RICEgenie

Predicting and Enhancing Paddy Crop Success

Crop yield prediction using machine learning – Paddy Harvest Prediction

24-25J-125

2024

RICEgenie
Predicting and Enhancing Paddy Crop Success

Team Members

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Co - Supervisor : DR.Harinda Fernando

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Overall Project Description

- Sri Lanka is experiencing an economic crisis due to unsustainable debt and persistent deficits, leading to a severe shortage of foreign currency. Agriculture, a vital sector, plays a crucial role in the economy and provides livelihoods for a significant portion of the population.

- Our research project aims to enhance paddy cultivation by leveraging advanced machine learning and image processing techniques. This includes predicting paddy yield, recommending optimal paddy varieties, and managing pests and weeds efficiently.

- By providing real-time, data-driven recommendations, the platform will help farmers optimize their practices, reduce losses, and promote sustainable farming, contributing to the economic stability and growth of Sri Lanka's agricultural sector.

Research Objectives

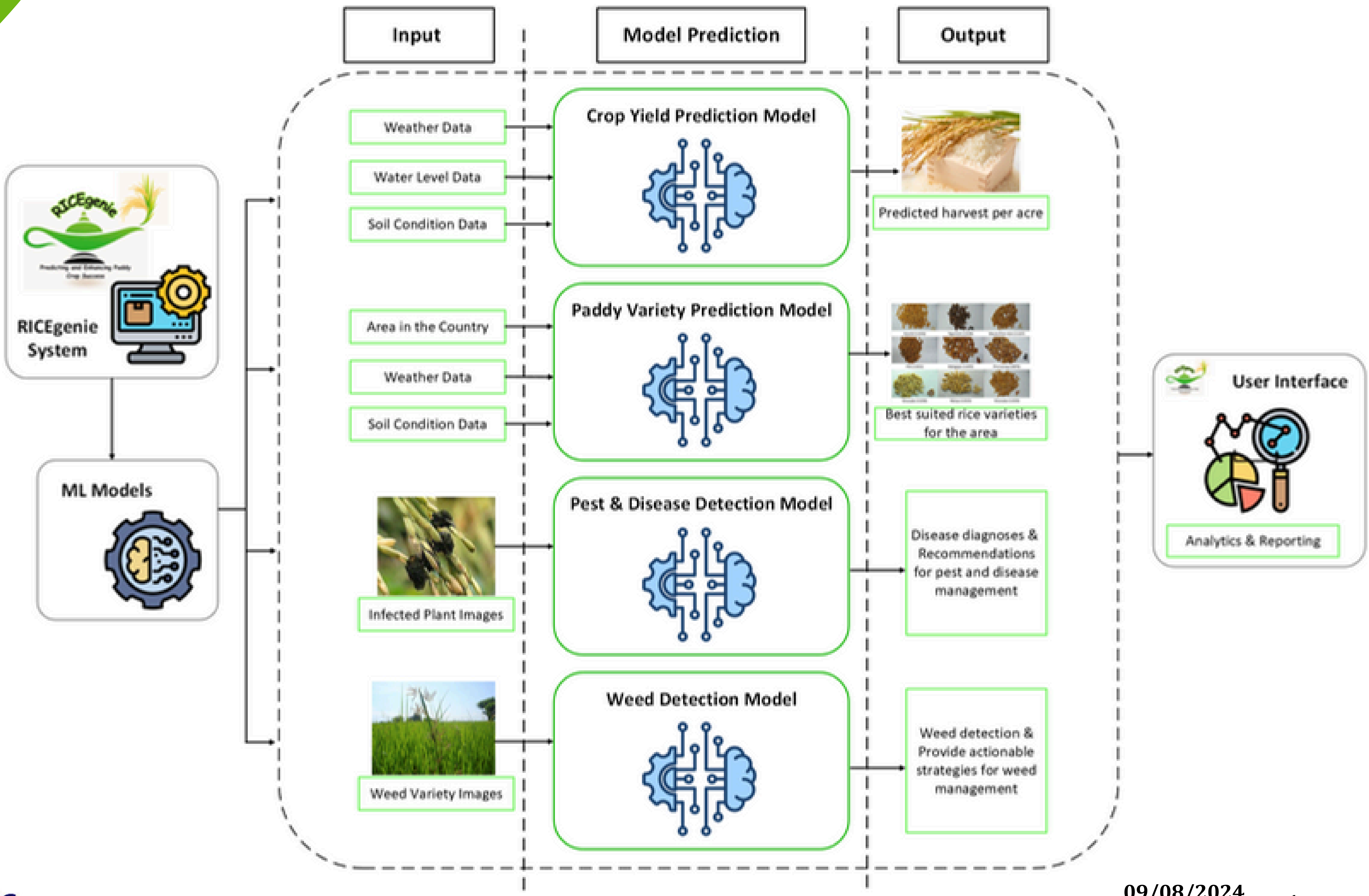
Main Objective:

- Develop an comprehensive platform to Enhance paddy cultivation in Sri Lanka by leveraging predictive models and image processing techniques.

Sub Objectives:

1. **Predict Harvest Yield:** Forecast paddy yields under varying conditions.
2. **Recommend Optimal Paddy Varieties:** Suggest suitable paddy types based on local conditions.
3. **Detect and Manage Pests and Diseases:** Use image processing for timely identification and treatment.
4. **Identify and Control Weeds:** Detect weed varieties and offer control strategies.

Overall System Diagram



Field Visits

Rice Research
Center -
Labuduwa
on 18th June 2024

Rice Research and
Development
Institute (RRDI) -
Bathalagoda
on 1st October 2024

REFERENCES

1. CropWat - https://www.fao.org/land-water/databases-and-software/cropwat/en/
2. STICS - https://www.quantitative-plant.org/model/STICS
3. APSIM - https://www.apsim.info/
4. CERES - https://ceresglobalagcorp.com/about/who-we-are/

IT21308352 | Jayathilaka D.H.R.A

Crop Yield Prediction System

Information Technology

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INTRODUCTION

- **Objective**: Develop a robust crop yield prediction model for paddy crops using machine learning.
- **Data Integration**: Analyze a comprehensive dataset, including historical yield data, weather conditions, soil health, and irrigation patterns.
- **Recommendations**: Incorporate a decision support framework to provide actionable insights and recommendations.
- **Benefits**: Enhance yield predictions, optimize agricultural practices, and improve resource management for increased productivity.

Challenges Encountered

- **Lack of Integration in Existing Models :**Current models do not integrate critical factors such as weather, water, and soil conditions effectively.
- **Feature Selection:** Determining which features are most relevant to yield prediction.
- **Model Accuracy:** This lack of comprehensive data integration leads to inaccuracies in yield predictions.
- **Scalability issues:** Many approaches do not scale well for large agricultural fields.
- **Lack of user-friendly interfaces and lack of Harvest prediction System:** There is a need for more emotionally and easy-to-use interfaces for farmers .

Specific and Sub Objectives

- **Specific Objectives :**
  - To provide the yield per hectare and provide suitable recommendations for farmers.

- **Sub Objectives :**
  - Collect historical data on paddy crop yields from Rice Research and Development Institute Bathalagoda.
  - Develop key features and train a machine learning model for accurate yield predictions.
  - Integrate the model into a decision support system with a user-friendly interface for farmers.

Methodology

- **Data Collection:** Gather historical data on paddy yields, weather conditions, soil health, and irrigation patterns from reliable sources.
- **Data Analysis**: Analyze the collected data to identify patterns and relationships between soil/climatic factors to predict the harvest
- **Pre-processing** :Prepare the dataset for model training by handling missing values, normalizing features, and encoding categorical variables.
- **Model Training :**Train a machine learning model using the processed dataset and fine-tune it for optimal performance.
- **Model Validation :** Split the dataset into training, validation, and test sets. Evaluate model performance using metrics like RMSE, MAE, and R^2.
- **Implementation:** Develop a user-friendly interface for farmers to input their local conditions and provide the harvest that they got and provide recommendations to increase the harvest

Data Overview

- **Dataset:** 10,000 entries, containing key features for paddy harvest prediction.
- **Features:** Likely include attributes such as area (in acres), seed variety, district, soil quality, weather conditions, and historical yields.
- **Goal:** Increase diversity and robustness of the model.

Rainfall (mm)		Relative Hu	Sunshine H	Wind Spee	Soil Type	Irrigation T	Water Sou	Paddy Vari	Fertilizer U	Area (hect	Soil Nitrog	Soil Phosp	Soil Potass	Pest Sever	Season	District	Yield (kg)
1407.3	32.2	60.2	9.1	11.3	Sandy	Rainfed	Well	BG 450	34	6.2	46	49	35	High	Maha	Polonnaru	38018.4
1412.7	30.7	66	7	10.9	Clay	Rainfed	Rainwater	BG 360	51	10.9	49	10	130	Medium	Yala	Jaffna	39752.3
1211	33.2	63.9	8.1	6.1	Loam	Tube Well	Well	BG 350	50.7	12.7	74	40	123	High	Maha	Batticaloa	38912.8
940.3	30.4	86.9	8.7	14.8	Loam	Rainfed	Well	BG 450	71	10.9	13	8	88	High	Yala	Batticaloa	38041
899.8	32.5	86.5	11	14.5	Loam	Rainfed	Well	BG 450	69.9	8.9	53	28	175	Medium	Maha	Polonnaru	39035.4
994.5	27.6	61.4	7.4	2.9	Loam	Canal	River	BG 250	94.2	15.2	32	20	122	Medium	Yala	Anuradhap	39884.8
900.4	32.9	64.8	11.2	12.4	Clay	Tube Well	Rainwater	BG 450	39.8	6	76	10	87	Medium	Maha	Hambanto	36228
1344.1	32.8	73.5	9.9	12	Loam	Rainfed	Rainwater	BG 350	22.9	17.2	98	49	51	High	Maha	Polonnaru	38029.2
1805.5	33.2	62.2	7.9	16.3	Loam	Rainfed	Rainwater	BG 250	81.1	14.3	96	8	76	Low	Maha	Mannar	42799.9
1196.5	29.3	79.2	11.7	7.7	Clay	Canal	River	BG 450	98.9	8.2	61	25	134	Low	Yala	Trincomal	41779
1004.3	25.1	84.6	10.2	13.5	Sandy	Canal	River	BG 350	27.6	18.2	20	45	72	Medium	Yala	Trincomal	36946
1350.7	33.5	89	7.6	13.8	Sandy	Tube Well	Well	BG 360	96.9	18.5	35	6	157	Low	Yala	Trincomal	42013.5
1150.1	25.6	72.8	7	13.6	Clay	Tube Well	River	BG 360	75.2	5.5	31	47	15	Medium	Yala	Hambanto	39336
1918.7	27.3	60.8	10.2	1.1	Loam	Rainfed	River	BG 350	51.7	17.4	99	39	183	Low	Maha	Polonnaru	43882.8
976.8	30.1	88.8	8.6	14.4	Sandy	Canal	Well	BG 250	31.5	18.4	29	35	17	High	Yala	Anuradhap	36027.2
1062.1	32.9	61.6	8.8	17.7	Clay	Canal	Well	BG 360	81.3	11.2	54	42	62	High	Maha	Jaffna	38897.6
800.6	26.4	83.2	11.5	15.6	Sandy	Tube Well	Rainwater	BG 350	42.8	5	67	26	186	Medium	Yala	Trincomal	37955
1975.9	32.9	84.8	11.8	1.9	Loam	Rainfed	Rainwater	BG 350	25.7	9.7	76	48	150	Low	Maha	Batticaloa	42311.4
1792.5	28.1	68	10.9	16.8	Clay	Canal	Rainwater	BG 450	53	9.4	49	31	188	Medium	Yala	Polonnaru	42845.2
1400	29.2	86.5	8.5	16.1	Clay	Canal	Well	BG 360	80	12.8	35	48	62	Medium	Maha	Batticaloa	41254.4
1200.7	33.9	65.2	10	9.1	Loam	Tube Well	Well	BG 250	45	5.5	23	27	180	High	Yala	Anuradhap	38467
1007.7	25.5	66.3	10.8	11	Loam	Canal	Well	BG 450	95	9.2	73	34	180	Medium	Maha	Hambanto	41436.8
896.6	30.3	87.3	10.8	1.4	Sandy	Tube Well	River	BG 250	76.1	15.2	53	37	109	High	Maha	Jaffna	38988
1299.7	32.9	81.3	7.1	8.9	Clay	Canal	Well	BG 450	21.1	15.9	98	10	183	Low	Maha	Ampara	38796
1611.5	30.7	86	8.1	17.7	Loam	Rainfed	River	BG 360	66.8	2.7	52	42	82	High	Maha	Anuradhap	4180.68

Data Analysis

```
Data columns (total 18 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Rainfall (mm)             10000 non-null  float64
 1   Temperature (°C)          10000 non-null  float64
 2   Relative Humidity (%)     10000 non-null  float64
 3   Sunshine Hours (hrs)      10000 non-null  float64
 4   Wind Speed (km/h)         10000 non-null  float64
 5   Soil Type                 10000 non-null  object
 6   Irrigation Type           10000 non-null  object
 7   Water Source              10000 non-null  object
 8   Paddy Variety             10000 non-null  object
 9   Fertilizer Usage (kg)     10000 non-null  float64
 10  Area (hectare)            10000 non-null  float64
 11  Soil Nitrogen (mg/kg)     10000 non-null  int64
 12  Soil Phosphorus (mg/kg)   10000 non-null  int64
 13  Soil Potassium (mg/kg)    10000 non-null  int64
 14  Pest Severity             10000 non-null  object
 15  Season                    10000 non-null  object
 16  District                  10000 non-null  object
 17   Yield (kg)               10000 non-null  float64
dtypes: float64(8), int64(3), object(7)
memory usage: 1.4+ MB
```

	Rainfall (mm)	Temperature (°C)	Relative Humidity (%)	Sunshine Hours (hrs)	Wind Speed (km/h)	Soil Type	Irrigation Type	Water Source	Paddy Variety	Fertilizer Usage (kg)	Area (hectare)	Soil Nitrogen (mg/kg)	Soil Phosphorus (mg/kg)	Soil Potassium (mg/kg)	Pest Severity	Season	District	Yield (kg)
0	1407.3	32.2	60.2	9.1	11.3	Sandy	Rainfed	Well	BG 450	34.0	6.2	46	49	35	High	Maha	Polonnaruwa	38018.4
1	1412.7	30.7	66.0	7.0	10.9	Clay	Rainfed	Rainwater	BG 360	51.0	10.9	49	10	130	Medium	Yala	Jaffna	39752.3
2	1211.0	33.2	63.9	8.1	6.1	Loam	Tube Well	Well	BG 350	50.7	12.7	74	40	123	High	Maha	Batticaloa	38912.8
3	940.3	30.4	86.9	8.7	14.8	Loam	Rainfed	Well	BG 450	71.0	10.9	13	8	88	High	Yala	Batticaloa	38041.0

Pre-processing

```python
categorical_features = ['Soil Type', 'Irrigation Type', 'Water Source',
                        'Paddy Variety', 'Pest Severity', 'Season', 'District']

numerical_features = X.select_dtypes(include=['float64', 'int64']).columns.tolist()
print("numerical_features", numerical_features)

numerical_features = [col for col in numerical_features if col not in categorical_features]
print("numerical_features =", numerical_features)

# Preprocessing: Encode categorical features
preprocessor = ColumnTransformer(
    transformers=[
        ('cat', OneHotEncoder(handle_unknown='ignore'), categorical_features)
    ],
    remainder='passthrough',  # Leave numerical features untouched
    force_int_remainder_cols=False  # Future-proof behavior
)

print("\nPreprocessor Details:")
print(preprocessor)
```

```
numerical_features ['Rainfall (mm)', 'Temperature (°C)', 'Relative Humidity (%)', 'Sunshine Hours (hrs)', 'Wind Speed (km/h)', 'Fertilizer Usage (kg)', 'Area (hectare)',
numerical_features = ['Rainfall (mm)', 'Temperature (°C)', 'Relative Humidity (%)', 'Sunshine Hours (hrs)', 'Wind Speed (km/h)', 'Fertilizer Usage (kg)', 'Area (hectare)'

Preprocessor Details:
ColumnTransformer(force_int_remainder_cols=False, remainder='passthrough',
                  transformers=[('cat', OneHotEncoder(handle_unknown='ignore'),
                                 ['Soil Type', 'Irrigation Type',
                                  'Water Source', 'Paddy Variety',
                                  'Pest Severity', 'Season', 'District'])])
```

3. Model Development

Algorithm Selection

1. Random Forest Regressor

```
MAE: 510.0285261251583
MSE: 4755389.907179633
RMSE: 2180.685650702465
R-squared: 0.9730830528786836
Mean Absolute Percentage Error (MAPE): 3.49%
Regression Accuracy: 96.51%
```

Accuracy : 96.51%%

2. Linear Regression

```
MAE: 8505.219688917525
MSE: 104963650.44756976
R-squared: 0.40587394852902126
Mean Absolute Percentage Error (MAPE): 81.04%
Regression Accuracy: 18.96%
```

Accuracy : 18.96%

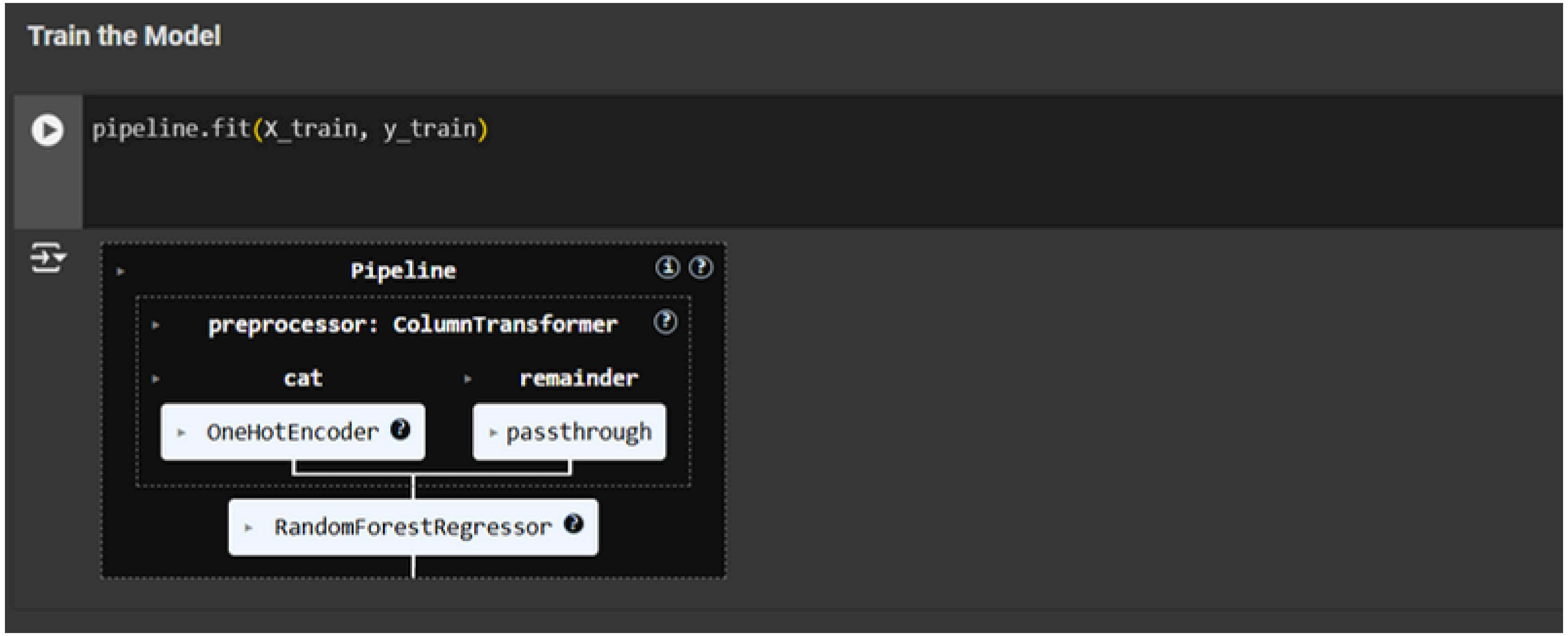
3. Gradient Boosting Regressor

```
MAE: 617.559723035567
MSE: 5151988.029699174
R-squared: 0.9708381873890726
Mean Absolute Percentage Error (MAPE): 4.88%
Regression Accuracy: 95.12%
```

Accuracy : 95.12%

- So comparing the accuracy of 3 Machine Learning Algorithms, with a Accuracy of 96.51% Random Forest Regressor has choosen to develop the Paddy Harvest Prediction model.

Train the model



Evaluation Metrices

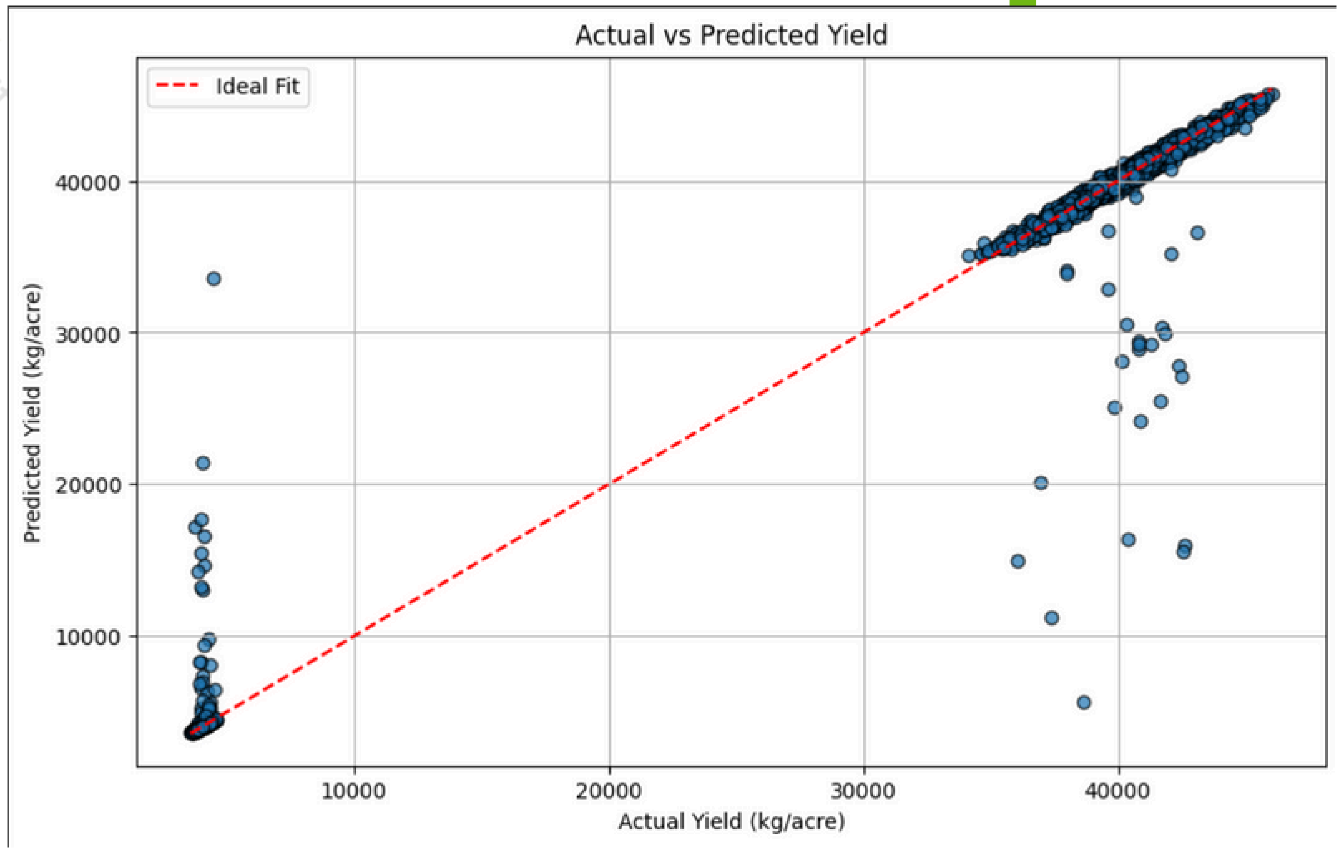
Accuracy of the model

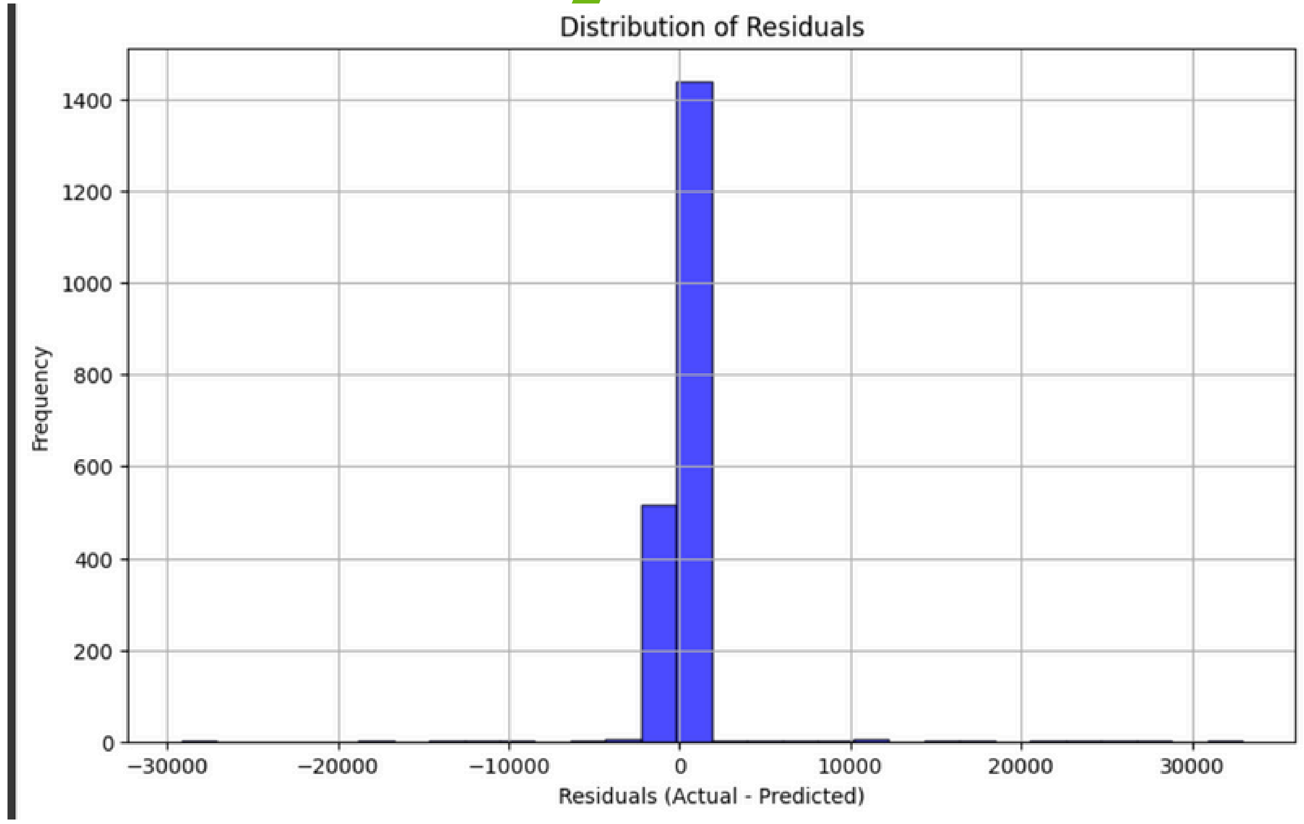
```
[ ] import numpy as np
    from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score

    # Predict using the trained model
    y_pred = pipeline.predict(X_test)

    # Example metric calculations
    mae = mean_absolute_error(y_test, y_pred)
    mse = mean_squared_error(y_test, y_pred)
    r2 = r2_score(y_test, y_pred)

    # Calculate RMSE
    rmse = np.sqrt(mse)

    # Print the metrics
    print(f"MAE: {mae}")
    print(f"MSE: {mse}")
    print(f"RMSE: {rmse}")
    print(f"R-squared: {r2}")

    # MAPE and Accuracy
    mape = np.mean(np.abs((y_test - y_pred) / y_test)) * 100
    accuracy = 100 - mape
    print(f"Mean Absolute Percentage Error (MAPE): {mape:.2f}%")
    print(f"Regression Accuracy: {accuracy:.2f}%")
```

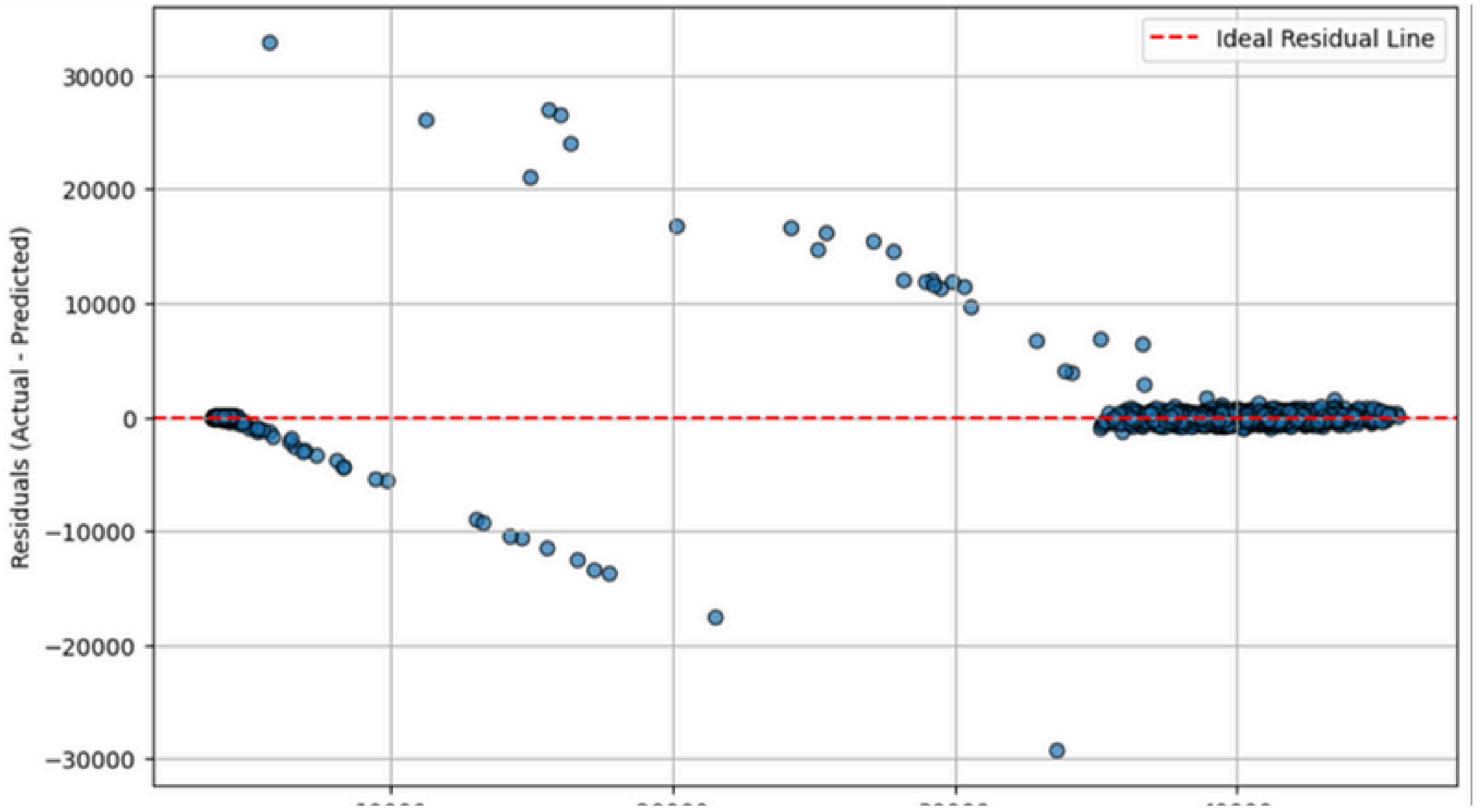
```
MAE: 510.0285261251583
MSE: 4755389.907179633
RMSE: 2180.685650702465
R-squared: 0.9730830528786836
Mean Absolute Percentage Error (MAPE): 3.49%
Regression Accuracy: 96.51%
```

Random Forest Regressor

Model performance Analysis







Random Forest Regressor

Optimization Techniques to improve Accuracy

- **Handle missing values**
- **Feature Selection & Preprocessing Optimization using pipleine**
- **Handling Categorical Variables Efficiently**
- **Hyperparameter Tuning**

