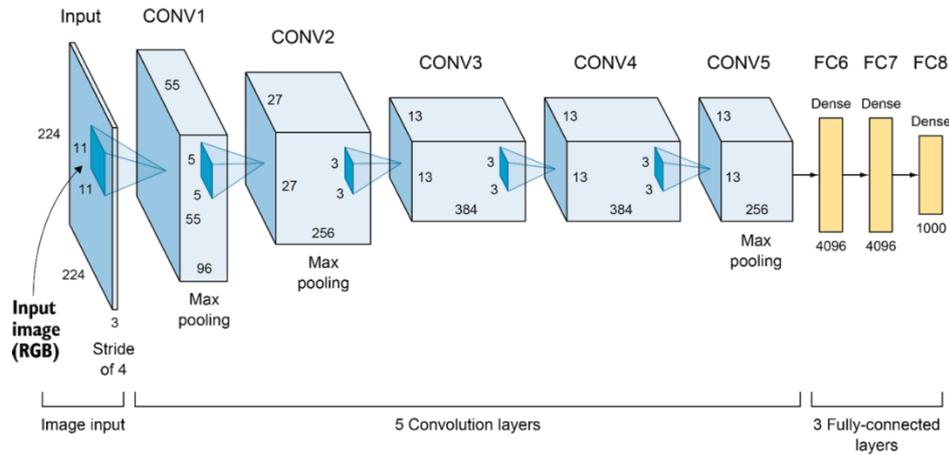
Fig. 6a. CNN Model Architecture

The soil dataset has been trained using CNN model and the dataset contains 4 types of soil images. Here we got the following results for soil model training. Fig, 6b shows the soil classes and Fig. 7 shows the CNN Layers.

Fig.6b: Soil Classes

Fig. 7. CNN Layers

The suggested sequential CNN structure consists of convolutional layers (Conv2D), batch normalization, and max-pooling (MaxPooling2D), systematically diminishing spatial sizes (e.g., 222×222 → 111×111) while enhancing feature channels (32 → 128). The model has 22.2 million parameters, 99.9% of which are trainable, and a memory requirement of 84.86 MB. Batch normalization facilitates stable training, and hierarchical down-sampling boosts feature extraction. The architecture reconciles computational efficacy with performance and is therefore resource-efficient for resource-limited applications. Layer-wise parameter distributions (e.g., 18,496 in second Conv2D) illustrate its streamlined structure.Fig. 8 shows the Test accuracy for soil classification

```
11/11 [==============================] – 2s 172ms/step – loss: 0.1823 – accuracy: 0.9174
Test Loss: 0.1823
Test Accuracy: 0.9174
```

Fig. 8.: Test Accuracy for Soil Classification

The model performed test accuracy at 91.74% and loss of 0.1823, indicating high classification performance. Convergence was smooth during training, finishing every epoch within around 172 milliseconds per step. The small value of the loss function guarantees solid generalization to the test set. Such outcomes confirm the validity of the introduced CNN structure for the specified task. Equilibrium between the speed (2s per epoch) and the accuracy points out its real-world usefulness. Fig. 9 shows the confusion matrix.
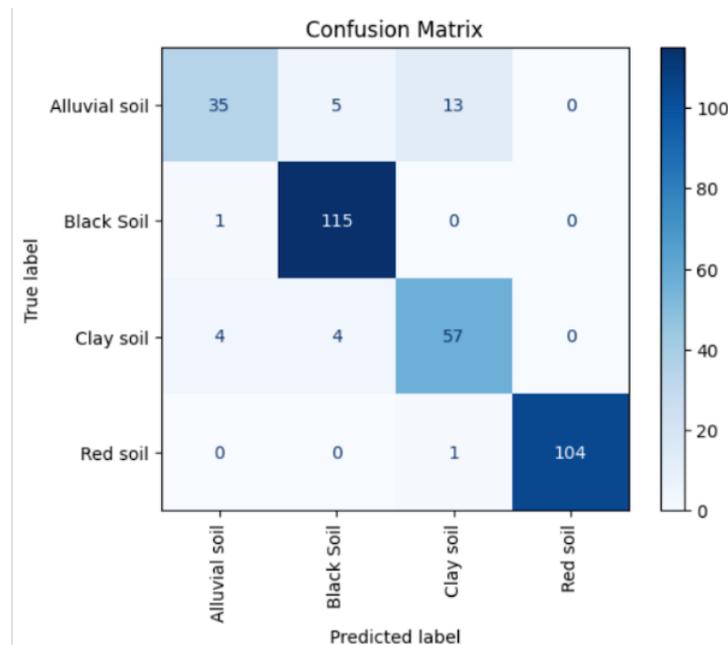

Fig. 9. Confusion Matrix

The model is highly accurate for Black Soil (115 correct predictions) but is confused in Alluvial and Clay Soil (13 misclassifications). Red Soil is moderately (57 correct) with some overlap in class predictions. The results reflect strong classification for different soil types but indicate difficulty in distinguishing similar textures. Fig.10 shows the classification report.

```
Classification Report:

                precision    recall   f1-score   support

Alluvial soil       0.88      0.66      0.75        53
  Black Soil        0.93      0.99      0.96       116
   Clay soil        0.80      0.88      0.84        65
    Red soil        1.00      0.99      1.00       105

    accuracy                            0.92       339
   macro avg        0.90      0.88      0.89       339
weighted avg        0.92      0.92      0.91       339
```

