AI-BASED SOLUTION FOR ADDRESSING PLANT DISEASES IN EGYPT'S FRUIT AND VEGETABLE CROPS

Turning Small Steps into Big Impact

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Introduction – Importance of Agriculture

Agriculture is a vital pillar of global stability and development. It plays a key role in:

- Ensuring food security for growing populations
- Providing income and employment for rural communities
- Driving economic growth, especially in developing nations
- Supporting sustainable use of natural resources
- Reducing poverty and strengthening community resilience

However, the agricultural sector faces major challenges such as:

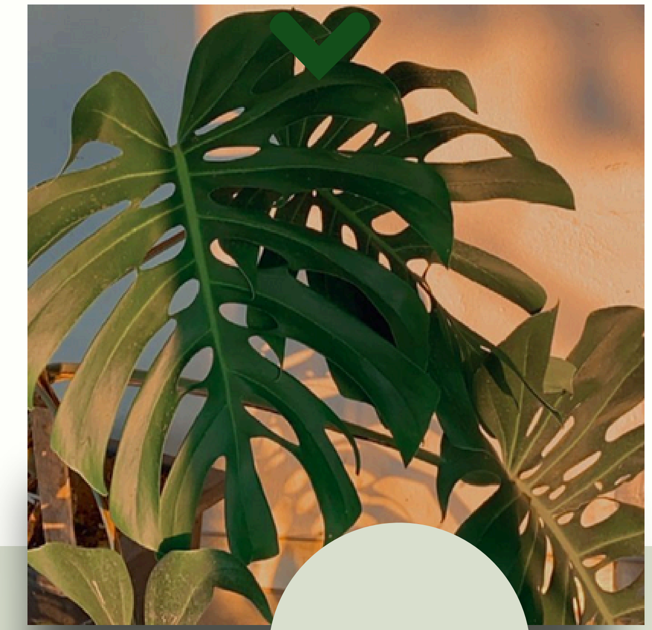
- Plant diseases & right tratment
- Climate change
- Water scarcity
- Soil degradation
- Limited access to expert support and technology

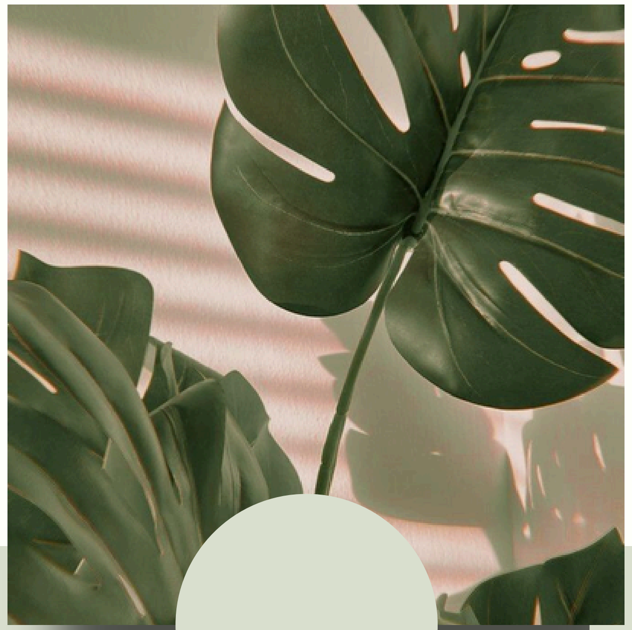
Proplem Defination

Planty Care focuses on three major problems farmers struggle with:

- Disease diagnosis: Similar symptoms make it hard to detect the correct disease, leading to wrong or late treatment.
- Fertilizer choice: Without soil insight, farmers use unsuitable fertilizers, harming crop health and soil quality.
- Crop selection: Poor crop-soil matching leads to low yield and wasted effort.

Planty Care solves these issues using real-time, AI-powered support through a simple mobile app.





Motivation

- Agriculture is Egypt's Lifeline, a major contributor to Egypt's GDP.
- With Egypt experiencing losses exceeding 20%
- 20–40% of global crop loss is caused by plant diseases (FAO).
- Over 500 million small-scale farmers worldwide lack access to expert advice.
- Misuse of fertilizers reduces soil quality and increases production costs.

Literature Review

Author & Year	Dataset	Methodology	Accuracy
Bouacida et al. 2024	PlantVillage dataset	small Inception model architecture	94.04%
Biswas et al. 2024	PlantVillage dataset	novel time-effective CNN architecture, described as an energy-efficient convolutional network (5× faster than Inception V3 and 2× faster than VGG19)	95.17%
Naveed et al. 2025	PlantVillage dataset	ResNet18	93%.

Objectives

1. Detect plant diseases & treatment using AI (ResNet-50)
2. Recommend the best crop using random forest
3. Suggest suitable fertilizer using XGBoot
4. Deliver all features through a developed Android mobile app (Java-based)
5. Data Security & Privacy Protection – Keeps user data safe

System Input & Output

Feature 1: Diseases Detection & Treatment Suggestion

Feature Input (Expected Input):

- (single image)

Feature Output (Expected Output):

- Disease Name
- Description
- Preventive measures and treatment tips
- Suggested Supplement

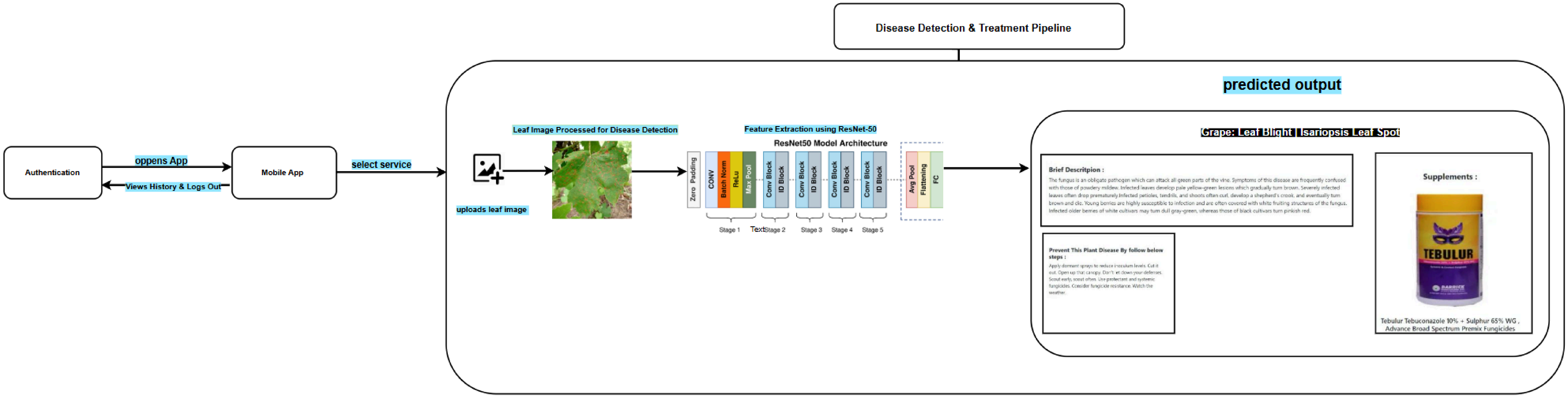
Feature 2: Crop Recommenadtion System

- **Feature Input:**
- Environmental data (temperature, rainfall, N ,P)
- **Feature Output:**
- Most suitable crop(s) for the given conditions

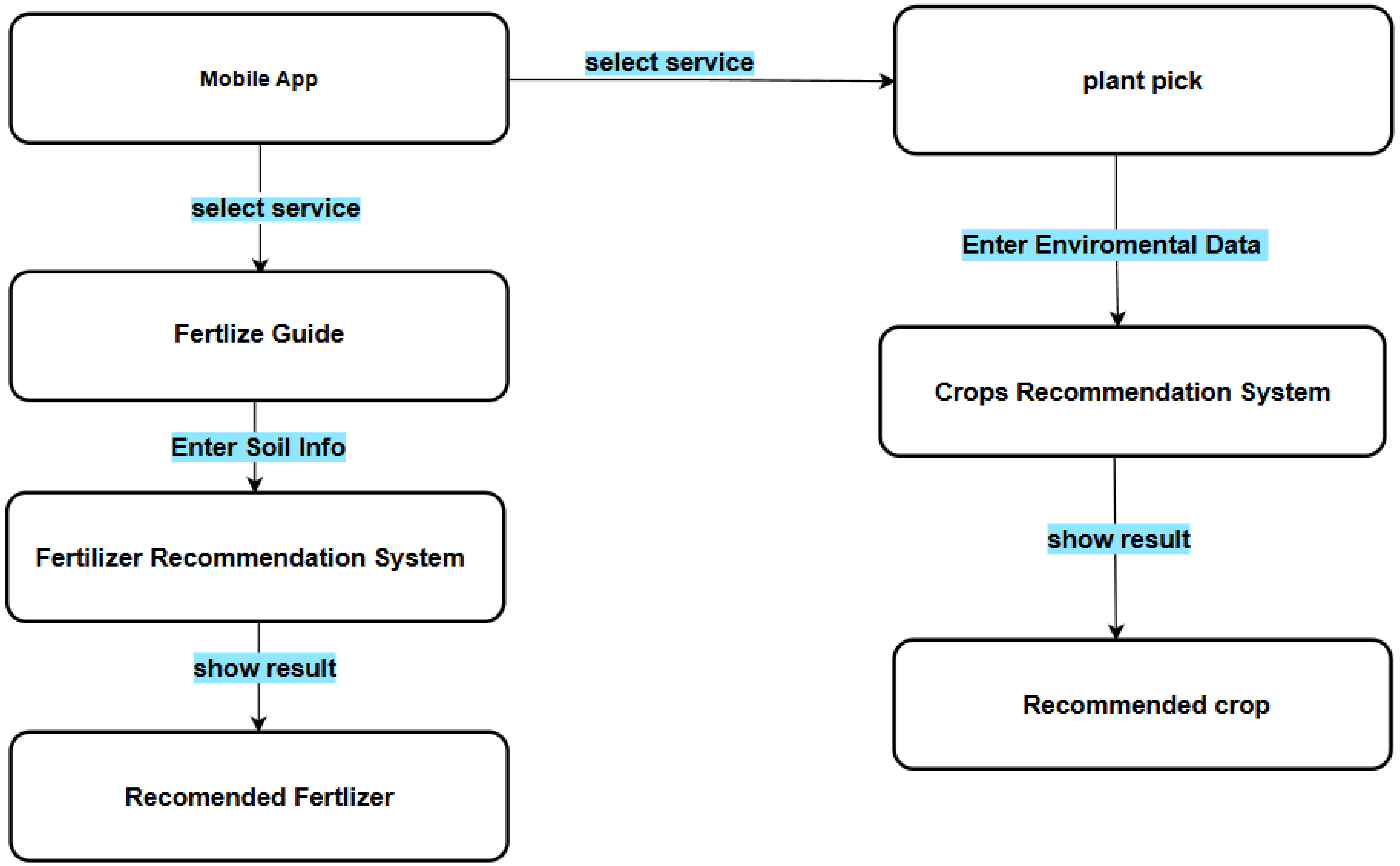
Feature 3: Fertilizer Recommendation System

- **Feature Input:**
- Soil information (N, P, K levels, pH, soil color)
- Selected plant (crop name)
- **Feature Output:**
- Best matching fertilizer for the selected crop and soil condition