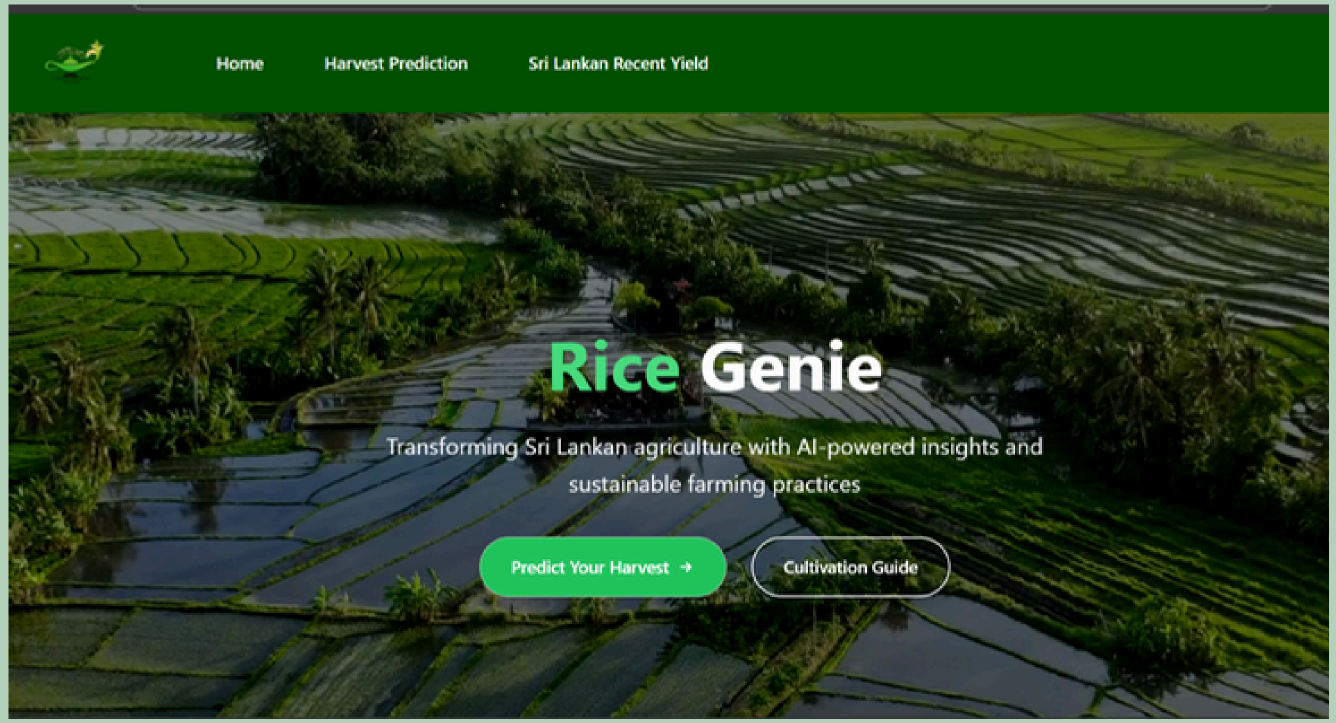
Hyperparameter Tuning

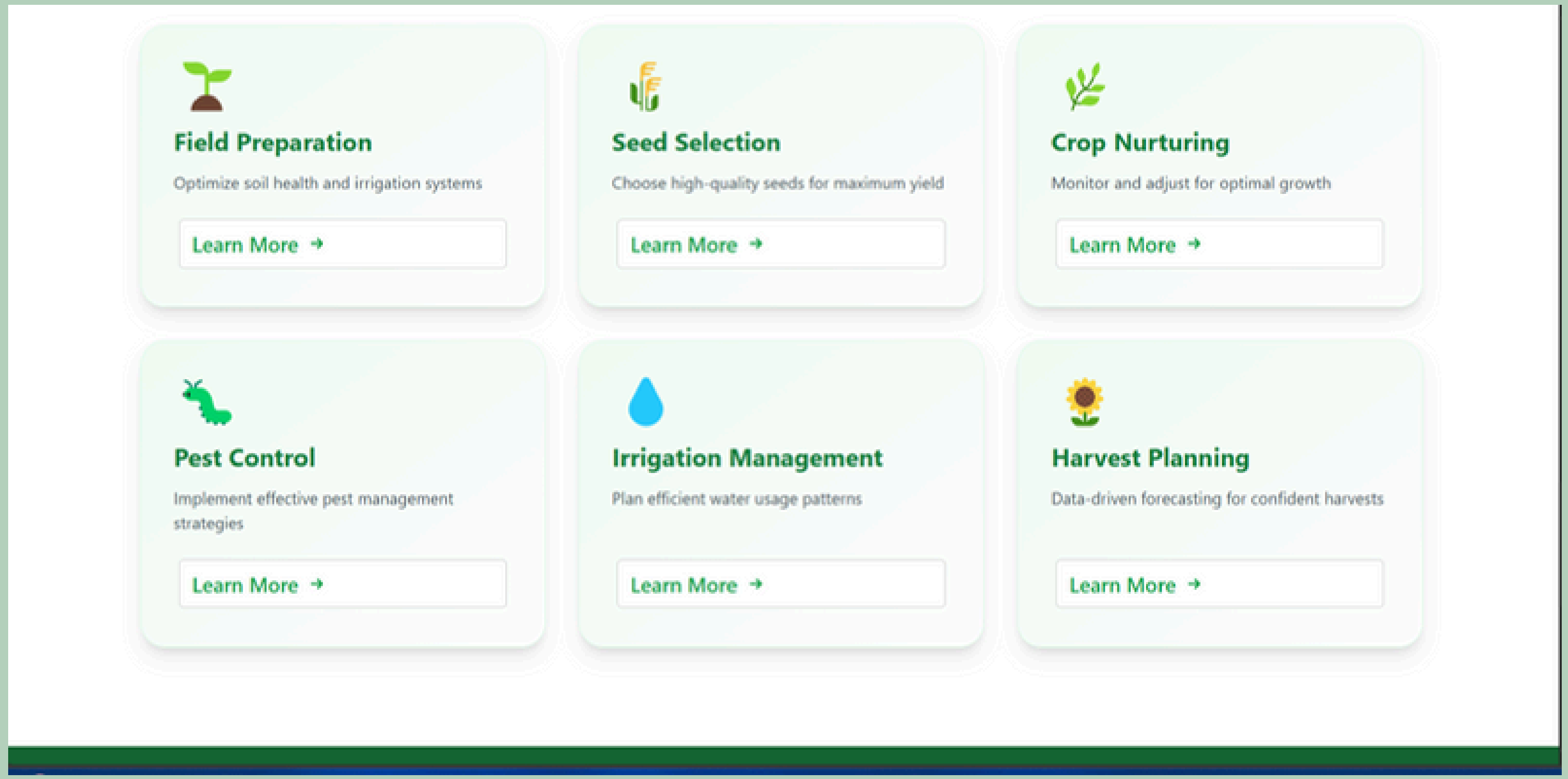
Create Pipeline for Preprocessing and Model

```
[ ]  pipeline = Pipeline(steps=[
         ('preprocessor', preprocessor),  # Data preprocessing step (scaling, encoding, etc.)

         ('model', RandomForestRegressor(
             n_estimators=150,            # Number of trees in the forest (reduces variance and prevents overfitting by averaging predictions)
             max_depth=18,                # Limits the depth of each tree to prevent overfitting by controlling model complexity
             min_samples_split=10,        # Requires at least 10 samples to split a node (prevents overly specific splits)
             min_samples_leaf=4,          # Ensures that each leaf node has at least 4 samples, preventing overfitting to small data variations
             random_state=42              # Ensures reproducibility of results (ensures the same splits each time for consistency in testing)
         ))
     ])
```

5. Web app Implementation

Home Page





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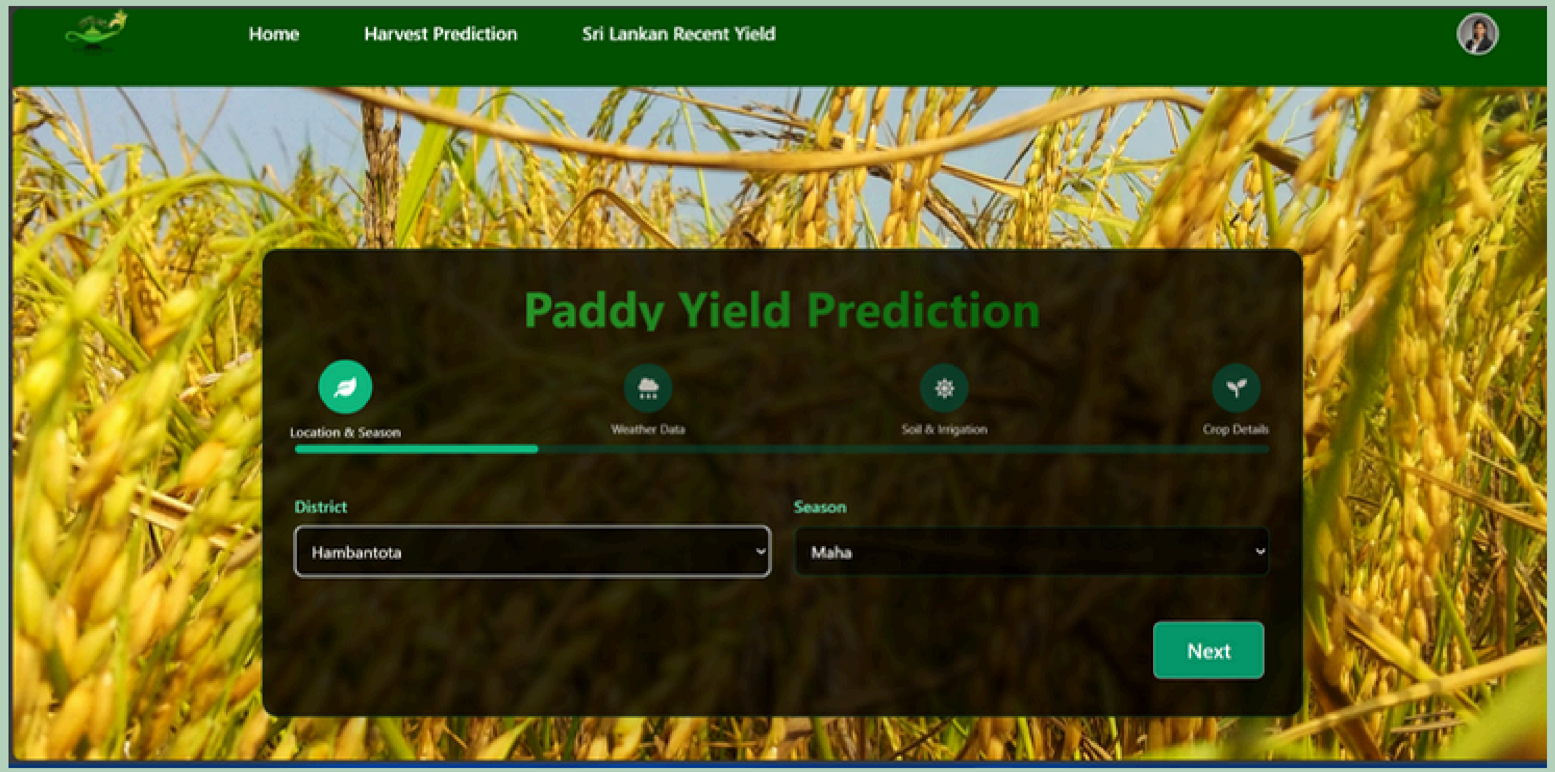
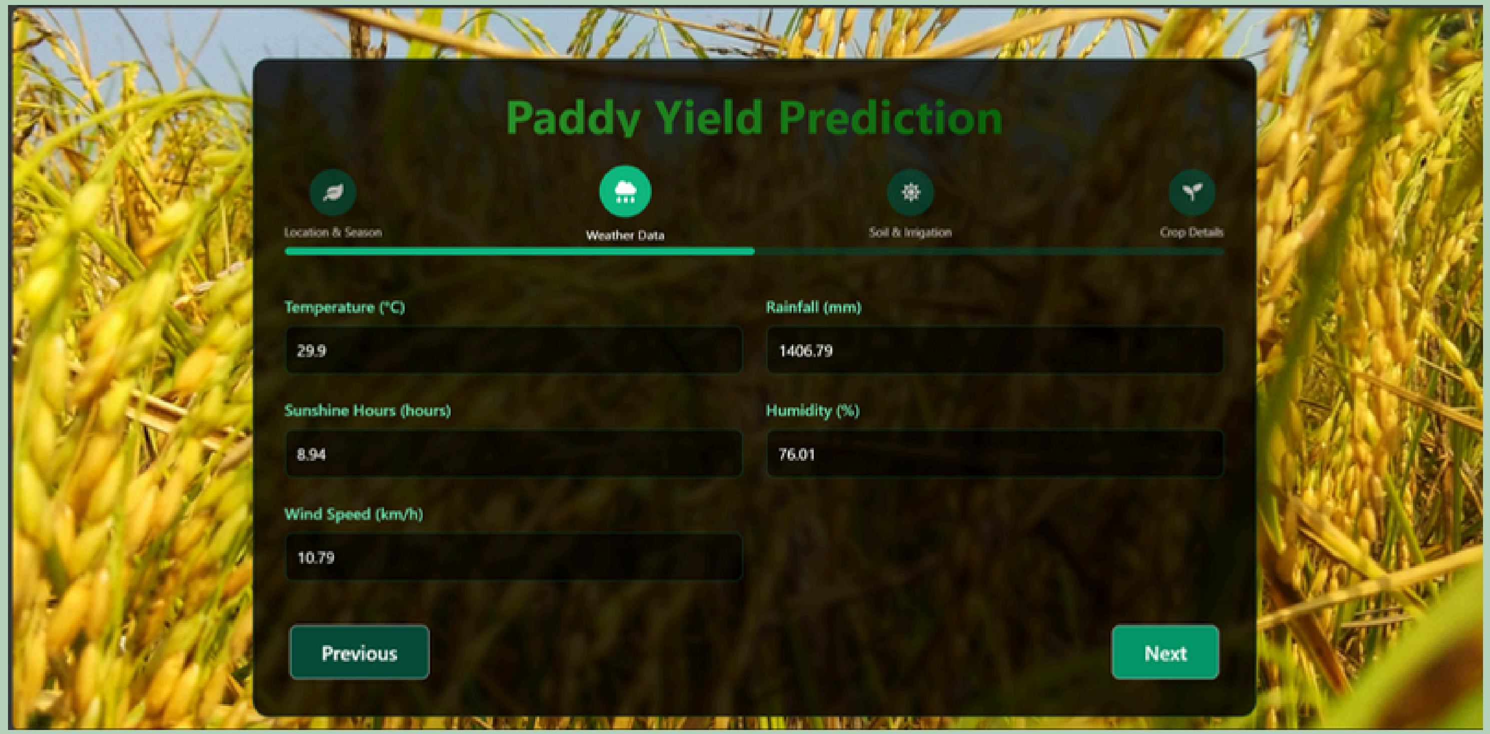
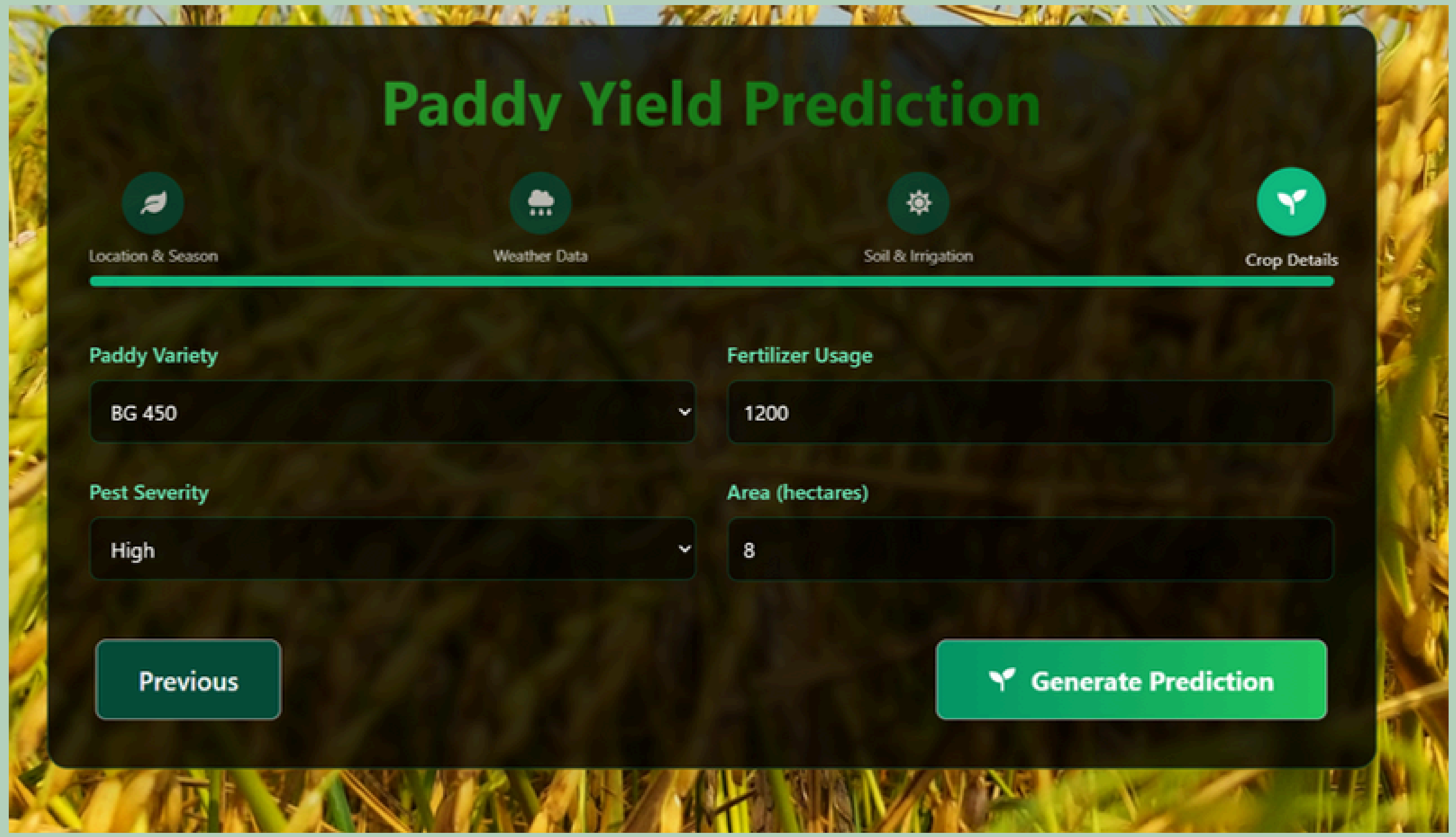
Input Page

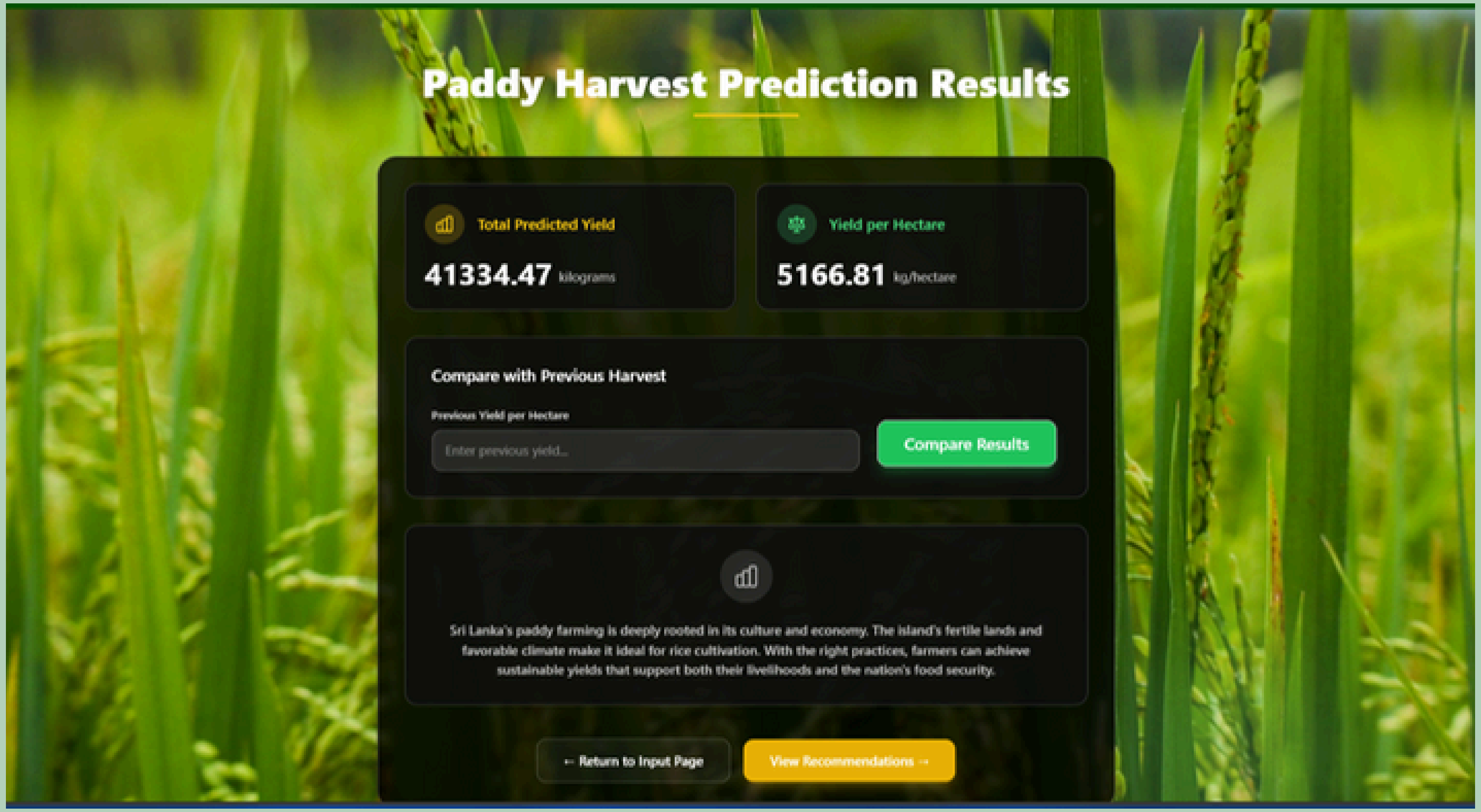

Home
Harvest Prediction
Sri Lankan Recent Yield
Paddy Yield Prediction
Location & Season
Weather Data
Soil & Irrigation
Crop Details
District
Hambantota
Season
Maha
Next

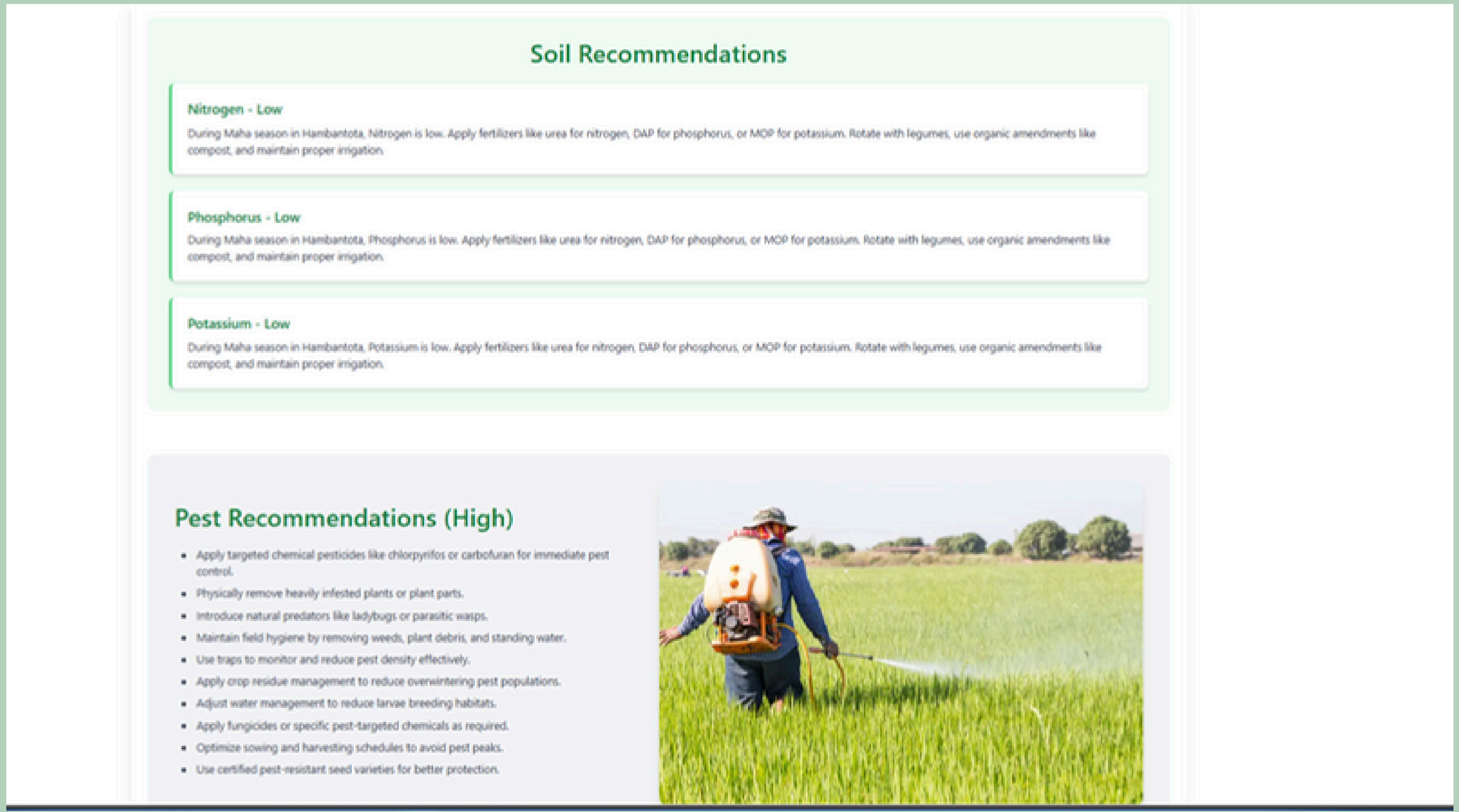

Paddy Yield Prediction
Location & Season
Weather Data
Soil & Irrigation
Crop Details
Temperature (°C)
29.9
Rainfall (mm)
1406.79
Sunshine Hours (hours)
8.94
Humidity (%)
76.01
Wind Speed (km/h)
10.79
Previous
Next


Paddy Yield Prediction
Location & Season
Weather Data
Soil & Irrigation
Crop Details
Soil Type
Loam
Irrigation Type
Canal
Water Source
Well
Soil Nitrogen (mg/kg)
8
Soil Phosphorus (mg/kg)
8
Soil Potassium (mg/kg)
8
Previous
Next

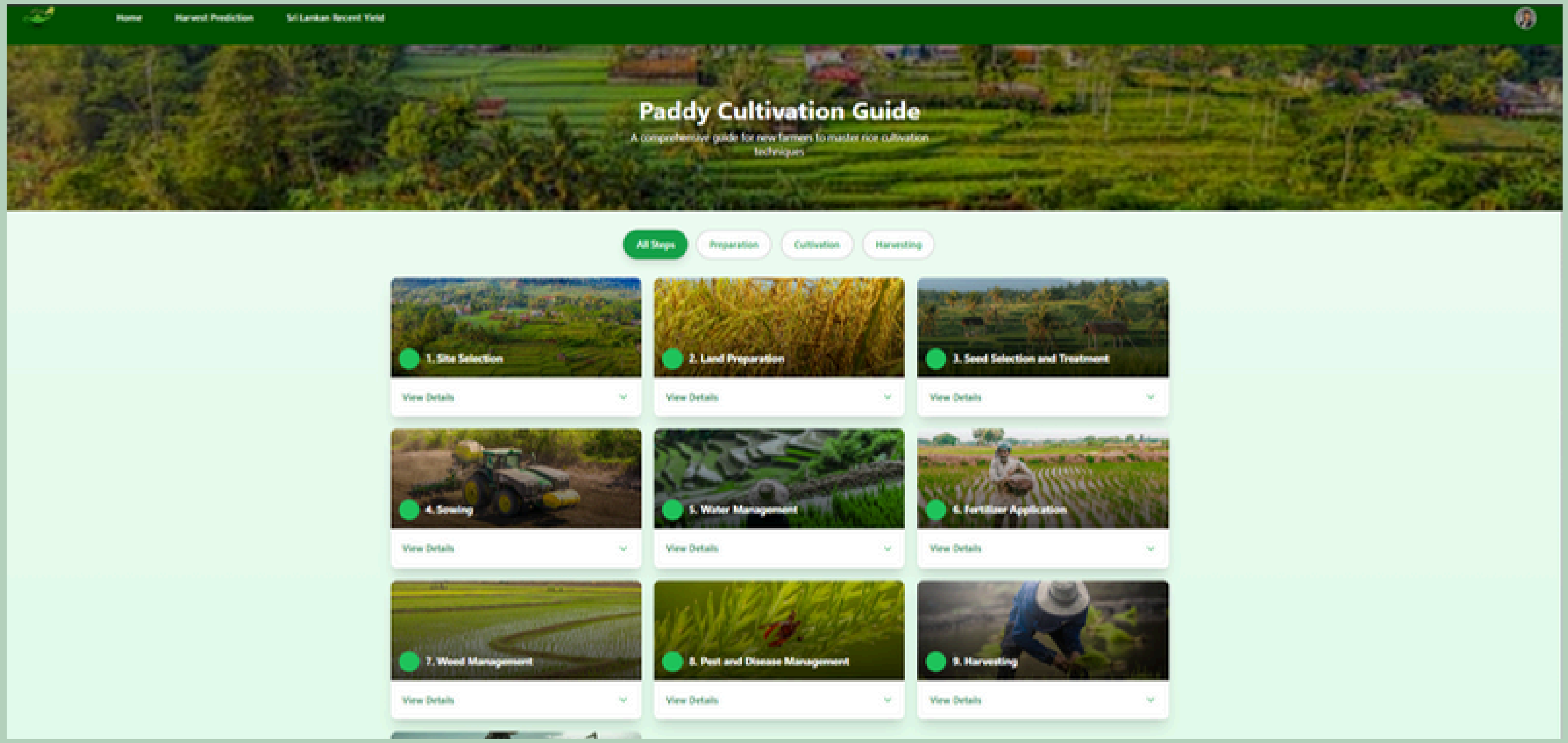

Paddy Yield Prediction
Location & Season
Weather Data
Soil & Irrigation
Crop Details
Paddy Variety
BG 450
Fertilizer Usage
1200
Pest Severity
High
Area (hectares)
8
Previous
Generate Prediction

Input Page and Recommendation Page





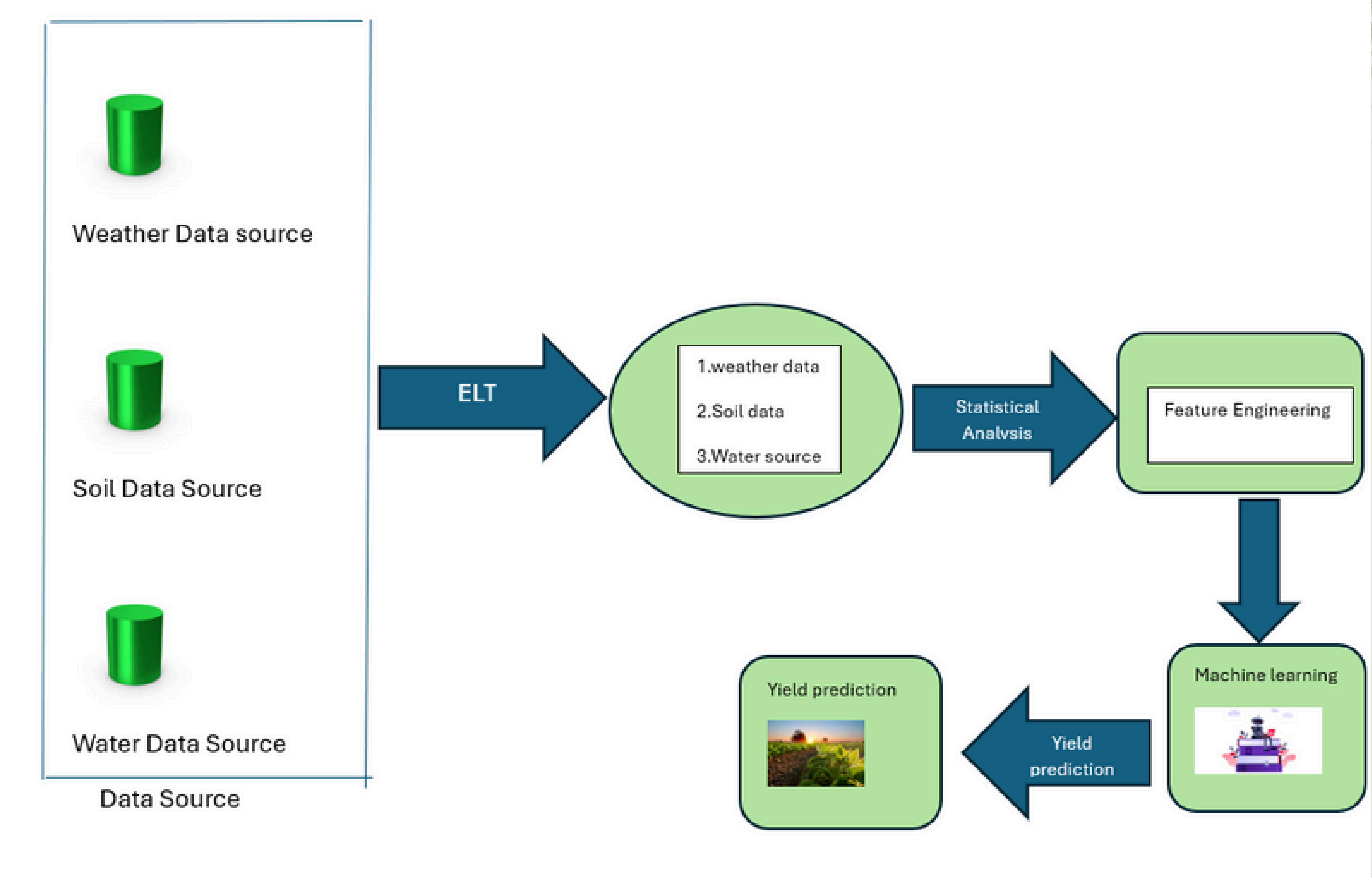
Paddy Cultivation Guide



Technologies

- Python (Back end)
- ML (Regression)
- ReactJS (Front end)
- Tailwind (for styles)
- Fast API
- Google Colab
- MySql
- Git Hub (Version control system)
- Trello(Project Management)