Fig. 10. Classification Report

III. RESULT & DISCUSSION

The homepage serves as the gateway to the integrated functionalities of the application. It shows Plant Disease Detection, Soil Type Analysis, and AI Chatbot. Each of them is accessible through visually distinct and easy-to-navigate buttons. This design ensures users can quickly choose the desired functionality, enhancing the overall user experience. Fig. 11 shows the Home page of Plant disease detection App and Fig. 12 shows the Plant Disease Detection Page.
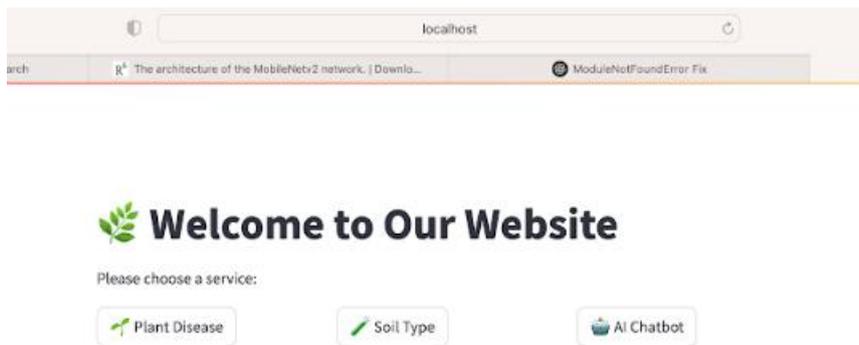
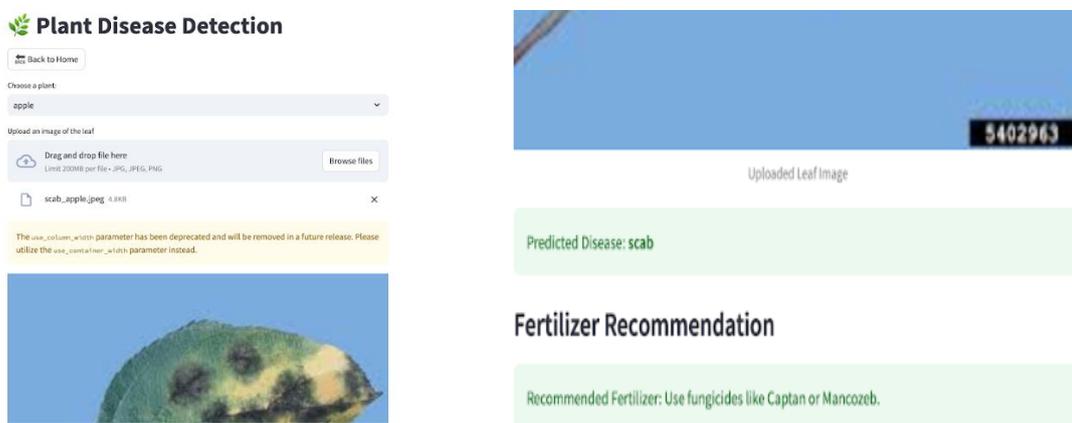Fig. 11. Home page of Plant disease detection App

Fig. 12. Plant Disease Detection Page

This figure illustrates the user interface of the plant disease detection system. This page allows farmers to upload plant leaf images, which are analyzed using the MobileNetV2 model to accurately detect diseases and recommend appropriate fertilizers.
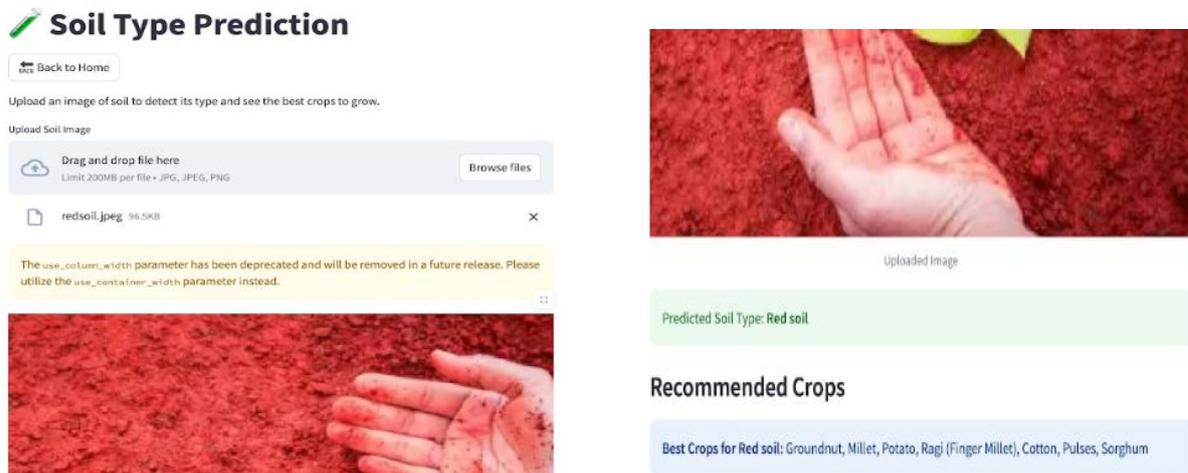

Fig. 13. Soil Type Classification Page

This fig. 13. illustrates the Soil Type Prediction functionality of the application. Farmers can upload an image of the soil, and the system processes it to classify the soil type using a CNN model. In this pic, the uploaded image of red soil has been successfully classified as Red Soil. Based on this classification, the application provides a list of recommended crops.

IV. CONCLUSION

The proposed Smart Farming AI Powered Assistant effectively incorporates Machine Learning to Address key challenges in modern agriculture. By enabling plant disease detection and soil type classification, the system helps farmers to make quick and better decisions, reduce resource wastage, and enhance crop yield. The use of lightweight and efficient models like MobileNetV2 and CNN ensures that the solution remain practical and deployable even in low-resource rural environments. Overall, this handful and user-friendly platform demonstrates significant potential to transform traditional farming into more intelligent, sustainable, and connected agricultural practice.

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