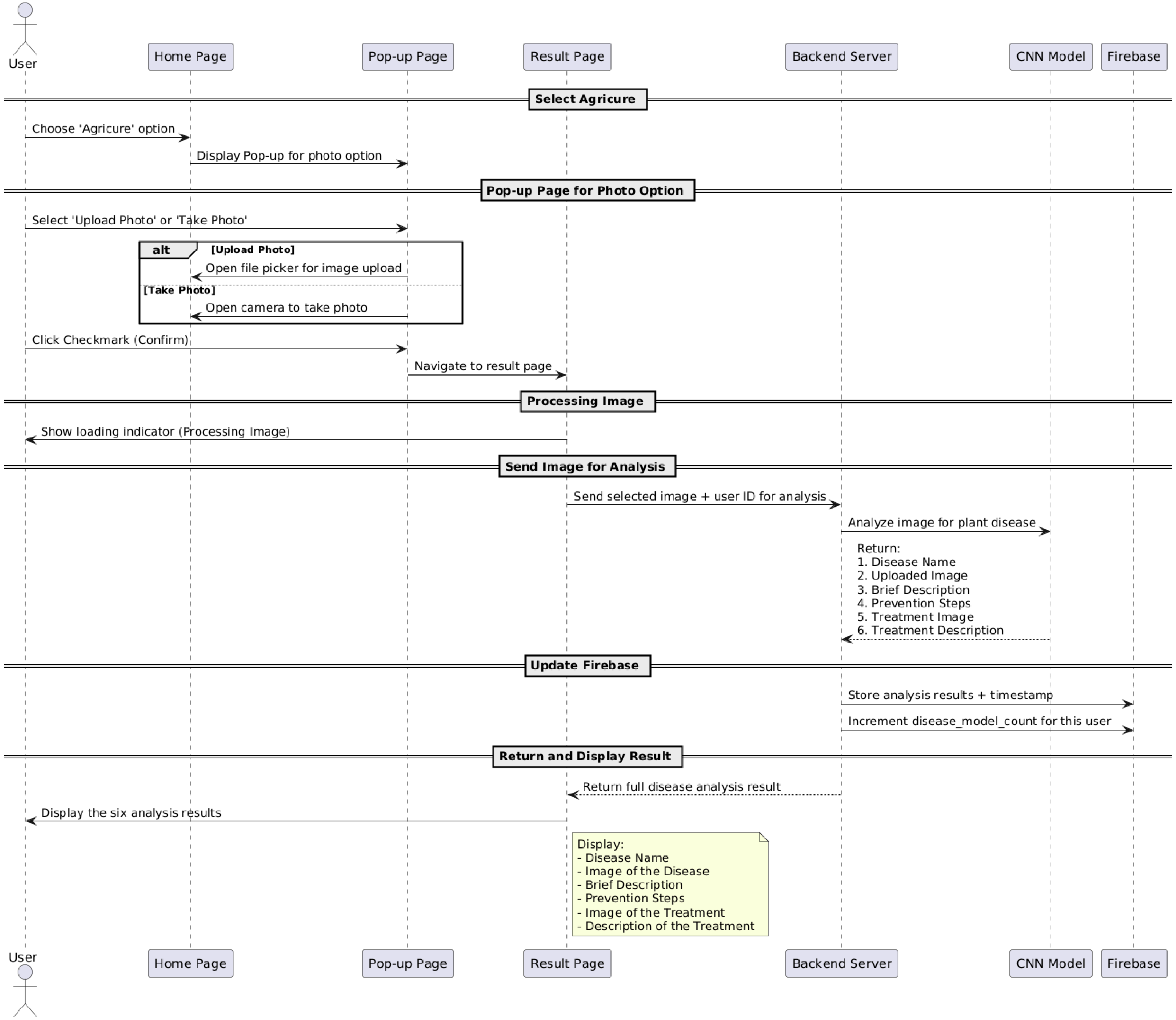
System Architecture Phase 1



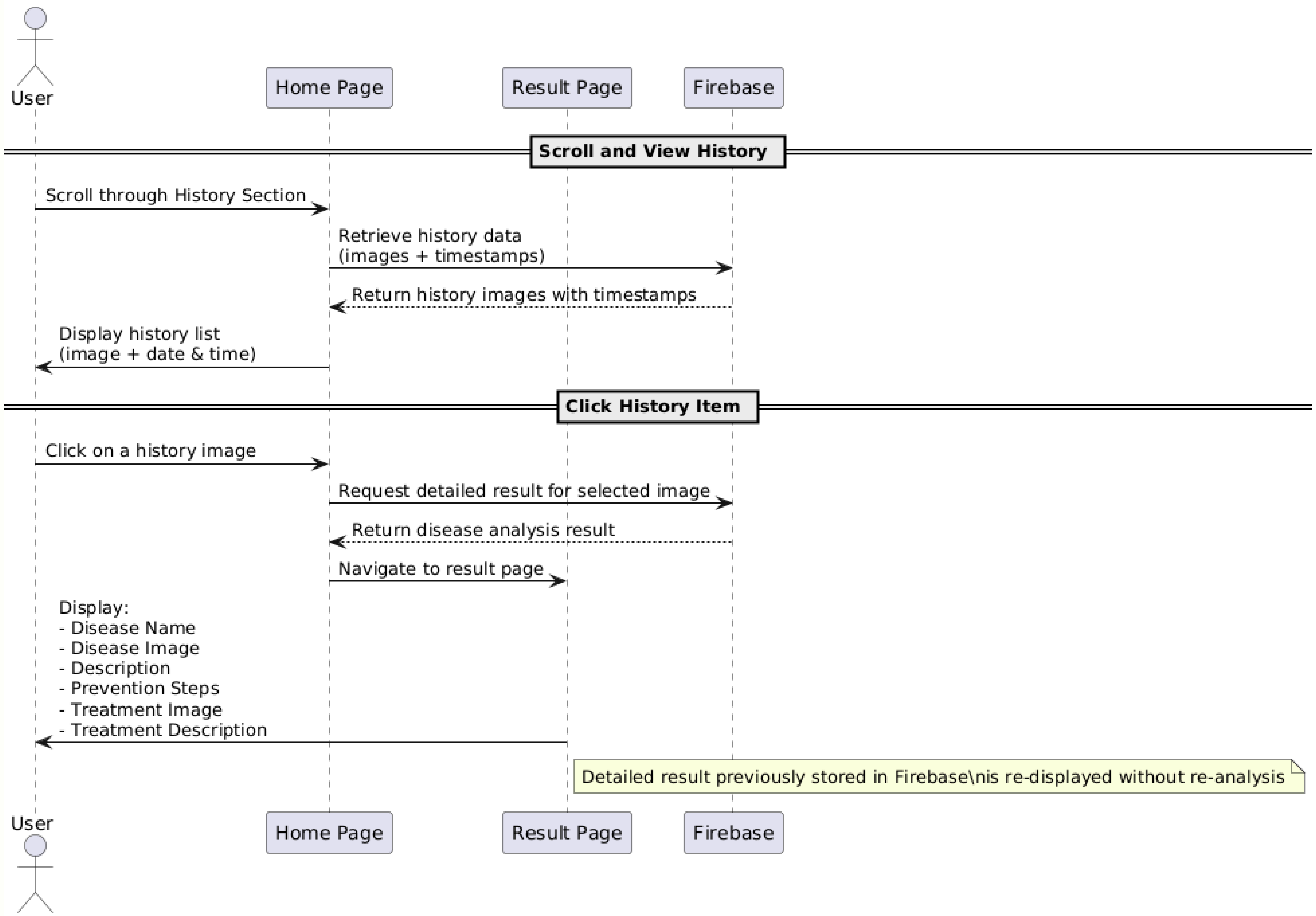
System Architecture Phase 2 Crop & Fertlizer guide



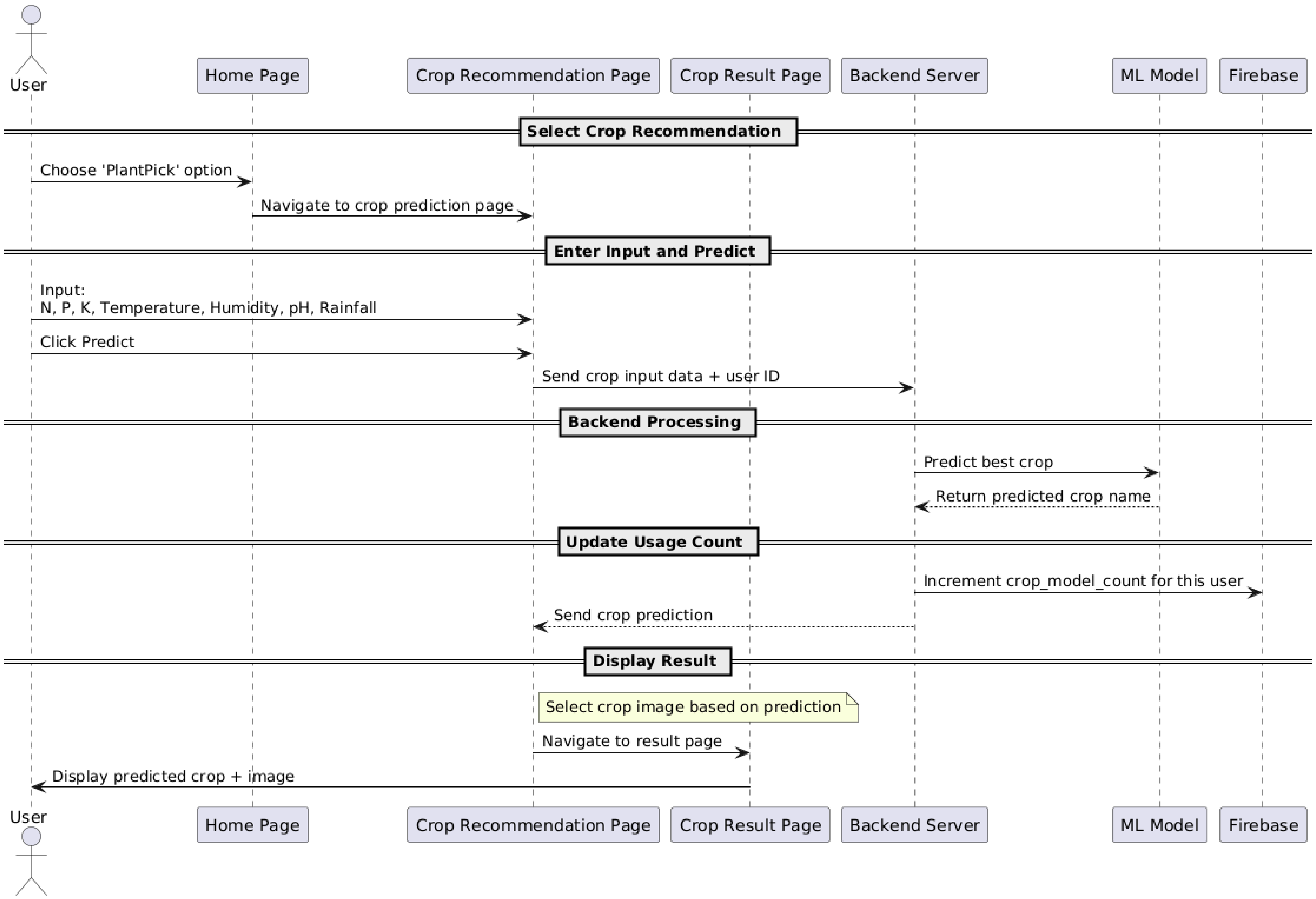
Sequence Diagram for Plant Disease Detection Feature