System Diagram



Requirements

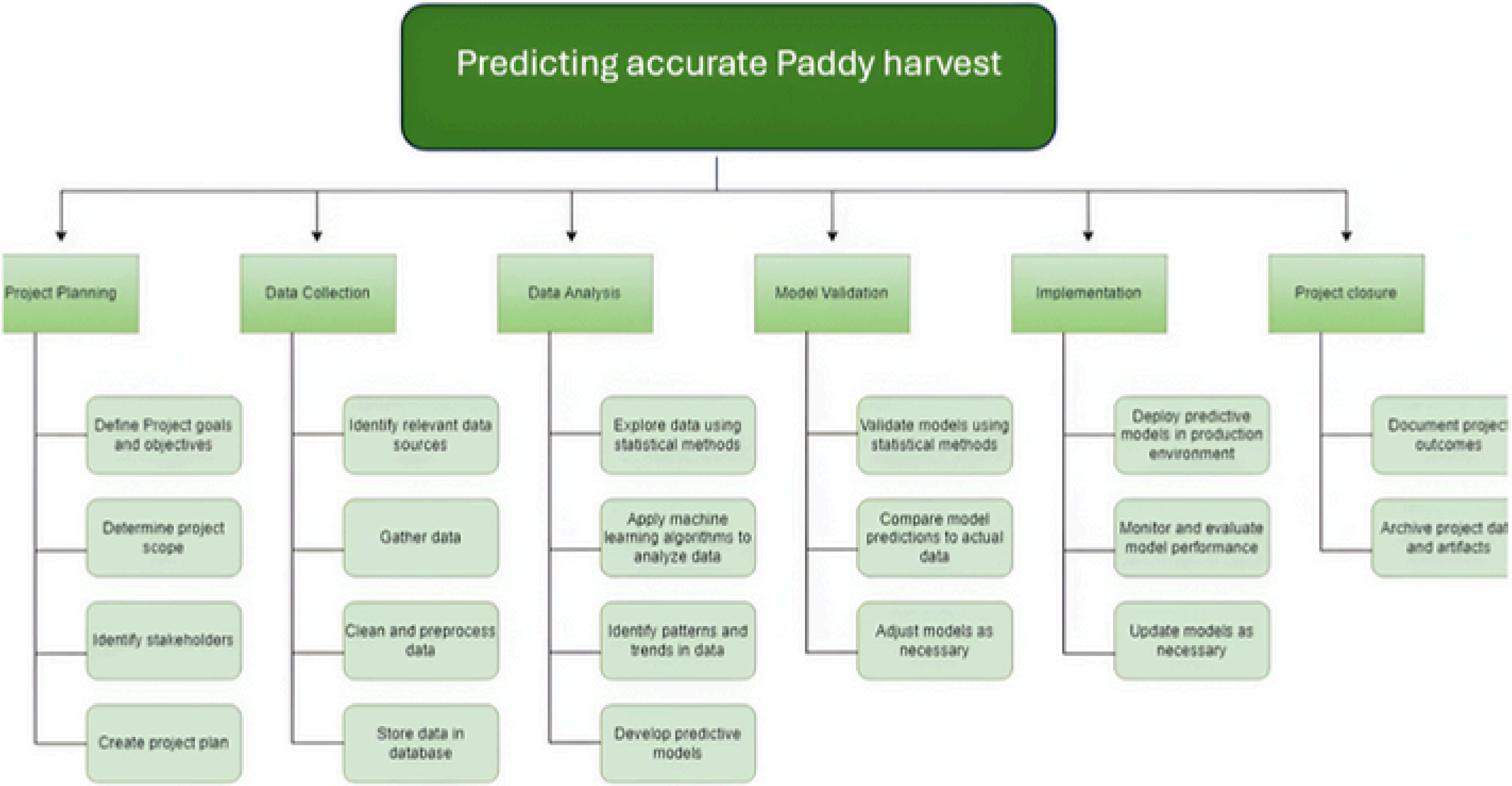
Non-functional requirements

- Availability
- Usability
- Performance
- Accuracy

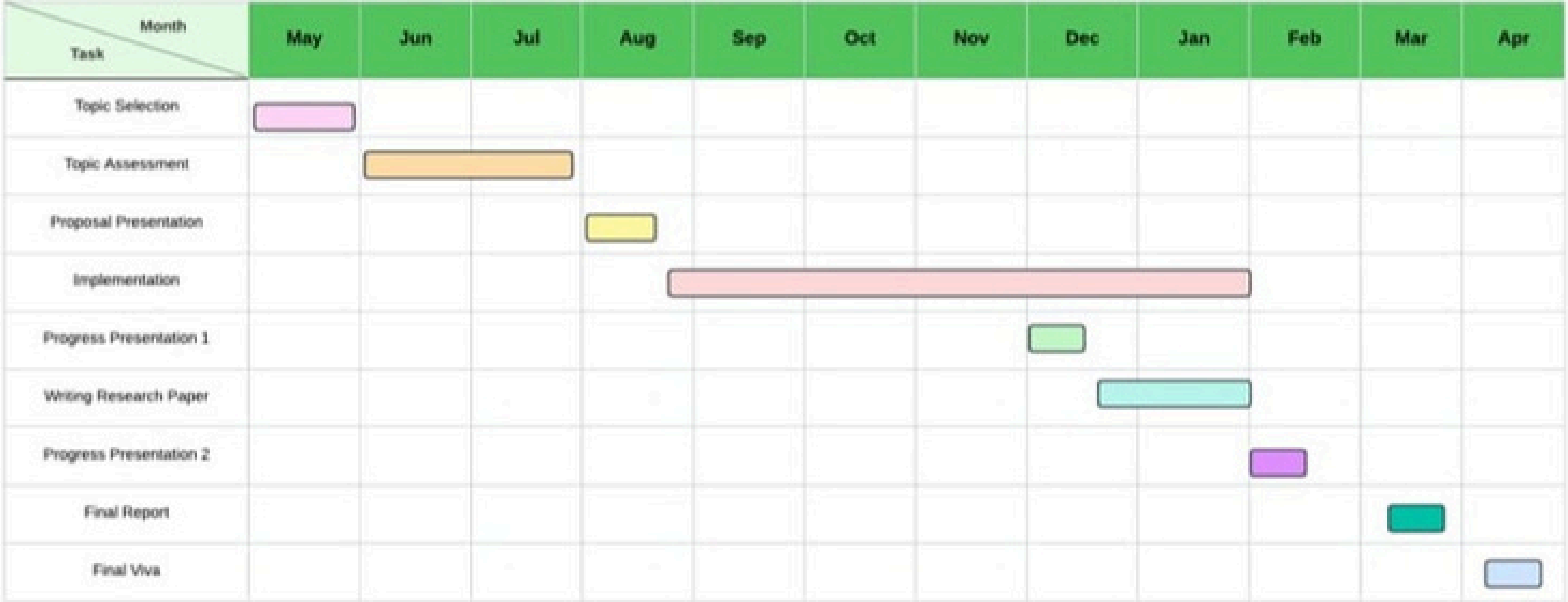
Functional requirements

- Yield Prediction
- Decision Support

Work Breakdown Structure



Gantt chart



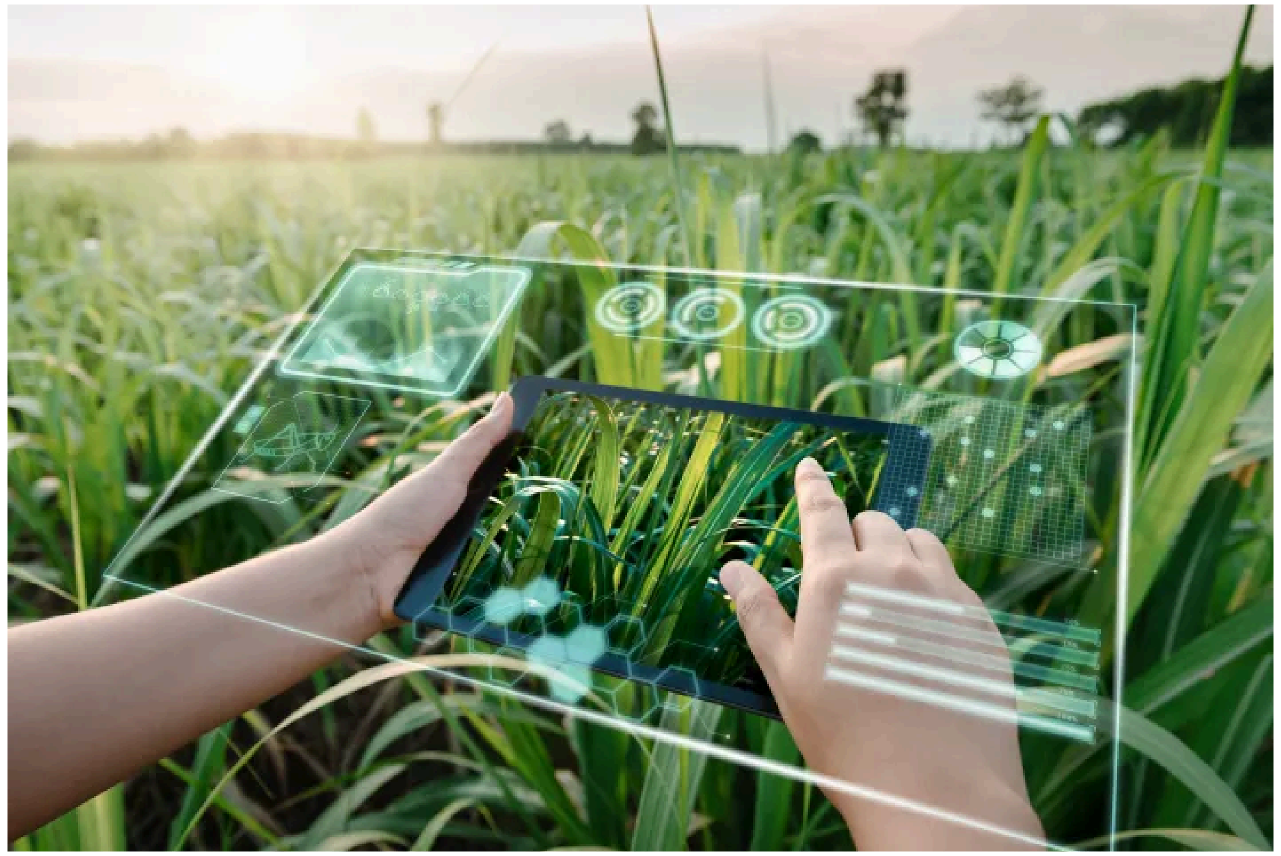
Month
Task
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Jan
Feb
Mar
Apr
Topic Selection
Topic Assessment
Proposal Presentation
Implementation
Progress Presentation 1
Writing Research Paper
Progress Presentation 2
Final Report
Final Viva

REFERENCES

1. Smith, J., & Doe, A. (2020). Soil Health Monitoring Using Advanced Machine Learning Techniques. Journal of Agricultural Research, 45(3), 234-245.
2. Lee, B., & Kim, H. (2019). Integrating Real-Time Irrigation Metrics with Predictive Models for Crop Yield Enhancement. International Journal of Smart Agriculture, 12(2), 150-165.
3. Patel, R., & Kumar, S. (2018). Utilizing Localized Weather Patterns for Accurate Crop Predictions. Agricultural Systems, 33(1), 98-110.

IT21225192 | Amarasinghe A.I.S.A

Pre Harvesting Diseases Detection & Mitigation System



External supervisor - DR.Rukmali Gunapala

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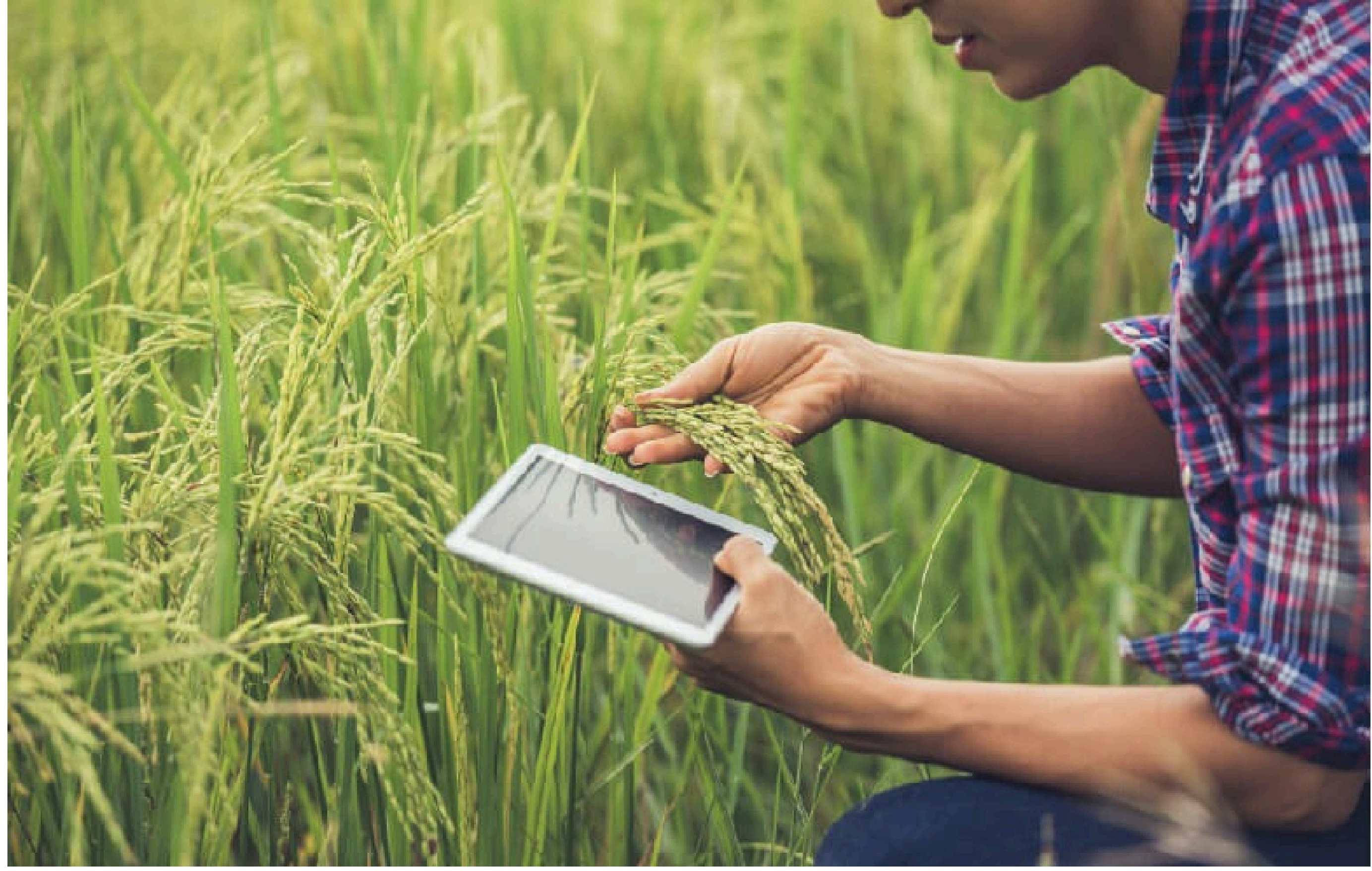
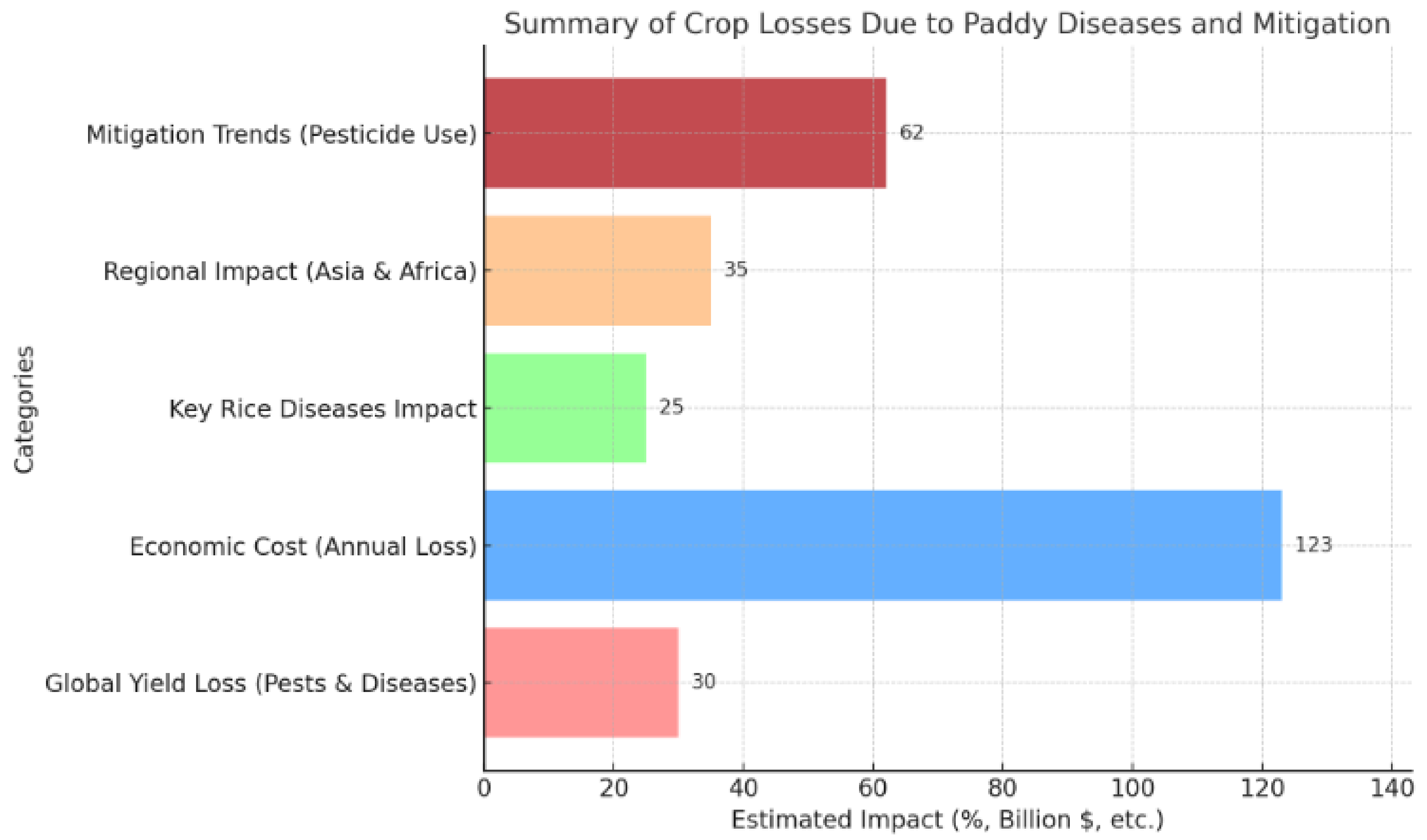
INTRODUCTION

Importance of Paddy Disease Identification ,

- **Pre harvesting Paddy diseases** can have a significant impact on crop yield and quality.
- It is important to identify the paddy diseases at an **early stage to prevent their spread and minimize** damage.
- **Image processing techniques** can be used to analyze digital images of plants and identify signs of disease.
- Image processing offers a promising approach for rapid and accurate detection of plant diseases, which can help to support more effective disease management and control strategies.



Statistics on crop losses due to paddy diseases



Research Gap

1. Limited focus on integrated solutions: Most existing studies focus only on disease detection, not on providing treatment recommendations.

2. Lack of real-time processing: Many methods do not offer real-time disease detection and treatment suggestions.

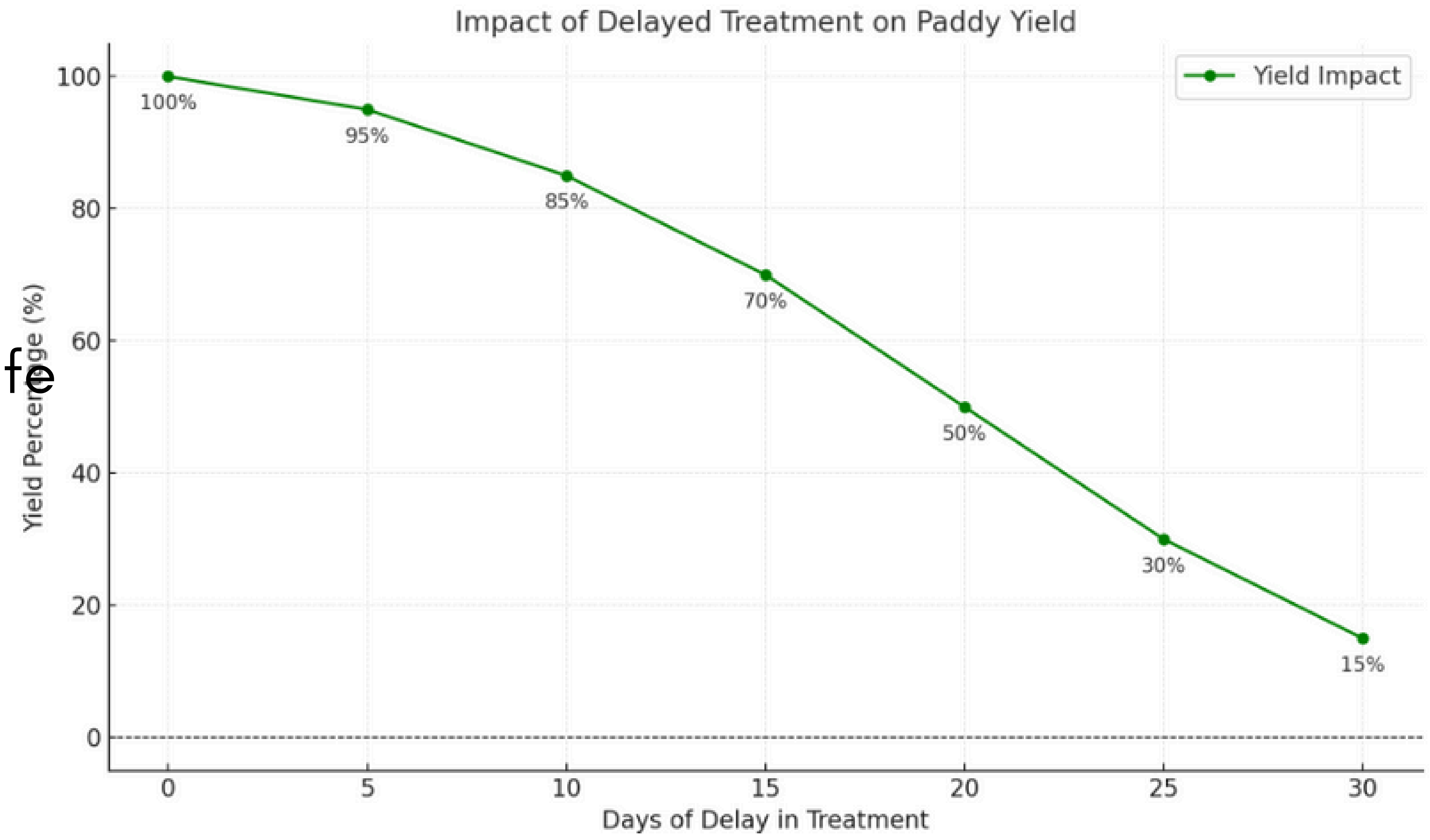
3.Insufficient accuracy: Current systems may not be accurate enough in identifying specific paddy diseases.

4. Scalability issues: Many approaches do not scale well for large agricultural fields.

5. Lack of user-friendly interfaces: There is a need for more emotionally and easy-to-use interfaces for farmers.

Research Problem

- Reduced crop yield
- Quality degradation and low marketability
- Higher production costs
- Crop loss due to reduced shelf life
- Economic losses



Specific and Sub Objectives

Specific Objectives :

a. **Monitor and maintain healthy growth** of commercially viable paddies by paddy
b. **Integrated Disease Detection and Treatment System**: While many systems focus solely on disease detection, our project stands out by integrating both detection and treatment recommendations in a single platform.

Sub Objectives :

- Provide **sustainable treatments** for paddy diseases
- **Generate report** of plant diseases
- **Customized Treatment Recommendations**: The treatment suggestions are tailored to the specific disease detected, considering factors like severity and local agricultural practices.

Requirements

Non-functional requirements

- Availability – Accessible
- Reliability – perform without Errors
- Performance – quickly
- Usability – easy to use

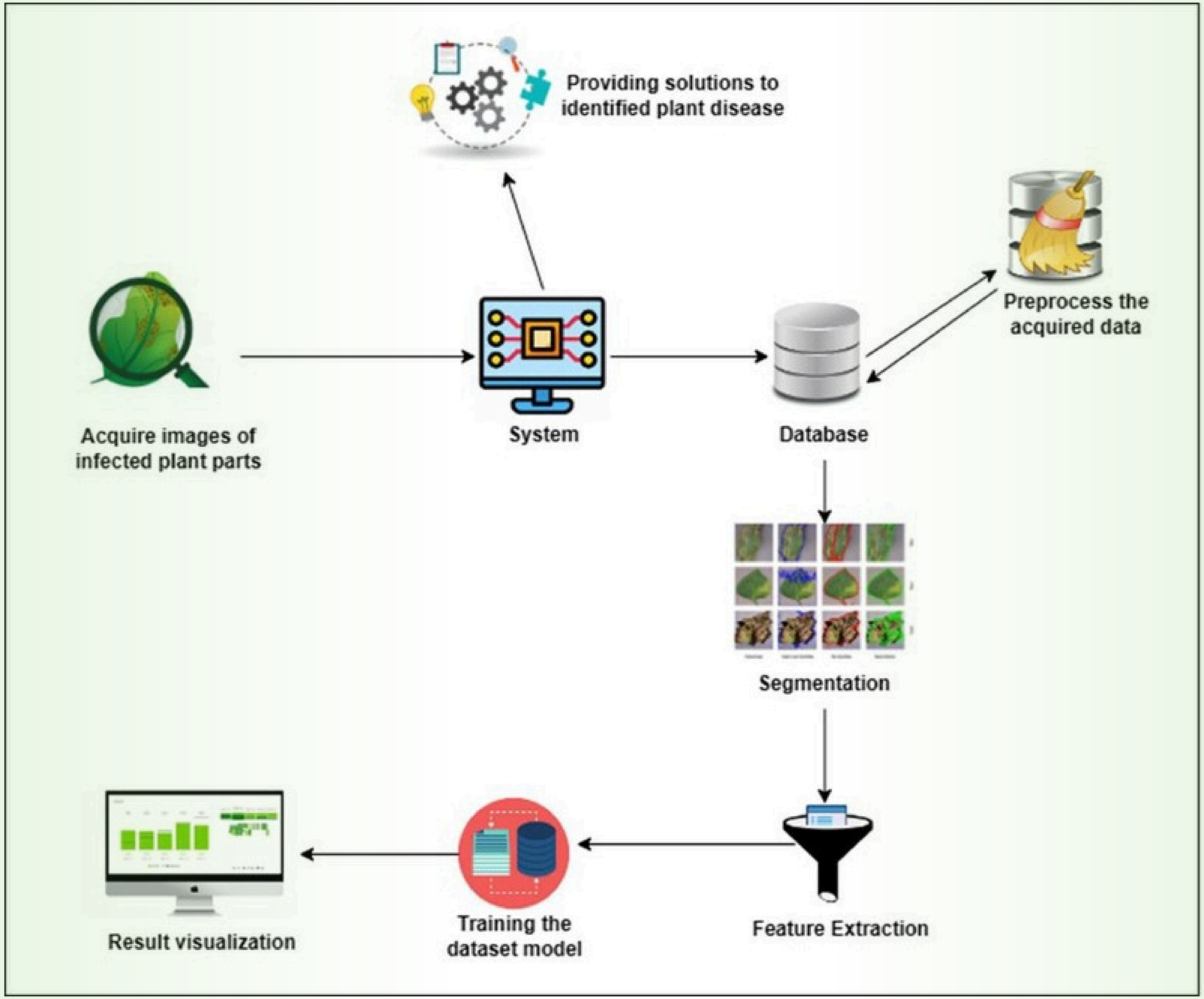
Functional requirements

- Ability to identify plant diseases
- Ability to suggest treatment to diseases

Methodology

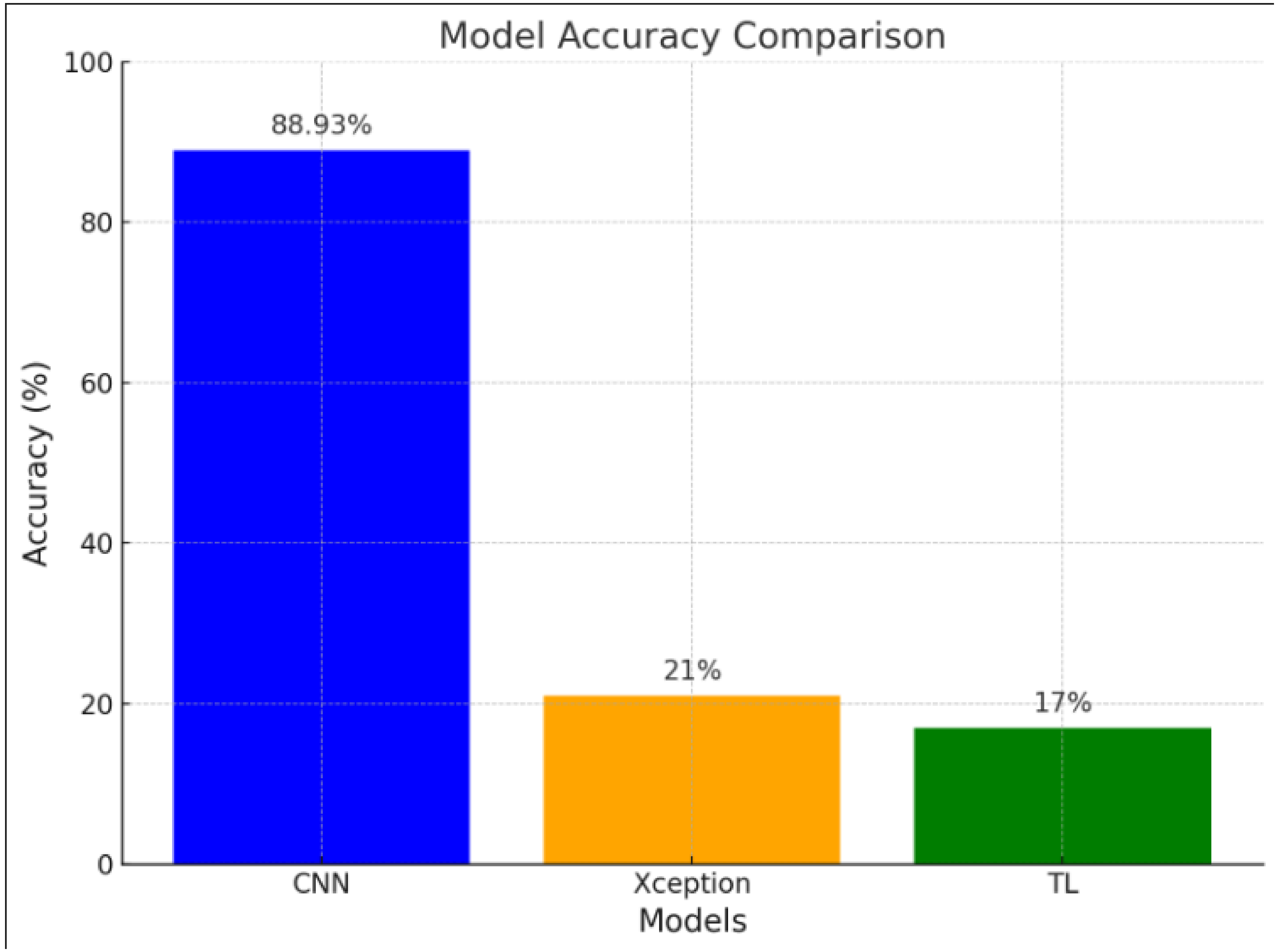
- **Image Acquisition** : capturing high quality images o f plants using digital cameras.
- **Pre-processing** : captured images are preprocessed to improve image
- **quality Segmentation:** separating the plant parts from the background and isolating the region of interest.
- **Feature Extraction :** Features are extracted from image ,these features may include color, texture, shape, or any other relevant features that can help distinguish between healthy and diseased plants.
- **Classification :** classifying the plant as either healthy or diseased. This involves using machine learning algorithms to train a model that can accurately predict the presence of disease in a given plant.
- **Visualization:** The results are visualized to provide a clear and concise output to the user. This includes highlighting the infected area in the image.
- **Diagnosis :** The system identifies the type of plant disease and suggests appropriate treatment measures, Based on the classification result

System Diagram

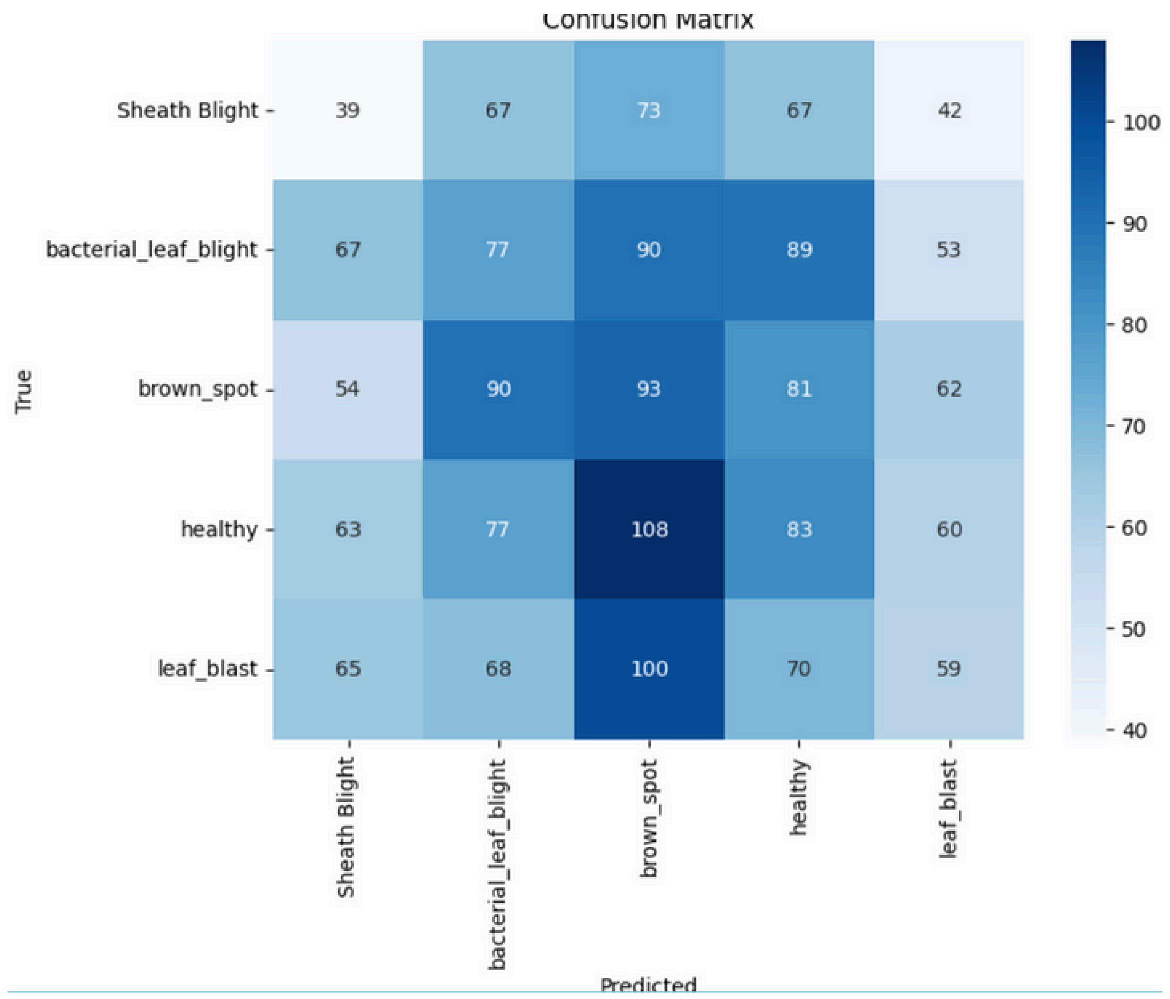


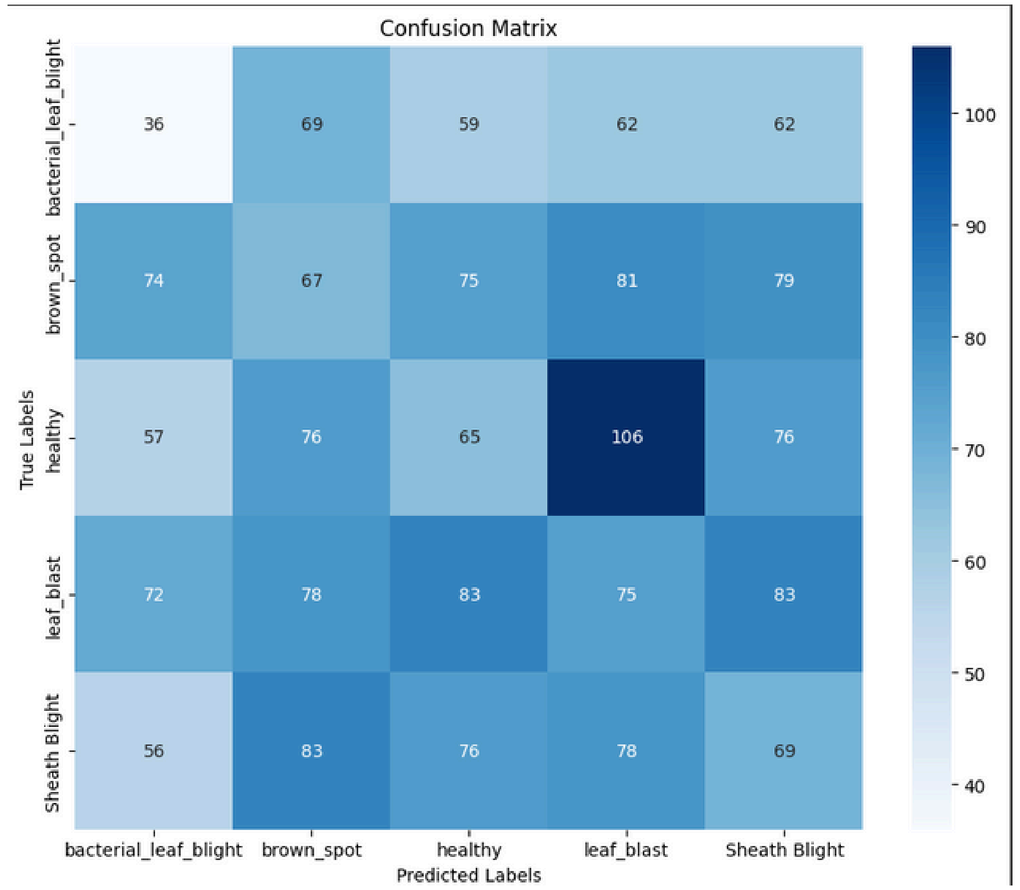
Performance Metrics

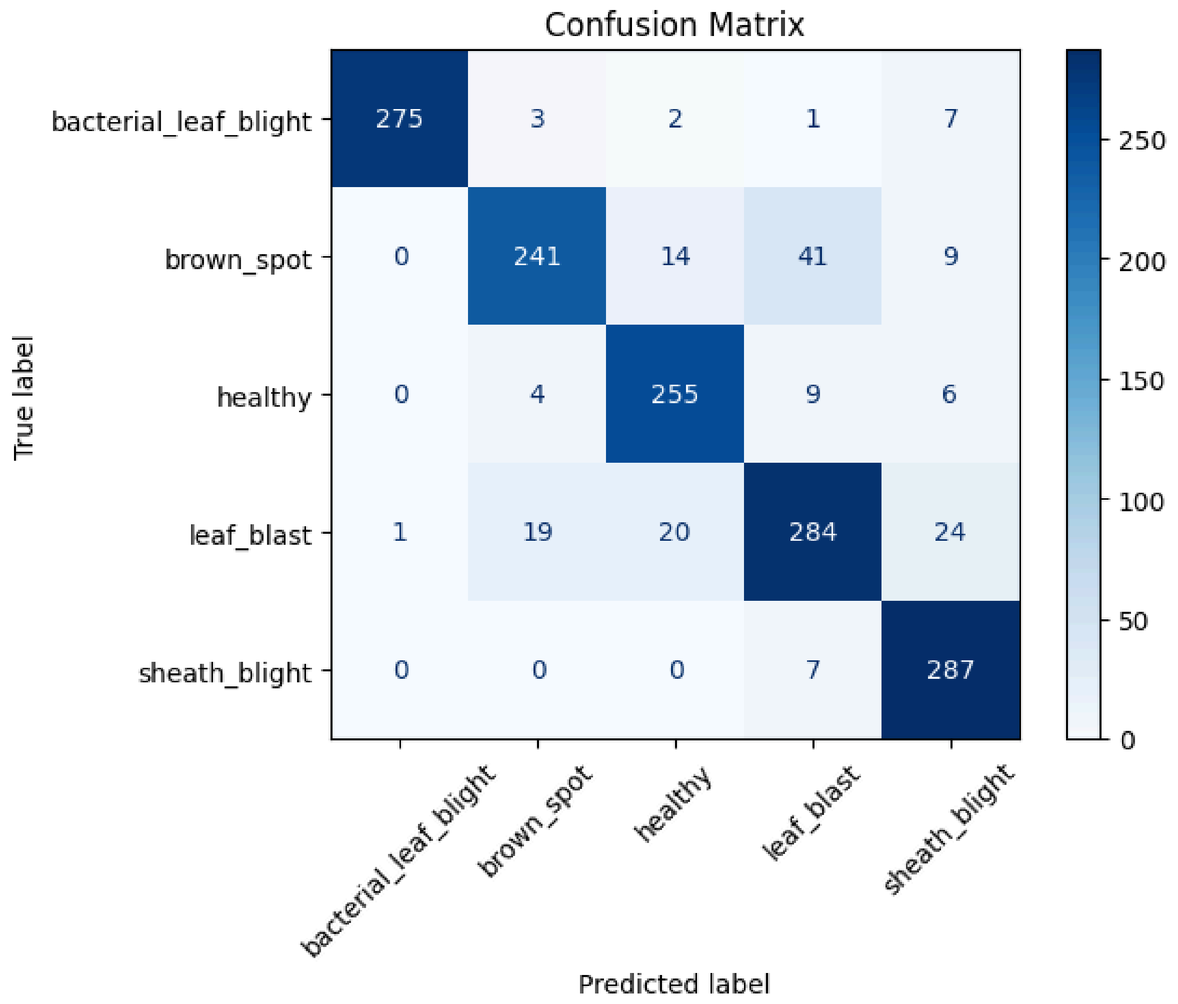
- CNN significantly outperforms other models with an accuracy of 88.93%, showcasing its robust architecture and effective data augmentation techniques.
- Xception and TL models demonstrate limited performance, achieving 21% and 17% accuracy, respectively.
- The bar chart underscores the superiority of CNN, making it the most reliable model for paddy disease identification.



Model performance Analysis



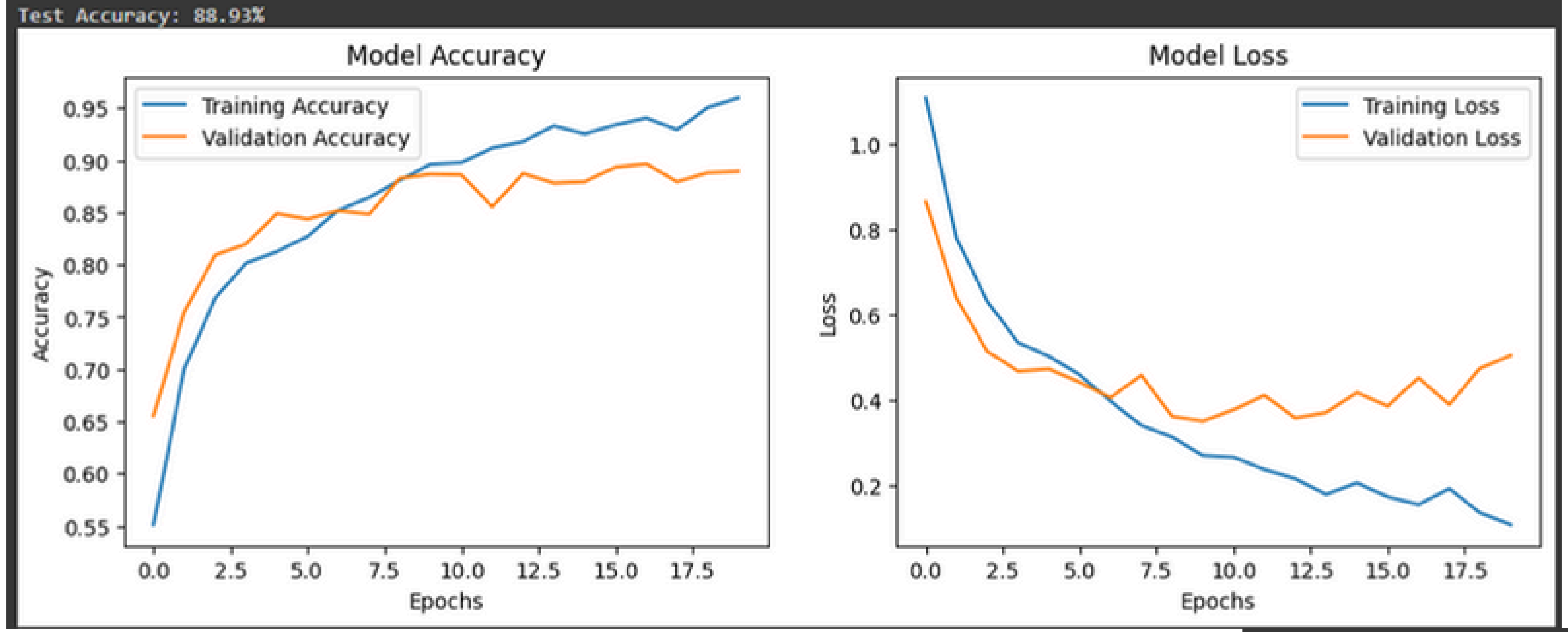




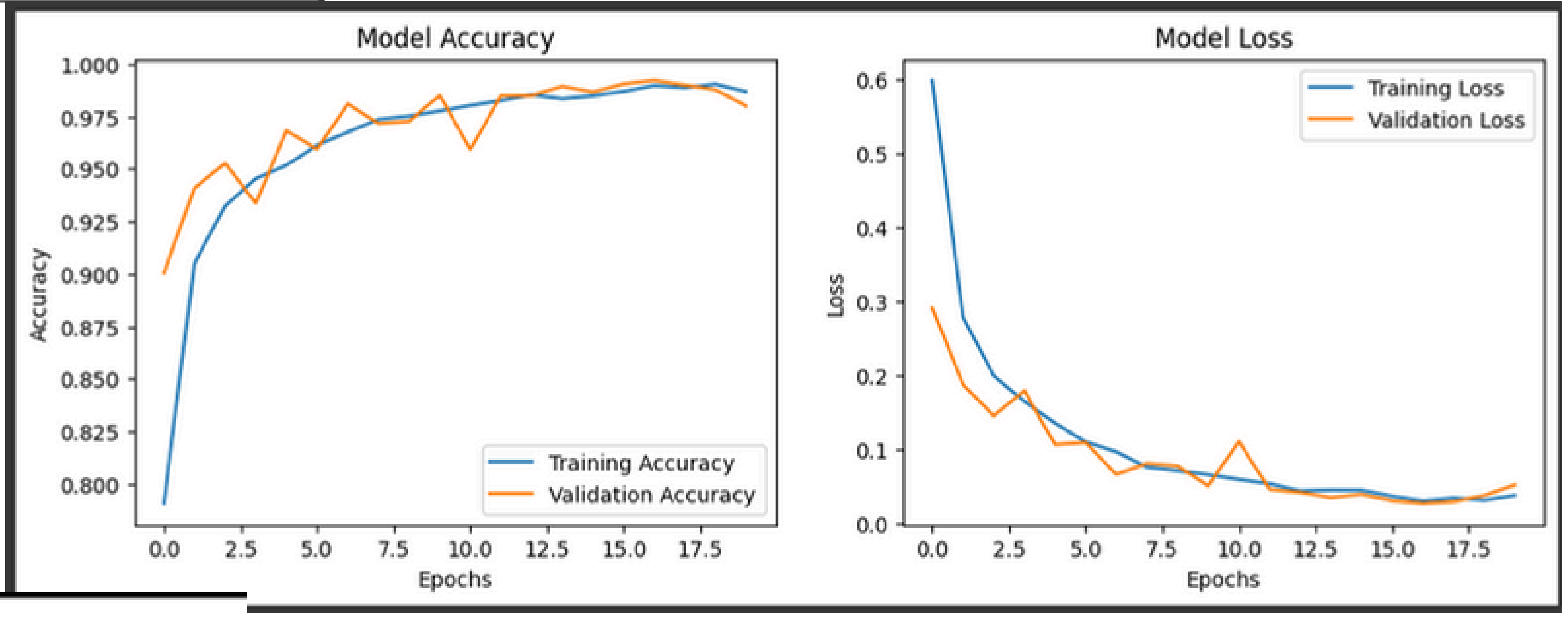
TL **Xception** **CNN**

The confusion matrices highlight the effectiveness of CNN compared to TL and Xception, emphasizing its superior accuracy and reliability for paddy disease identification. Further optimization in TL and Xception may improve their performance.

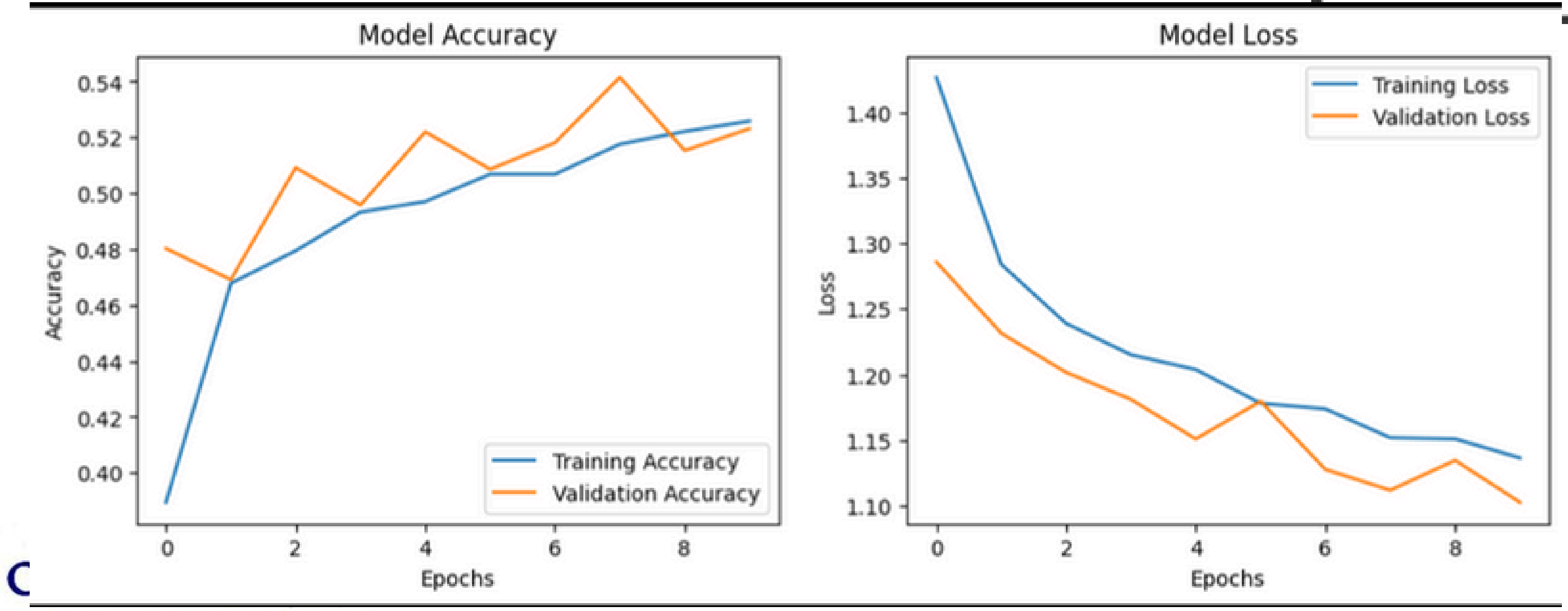
CNN



Xception



TL



Effective performance relies on selecting the right architecture and balancing model capacity with dataset complexity.

Why Choose CNN Over Xception & Transfer Learning?

Lightweight & Optimized

- Custom CNN is smaller & faster than deep pre-trained models.
- Requires less computational power for training & inference.

Domain-Specific Learning

- Learns paddy disease-specific features instead of general patterns.
- No unnecessary pre-trained features, reducing overfitting.

Better for Small Datasets

- Unlike TL, it doesn't depend on large datasets for fine-tuning.
- Works well with data augmentation & regularization.

Efficient for Real-Time Applications

- Lower memory usage and faster inference than Xception.
- Easier to deploy on edge devices like mobile apps.

Import Libraries

```python
# Import libraries
import os
import cv2
import numpy as np
import matplotlib.pyplot as plt
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout
from tensorflow.keras.utils import to_categorical
from tensorflow.keras.optimizers import Adam
from sklearn.model_selection import train_test_split
```

Image Processing:
- os, cv2 (OpenCV): For handling files and image processing.

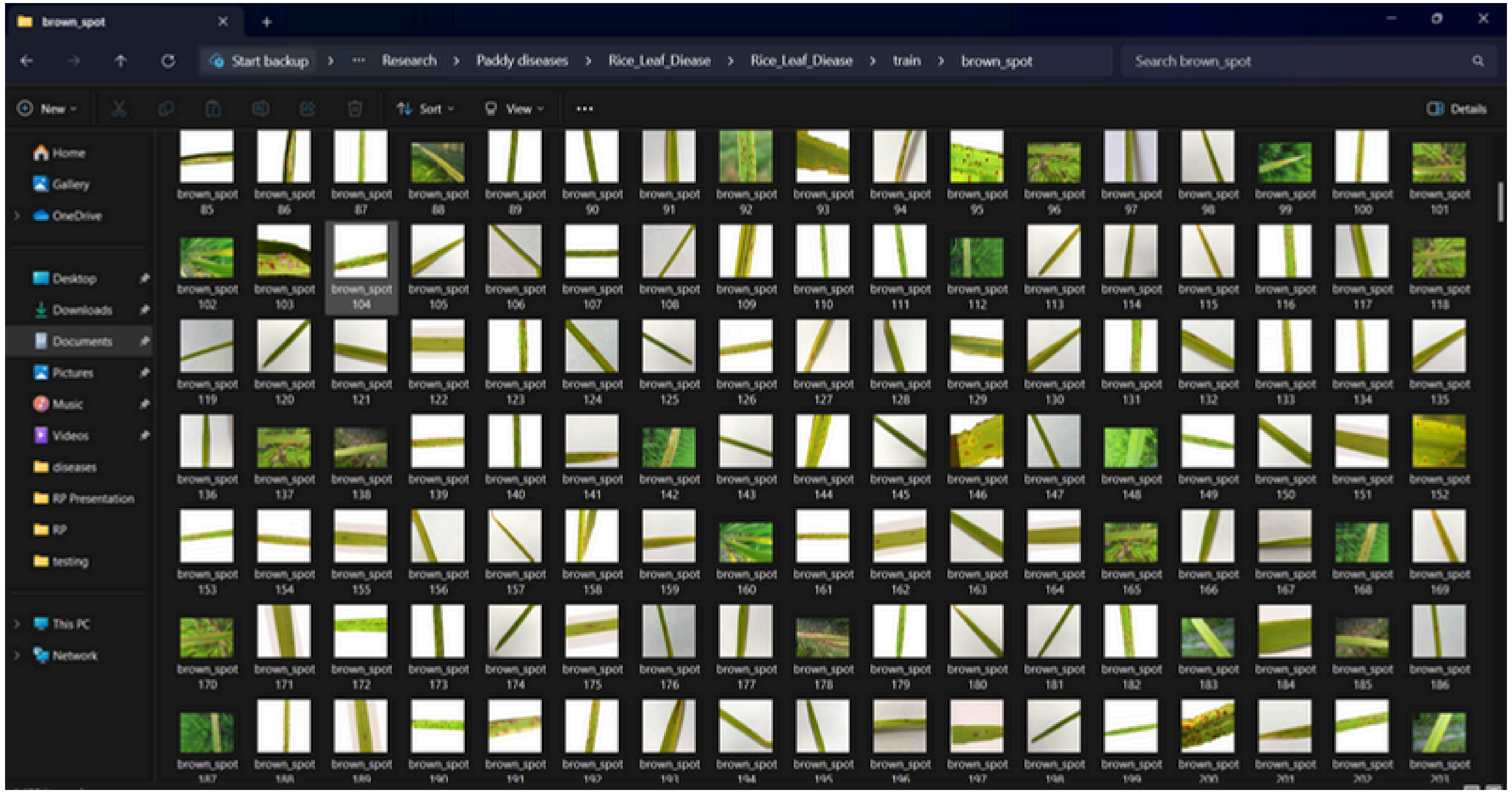
Data Handling & Visualization:
- numpy: For numerical computations.
- matplotlib: To visualize data and results.

Deep Learning:
- tensorflow.keras: For building and training the CNN model.
  - Layers: Conv2D, MaxPooling2D, Dropout, Flatten, Dense
  - Optimizer: Adam.
- to_categorical: Converts class labels to one-hot encoded for classification tasks.

Data Splitting:
- sklearn: Splits data into training and testing sets.

Data Collection

- **Dataset:** 5 classes with near 3000 images per class (augmented and non-augmented).
- **Goal:** Increase diversity and robustness of the model.



Model Training

- **Model:** CNN (Convolutional Neural Network) selected because of high accuracy.(88.93%)

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 126, 126, 32)	896
max_pooling2d (MaxPooling2D)	(None, 63, 63, 32)	0
conv2d_1 (Conv2D)	(None, 61, 61, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 30, 30, 64)	0
conv2d_2 (Conv2D)	(None, 28, 28, 128)	73,856
max_pooling2d_2 (MaxPooling2D)	(None, 14, 14, 128)	0
flatten (Flatten)	(None, 25088)	0
dense (Dense)	(None, 128)	3,211,392
dropout (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 5)	645

Total params: 3,305,285 (12.61 MB)
Trainable params: 3,305,285 (12.61 MB)
Non-trainable params: 0 (0.00 B)

	precision	recall	f1-score	support
bacterial_leaf_blight	1.00	0.95	0.98	288
brown_spot	0.90	0.79	0.84	305
healthy	0.88	0.93	0.90	274
leaf_blast	0.83	0.82	0.82	348
sheath_blight	0.86	0.98	0.92	294
accuracy			0.89	1509
macro avg	0.89	0.89	0.89	1509
weighted avg	0.89	0.89	0.89	1509

Model Training

Image preprocessing:

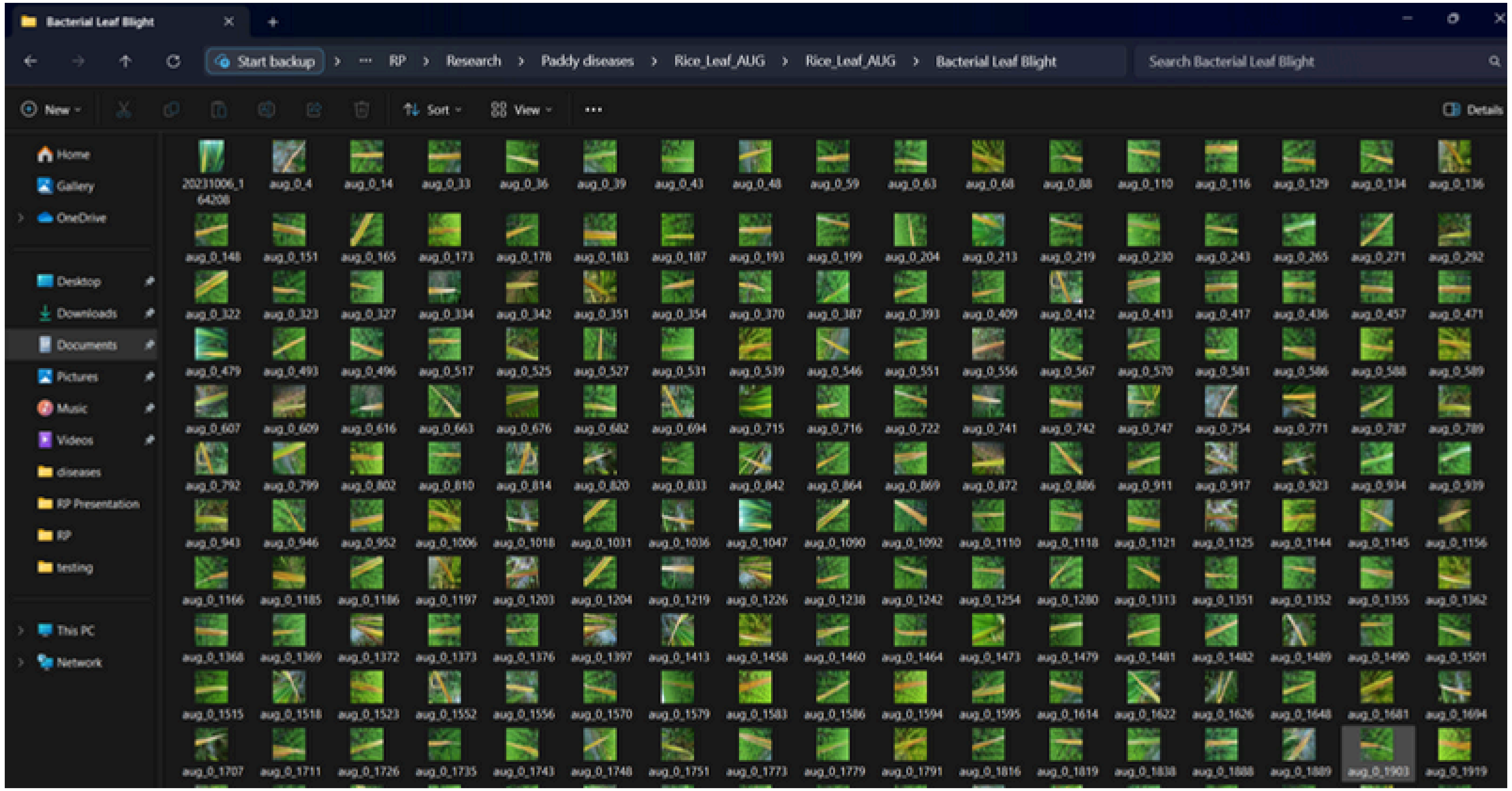
- Preprocessing: Resizing and normalizing images.

```python
# Image Preprocessing
def preprocess_image(img_path):
    try:
        # Load the image with reduced memory consumption
        img = cv2.imread(img_path, cv2.IMREAD_UNCHANGED)
        if img is None:
            raise ValueError(f"Image at {img_path} could not be read. Check the file.")

        # Resize the image to 128x128 pixels
        img_resized = cv2.resize(img, (128, 128))

        # Normalize pixel values to [0, 1]
        img_normalized = img_resized / 255.0
        return img_normalized
    except Exception as e:
        print(f"Error processing image {img_path}: {e}")
        return None  # Skip this image
```

Model Training

Training Process:

- Augmentation: Flip, rotate, and adjust brightness.



Reduce overfitting

```python
# Add convolutional layers with MaxPooling
model.add(Conv2D(32, (3, 3), activation='relu', input_shape=(128, 128, 3)))
model.add(MaxPooling2D((2, 2)))
model.add(Conv2D(64, (3, 3), activation='relu'))
model.add(MaxPooling2D((2, 2)))
model.add(Conv2D(128, (3, 3), activation='relu'))
model.add(MaxPooling2D((2, 2)))

# Flatten the output and add Dense layers
model.add(Flatten())
model.add(Dense(128, activation='relu'))
model.add(Dropout(0.5))  # Regularization to reduce overfitting
model.add(Dense(num_classes, activation='softmax'))  # Output layer

# Compile the Model
model.compile(optimizer=Adam(learning_rate=0.001),
              loss='categorical_crossentropy',
              metrics=['accuracy'])
```

- Input Shape: 128x128x3 (RGB images)

Feature Extraction:

- Conv2D + ReLU: Extract features with filters of sizes 32, 64, and 128.
- MaxPooling: Downsample to reduce spatial dimensions.

Classification:

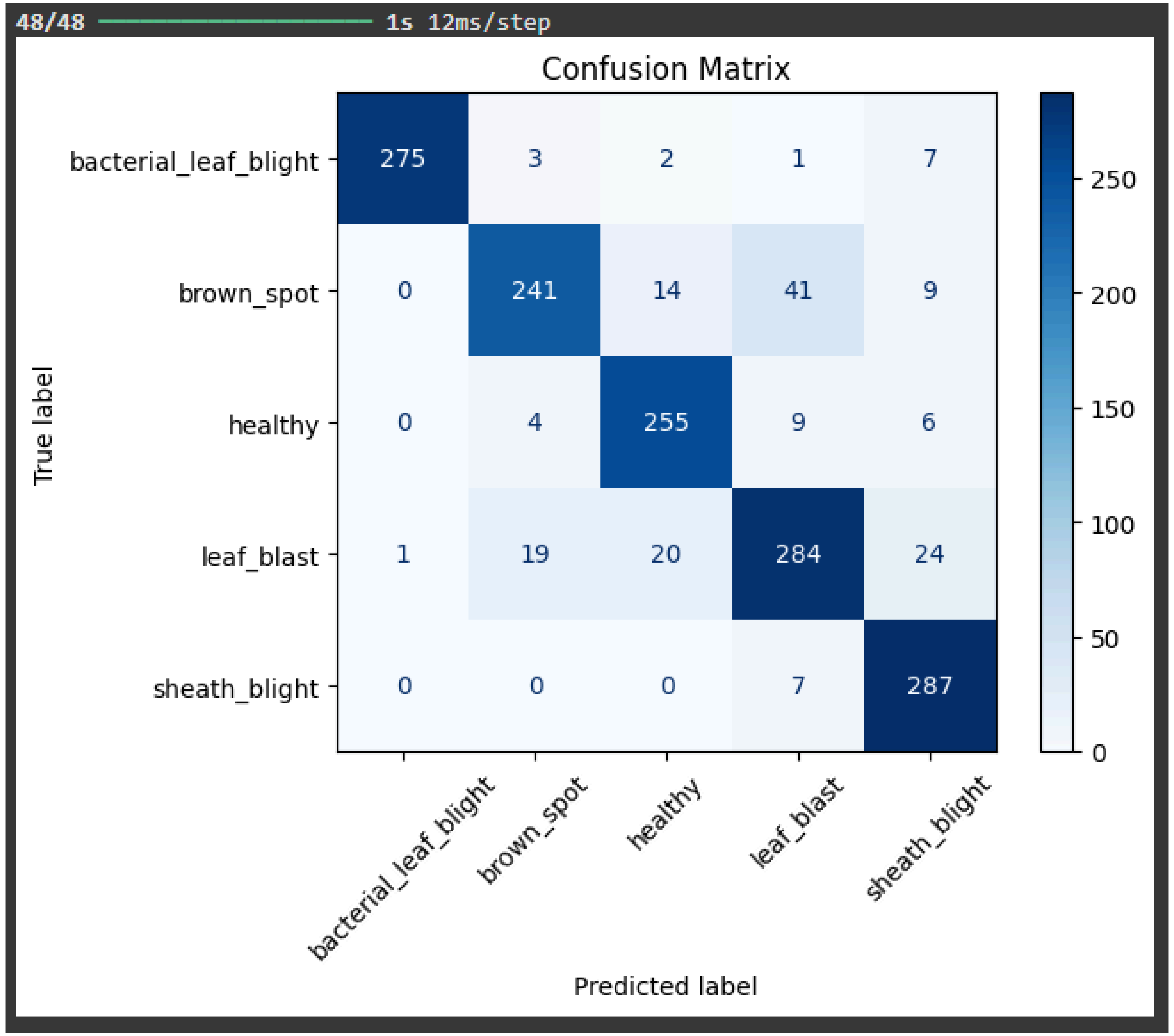
- Flatten: Convert feature maps into a 1D vector.
- Dense Layers: Fully connected layers for prediction.
- Dropout: 50% regularization to **reduce overfitting**.
- Output Layer: **Softmax** activation for multi-class classification.