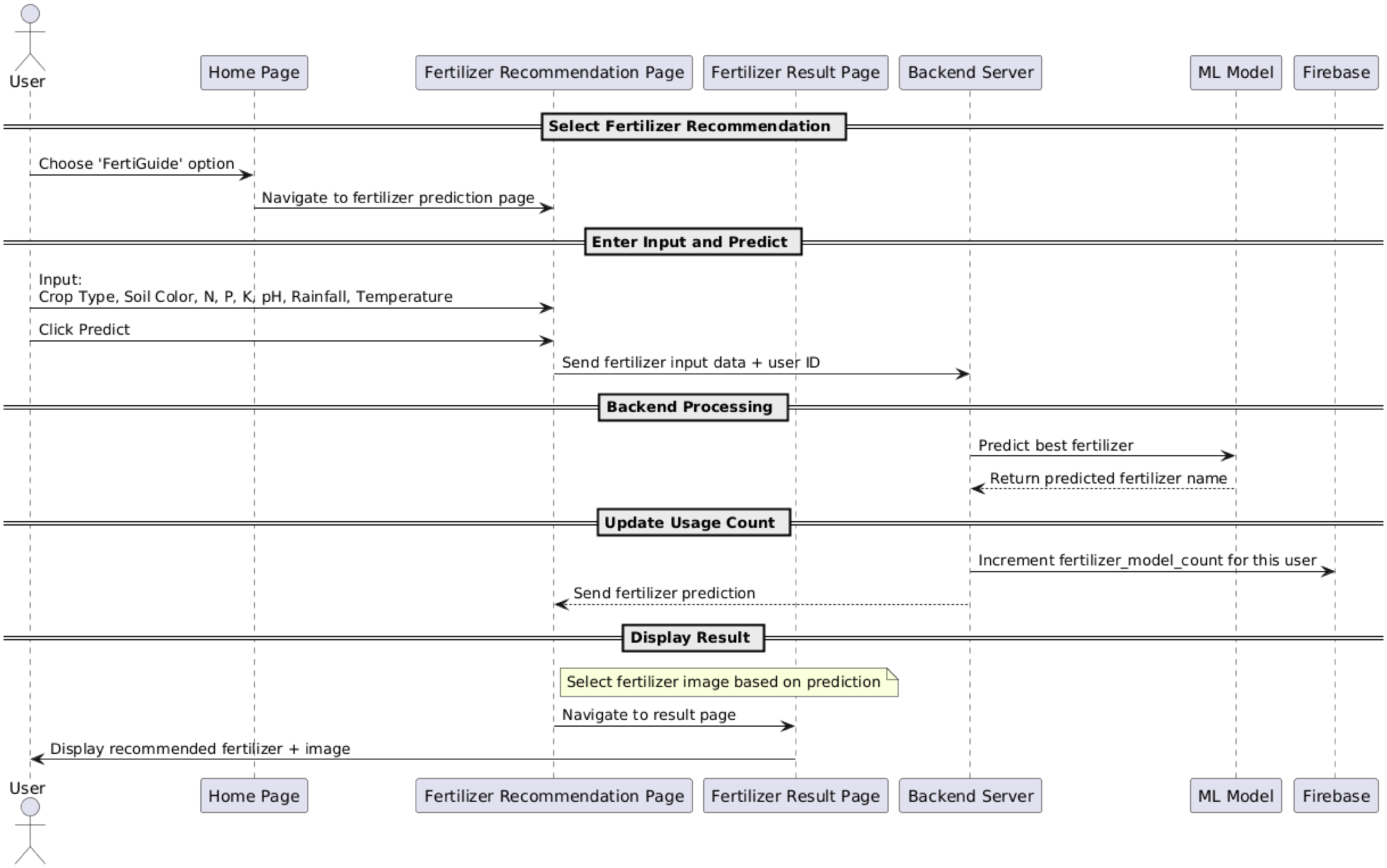
Sequence Diagram for History



Sequence Diagram for Crop Recommendation Feature



Sequence Diagram for Fertilizer Prediction Feature



DATASETS

In this project we used 3 datasets:

1- New plant disease dataset (images).
   1.1- supplement_info(csv).
   1.2- disease_info(csv).

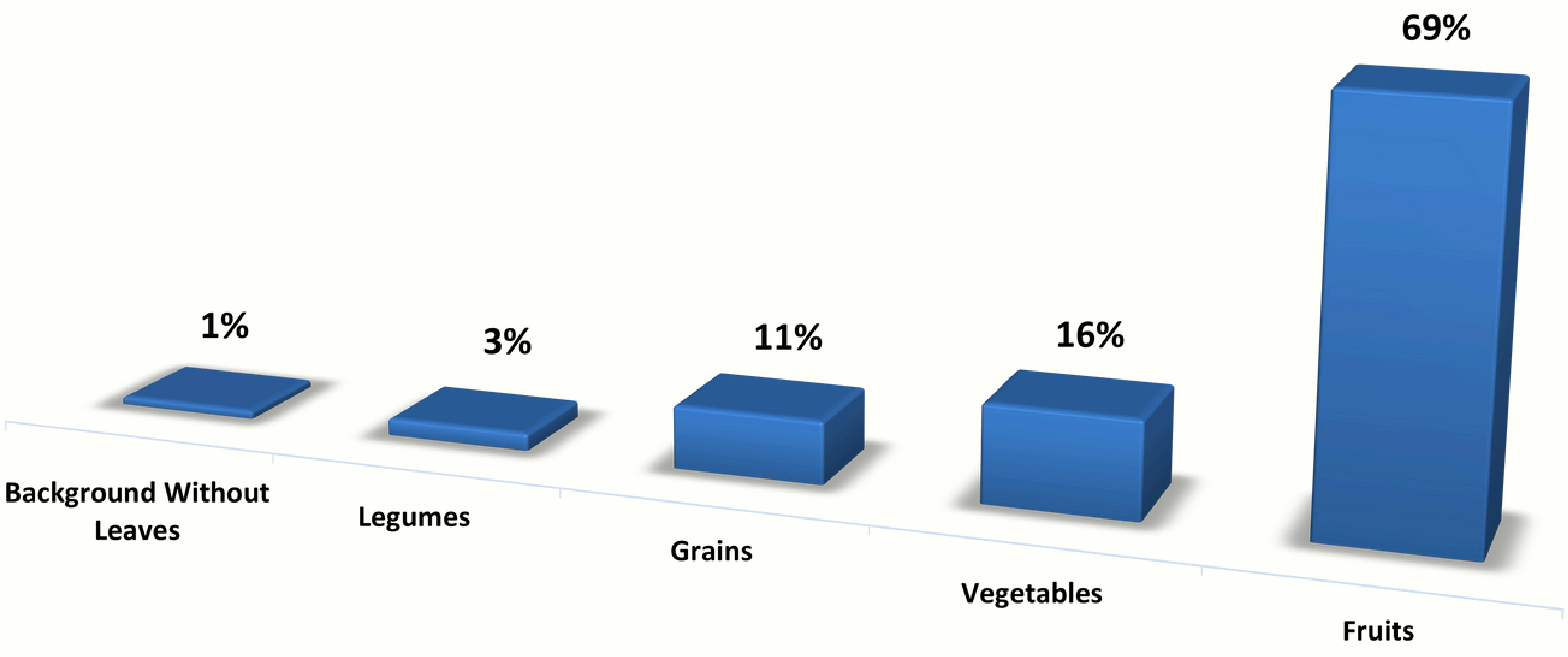
2- Crop Recommendation dataset(csv).

3- Crop and fertilizer dataset(csv).

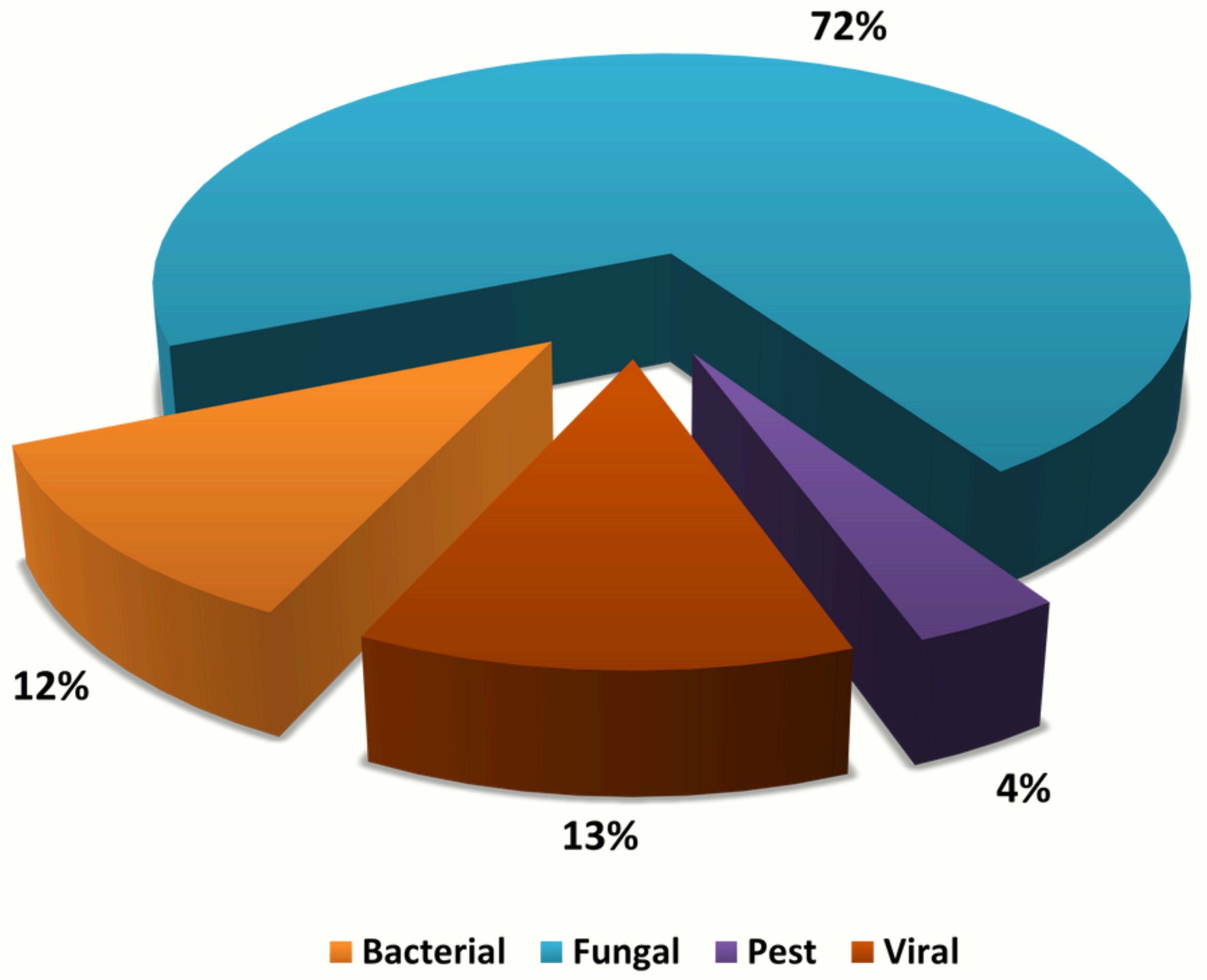
Visualization of Plant Disease Dataset

Total Classes	38
Total Plants Leaves	13
Total Plant Types	4
Total Fruits	8
Total Vegetables	3
Total Legumes	1
Total Grains	1
Total Diseases	19
Total Treatments	37
Total Train Images	69,428
Total Val Images	17,336
Total Test Images	54