Compilation:

- Optimizer: **Adam** (learning rate = 0.001).
- Loss Function: **Categorical Crossentropy.**
- Evaluation Metric: Accuracy.

Design

- **matrix visualization of CNN model**



Treatment Recommendation

Process:

- Match predicted class with predefined treatment plans.

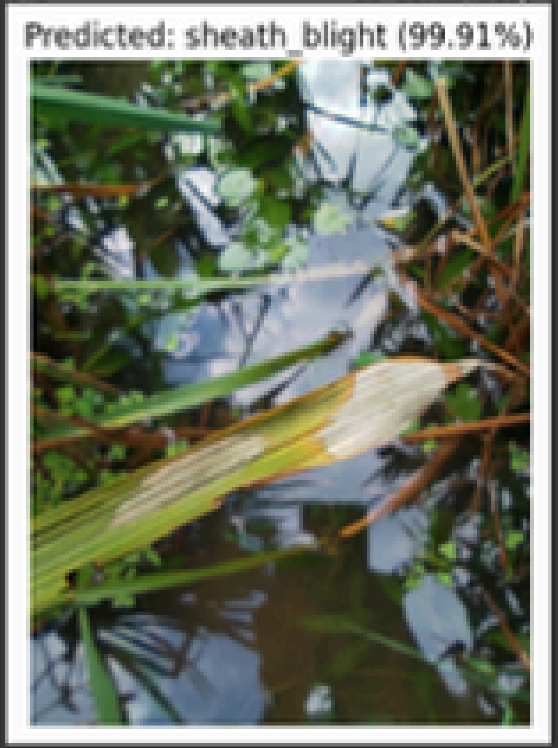
```
[ ] import pickle

    # Define the data in a dictionary format
    treatment_data = {
        'bacterial_leaf_blight': {
            'Name': 'Bacterial Leaf Blight',
            'Symptoms': 'Yellowing of leaves, water-soaked lesions, leaf wilting, and dieback.',
            'Treatment (Brand Names)': 'Kocide 3000, Agrimycin 100',
            'How to Use': 'Spray when symptoms appear; repeat every 7-10 days.',
            'Recommendations': 'Use resistant rice varieties. Improve drainage. Maintain proper hygiene in the field.'
        },
        'brown_spot': {
            'Name': 'Brown Spot',
            'Symptoms': 'Brown, circular spots on leaves, yellowing around spots, stunted growth.',
            'Treatment (Brand Names)': 'Tilt, Folicur',
            'How to Use': 'Apply at the first signs of disease; follow label instructions.',
            'Recommendations': 'Rotate crops and practice good field management. Use resistant varieties.'
        },
        'healthy': {
            'Name': 'Healthy',
            'Symptoms': 'No visible symptoms; healthy leaf color and structure.',
            'Treatment (Brand Names)': 'N/A',
            'How to Use': 'Continue regular monitoring and maintain good practices.',
            'Recommendations': 'Regularly inspect fields for early detection of diseases.'
        },
        'leaf_blast': {
            'Name': 'Leaf Blast',
            'Symptoms': 'Elliptical, greenish-gray lesions with a white center; can cause rapid plant death.',
            'Treatment (Brand Names)': 'Blast-Off, Tricyclazole (Beam)',
            'How to Use': 'Apply fungicide at the first sign of symptoms; repeat every 10-14 days if needed.',
            'Recommendations': 'Plant resistant varieties; monitor environmental conditions.'
        },
        'sheath_blight': {
            'Name': 'Sheath Blight',
            'Symptoms': 'Irregular, water-soaked lesions on the leaf sheath; can lead to lodging.',
            'Treatment (Brand Names)': 'Raxil, Headline',
            'How to Use': 'Apply at tillering stage or at first signs; follow label recommendations.',
            'Recommendations': 'Maintain proper irrigation and avoid excessive nitrogen fertilization.'
        }
    }
```

Treatment Recommendation

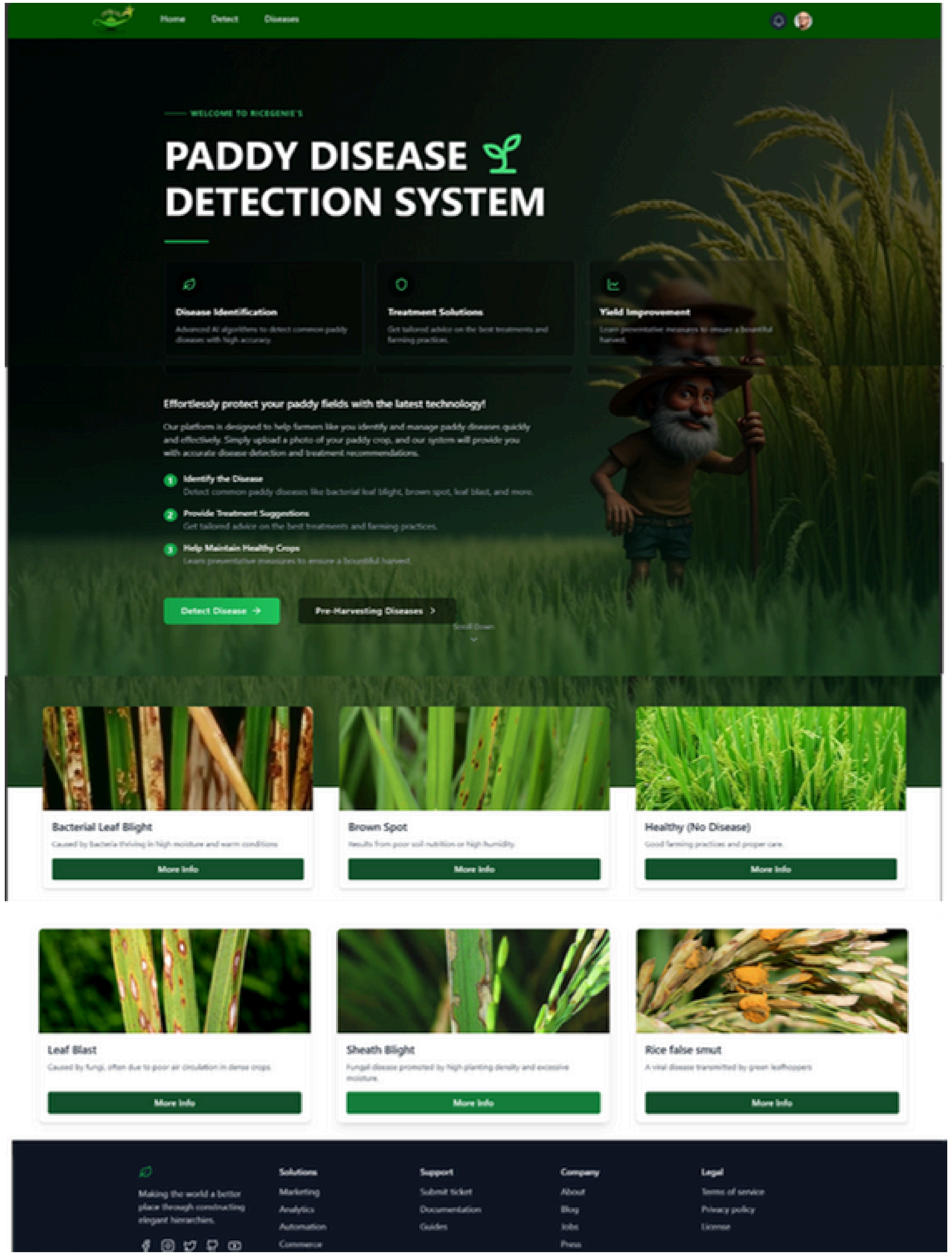
Process:

- Display treatments, including disease names, application methods, and prevention tips.

```
WARNING:absl:Compiled the loaded model, but the compiled metrics have yet to be built. `model.compile_metrics` will be empty until you train or evaluate the model.
Model loaded successfully.
Treatment data loaded successfully.
Available Treatment Classes: ['bacterial_leaf_blight', 'brown_spot', 'healthy', 'leaf_blast', 'sheath_blight']
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
```

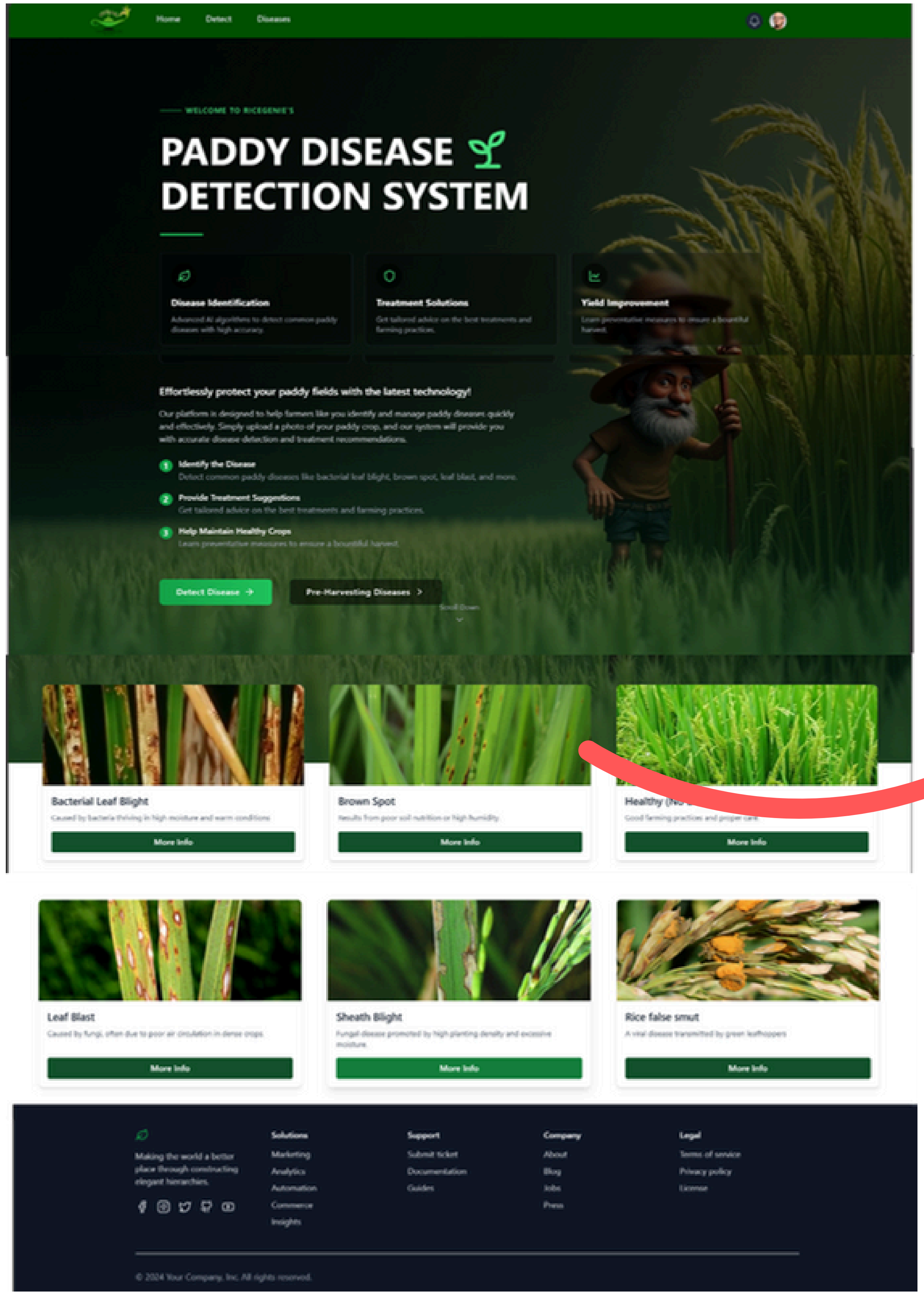


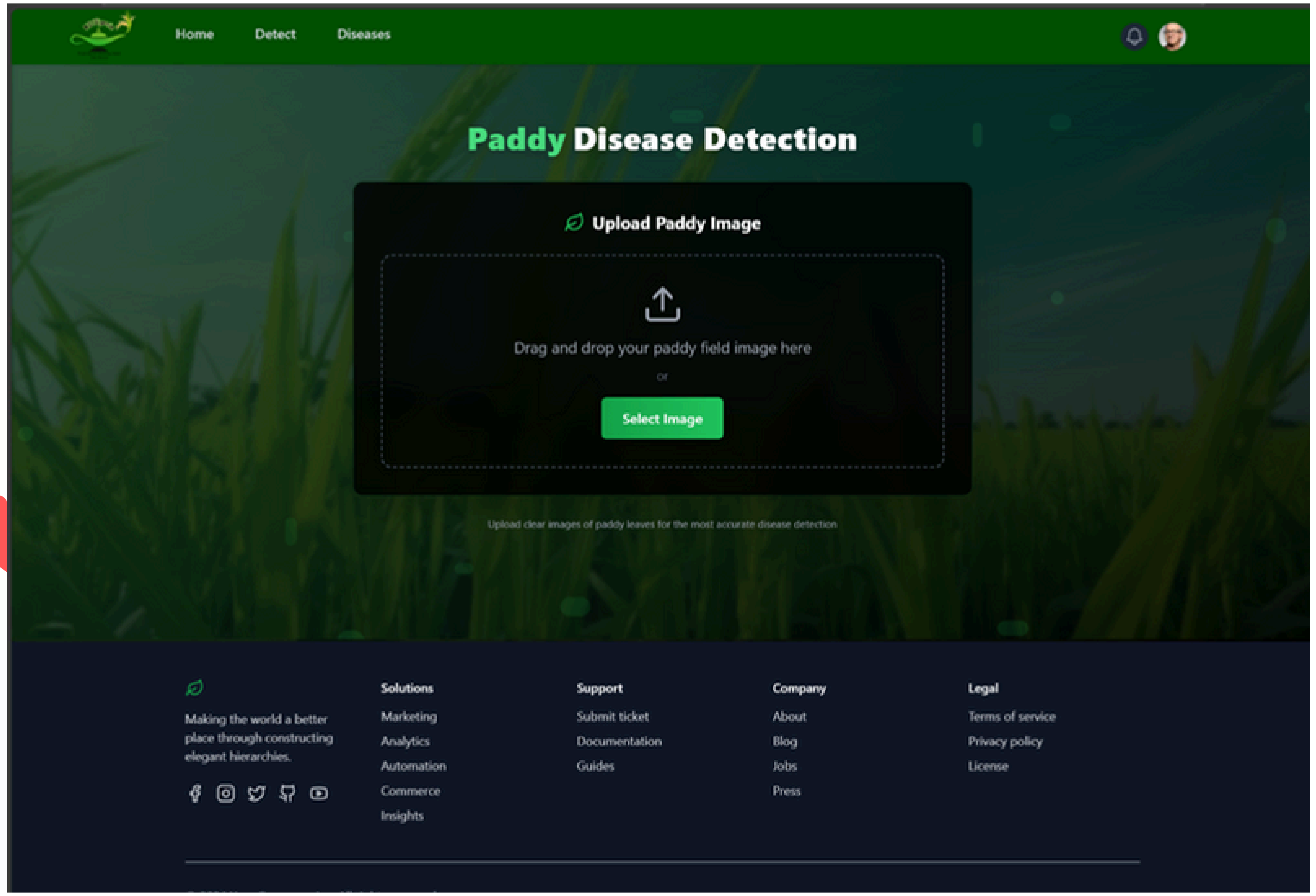

```
--- Treatment Suggestions ---
Disease Class: sheath_blight
Name: Sheath Blight
Symptoms: Irregular, water-soaked lesions on the leaf sheath; can lead to lodging.
Treatment (Brand Names): Raxil, Headline
How to Use: Apply at tillering stage or at first signs; follow label recommendations.
Recommendations: Maintain proper irrigation and avoid excessive nitrogen fertilization.
```



Requirements

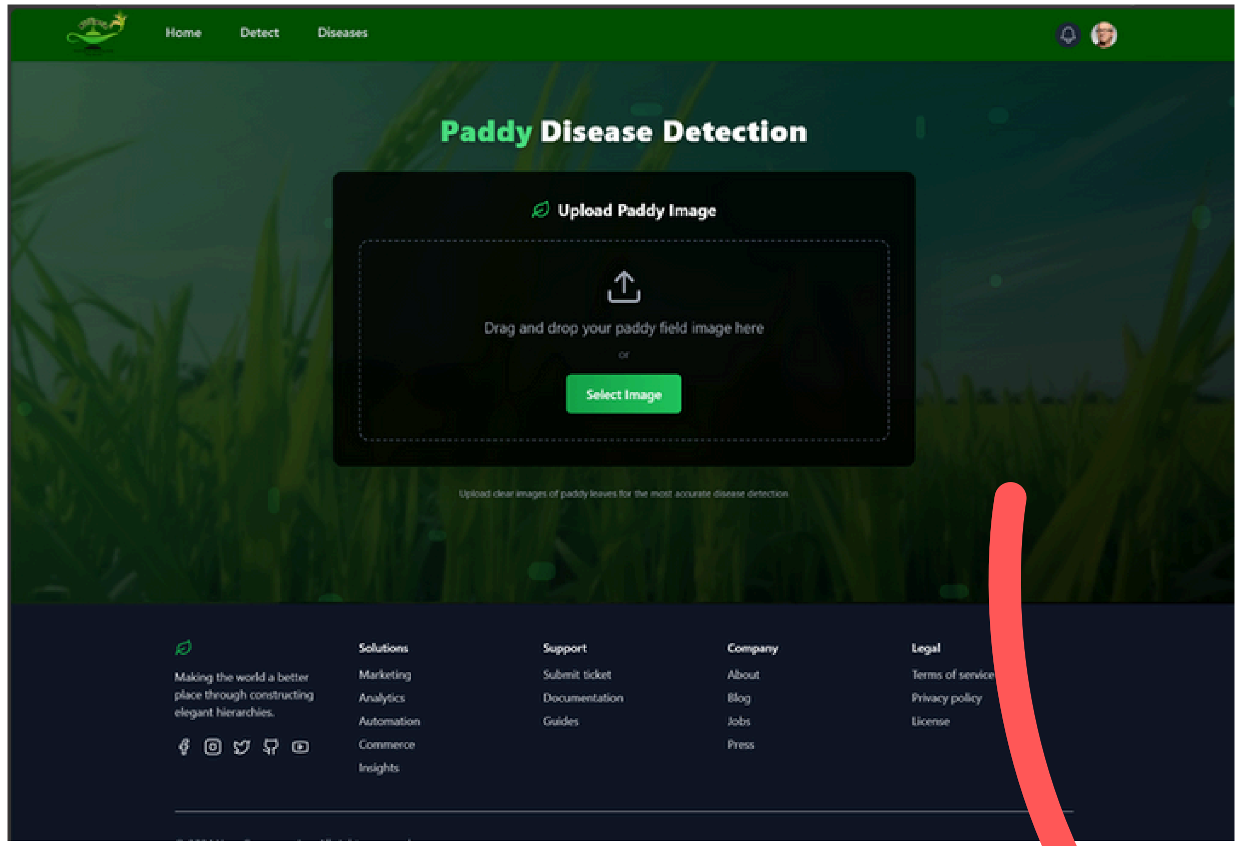
- **Log:** Farmers log to the Detect &Manage Diseases tab which user-friendly app interface.

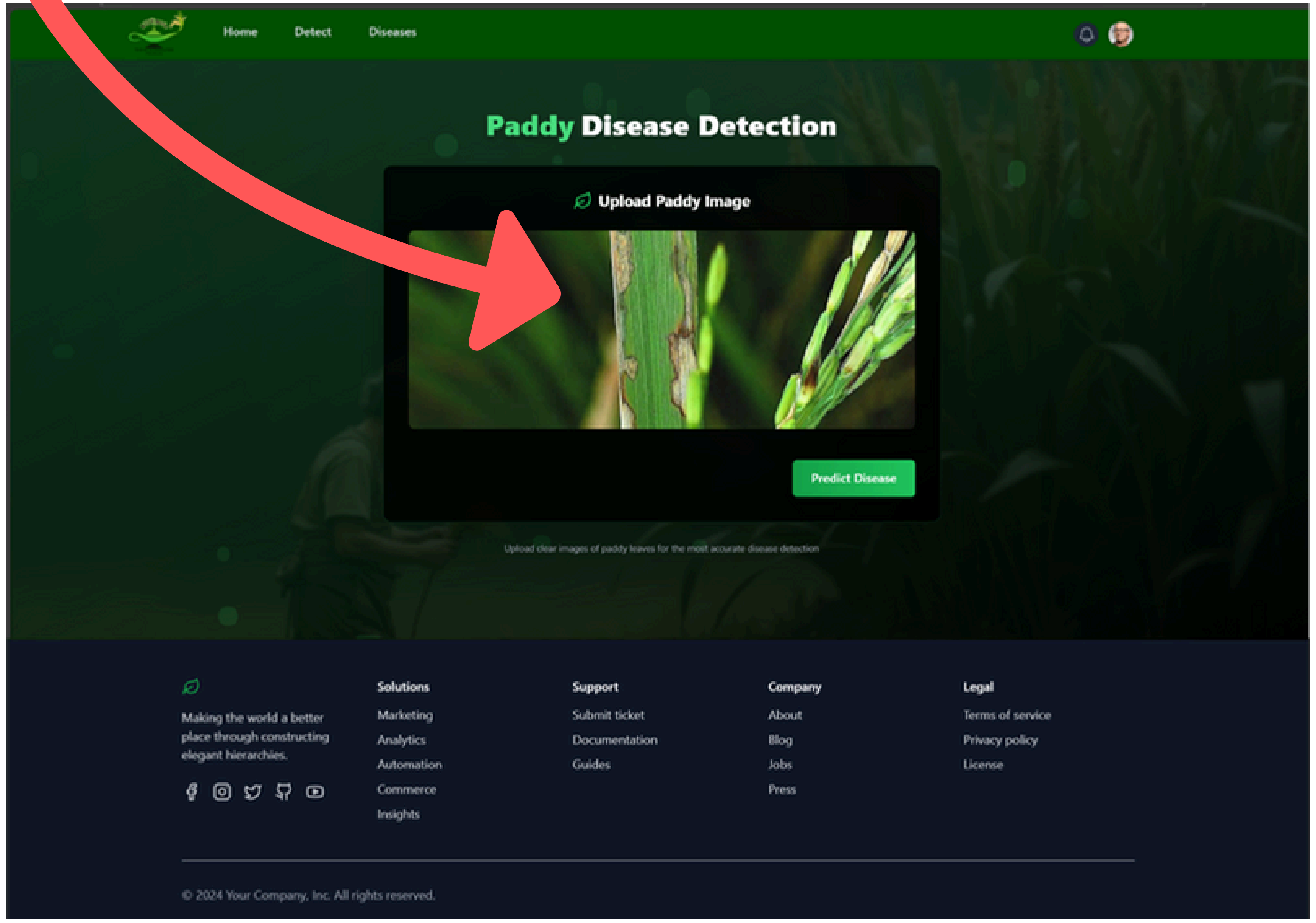




Requirements

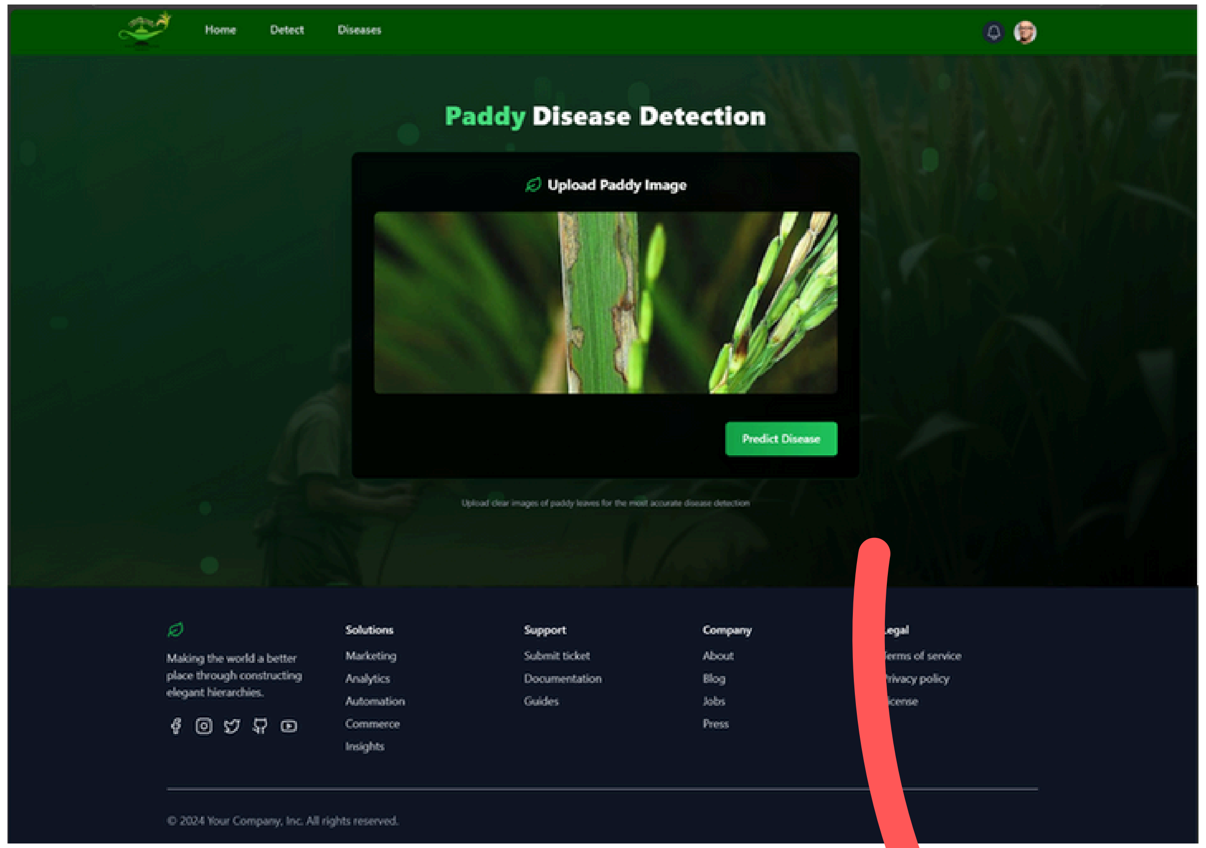
Input: Farmer-uploaded images via a user-friendly app interface.

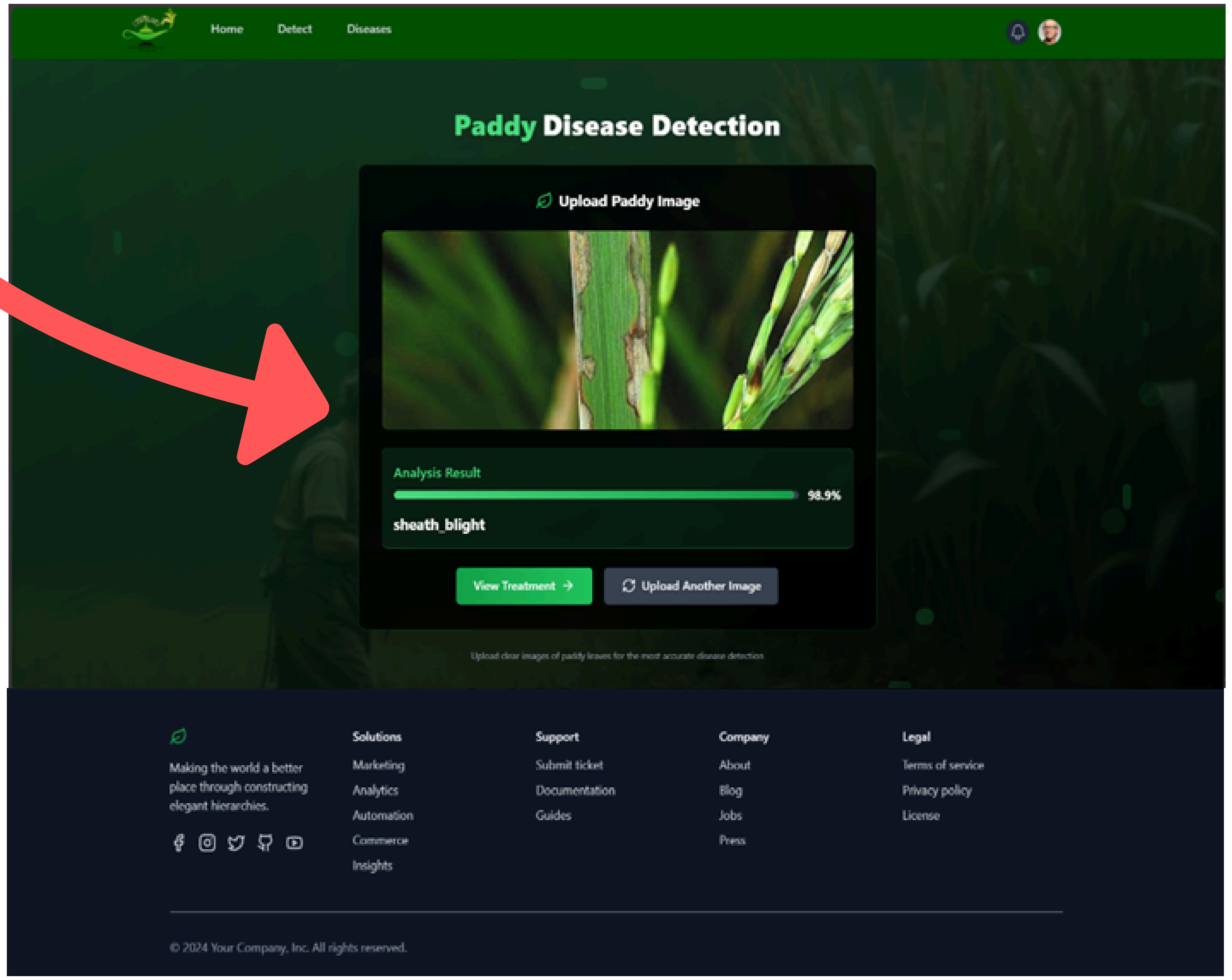




Requirements

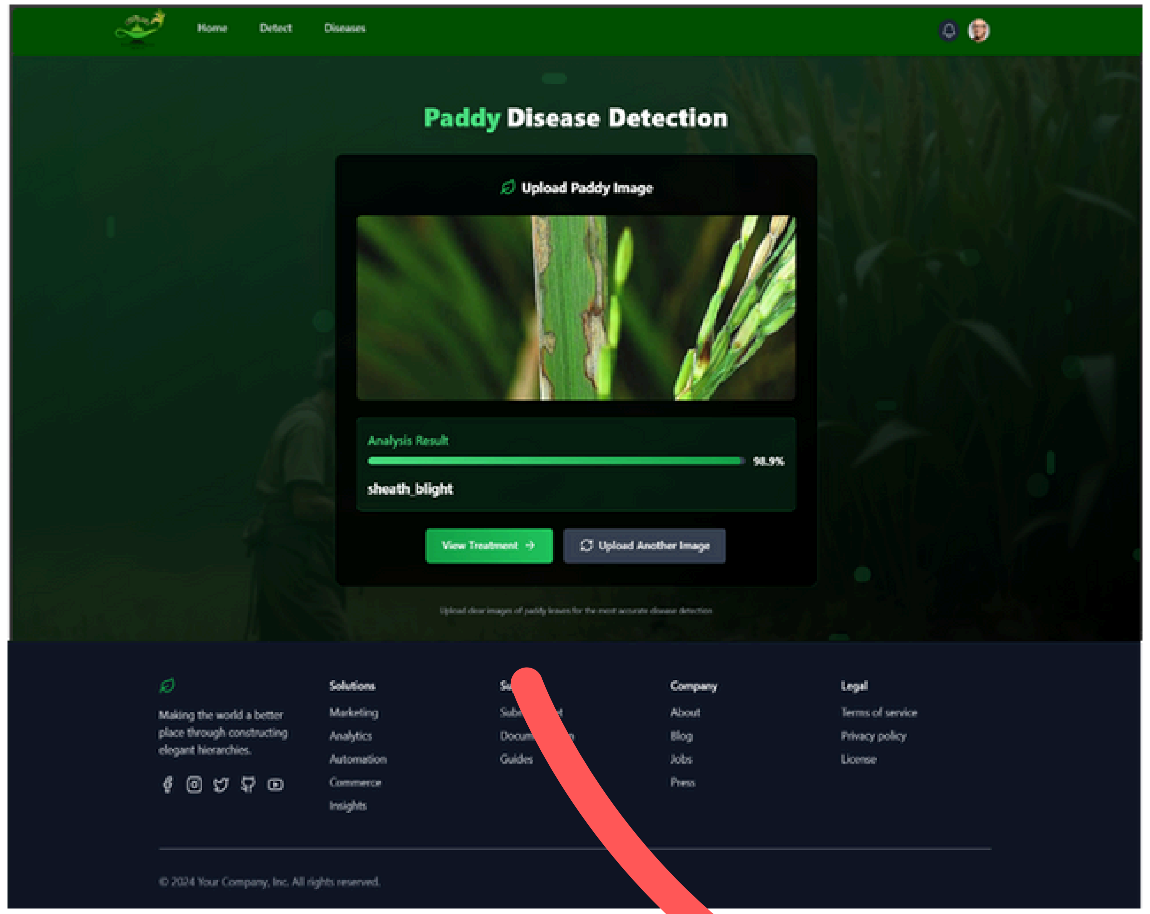
Output: Disease identification and treatment recommendations.

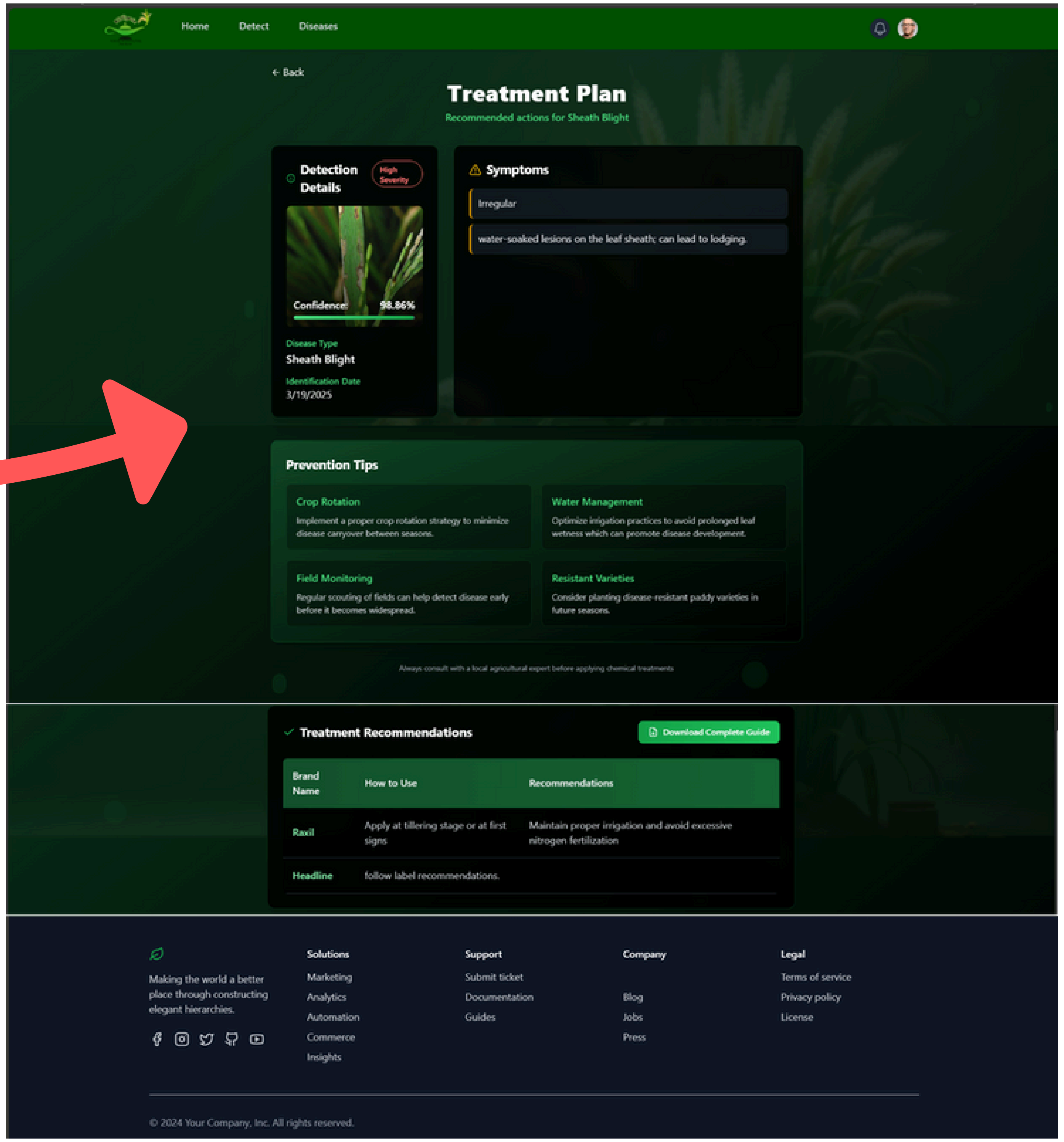




Requirements

Output: Disease identification and treatment recommendations.





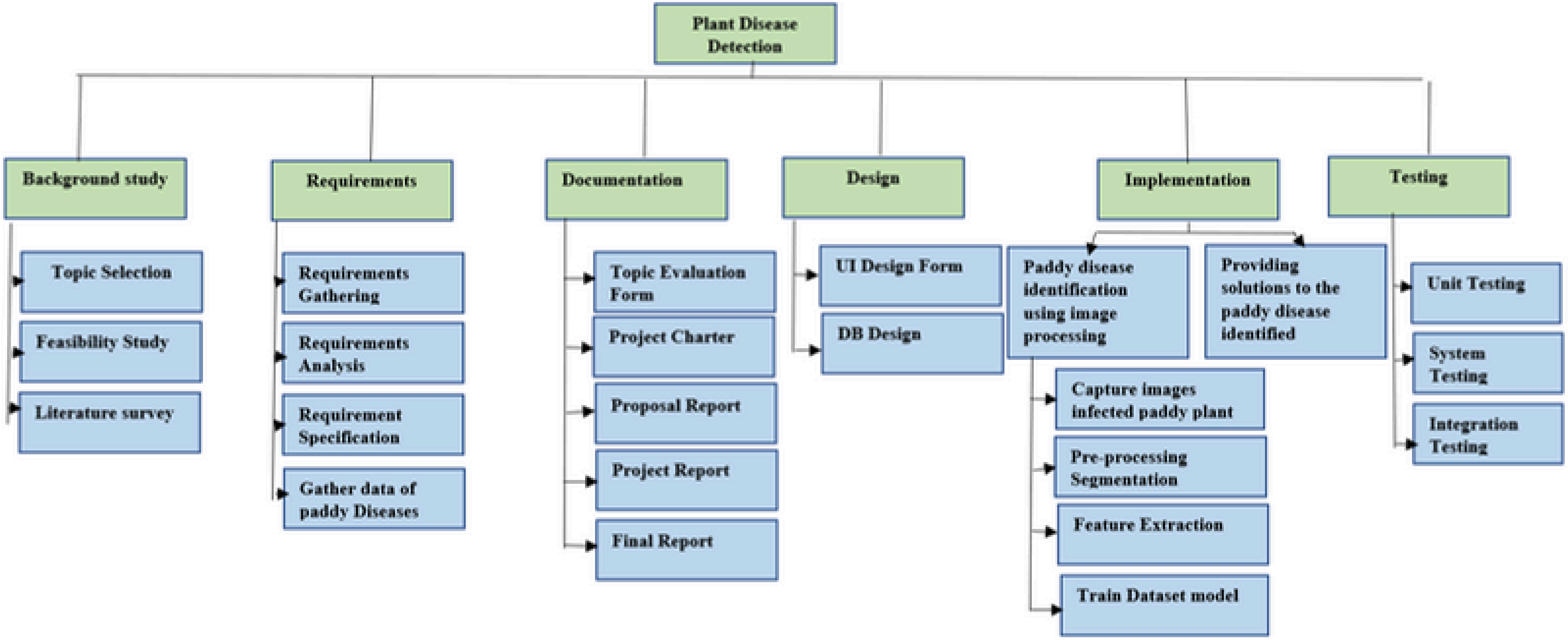
Requirements

Output: Disease identification and treatment recommendations.

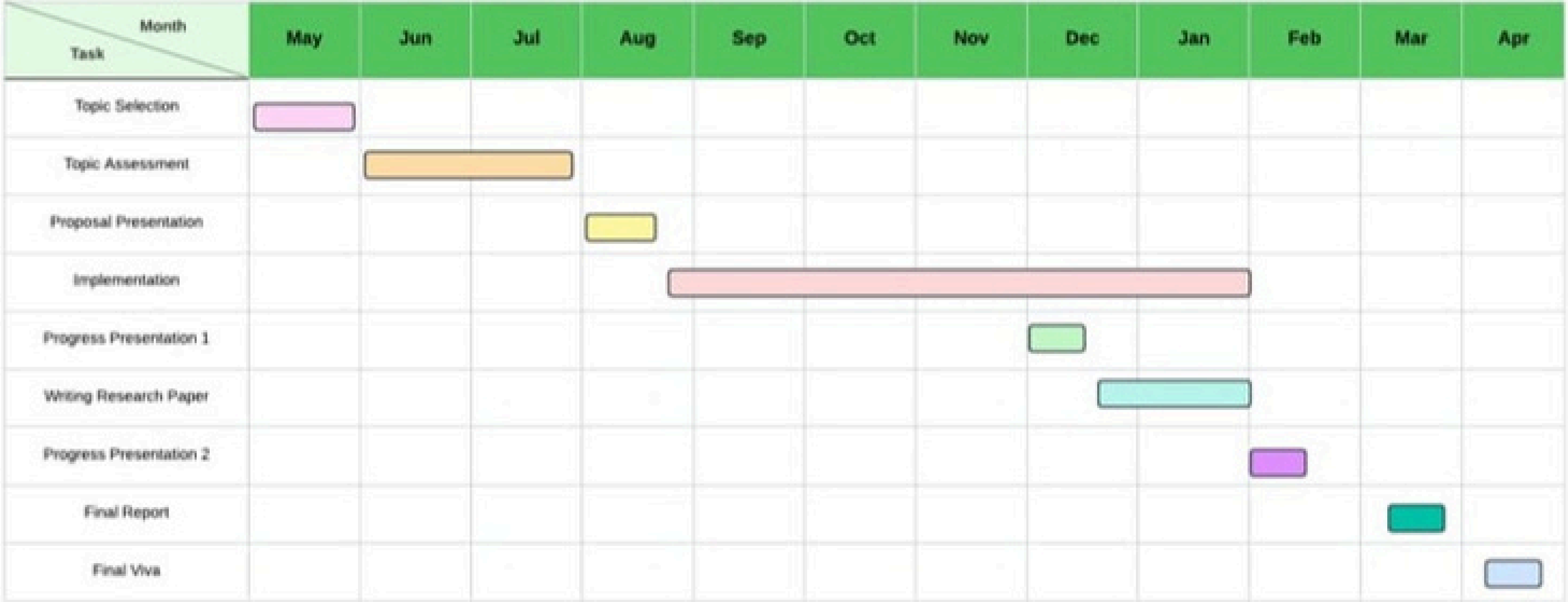
Technologies

- Python (Back end)
- Tensor Flow (Framework)
- Deep learning (Classificatior
- ViteJS (Front end)
- Tailwind (for styles)
- Fast API
- Google Colab
- Git Hub (Version control system)
- Trello(Project Management)

Work Breakdown Structure



Gantt chart



Month
Task
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Jan
Feb
Mar
Apr
Topic Selection
Topic Assessment
Proposal Presentation
Implementation
Progress Presentation 1
Writing Research Paper
Progress Presentation 2
Final Report
Final Viva

REFERENCES

[1]https://www.researchgate.net/publication/344933690_Detection_and_Recognition_of_Paddy_Plant_Leaf_Diseases_using_Machine_Learning_Technique

[2] Kumar, R. et al. (2022) A systematic analysis of machine learning and deep learning based approaches for Plant Leaf Disease Classification: A Review, Journal of Sensors. Hindawi. Available at: https://doi.org/10.1155/2022/3287561 (Accessed: March 27, 2023).

[3] Kumar, R. et al. (2023) A systematic analysis of machine learning and deep learning based approaches for Plant Leaf Disease Classification: A Review, Journal of Sensors.

IT21227868 | PIYUMANI K.V.P

Paddy Variety Prediction System

Information Technology

INTRODUCTION

This Research component which The Paddy Variety Prediction Model aims to ,

- **Identify the most suitable paddy varieties for specific regions in Sri Lanka**

- Based on local soil and weather conditions. By leveraging data analytics and machine learning techniques, this model seeks to optimize paddy cultivation, enhance crop yield, and improve economic outcomes for farmers.

Research Gap

- Currently, there is a lack of integrated systems that consider local environmental conditions for predicting the best-suited paddy varieties for different regions in the contry. While various studies have explored crop yield prediction, specific focus on paddy variety suitability under diverse environmental conditions is limited. This project fills this gap by providing a comprehensive model that aids farmers in selecting the optimal paddy variety for their fields.

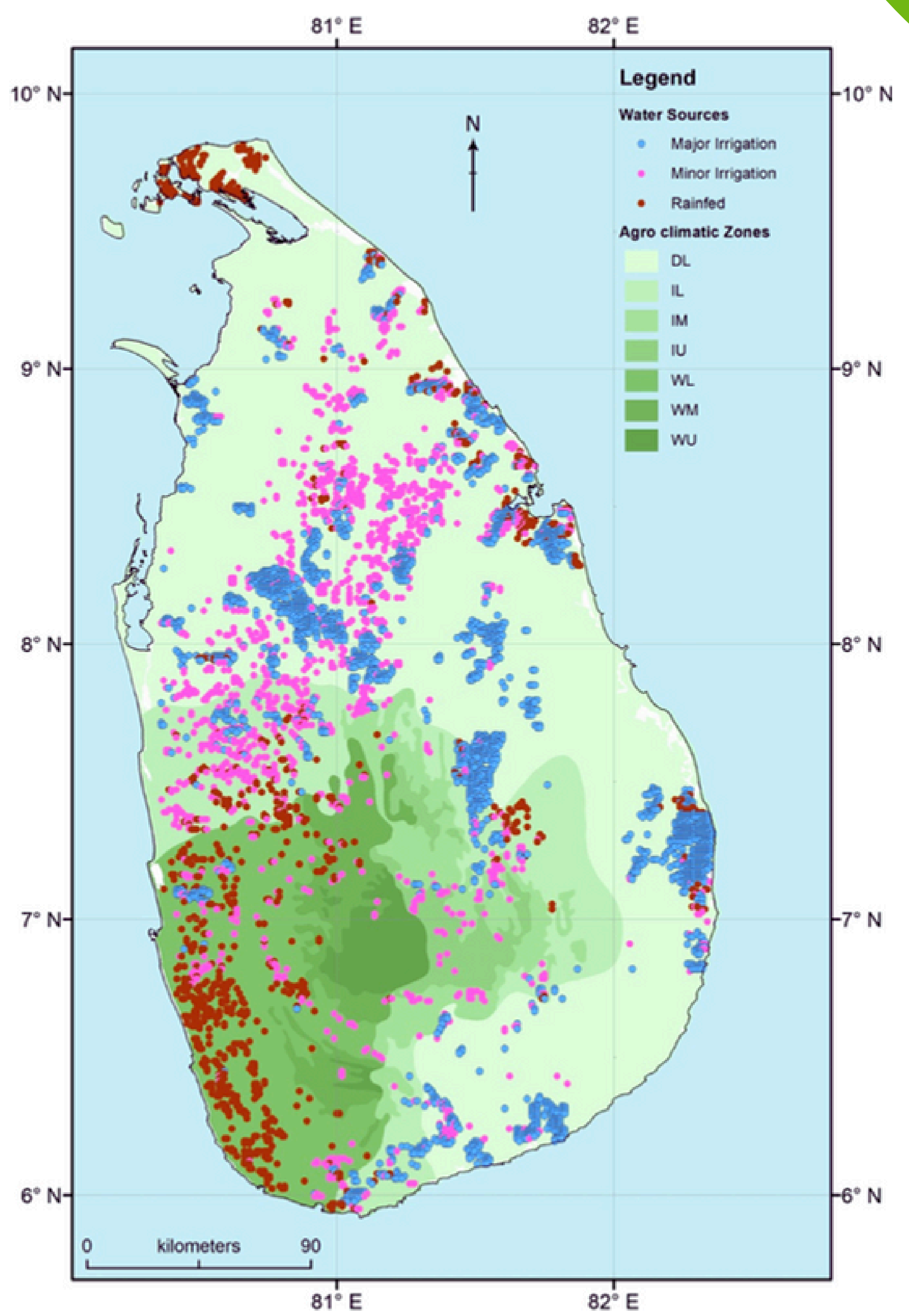
Research Problem

The primary research problem is to establish a predictive relationship between different paddy varieties and the local environmental conditions, such as soil type, pH, moisture, temperature, and nutrient levels. The challenge lies in accurately predicting which paddy varieties can thrive in specific conditions to maximize yield and resilience to environmental stressors.

Specific and Sub Objectives

- **Specific Objectives :**
  - To develop a predictive model for determining the suitability of paddy varieties based on environmental data.

- **Sub Objectives :**
  - Collect and analyze data on paady varieties, various soil parameters (pH, moisture, nutrient content) and weather conditions (temperature, rainfall).
  - Identify the key factors influencing the growth and yield of different paddy varieties.
  - Develop a machine learning model to predict the most suitable paddy variety for an area of the country under given set of environmental conditions.



Mapping Productivity-related Spatial Characteristics in Rice-based Cropping Systems in Sri Lanka

Methodology

- **Data Collection:**Gather data on soil properties (pH, NPK levels, soil moisture), and climatic conditions (temperature, humidity, rainfall) from relevant agricultural departments and field studies.

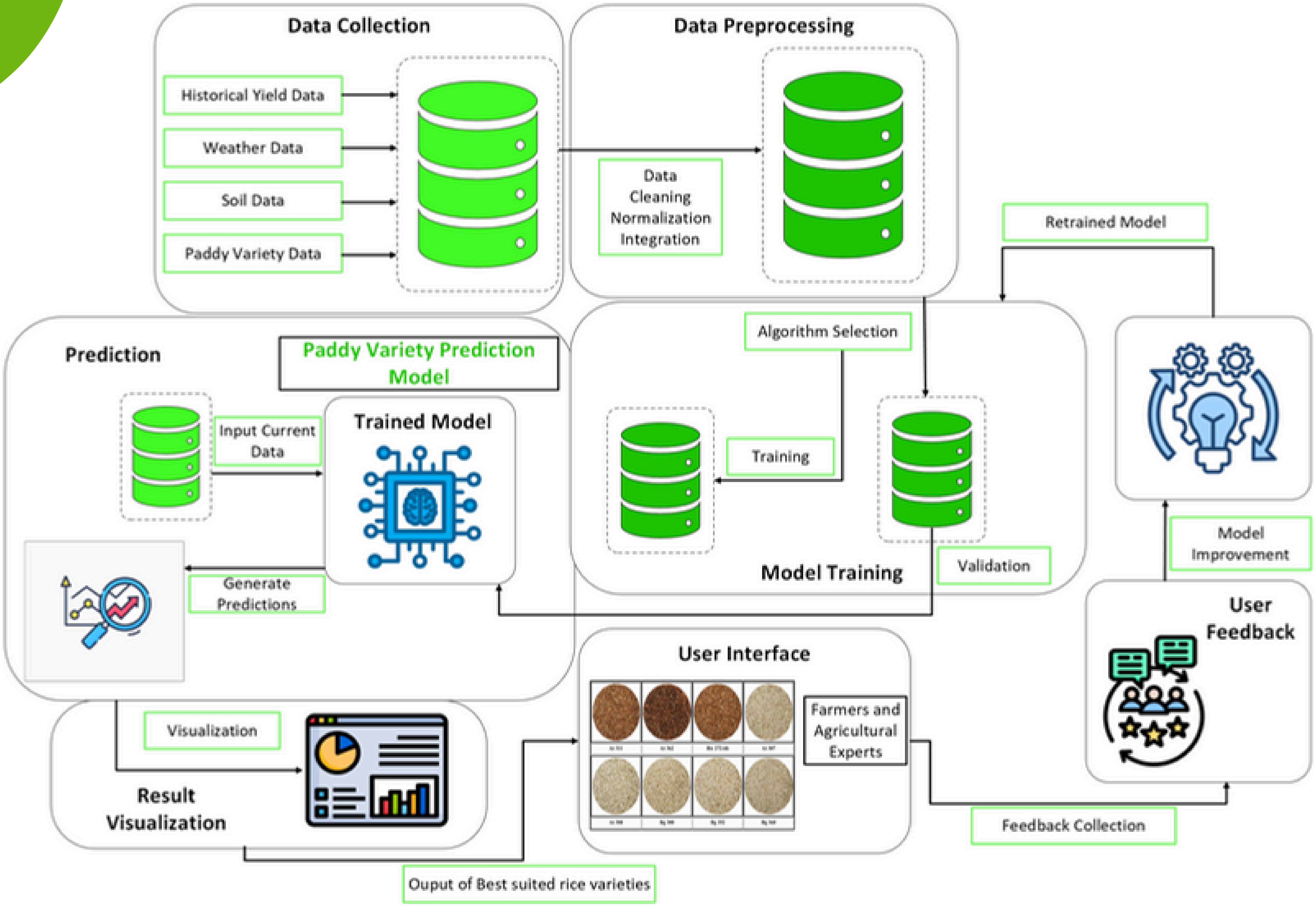
- **Data Analysis:**Analyze the collected data to identify patterns and relationships between soil/climatic factors and paddy variety performance.

- **Model Development:**Use machine learning techniques, such as decision trees, support vector machines, or neural networks, to develop a predictive model.
- Train the model on historical data to learn the relationship between environmental conditions and paddy variety yield.

- **Model Validation:**Validate the model using a separate dataset to assess its accuracy and reliability in predicting suitable paddy varieties.

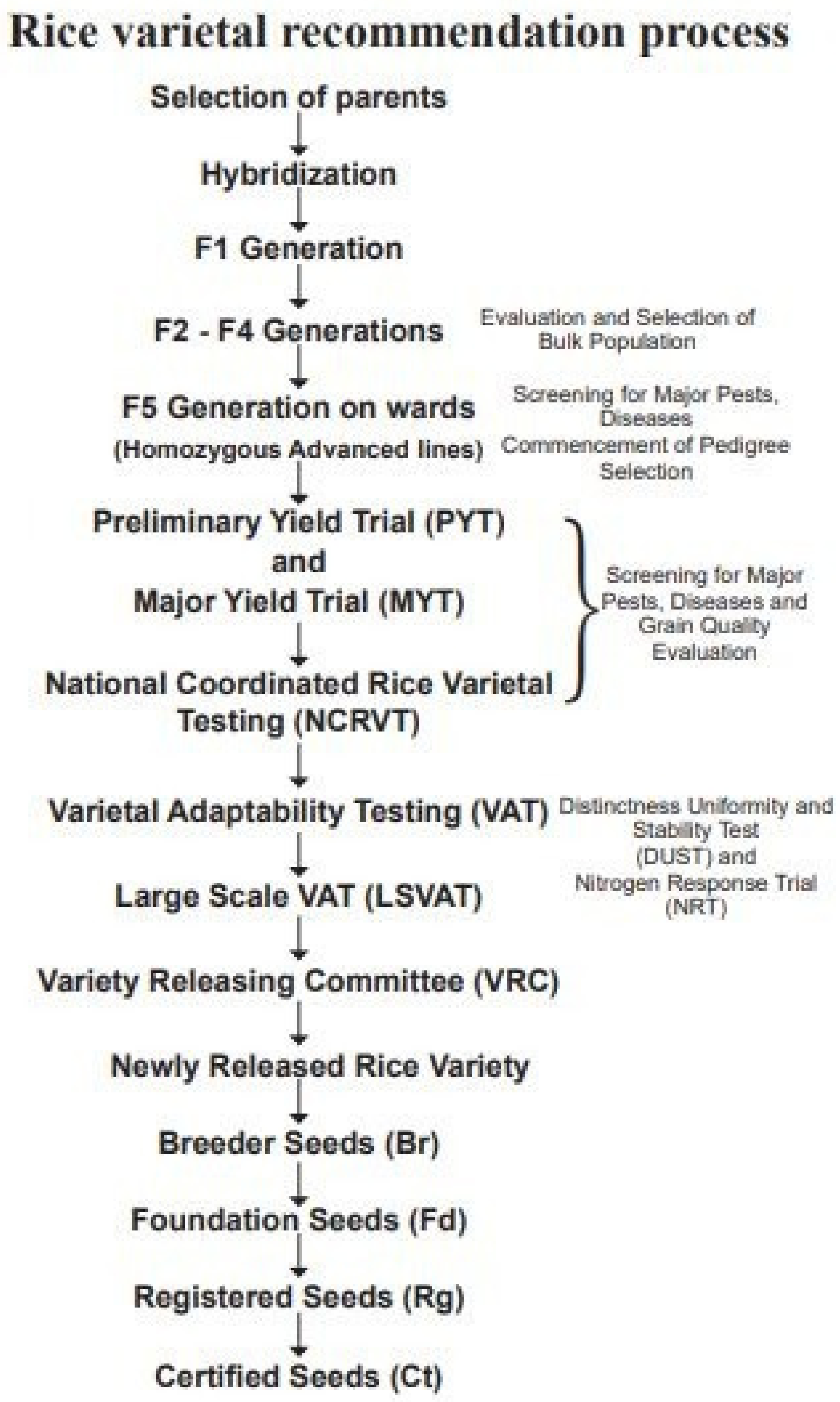
- **Implementation:**Develop a user-friendly interface for farmers to input their local conditions and receive recommendations on the best-suited paddy varieties.

System Diagram

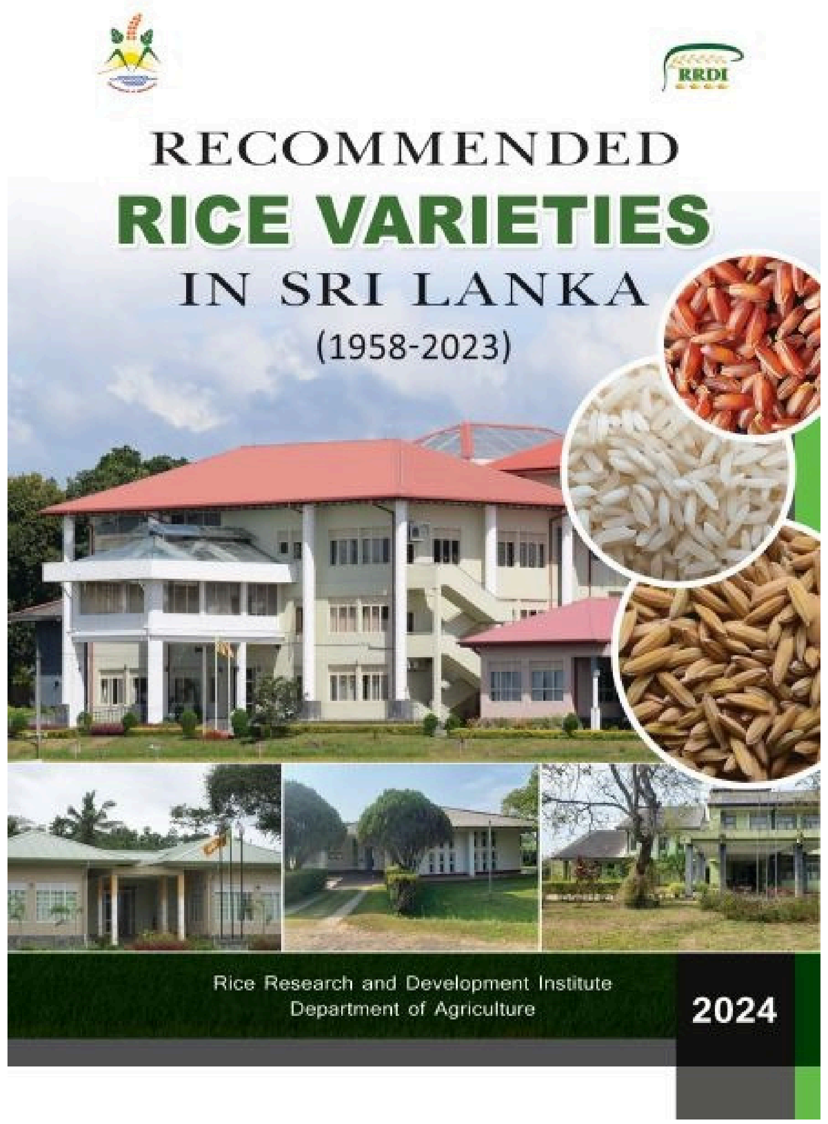


1. Data Collection

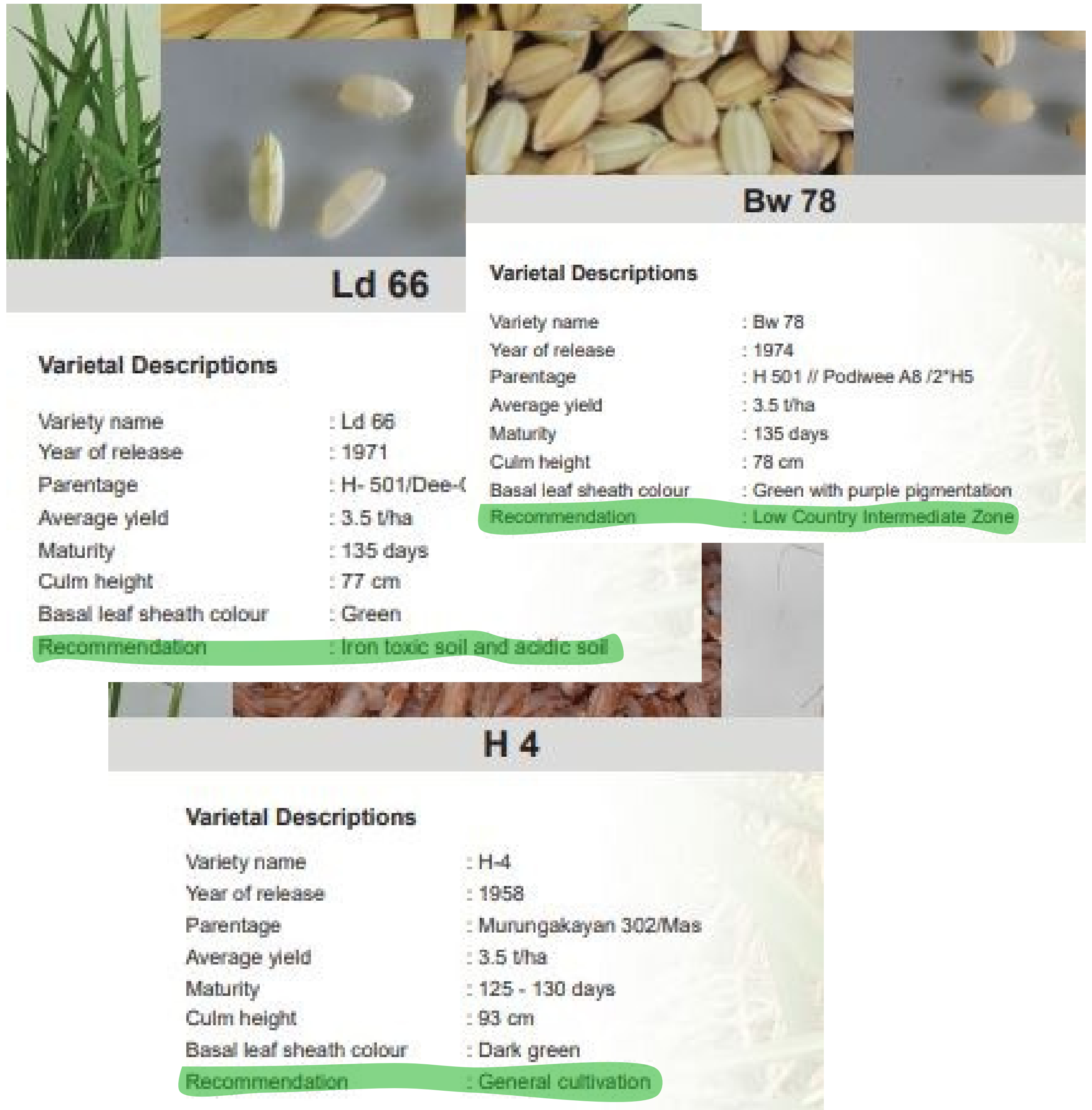
- Sri Lanka's Rice cultivation has a process of recommending the Rice varieties with a scientific aspect.



- After the completion of the process they categorized the rice varieties with the recommendations that are favourable for the growth of a particular rice variety.