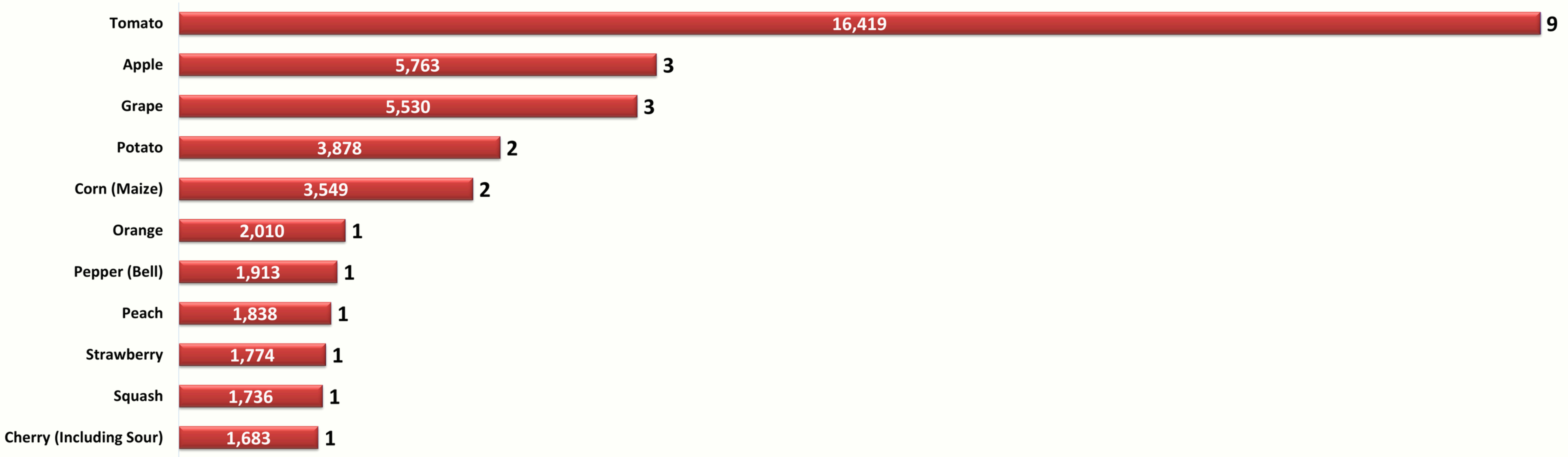
Images Distribution Ratio



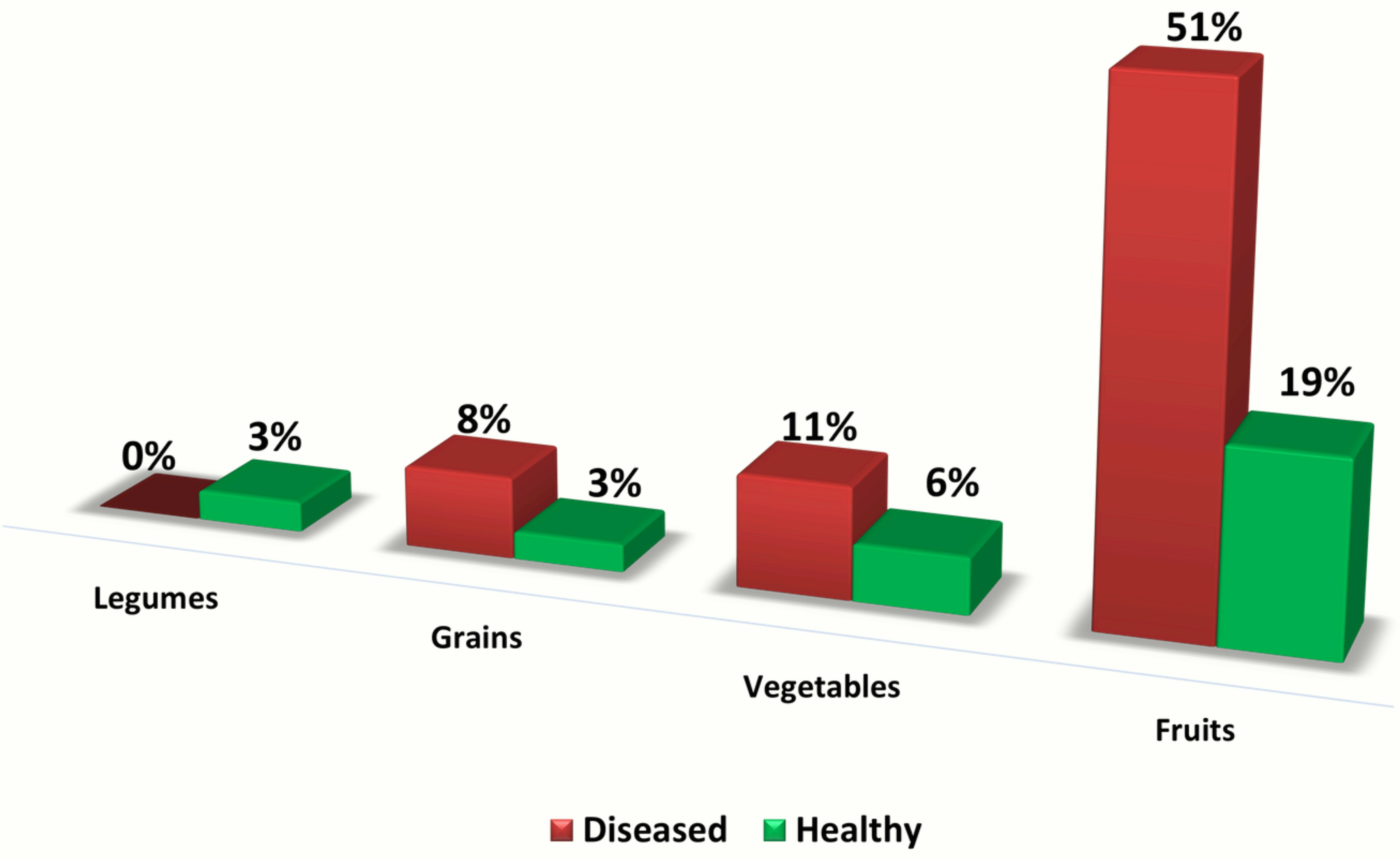
Distribution of Disease Types



Visualization of Plant Disease Dataset (Cont.)



Plants with the Highest Disease Cases



Diseased Plants Vs Healthy Plants

Feature 1 : Plant Disease Detection

🗂️ **Dataset Overview (New Plant Diseases Dataset)**
Source: Kaggle
Size: 86,818
Classes: 38 (includes healthy and diseased leaf categories)
Crops Covered: Tomato, Potato, Corn, Apple, etc.
Split:
Training: 69,428
Validation: 17,336
Testing: 54
Image Size: Resized to 128×128 pixels
✅ **Purpose: Used for image-based classification of plant health conditions.**

📚 **Supporting Dataset (Plant Disease & Supplement Info Dataset)**
Includes:

1. **Disease name**
2. **Symptoms description**
3. **Treatment steps**
4. **Reference image URLs**
5. **Goal: Provides educational feedback and actionable treatment recommendations post-diagnosis.**

Common Plant Diseases in Egypt

Corn – Cercospora leaf spot Gray leaf spot, Common rust, and Northern Leaf Blight, which lower grain quality .

Tomato – Prone to late blight, bacterial spot, and early blight, leading to fruit rot and reduced production.

Grapes – Affected by downy mildew, powdery mildew, and black rot, causing poor fruit quality and yield loss .

Model 1: ResNet-50 Implementation

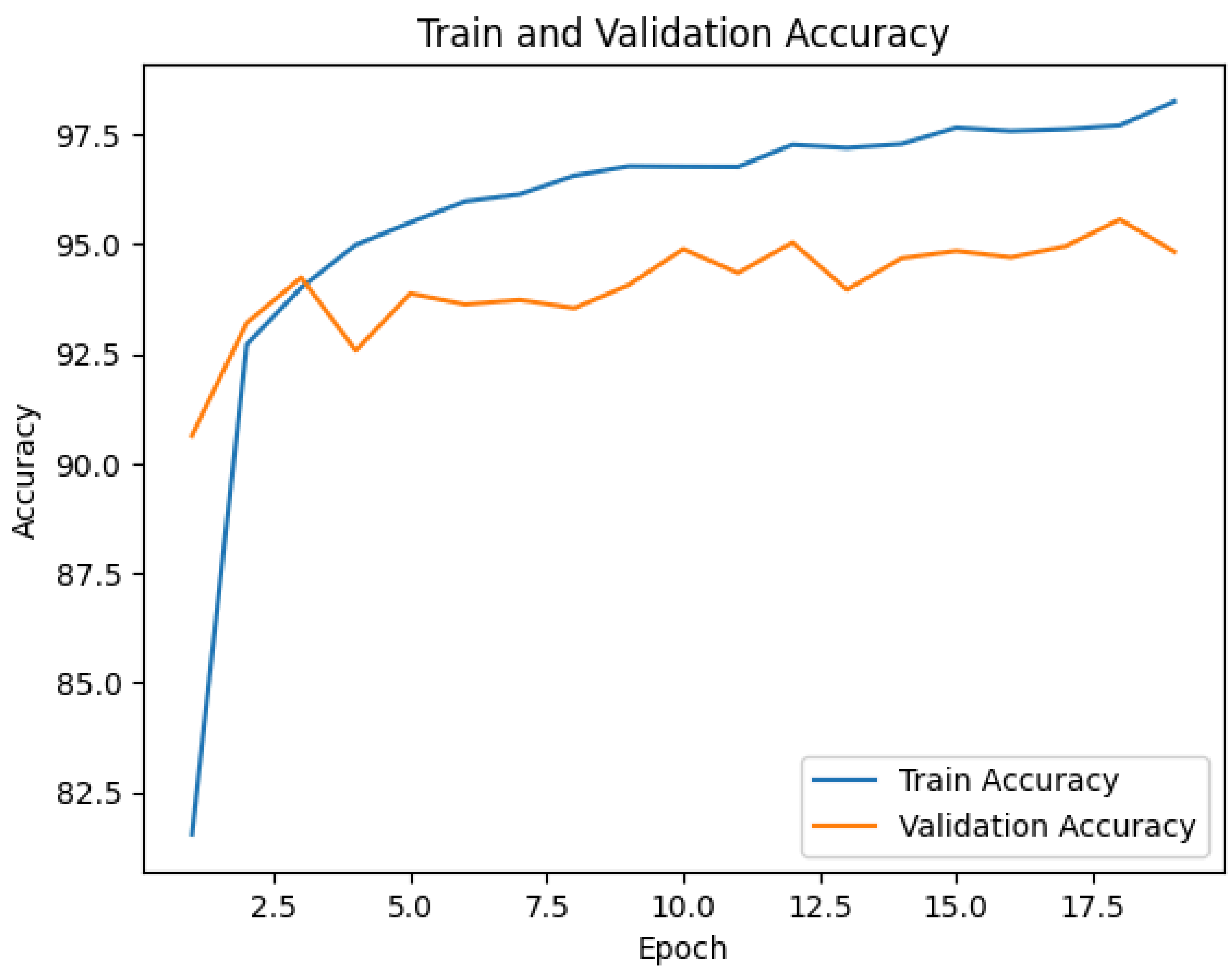
ResNet-50
Algorithm: ResNet-50 (Deep Convolutional Neural Network)
Architecture: 48 conv layers, MaxPooling, AvgPooling, and fully connected layers
Key Feature: Uses residual blocks to solve the vanishing gradient problem, allowing deeper and more stable training
Purpose: High-accuracy classification of plant diseases from leaf images

⚙ **Training Details**

Activation Function: Softmax
Optimizer: AdamW (learning rate: 0.001)
Train / Validation / Test Split: 80% / ~19% / ~1%
Reproducibility: Random seed set for consistent training results

Model 1: ResNet-50 Results

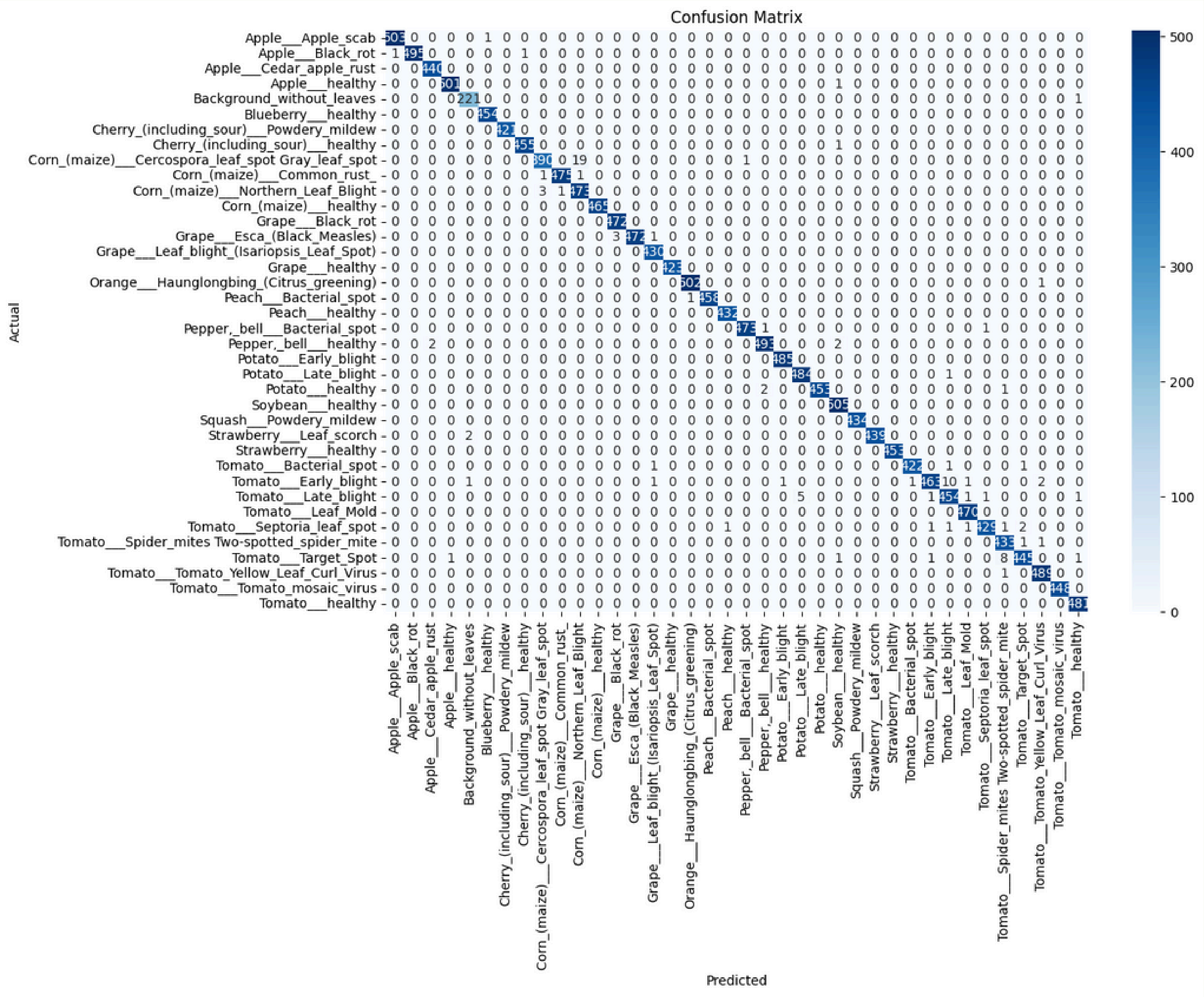
```
[Validation] Epoch 17, Batch 210: Loss = 0.0000
[Validation] Epoch 17, Batch 220: Loss = 0.0597
[Validation] Epoch 17, Batch 230: Loss = 0.0042
[Validation] Epoch 17, Batch 240: Loss = 0.0002
[Validation] Epoch 17, Batch 250: Loss = 0.0009
[Validation] Epoch 17, Batch 260: Loss = 0.0709
[Validation] Epoch 17, Batch 270: Loss = 0.0007
[Validation] Epoch 17, Batch 280: Loss = 0.0023
Epoch 17, Train Accuracy: 99.33%, Validation Accuracy: 99.42%
✅ Best model checkpoint saved at /content/best_model_checkpoint_epoch_17.pth
```



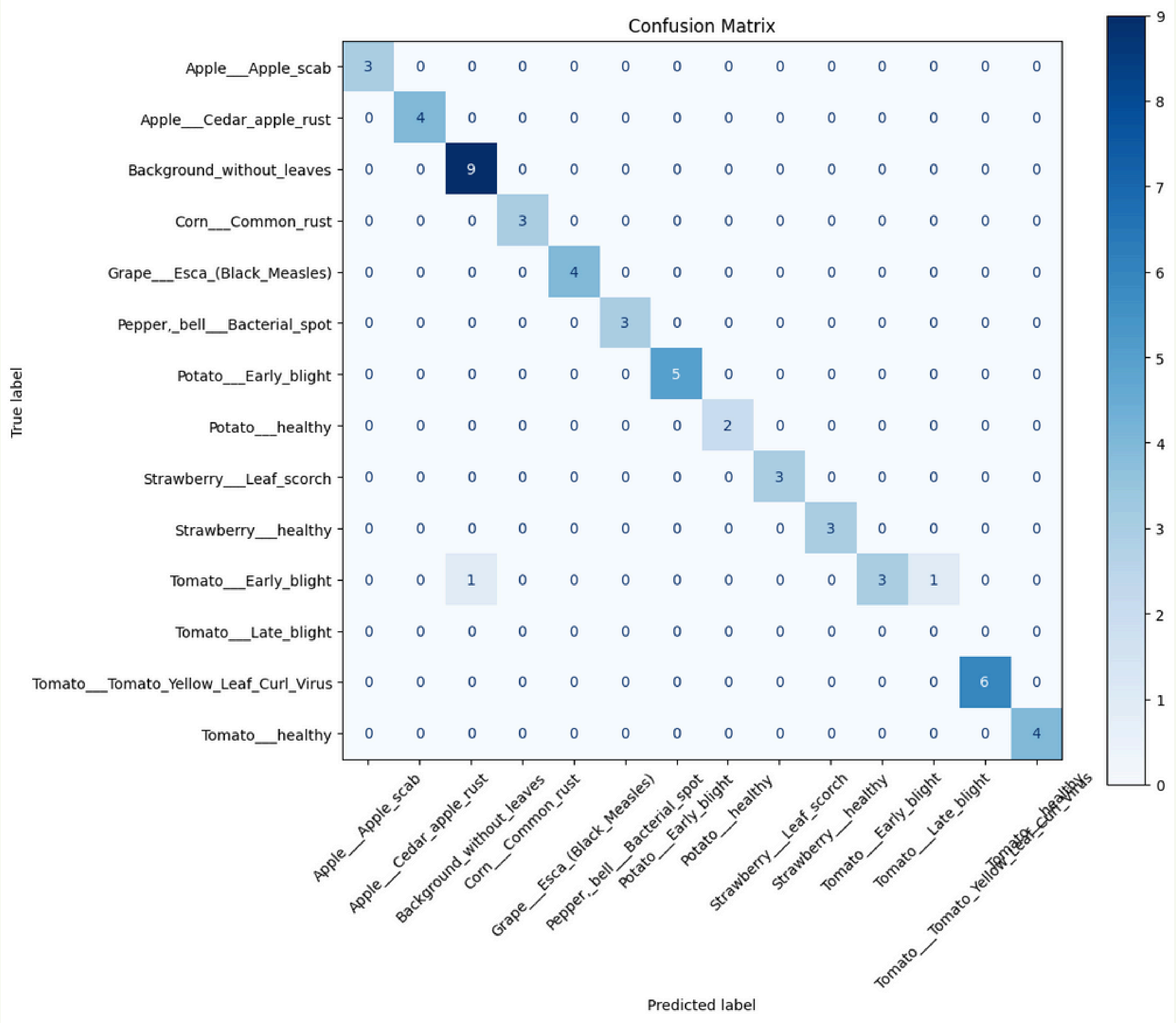
Epoch 17, Train Accuracy: 99.33%, Validation Accuracy: 99.42%

Model 1: ResNet50 Results (Cont.)

validation confusion matrix



test confusion matrix



Average Validation Loss: 0.0191
Validation Accuracy: 99.42%

Test Accuracy: 96.30%

Here We Show Inputs And Predicted Outputs

Strawberry Leaf scorch

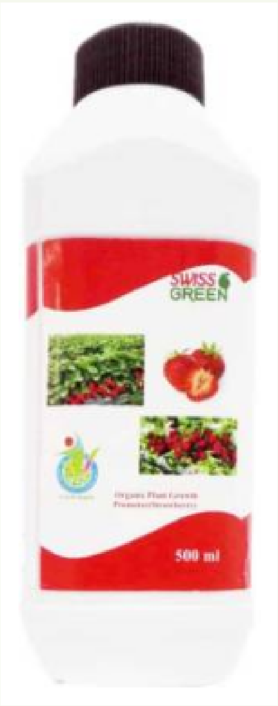
Breif Description

Leaf scorch symptoms are very similar to the early stages of common (Mycosphaerella) leaf spot, with irregular dark purple spots being scattered over the upper leaf surface. As the spots enlarge, they begin to look like drops of tar, and are actually the accumulations of black fruiting bodies (acervuli) of the fungus. The centers of the spots remain purple (in Mycosphaerella leaf spot they are white) and there is no well-defined lesion border. In heavy infections, these regions coalesce and the tissue between the lesions often takes on a purplish to bright red color that is dependent on cultivar, temperature, or other factors. The leaves eventually turn brown, dry up, and curl at the margins giving the leaf a scorched appearance. Examination of the acervuli and conidial morphology can help to distinguish between leaf spot and leaf scorch at this advanced stage of disease. On the upper leaf surfaces of leaf scorch lesions, the acervuli are dark with glistening spore masses and dark apothecia. Petiole lesions are elongate, sunken, with a purplish to brown color and can kill the leaf by girdling the petiole. Runners, fruit stalks, fruit and caps can also become infected. Plants may become weakened and the number and vigor of crowns reduced. Infection predisposes the plants to winter and drought stress. In severe infestations, flowers and fruit may die.

Prevent This plant disease by follow below steps

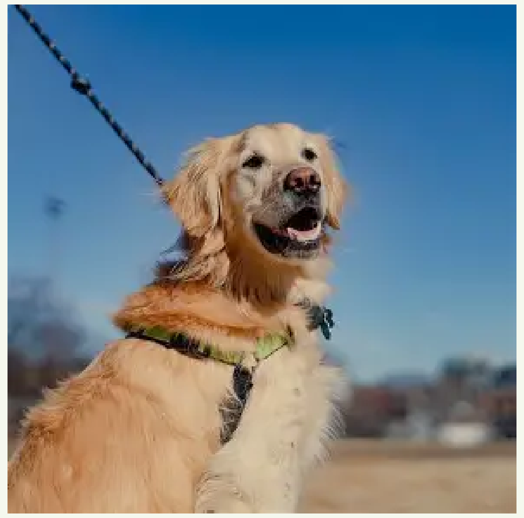
"While leaf scorch on strawberry plants can be frustrating, there are some strategies which home gardeners may employ to help prevent its spread in the garden. The primary means of strawberry leaf scorch control should always be prevention. Since this fungal pathogen overwinters on the fallen leaves of infected plants, proper garden sanitation is key. This includes the removal of infected garden debris from the strawberry patch, as well as the frequent establishment of new strawberry transplants. The creation of new plantings and strawberry patches is key to maintaining a consistent strawberry harvest, as older plants are more likely to show signs of severe infection.",

Supplements :



SWISS GREEN ORGANIC PLANT GROWTH PROMOTER STRAWBERRY Fertilizer

Input



invalid

Feature 2 : (Crop Recommendation)