Recommended rice varieties book published by Rice Research and Development Institute – Bathlagoda, Sri Lanka



Ld 66

Varietal Descriptions

Variety name	: Ld 66
Year of release	: 1971
Parentage	: H- 501/Dee-(
Average yield	: 3.5 t/ha
Maturity	: 135 days
Culm height	: 77 cm
Basal leaf sheath colour	: Green
Recommendation	: Iron toxic soil and acidic soil

Bw 78

Varietal Descriptions

Variety name	: Bw 78
Year of release	: 1974
Parentage	: H 501 // Podiwee A8 /2*H5
Average yield	: 3.5 t/ha
Maturity	: 135 days
Culm height	: 78 cm
Basal leaf sheath colour	: Green with purple pigmentation
Recommendation	: Low Country Intermediate Zone

H 4

Varietal Descriptions

Variety name	: H-4
Year of release	: 1958
Parentage	: Murungakayan 302/Mas
Average yield	: 3.5 t/ha
Maturity	: 125 - 130 days
Culm height	: 93 cm
Basal leaf sheath colour	: Dark green
Recommendation	: General cultivation

	Variety Name	Year o	Parentage	Average	Maturity	Age Gro	Basal Leaf She	Recommendation	Brown R	Milling Re	Head Ric	Gelatinization	1000 Grain	Grain Shape	Pericar	Bushe	Reaction to Pest and
2	H 4	1958	Murungakayan 302/	3.5	125-130	4-4.5	Dark green	General cultivation	80	72.7	61.4	High	28.3	Long Medium	Red	20.8	Brown Planthopper:
3	H 7	1964	Pachchaperumal/M	3.6	105	3.5	Green	General cultivation	79.4	72.3	60	Intermediate	23.6	Intermediate Me	White	21.2	Blast: R, Bacterial Le
4	H 8	1966	H 4/Podiwee A8	3.7	135	4-4.5	Green	General cultivation	76.61	73.4	52	High	18.2	Short Round	White	22.3	Blast: MR, Bacterial L
5	H 9	1968	C104/Mas/Panduru	3	155	5-6	Green	General cultivation	80.4	74	70.7	High	22.5	Intermediate Me	White	20.4	Blast: Susceptible, B
6	H 10	1968	Pachchaperumal/M	3	90	3	Green	General cultivation	76.61	73.4	52	High	26	Intermediate Me	Red	19.5	Blast: Susceptible, B
7	62-355	1968	Pachchaperumal/H	3.9	90-95	3	Green	Rainfed areas	75.6	72	57.5	Intermediate	29	Intermediate Bo	Red	17.5	Brown Planthopper:
8	Bg 11-11	1970	Engkatek/2*H 8	4.5	125-130	4-4.5	Purple	General cultivation	79	72.2	62.3	Intermediate	13.8	Short Round	White	21.7	Brown Planthopper:
9	Bg 34-6	1971	IR 8-246///Pachchaı	5.5	105	3	Green	General cultivation	79.2	72.2	67.1	Intermediate	25.5	Intermediate Bo	Red	21.3	Blast: Susceptible, B
10	Bg 34-8	1971	IR-246///Pachchape	6.1	96	3	Green	General cultivation	80.4	74	70.7	Intermediate	26	Intermediate Bo	White	21.7	Brown Planthopper:
11	Ld 66	1971	H-501/Dee-Geo-Wc	3.5	135	4-4.5	Green	Iron toxic soil and acidic	79.3	72.9	63.8	High	21.6	Intermediate Me	White	22.1	Blast: Susceptible, B
12	MI 273	1971	Gamma Irradiated H	4.2	135	4-4.5	Green	General cultivation	80.4	74	70.7	Intermediate	28.4	Long Medium	Red	22.5	Brown Planthopper:
13	Bg 3-5	1973	BG 94-1/BG 350	3.8	100	3	Green	General cultivation	78.2	70.5	60.8	Intermediate	24.5	Medium Slender	White	22.5	Brown Planthopper:
14	Bg 94-1	1975	IR 262/Ld 66	4.1	105	3	Green	General cultivation	79.3	72.9	63.8	High-Intermed	28.3	Long Medium	White	20.8	Brown Planthopper:
15	At 16	1977	IR 8/H4	3.8	105	4-4.5	Green	Southern province	79	72.2	62.3	High	28.4	Intermediate Me	Red	19.1	Blast: Moderately Re
16	Bg 90-2	1975	IR 262/Remadja	6.5	120	4-4.5	Green	General cultivation	78.6	72.9	63.7	Intermediate	29.3	Long Medium	White	22.1	Brown Planthopper:
17	Bw 78	1974	H 501 // Podiwee A	3.5	135	4-4.5	Green with pu	Low Country Intermedia	79.3	72.9	63.8	High	20.2	Short Round	White	22.2	Brown Planthopper:
18	Bg 94-2	1978	IR 262/Ld 66	5.9	105	3	Green	General cultivation	81.4	76.7	71.1	High	25.6	Long Medium	Red	22.3	Brown Planthopper:
19	Bw 361	2002	IR 36 / Bw 267-3-11	4.5	105	3.5	Green	General cultivation	81.3	74.4	64.1	Low	21.4	Intermediate Me	Red	21	Brown Planthopper:
20	Bw 361	2002	IR 36 / Bw 267-3-11	4.5	105	3.5	Green	Iron toxic soil and acidic	81.3	74.4	64.1	Low	21.4	Intermediate Me	Red	21	Brown Planthopper:
21	At 362	2002	At 85-2/Bg 380	6	110	3.5	Green	General cultivation	78.3	68.6	54.2	Low	25.7	Long Medium	Red	20.6	Brown Planthopper:
22	Bg 310	2014	Bg 300/Pokkali	5.6	95-98	3	Green	Saline prone areas	81.4	76.7	71.1	Intermediate	27.5	Intermediate Bo	White	21.3	Brown Planthopper:
23	At 373	2014	IR 70422-66-5-2/Bg	4.9	103	3.5	Green	General cultivation	80.1	73.3	67.6	High-Intermed	10.5	Short Oblong	White	19.8	Brown Planthopper:

Sheet1

- So by extracting the data reguarding the rice varietis it has created a comprehensive data set of currently recommended rice varieties to grow in Sri Lanka.

- And with using the data on different climate zones and environmental conditions in Sri Lanka inco-operate with the data of Department of Census and Statistics - Sri Lanka, a comprehensive and robust data set has created reguarding 25 districs of Sri Lanka.

	Province	District	Annual Temperature	Annual Humidity	Annual Rainfall	Recommendation
2	Western Province	Colombo	High	Normal	High	General cultivation
3	Western Province	Gampaha	High	Normal	High	General cultivation
4	Western Province	Gampaha	High	Normal	High	Low Country Wet Zone
5	Western Province	Kalutara	Normal	Normal	High	General cultivation
6	Western Province	Kalutara	Normal	Normal	High	Low Country Wet Zone
7	Western Province	Kalutara	Normal	Normal	High	Coastal saline areas
8	Western Province	Kalutara	Normal	Normal	High	Kalutara and Galle Districts
9	Central Province	Kandy	Normal	Normal	Normal	General cultivation
10	Central Province	Kandy	Normal	Normal	Normal	High potential area
11	Central Province	Matale	Low	High	Normal	General cultivation
12	Central Province	Matale	Low	High	Normal	Rainfed areas
13	Central Province	Nuwara Eliya	Low	High	Normal	General cultivation
14	Central Province	Nuwara Eliya	Low	High	Normal	Rainfed areas
15	Southern Province	Galle	High	High	Normal	General cultivation
16	Southern Province	Galle	High	High	Normal	Wet Zone
17	Southern Province	Galle	High	High	Normal	Kalutara and Galle Districts
18	Southern Province	Matara	Normal	High	Normal	General cultivation
19	Southern Province	Matara	Normal	High	Normal	Wet Zone
20	Southern Province	Hambantota	High	Normal	Low	General cultivation
21	Southern Province	Hambantota	High	Normal	Low	Saline prone areas
22	Southern Province	Galle	High	High	Normal	Southern province
23	Southern Province	Matara	Normal	High	Normal	Southern province
24	Southern Province	Hambantota	High	Normal	Low	Southern province

SriLankaDistricts

2. Data Analysis

- Load the both data sets into dataframes and combine both into single dataframe using inner join under referrence of "Recommendation" column and create a unified dataset.

```python
# Load the datasets
varieties_file_path = '/content/drive/MyDrive/Rice Genie/RiceVarietiesData.xlsx'
district_file_path = '/content/drive/MyDrive/Rice Genie/SriLankaDistricts.csv'

varieties_data = pd.read_excel(varieties_file_path, sheet_name='Sheet1')
district_data = pd.read_csv(district_file_path)

#combined_data = pd.merge(varieties_data, district_data, how='cross')
combined_data = pd.merge(varieties_data, district_data, how='inner', on='Recommendation')
```

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U
1	Variety Na	Year of Re	Parentage	Average Yi	Maturity (d	Age Group	Basal Leaf	Recomme	Brown Ric	Milling Re	Head Rice	Gelatiniza	1000 Grain	Grain Sha	Pericarp C	Bushel We	Reaction t	Province	District	Annual Te	Annua
2	H 4	1958	Murungak	3.5	125-130	4-4.5	Dark greei	General ci	80	72.7	61.4	High	28.3	Long Medi	Red	20.8	Brown Pla	Western P	Colombo	High	Norm
3	H 4	1958	Murungak	3.5	125-130	4-4.5	Dark greei	General ci	80	72.7	61.4	High	28.3	Long Medi	Red	20.8	Brown Pla	Western P	Gampaha	High	Norm
4	H 4	1958	Murungak	3.5	125-130	4-4.5	Dark greei	General ci	80	72.7	61.4	High	28.3	Long Medi	Red	20.8	Brown Pla	Western P	Kalutara	Normal	Norm
5	H 4	1958	Murungak	3.5	125-130	4-4.5	Dark greei	General ci	80	72.7	61.4	High	28.3	Long Medi	Red	20.8	Brown Pla	Central Pr	Kandy	Normal	Norm
6	H 4	1958	Murungak	3.5	125-130	4-4.5	Dark greei	General ci	80	72.7	61.4	High	28.3	Long Medi	Red	20.8	Brown Pla	Central Pr	Matale	Low	High
7	H 4	1958	Murungak	3.5	125-130	4-4.5	Dark greei	General ci	80	72.7	61.4	High	28.3	Long Medi	Red	20.8	Brown Pla	Central Pr	Nuwara El	Low	High
8	H 4	1958	Murungak	3.5	125-130	4-4.5	Dark greei	General ci	80	72.7	61.4	High	28.3	Long Medi	Red	20.8	Brown Pla	Southern I	Galle	High	High
9	H 4	1958	Murungak	3.5	125-130	4-4.5	Dark greei	General ci	80	72.7	61.4	High	28.3	Long Medi	Red	20.8	Brown Pla	Southern I	Matara	Normal	High
10	H 4	1958	Murungak	3.5	125-130	4-4.5	Dark greei	General ci	80	72.7	61.4	High	28.3	Long Medi	Red	20.8	Brown Pla	Southern I	Hambantc	High	Norm
11	H 4	1958	Murungak	3.5	125-130	4-4.5	Dark greei	General ci	80	72.7	61.4	High	28.3	Long Medi	Red	20.8	Brown Pla	Northern I	Jaffna	High	Norm
12	H 4	1958	Murungak	3.5	125-130	4-4.5	Dark greei	General ci	80	72.7	61.4	High	28.3	Long Medi	Red	20.8	Brown Pla	Northern I	Kilinochcl	Normal	Norm
13	H 4	1958	Murungak	3.5	125-130	4-4.5	Dark greei	General ci	80	72.7	61.4	High	28.3	Long Medi	Red	20.8	Brown Pla	Northern I	Mannar	High	Norm
14	H 4	1958	Murungak	3.5	125-130	4-4.5	Dark greei	General ci	80	72.7	61.4	High	28.3	Long Medi	Red	20.8	Brown Pla	Northern I	Vavuniya	High	Norm
15	H 4	1958	Murungak	3.5	125-130	4-4.5	Dark greei	General ci	80	72.7	61.4	High	28.3	Long Medi	Red	20.8	Brown Pla	Northern I	Mullaitivu	Normal	Norm
16	H 4	1958	Murungak	3.5	125-130	4-4.5	Dark greei	General ci	80	72.7	61.4	High	28.3	Long Medi	Red	20.8	Brown Pla	Eastern Pr	Trincomal	High	Norm
17	H 4	1958	Murungak	3.5	125-130	4-4.5	Dark greei	General ci	80	72.7	61.4	High	28.3	Long Medi	Red	20.8	Brown Pla	Eastern Pr	Batticaloa	High	Norm
18	H 4	1958	Murungak	3.5	125-130	4-4.5	Dark greei	General ci	80	72.7	61.4	High	28.3	Long Medi	Red	20.8	Brown Pla	Eastern Pr	Ampara	High	High
19	H 4	1958	Murungak	3.5	125-130	4-4.5	Dark greei	General ci	80	72.7	61.4	High	28.3	Long Medi	Red	20.8	Brown Pla	North Wes	Kurunegal	High	Low

Data Pre-Processing

- Convert "Matuarity" column values into numeric averages which we will use as a feature and also uses to categorize the life span of paddy varieties into age groups.

```python
def convert_maturity_to_numeric(value):
    if isinstance(value, str) and '-' in value:
        parts = value.split('-')
        return (int(parts[0]) + int(parts[1])) / 2
    try:
        return float(value)
    except ValueError:
        return np.nan

# Convert 'Maturity (days)' to numeric averages
combined_data['Maturity (days)'] = combined_data['Maturity (days)'].apply(convert_maturity_to_numeric)
combined_data.dropna(subset=['Maturity (days)'], inplace=True)
```

```python
# Create a list of recommendation keywords/phrases that indicate suitability
recommendation_keywords = [
    "Low Country Wet Zone",
    "High potential area",
    "Rainfed areas",
    "Wet Zone",
    "Saline prone areas",
    "Northern region",
    "Saline areas",
    "Iron toxic soil and acidic soil",
    "Major irrigation in Dry Zone and Intermediate Zone",
    "Southern province",
    "High potential areas in Low Country Wet Zone",
    "Dry Zone",
    "Rainfed areas of Dry and Intermediate Zone",
    "General cultivation"
]

# Creating a new column 'Suitability' based on multiple recommendation criteria
combined_data['Suitability'] = combined_data.apply(
    lambda row: 1 if (any(keyword.lower() in str(row['Recommendation']).lower() for keyword in recommendation_keywords)
                 and row['Average Yield (t/ha)'] >= 5.0) else 0,
    axis=1
)
```

- Using the Recommendation keywords a new column named "Suitability" has created base on multiple recommendation criteiria.

3. Model Development

Algorithm Selection

1. Random Forest Classifier

	precision	recall	f1-score	support
0	1.00	1.00	1.00	141
1	1.00	1.00	1.00	147
accuracy			1.00	288
macro avg	1.00	1.00	1.00	288
weighted avg	1.00	1.00	1.00	288

Accuracy: 100.00%

Accuracy : 100%

2. Gradient Boosting Classifier

Accuracy (Gradient Boosting): 0.9965277777777778

	precision	recall	f1-score	support
0	1.00	1.00	1.00	284
1	0.80	1.00	0.89	4
accuracy			1.00	288
macro avg	0.90	1.00	0.94	288
weighted avg	1.00	1.00	1.00	288

Mean Cross-Validation Score (Gradient Boosting): 0.9128992450638792

Accuracy : 99.65%

3. Logistic Regression

Accuracy (Logistic Regression): 0.9895833333333334

	precision	recall	f1-score	support
0	1.00	0.98	0.99	141
1	0.98	1.00	0.99	147
accuracy			0.99	288
macro avg	0.99	0.99	0.99	288
weighted avg	0.99	0.99	0.99	288

Accuracy : 98.95%

4. Support Vector Classifier

Accuracy (Support Vector Classifier): 0.6111111111111112

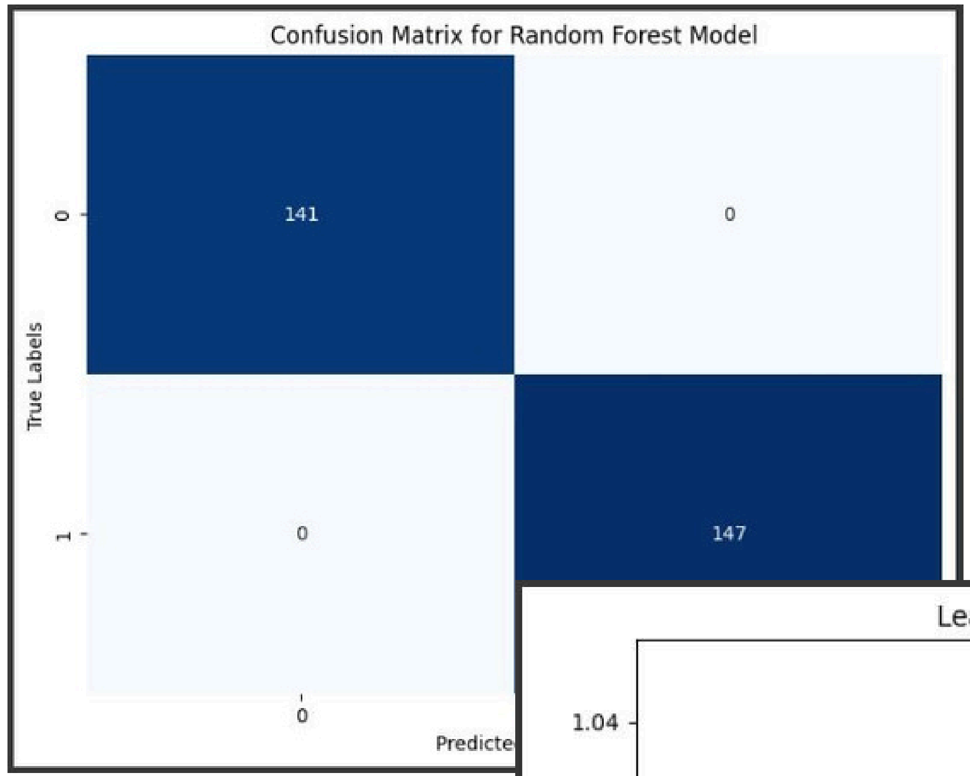
	precision	recall	f1-score	support
0	0.89	0.23	0.37	141
1	0.57	0.97	0.72	147
accuracy			0.61	288
macro avg	0.73	0.60	0.54	288
weighted avg	0.73	0.61	0.55	288

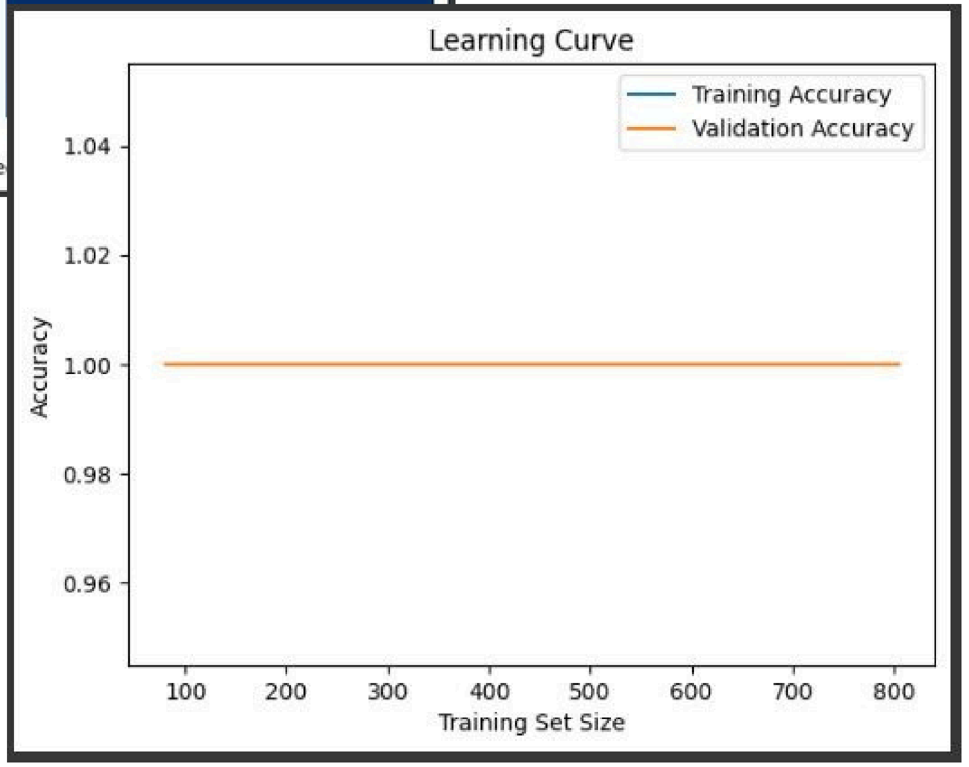
Accuracy : 61.11%

- When comparing the accuracy of 4 Machine Learning Algorithms, with a Accuracy of 100% Random Forest Classifier hold the lead. BUT,

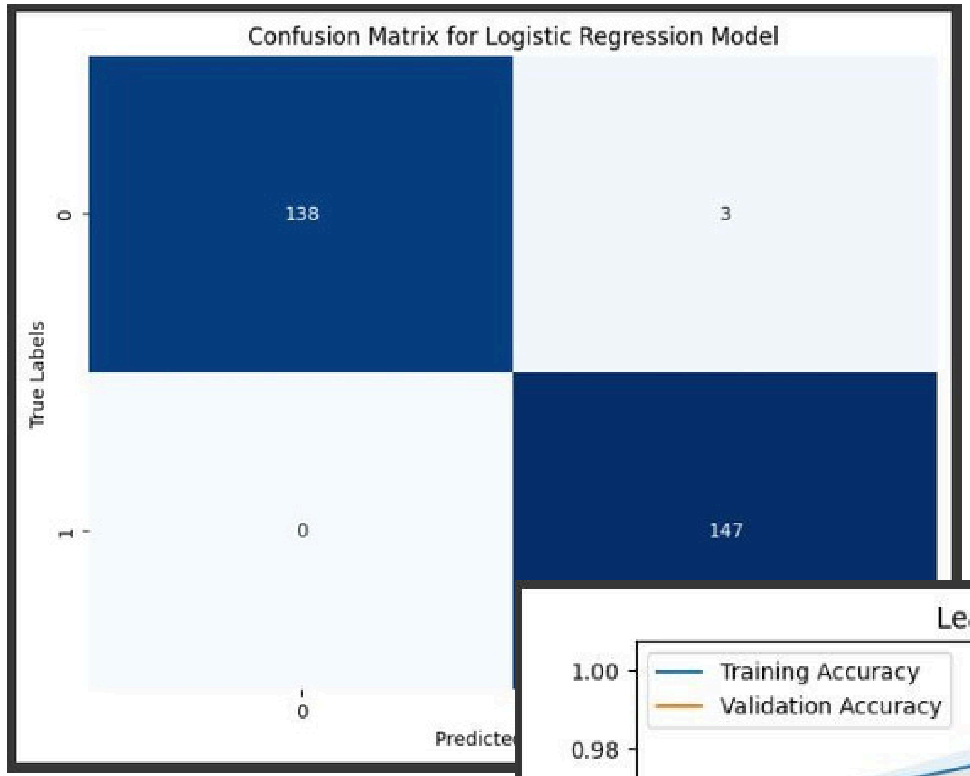
3. Model Development

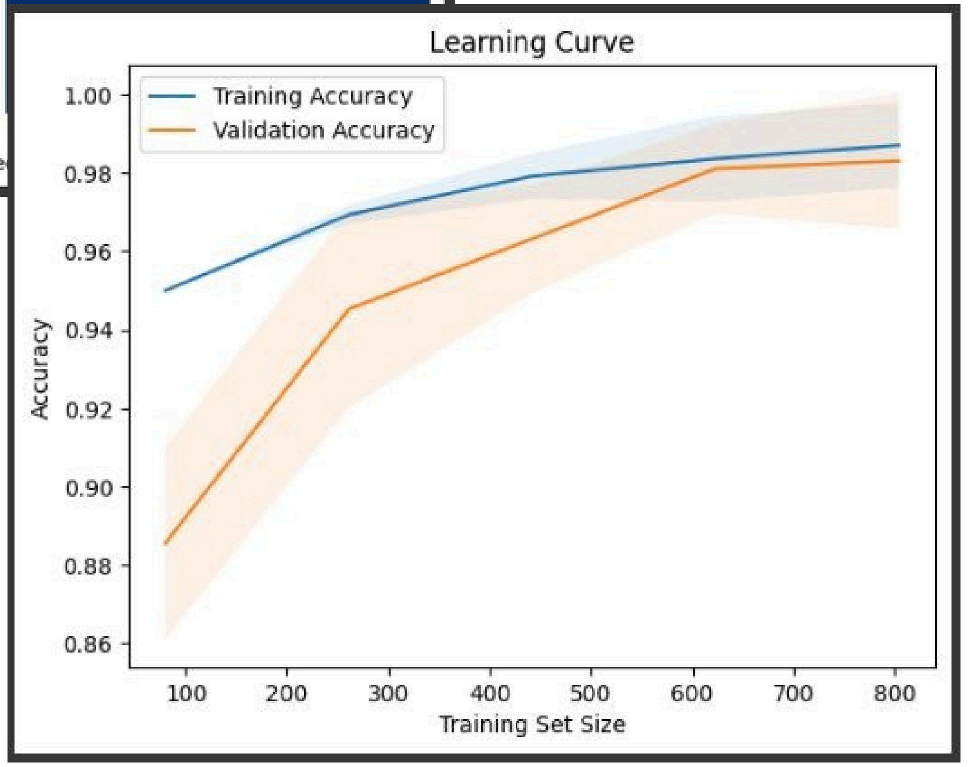
Algorithm Selection





- Confusion Matrix & Learning Curve for Random Forest Model





- Confusion Matrix & Learning Curve for Logistic Regression Model

- Eventhough Random Forest Model has the highest accuracy, Logistic Regression is less prone to overfitting compared to complex models like Random Forest or Gradient Boosting and also It is computationally efficient, a simple and interpretable model, Logistic regression has choosen to develop the Rice Variety Prediction Model.

3. Model Development

- Logistic Regression Model is trained using defined features and classify the Suitability of rice varieties.

```python
from sklearn.preprocessing import LabelEncoder

le_temperature = LabelEncoder()
le_rainfall = LabelEncoder()

# Encoding 'AnnualTemperature' and 'Annual Rainfall' into numerical values
combined_data['Annual Temperature'] = le_temperature.fit_transform(combined_data['Annual Temperature'])
combined_data['Annual Rainfall'] = le_rainfall.fit_transform(combined_data['Annual Rainfall'])

# Define features (X) and target (y)
features = [
    'Average Yield (t/ha)', 'Maturity (days)', 'Annual Temperature', 'Annual Rainfall'
]
X = combined_data[features]
y = combined_data['Suitability']
```

```python
from sklearn.model_selection import train_test_split

# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

from sklearn.linear_model import LogisticRegression

# Train the Logistic Regression model
logreg_model = LogisticRegression(max_iter=1000, random_state=42)
logreg_model.fit(X_train, y_train)

from sklearn.metrics import classification_report, accuracy_score

# Predict and evaluate the model
y_pred = logreg_model.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
report = classification_report(y_test, y_pred)

print("Accuracy (Logistic Regression):", accuracy)
print(report)
```

Logistic Regression model Accuracy:

```
Accuracy (Logistic Regression): 0.9895833333333334
              precision    recall  f1-score   support

           0       1.00      0.98      0.99       141
           1       0.98      1.00      0.99       147

    accuracy                           0.99       288
   macro avg       0.99      0.99      0.99       288
weighted avg       0.99      0.99      0.99       288
```

4. Model Validation

Mean Cross vaidation score for Logistic Regression model :

```
from sklearn.model_selection import cross_val_score
import numpy as np

# Perform 5-fold cross-validation
cv_scores = cross_val_score(logreg_model, X, y, cv=10, scorir
mean_cv_score = np.mean(cv_scores)
print("Mean Cross-Validation Score (Logistic Regression):", m
```

```
Mean Cross-Validation Score (Logistic Regression): 0.98125
```

Training accuracy & Validation accuracy
for Logistic Regression model :

```
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score

X_train, X_temp, y_train, y_temp = train_test_split(X, y, test_size=0.3, random_state=42)
X_val, X_test, y_val, y_test = train_test_split(X_temp, y_temp, test_size=0.5, random_state=42)


# Training accuracy
y_train_pred = logreg_model.predict(X_train)
train_accuracy = accuracy_score(y_train, y_train_pred)

# Validation accuracy
y_val_pred = logreg_model.predict(X_val)
val_accuracy = accuracy_score(y_val, y_val_pred)

print(f"Training Accuracy: {train_accuracy * 100}")
print(f"Validation Accuracy: {val_accuracy * 100}")
```

```
Training Accuracy: 98.30845771144278
Validation Accuracy: 98.6046511627907
```

5. Model Implementation

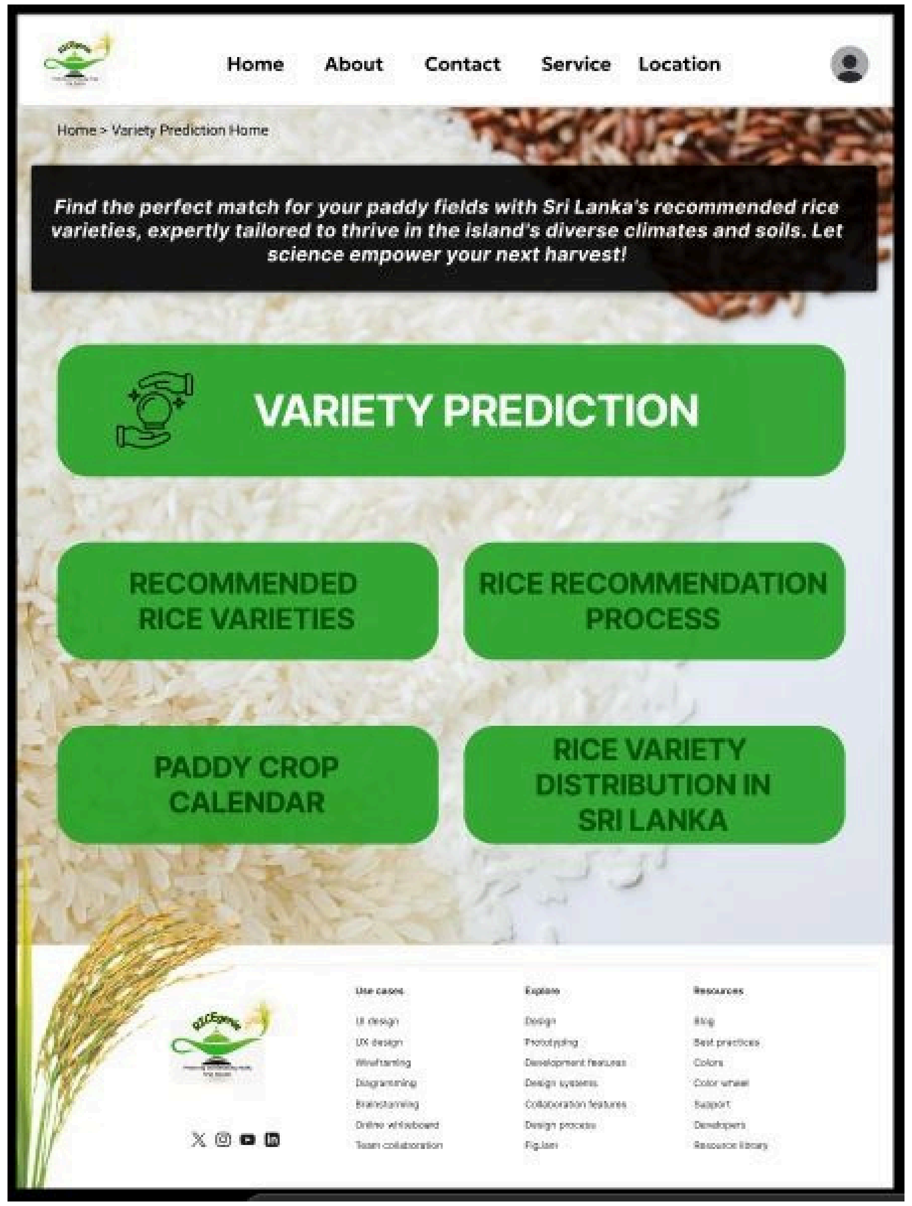
- Logistic Regression model implementation:

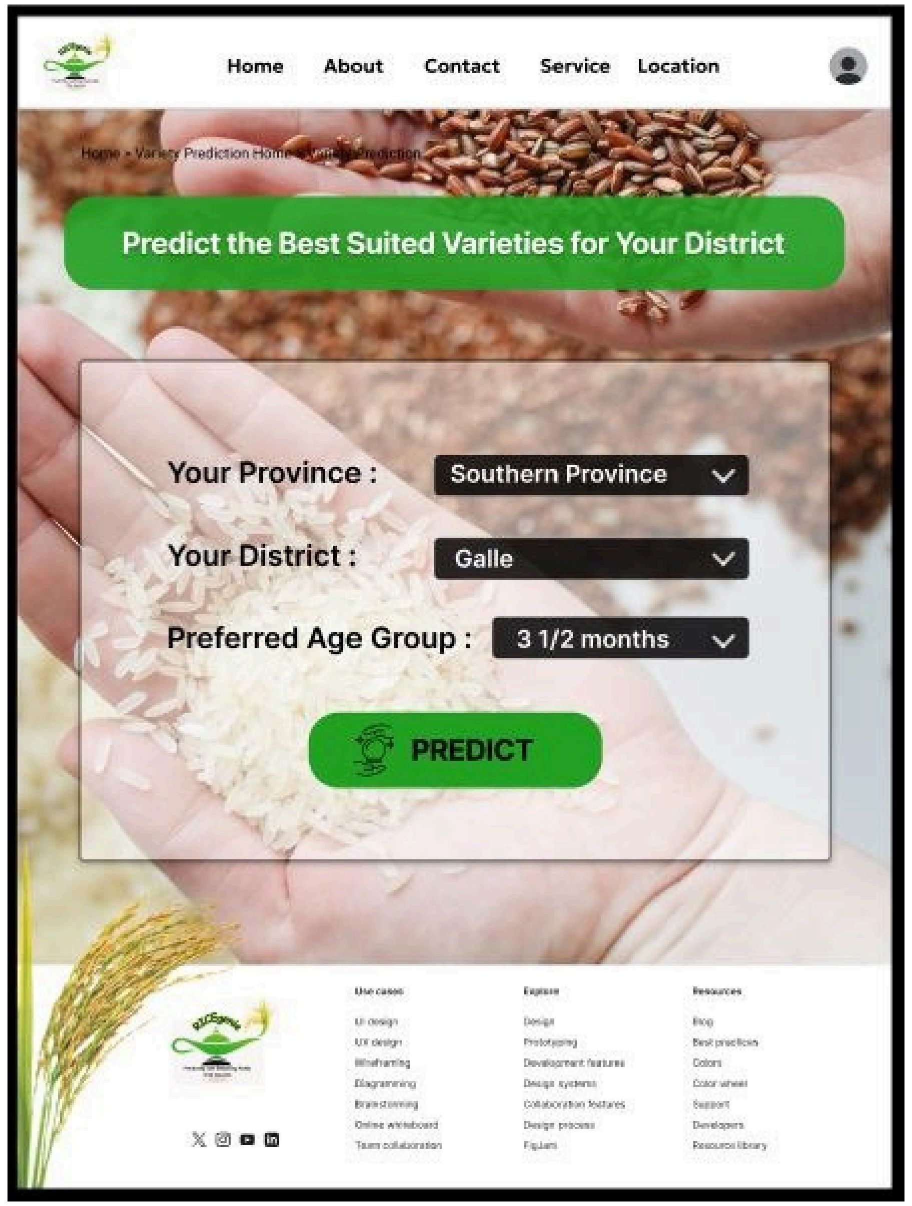
```python
def predict_suitable_varieties_for_district(province_name, district_name, district_data, varieties_data, model):
    # Filter the district data by the specified province and district
    district_conditions = district_data[
        (district_data['Province'] == province_name) &
        (district_data['District'] == district_name)
    ]

    if district_conditions.empty:
        raise ValueError(f"No data found for district '{district_name}' in province '{province_name}'.")

    # Extract the environmental conditions for prediction
    district_conditions = district_conditions.iloc[0]
    annual_temperature = le_temperature.transform([district_conditions['Annual Temperature']])[0]
    annual_rainfall = le_rainfall.transform([district_conditions['Annual Rainfall']])[0]

    # Prepare the prediction data
    prediction_data = varieties_data.copy()
    prediction_data['Annual Temperature'] = annual_temperature
    prediction_data['Annual Rainfall'] = annual_rainfall

    # Ensure 'Maturity (days)' is numeric
    prediction_data['Maturity (days)'] = prediction_data['Maturity (days)'].apply(convert_maturity_to_numeric)
    prediction_data.dropna(subset=['Maturity (days)'], inplace=True)

    # Add 'Age Group' if not already present
    if 'Age Group' not in prediction_data.columns:
        prediction_data['Age Group'] = prediction_data['Maturity (days)'].apply(map_to_age_group)

    # Prepare features for prediction
    X_pred = prediction_data[['Average Yield (t/ha)', 'Maturity (days)', 'Annual Temperature', 'Annual Rainfall']]

    # Predict suitability for each variety
    prediction_data['Suitability'] = model.predict(X_pred)
```

✓ 35s completed at 11:14 PM

5. Web app Implementation

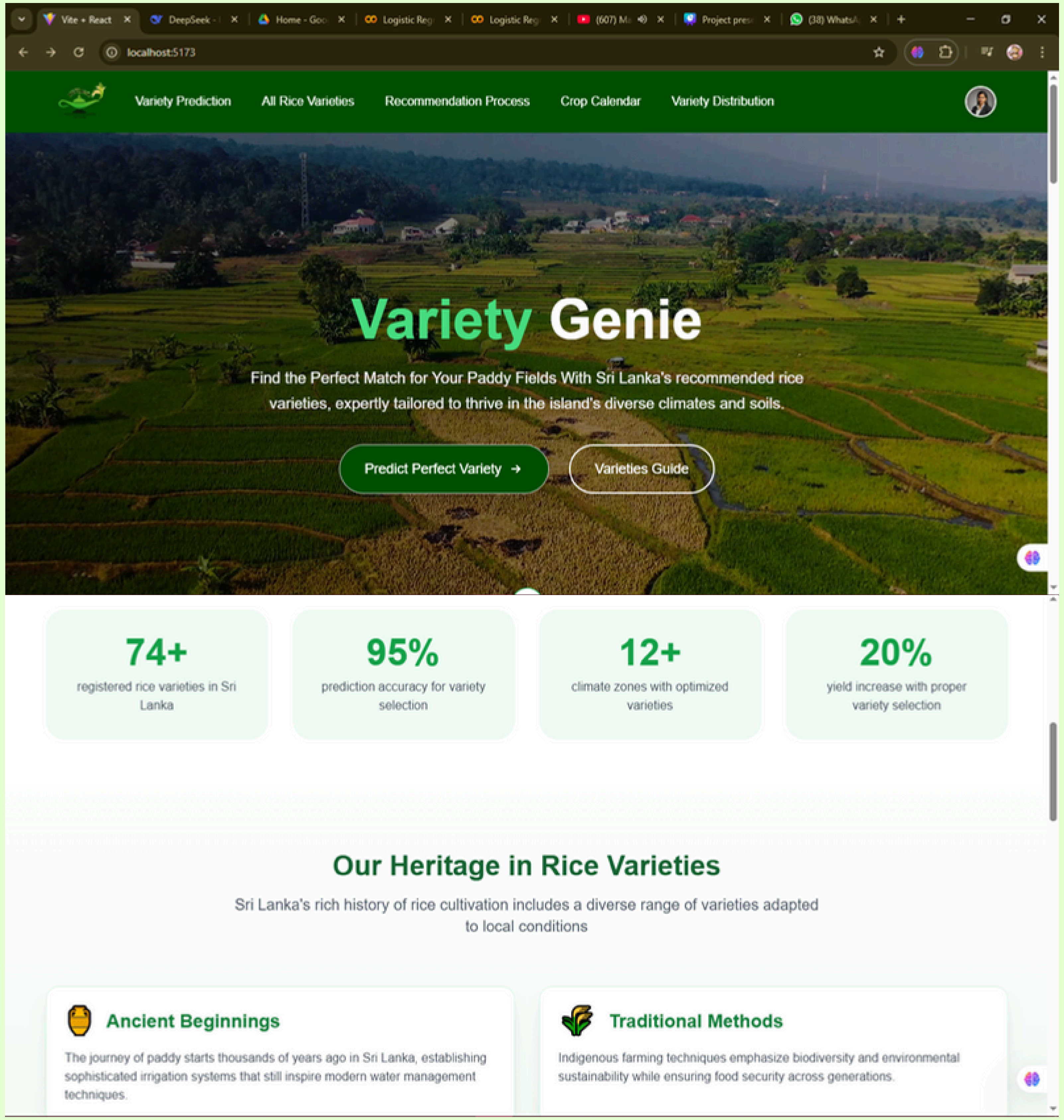
- UI Designed for the Paddy Variety Prediction interface of the RICEgenie web app.