📊 **Dataset Overview**

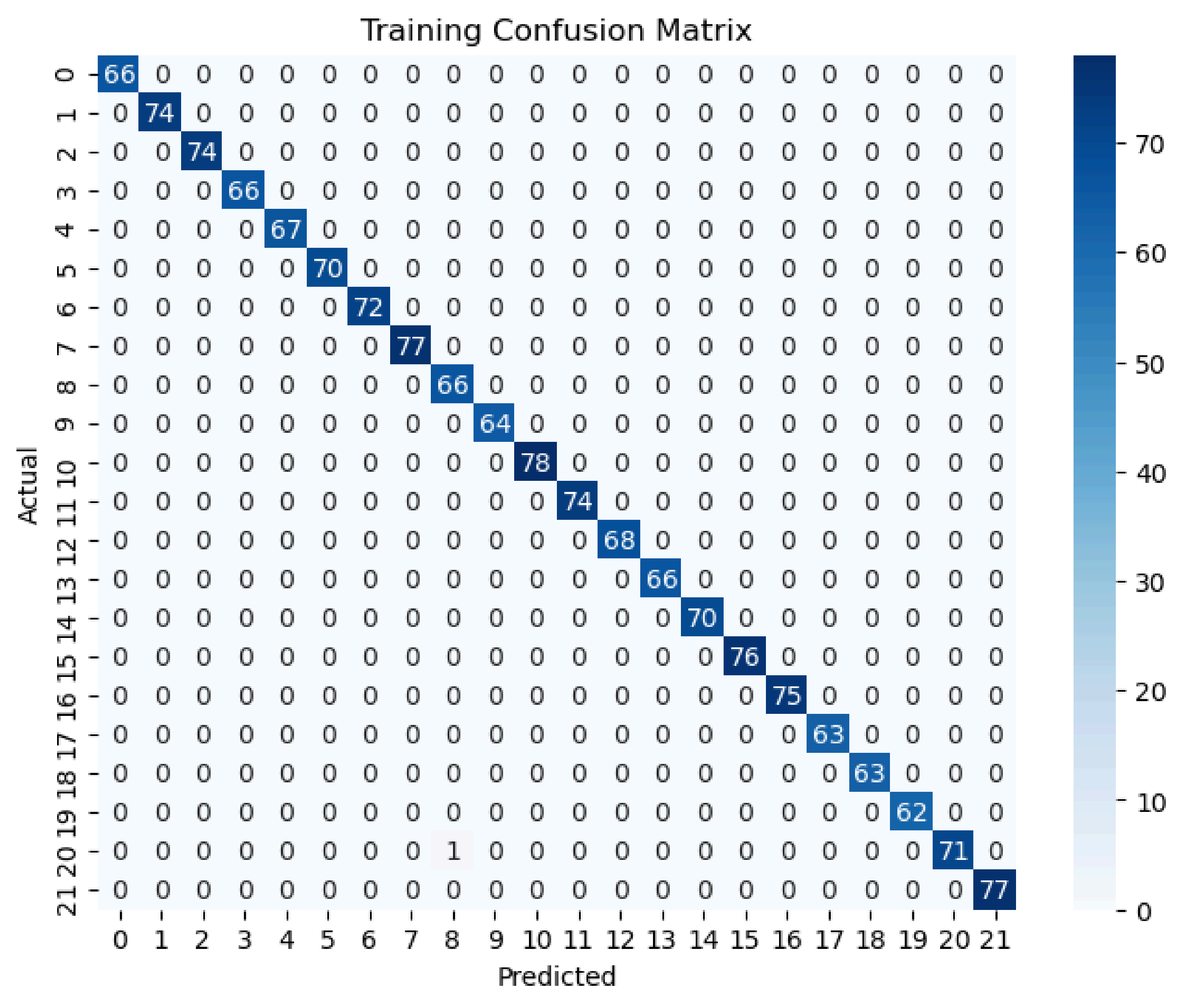
- **Name: Crop Recommendation Dataset**
- **Size: 2,200 instances (1540 train,594 val,66test)**
- **Features (7 total):**
  - **Soil nutrients: Nitrogen (N), Phosphorus (P), Potassium (K) [kg/ha]**
  - **Climate factors: Temperature (°C), Humidity (%), Rainfall (mm)**
  - **Soil pH**
- **Target: Multi-class classification (e.g., rice, maize, cotton, etc.)**
- **Split: 70% training – 27% validation-3% testing**

- **Algorithm: Random Forest (Ensemble Machine Learning Model)**
- **Why Used:**
- **High prediction accuracy**
- **Handles complex and varied environmental data**
- **Robust under different farming conditions**

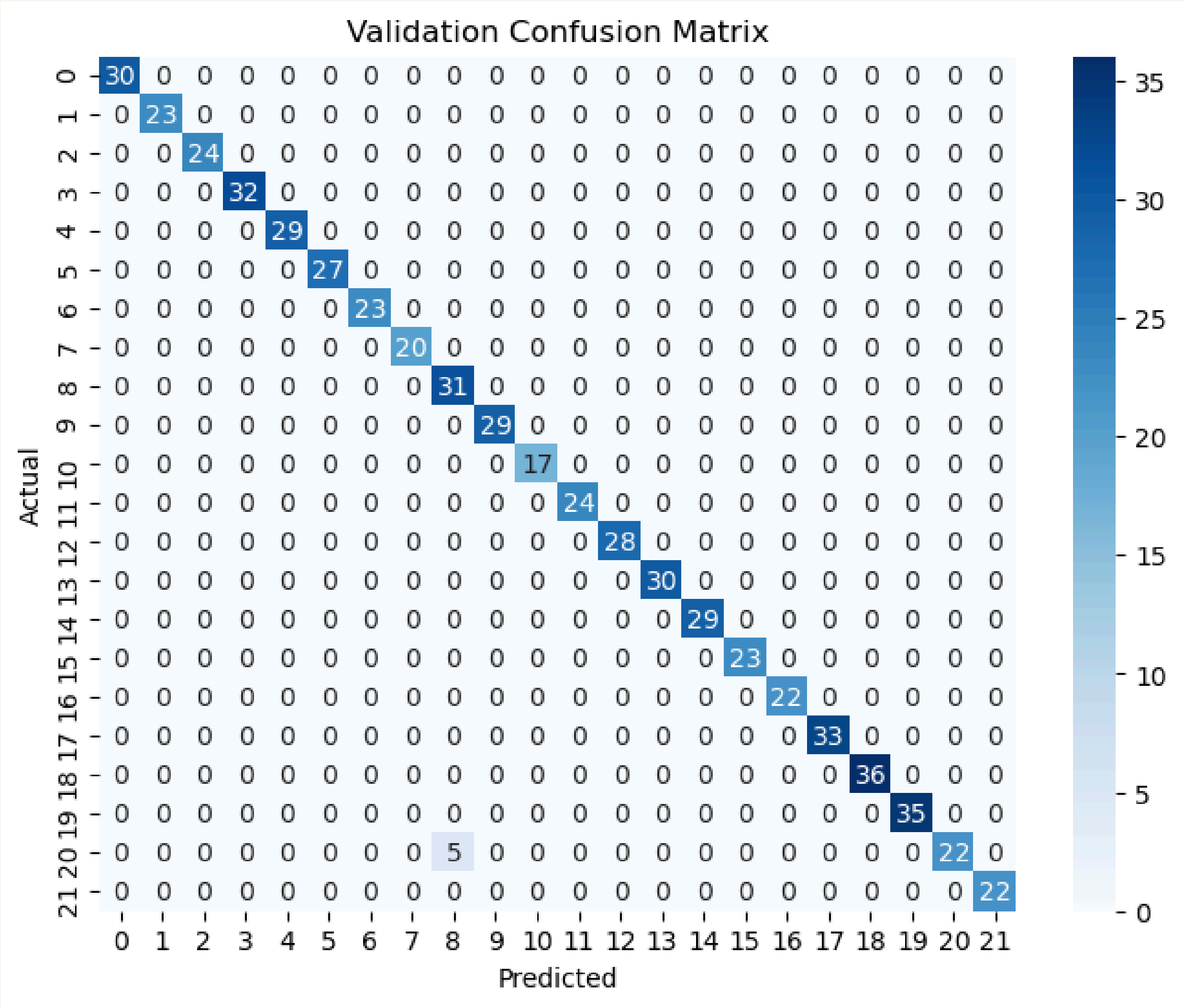
Model 2: Random Forest Results

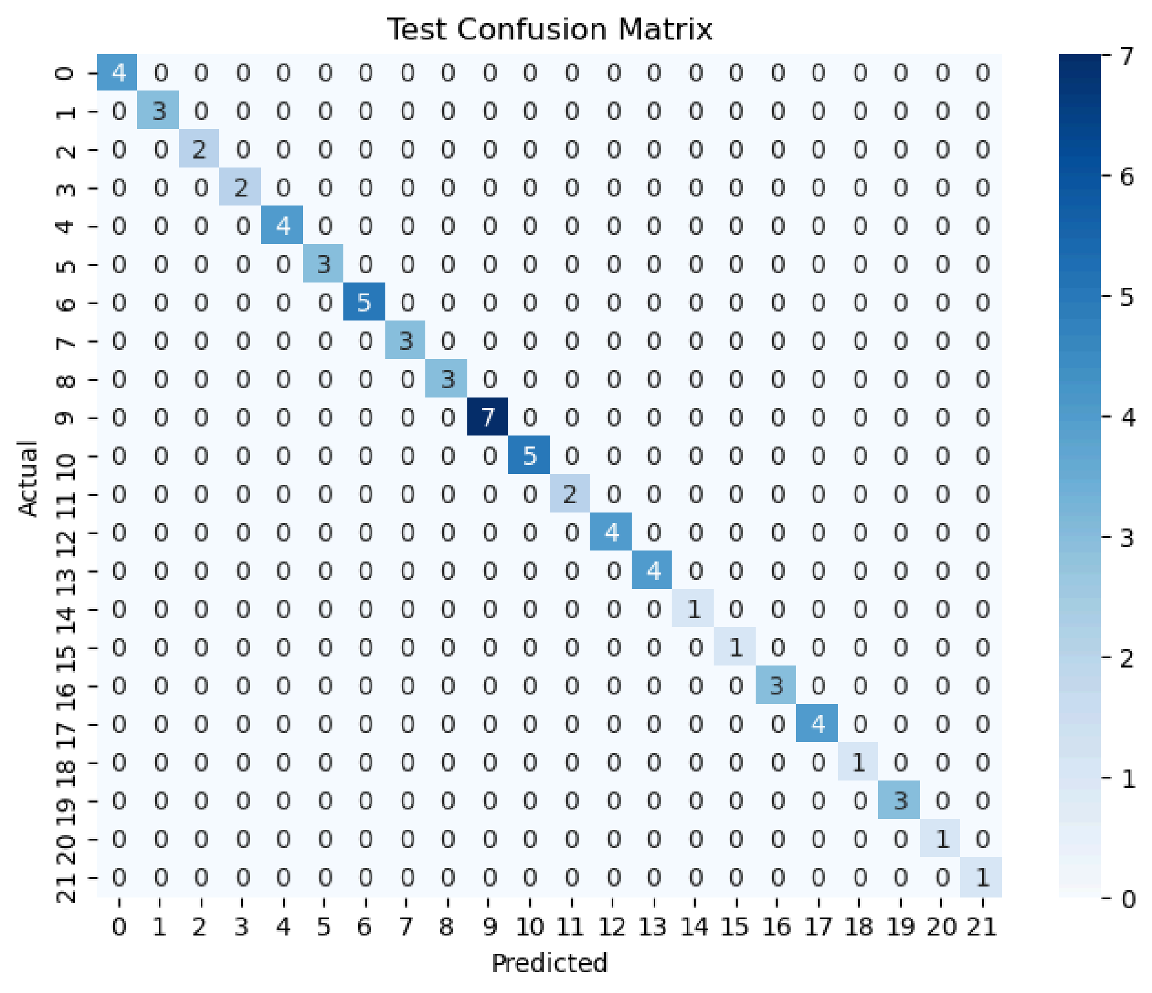
```python
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV
from sklearn import metrics
from sklearn.metrics import confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt

random_forest = RandomForestClassifier(random_state=2, n_jobs=-1)

param_grid = {
    'n_estimators': [50, 100, 200],
    'max_depth': [3, 5, 10, None],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'criterion': ['gini', 'entropy'],
}


grid_search = GridSearchCV(random_forest, param_grid, cv=5, scoring='accuracy', n_jobs=-1, verbose=1)
grid_search.fit(Xtrain, Ytrain)


best_params = grid_search.best_params_



best_random_forest = RandomForestClassifier(**best_params, random_state=2, n_jobs=-1)
best_random_forest.fit(Xtrain, Ytrain)
predicted_values_tarin = best_random_forest.predict(Xtrain)
```

Training Accuracy: 99.94%



Model 2: Random Forest Results (Cont.)






```
import joblib
import numpy as np
model = joblib.load("Random_forest.joblib")

data = np.array([[3, 26, 40, 24, 90, 6, 112]])

prediction = model.predict(data)
print("Prediction:", prediction)

Prediction: ['pomegranate']
```

Validation Accuracy: 99.16%

Test Accuracy: 100.00%

Output

🌿 Feature3: Fertilizer Recommendation

📊 **Dataset Overview**

Name: Crop and Fertilizer Recommendation Dataset
Size: 4,513 records
Key Features:
Soil and Environment: Nitrogen (N), Phosphorus (P), Potassium (K), pH, Rainfall, Temperature
Categorical Data: District Name, Soil Color (encoded numerically)
Target: Recommended Fertilizer type (multi-class classification)
Additional Fields: Recommended Crop, Educational Link
Diversity: Data collected from multiple districts covering various geographical and climate conditions

🧠 **Model Used: XGBoost**

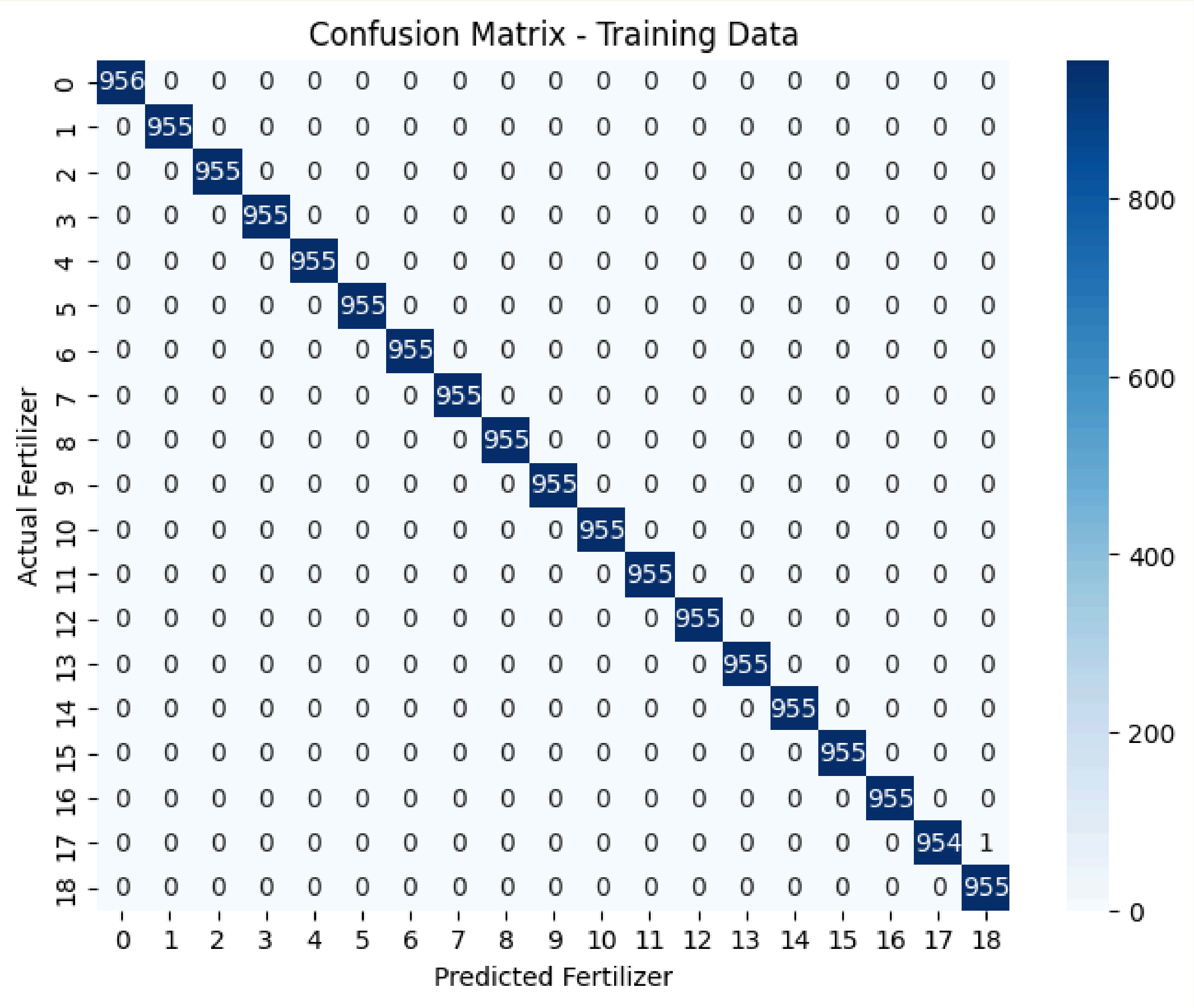
We selected XGBoost due to its:

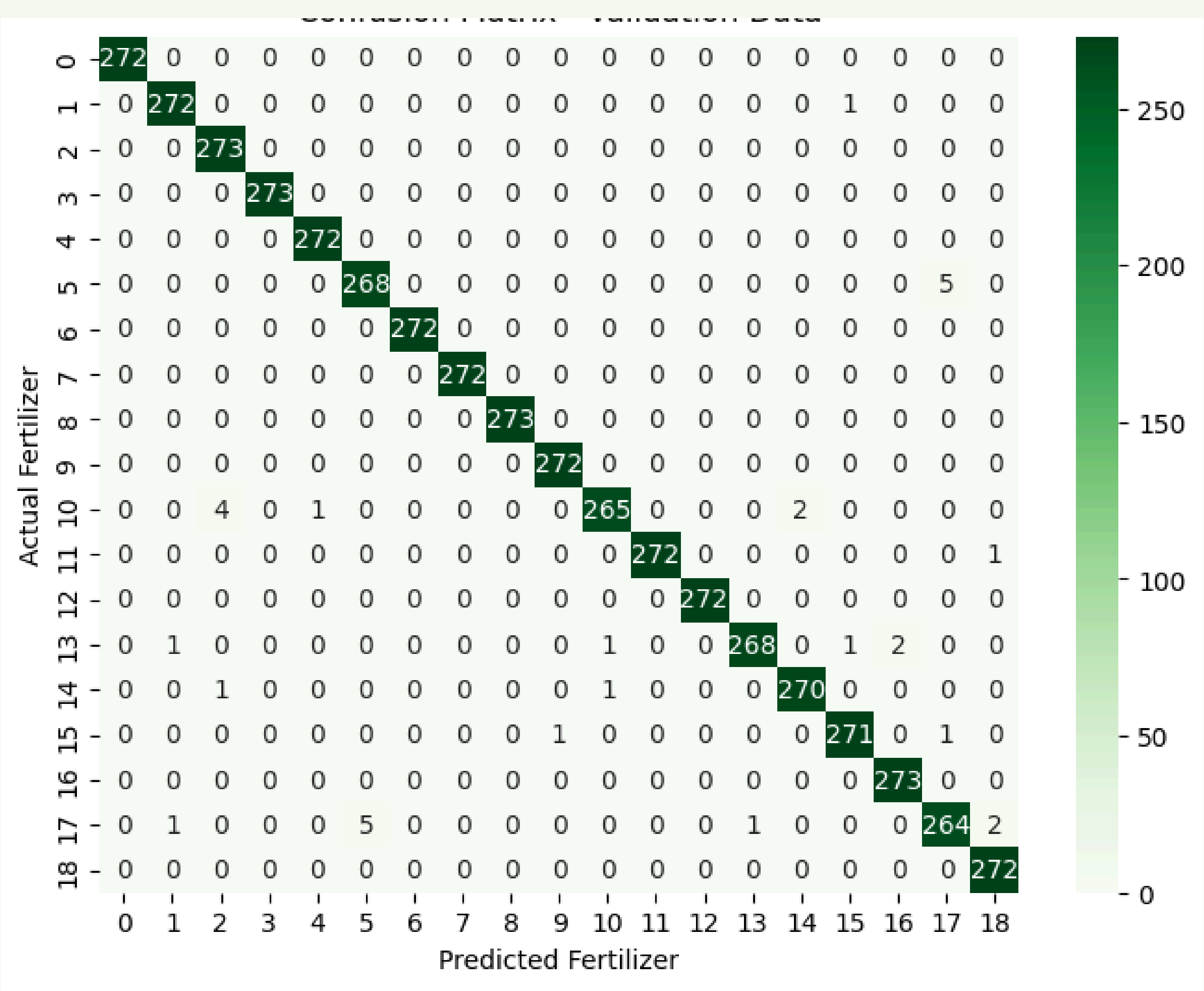
1. **High accuracy and efficiency**
2. **Excellent performance on imbalanced datasets**
3. **Built-in regularization that reduces overfitting and improves generalization**
4. **Split : 70% training - 20% validation - 10% testing**

Model 3: XGBoost Results

```python
from xgboost import XGBClassifier
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns

# Train the model
model = XGBClassifier(
    n_estimators=300,
    learning_rate=0.5,
    max_depth=5,
    subsample=1,
    colsample_bytree=1,
    random_state=42,
    eval_metric='mlogloss'
)
model.fit(X_train, y_train)
```

Model 3: XGBoost Results (Cont.)

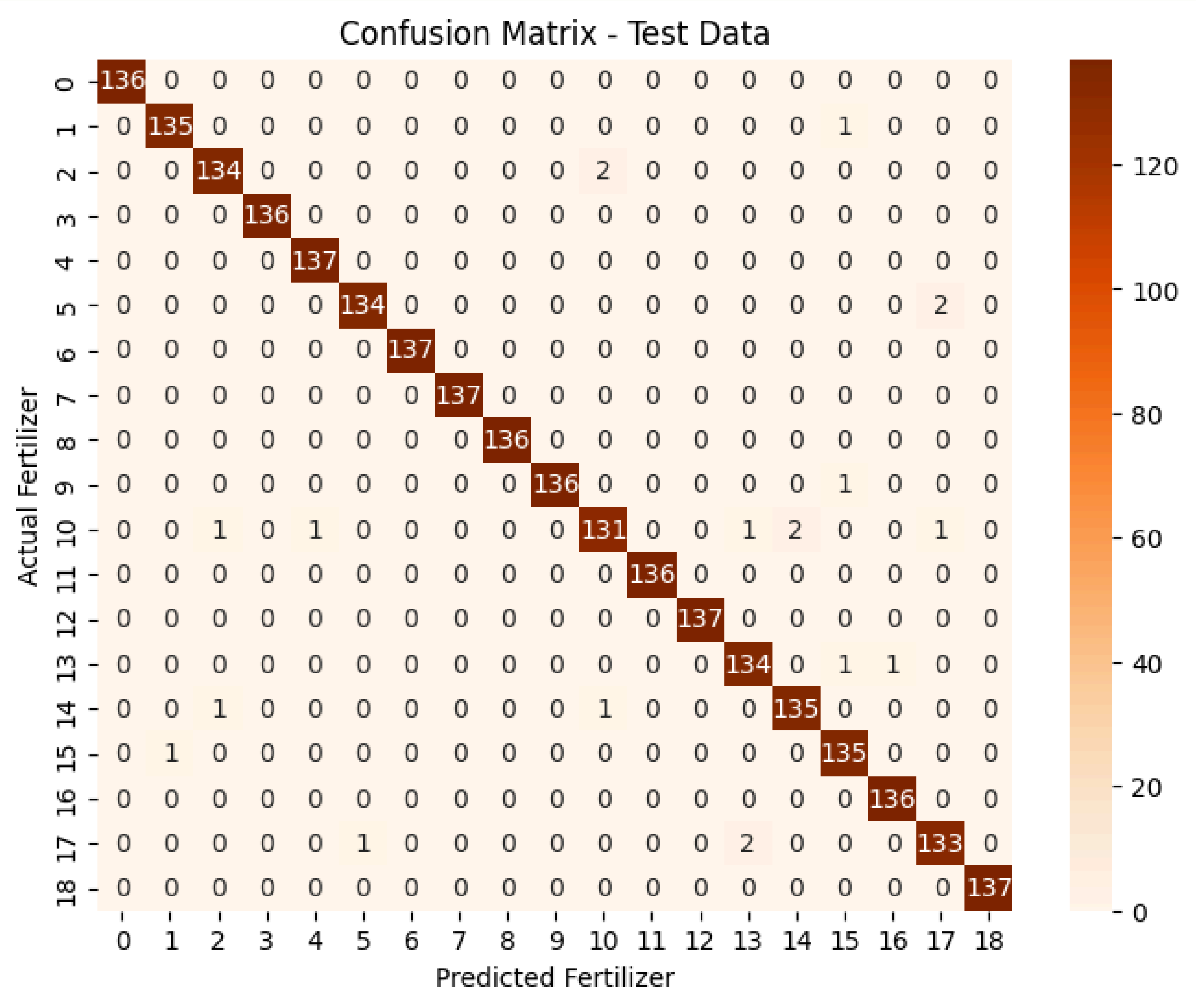




Training Accuracy: 99.99%

Validation Accuracy: 99.38%

Model 3: XGBoost Results (Cont.)




```
Test Accuracy: 99.23%
```

```python
import joblib
import numpy as np

model = joblib.load("fertilizer_prediction_model.pkl")

input_data_json = {
    "Soil_color": "Black",
    "Nitrogen": 75.00,
    "Phosphorus": 50.00,
    "Potassium": 100.00,
    "pH": 6.50,
    "Rainfall": 1000.00,
    "Temperature": 20.00,
    "Crop": "Maize"
}
prediction_result = predict_fertilizer(input_data_json)
print(prediction_result)
```

```
{'predicted_fertilizer': 'Urea'}
```

Output

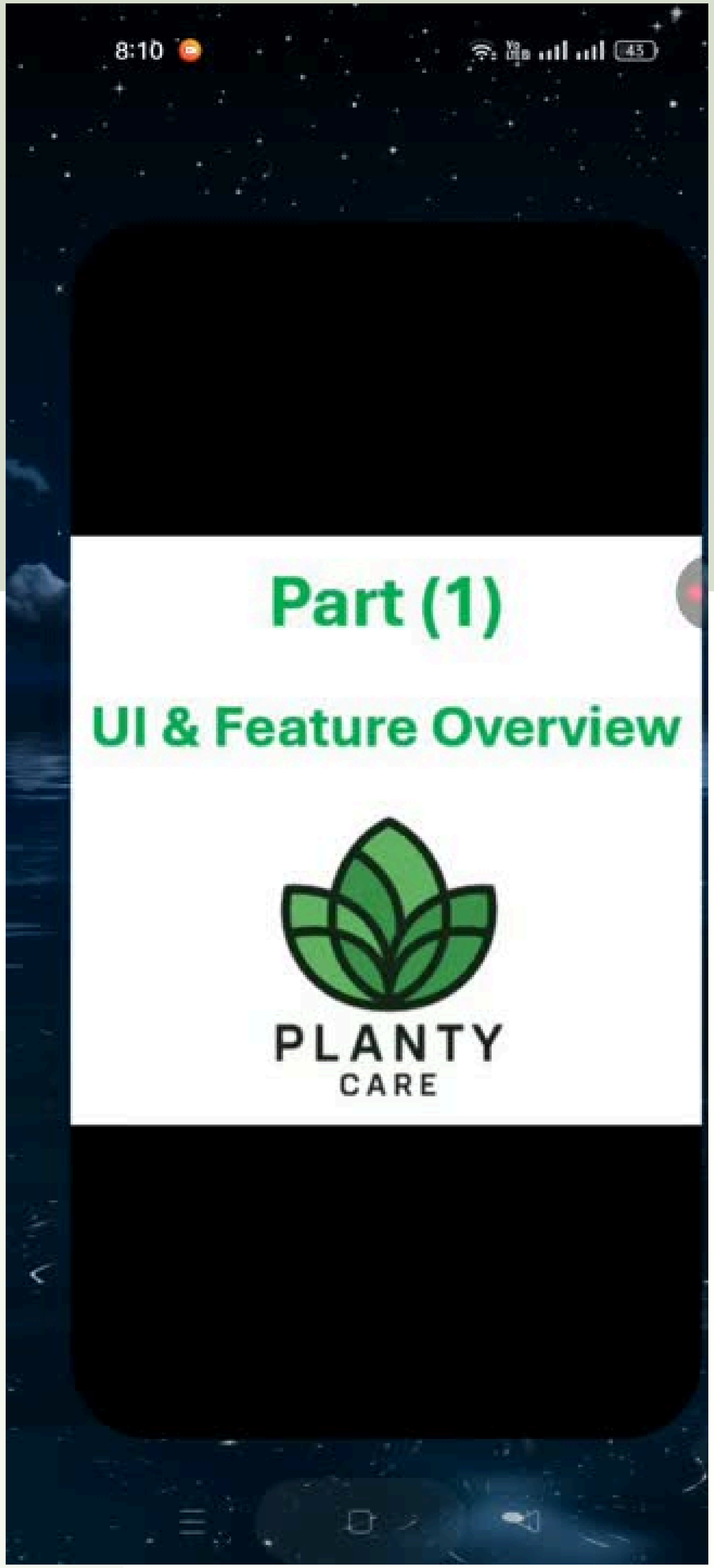
Demo of App

Some shots from our app

Light Mode

Dark Mode

Demo of App Part 1



Video Link

Demo of App Part 2

Video Link

🌿 Future Improvements – Planty Care

- **Smart Sensor Integration:** Real-time data from soil moisture, temperature, pH, and light sensors(IoT).
- **Real-time Image Scanning using Ai:** Instant plant disease detection via camera — no manual uploads needed
- **Tracking Disease Progress with Growing Data:** A system that keeps track of plant disease over time and works well even if more people use it.

Conclusion

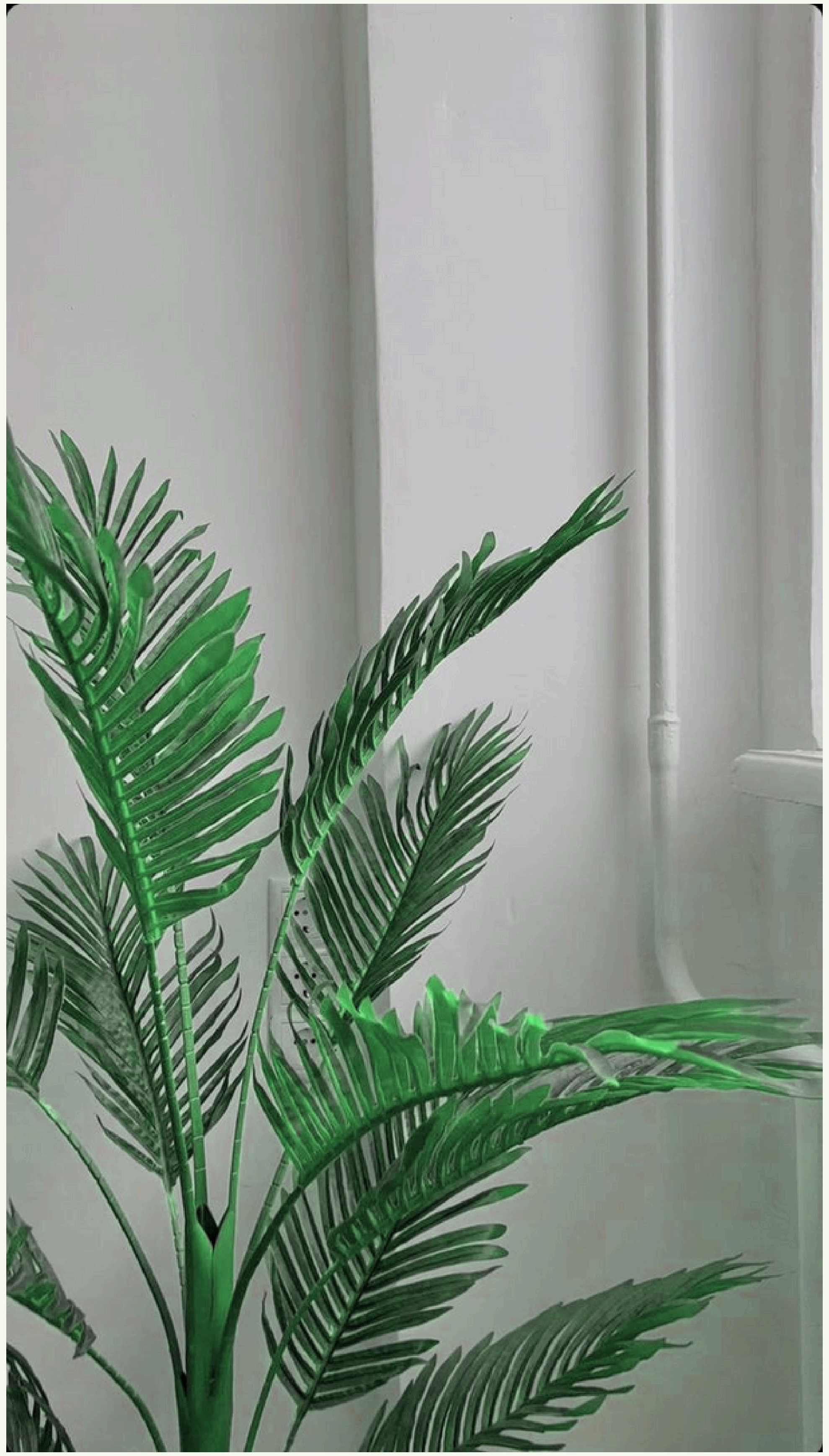
- AI-powered mobile app for smart farming support
- Detects plant diseases using ResNet-50 (deep learning)
- Recommends suitable crops via Random Forest model
- Suggests optimal fertilizers using XGBoost algorithm
- User-friendly, on-the-go access for farmers
- Boosts productivity and encourages sustainable agriculture

Refernces

1) Bouacida, I., Farou, B., Djakhdjakha, L., Seridi, H., & Kurulay, M. (2025). Innovative deep learning approach for cross-crop plant disease detection: A generalized method for identifying unhealthy leaves. Information Processing in Agriculture, 12(1), 54-67.

2) Biswas, S., Saha, I., & Deb, A. (2024). Plant disease identification using a novel time-effective CNN architecture. Multimedia Tools and Applications, 83(35), 82199-82221.

3) Naveed, F., Masih, A., Mahmood, J., Ahmed, M., Ali, A., Saddiqa, A., ... & Agbozo, E. (2025). Sustainable AI for plant disease classification using ResNet18 in few-shot learning. Array, 26, 100395.



We hope you find our project valuable.

THANK YOU!

Repo github of our project