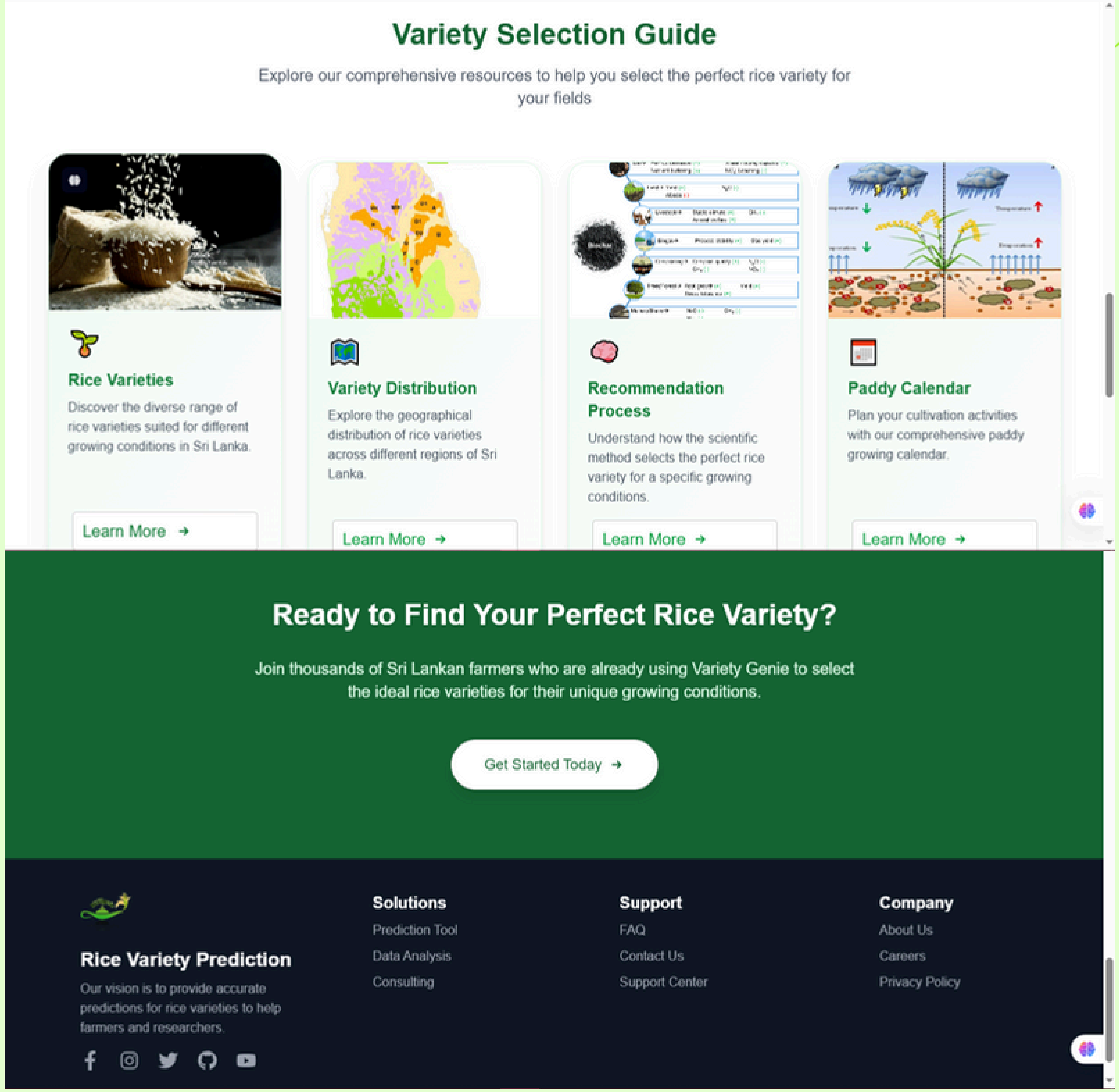




5. Web app Implementation

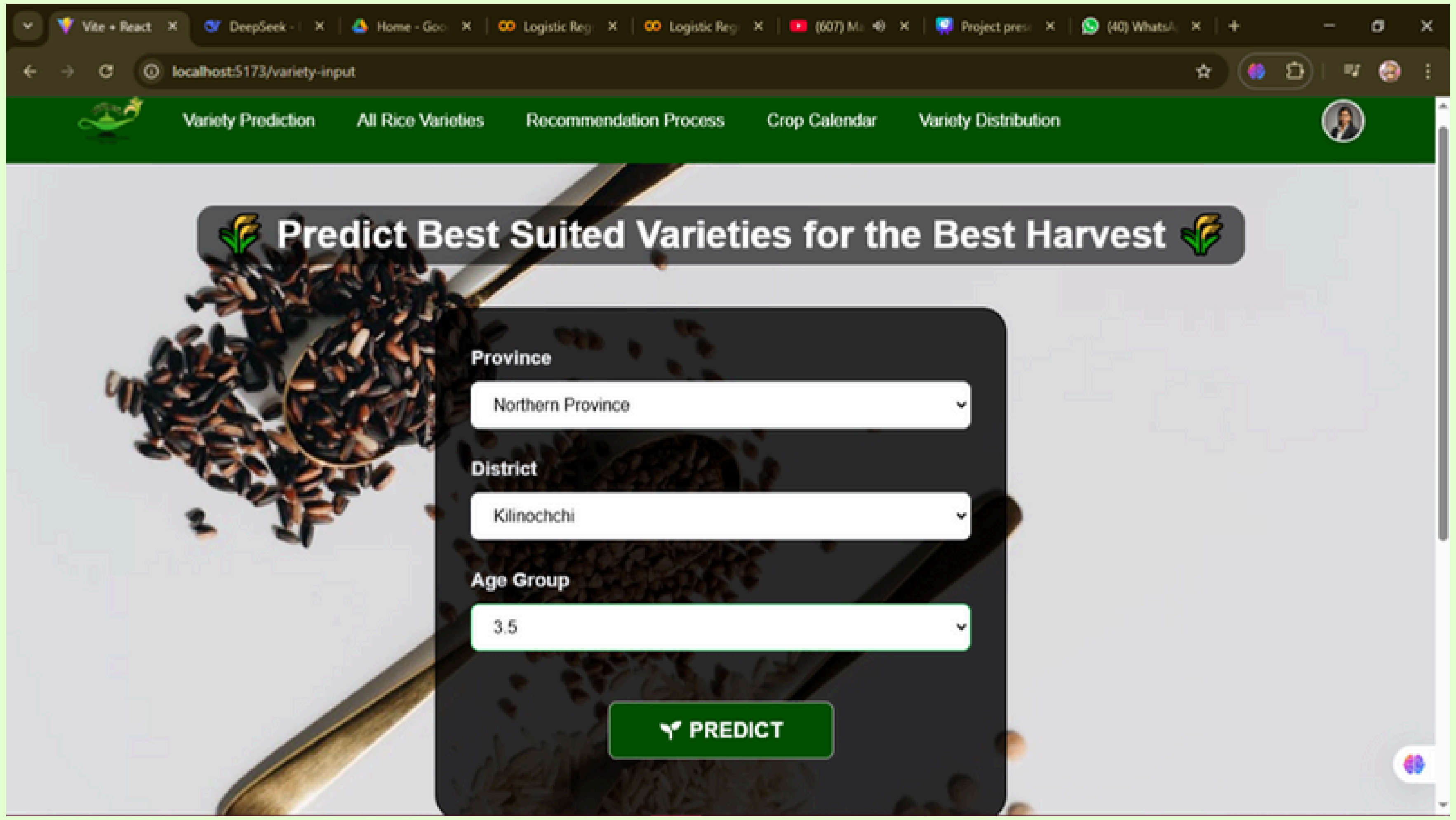
Home Page



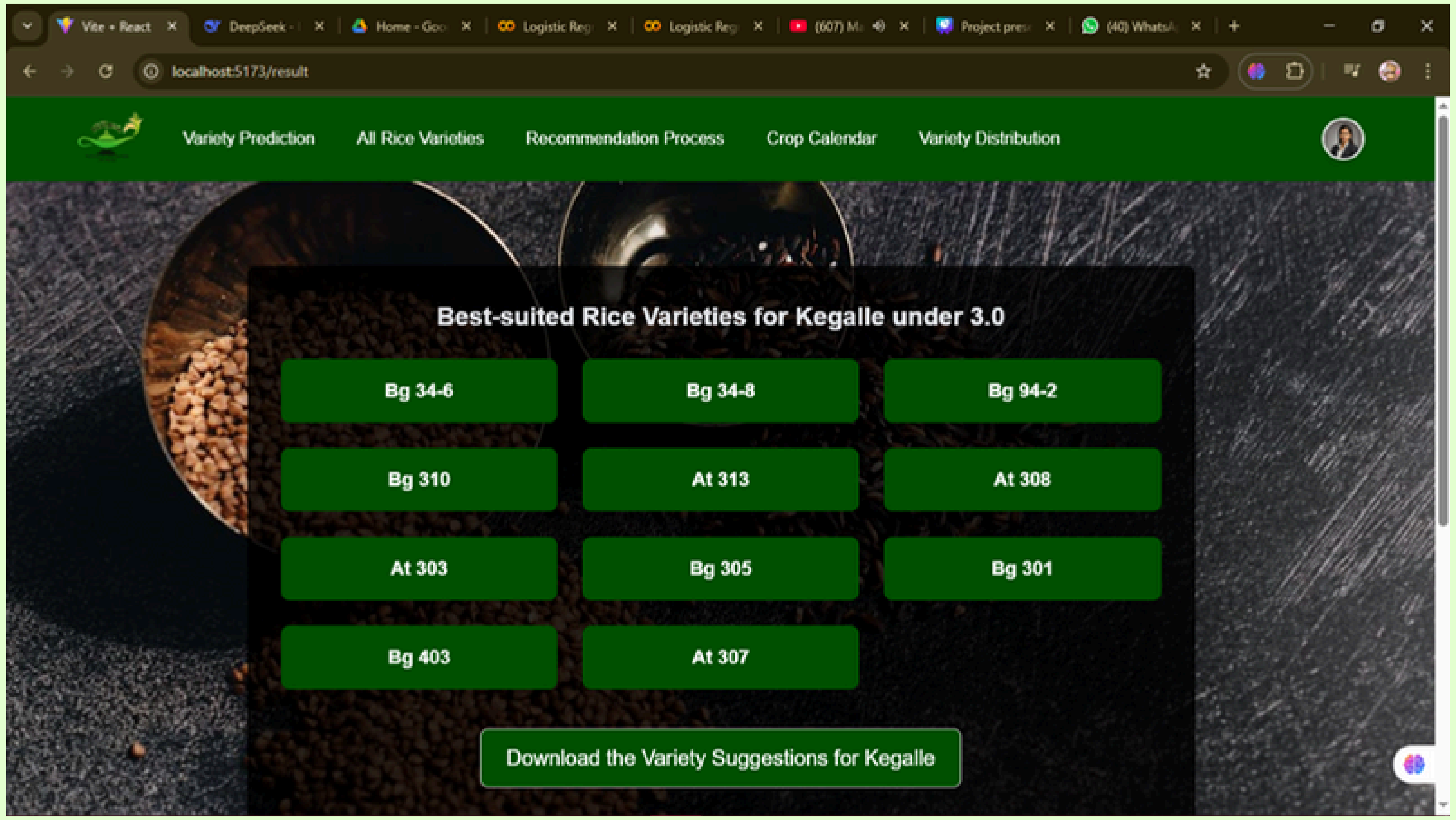


5. Web app Implementation

Data Input Page for Prediction

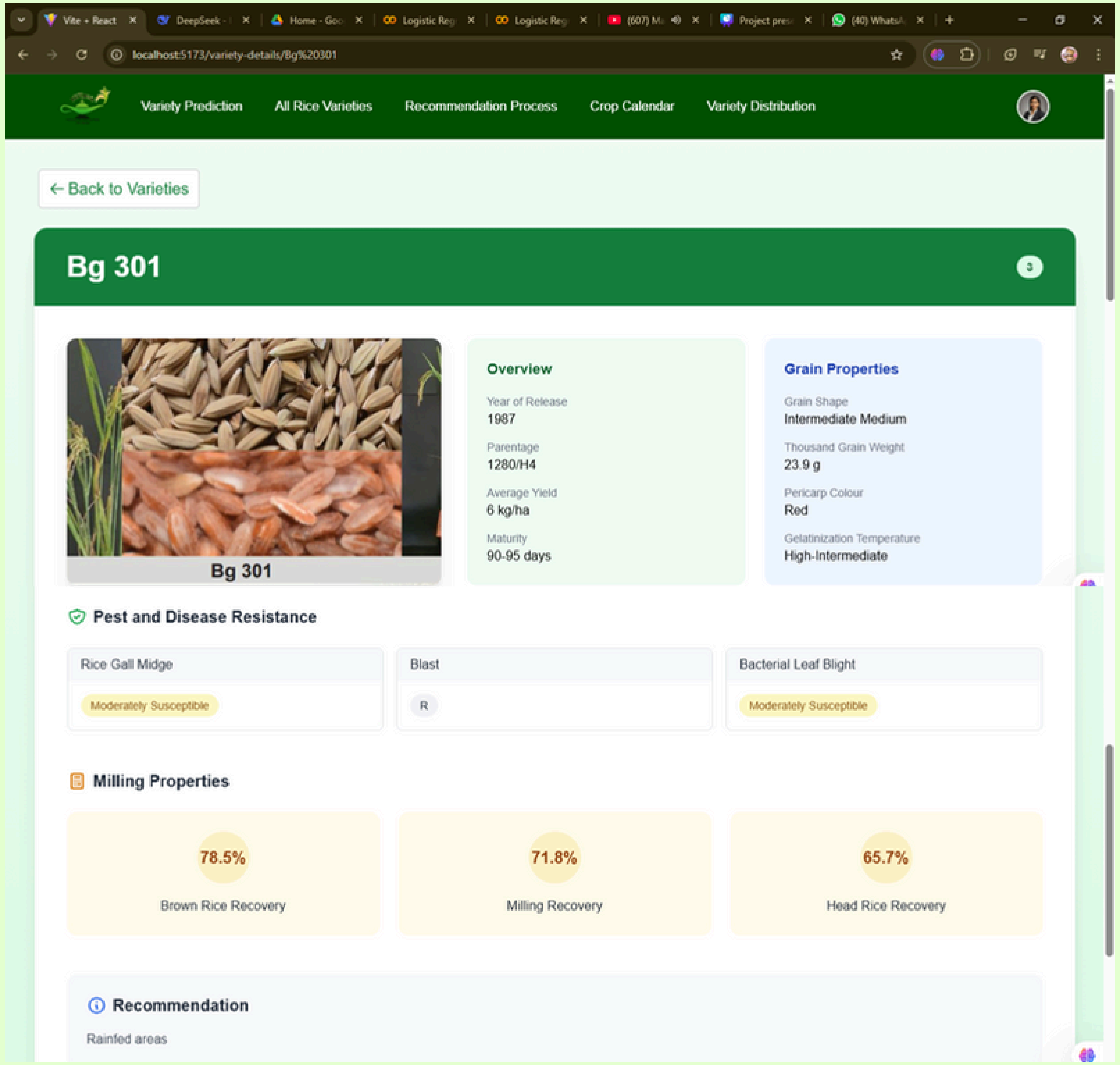


Predicted Results of Varieties

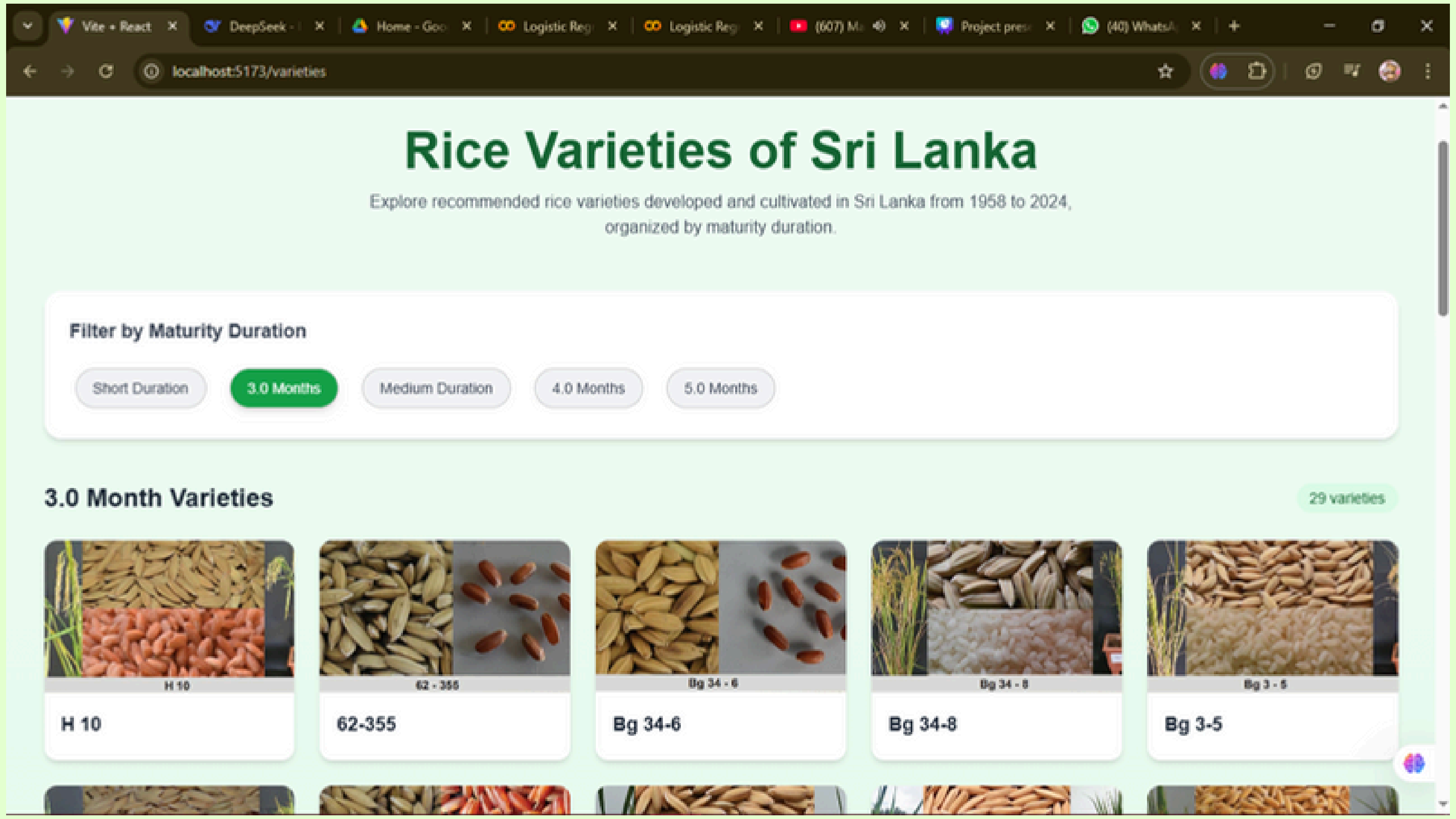


5. Web app Implementation

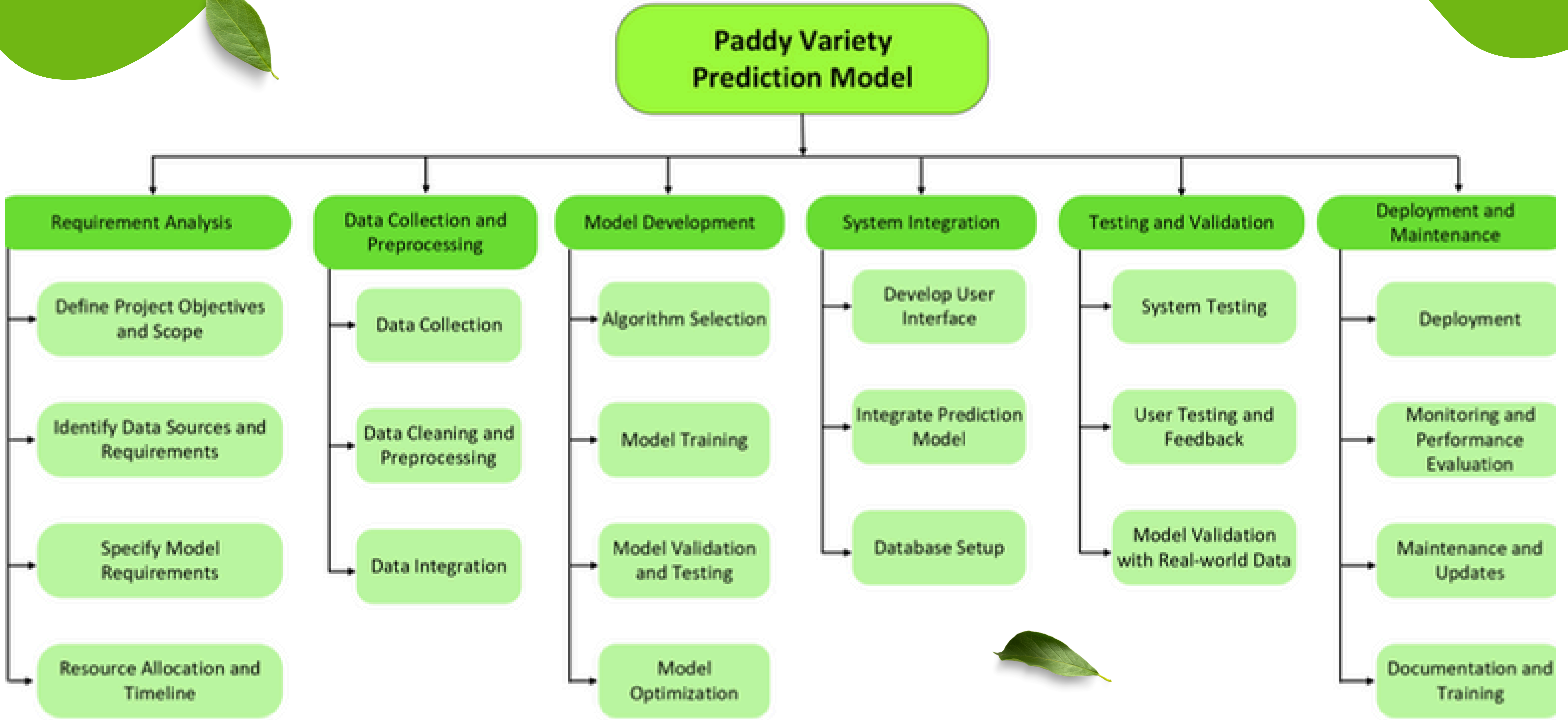
Descriptive Details of a variety



All Rice Varieties in Sri Lanka



Work Breakdown Structure



Requirements

Non-functional requirements

- Accessibility: Ensure the system is accessible to all users, including farmers with limited technical expertise.
- Reliability: The model should provide consistent and accurate predictions.
- Performance: The system should deliver predictions promptly.
- Usability: The interface should be intuitive and easy to use.

Functional requirements

- Ability to analyze environmental data.
- Ability to predict the best paddy variety for specific conditions.

Technologies

- Python (Back end)
- ML (Regression)
- ReactJS (Front end)
- Tailwind (for styles)
- Fast API
- Google Colab
- MySql
- Git Hub (Version control system)
- Trello(Project Management)

Gantt chart

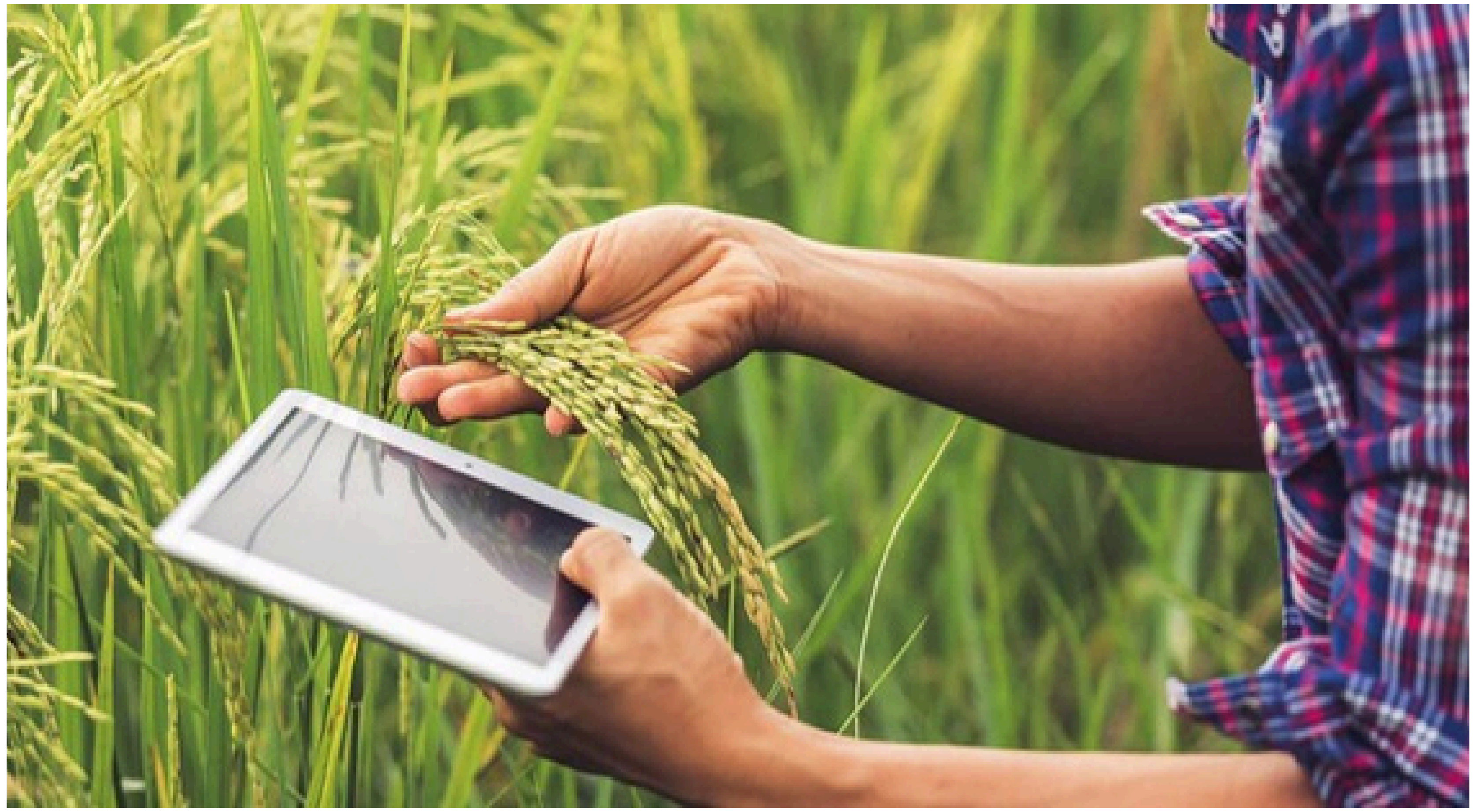
Month
Task
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Jan
Feb
Mar
Apr
Topic Selection
Topic Assessment
Proposal Presentation
Implementation
Progress Presentation 1
Writing Research Paper
Progress Presentation 2
Final Report
Final Viva

REFERENCES

1. H. A. R. T. I. "Rice Varieties and Their Characteristics," Hector Kobbekaduwa Agrarian Research and Training Institute, Colombo, Sri Lanka, Research Report No. 186, Accessed: Aug. 08, 2024. [Online]. Available: H. A. R. T. I. "Rice Varieties and Their Characteristics," Hector Kobbekaduwa Agrarian Research and Training Institute, Colombo, Sri Lanka, Research Report No. 186, Accessed: Aug. 08, 2024. [Online]. Available:https://www.harti.gov.lk/images/download/reasearch_report/new1/186.pdf
2. "Climate Change Ready Rice," International Rice Research Institute (IRRI), Accessed: Aug. 08, 2024. [Online]. Available: http://www.knowledgebank.irri.org/step-by-step-production/pre-planting/rice-varieties/item/climate-change-ready-rice
3. A. Gunawardena, H. Munasinghe, and W. Wickramasinghe, "Assessment of the suitability of temperature and relative humidity for rice cultivation in rainfed lowland paddy fields in Kurunegala district," Accessed: Aug. 08, 2024. [Online]. Available: https://www.researchgate.net/publication/319227475_Assessment_of_the_suitability_of_temperature_and_relative_humidity_for_rice_cultivation_in_rainfed_lowland_paddy_fields_in_Kurunegala_district

IT21227318 | Jayasekara S.S.D

Weed Detection & Mitigation System



Information
Technology

INTRODUCTION

- **This Research component is about,**
  - Identify and mitigate weed varieties in paddy fields
- **By using an accurate weed detection and mitigation system will enhance productivity and reduce losses.**
- **For real-time weed management, machine learning and image processing can be used to find innovative solutions .**

RESEARCH GAP & PROBLEM

- Traditional weed detection relies on manual identification, which is time-consuming and less accurate.
- Bad mitigation strategies can cause huge negative impacts not only on paddy yield but also on properties like soil and water !!
- Lack of integrated solutions that provide both detection and mitigation recommendations.

RESEARCH PROBLEM

Building a system that offers accurate mitigation strategies based on detected weed species.

- Build an automated system to detect and classify weed species accurately and recommend mitigation strategies with a user-friendly user interface.

SPECIFIC AND SUB OBJECTIVES

- **Specific Objectives :**
  - Enhance paddy crop yield by reducing losses (by developing this system).

- **Sub Objectives :**
  - Develop an Image Classification Model for Weed Detection: Train a model to identify and classify weeds.
  - Implement a Weed Mitigation Recommendation System: Suggest effective control strategies for detected weeds.

METHODOLOGY

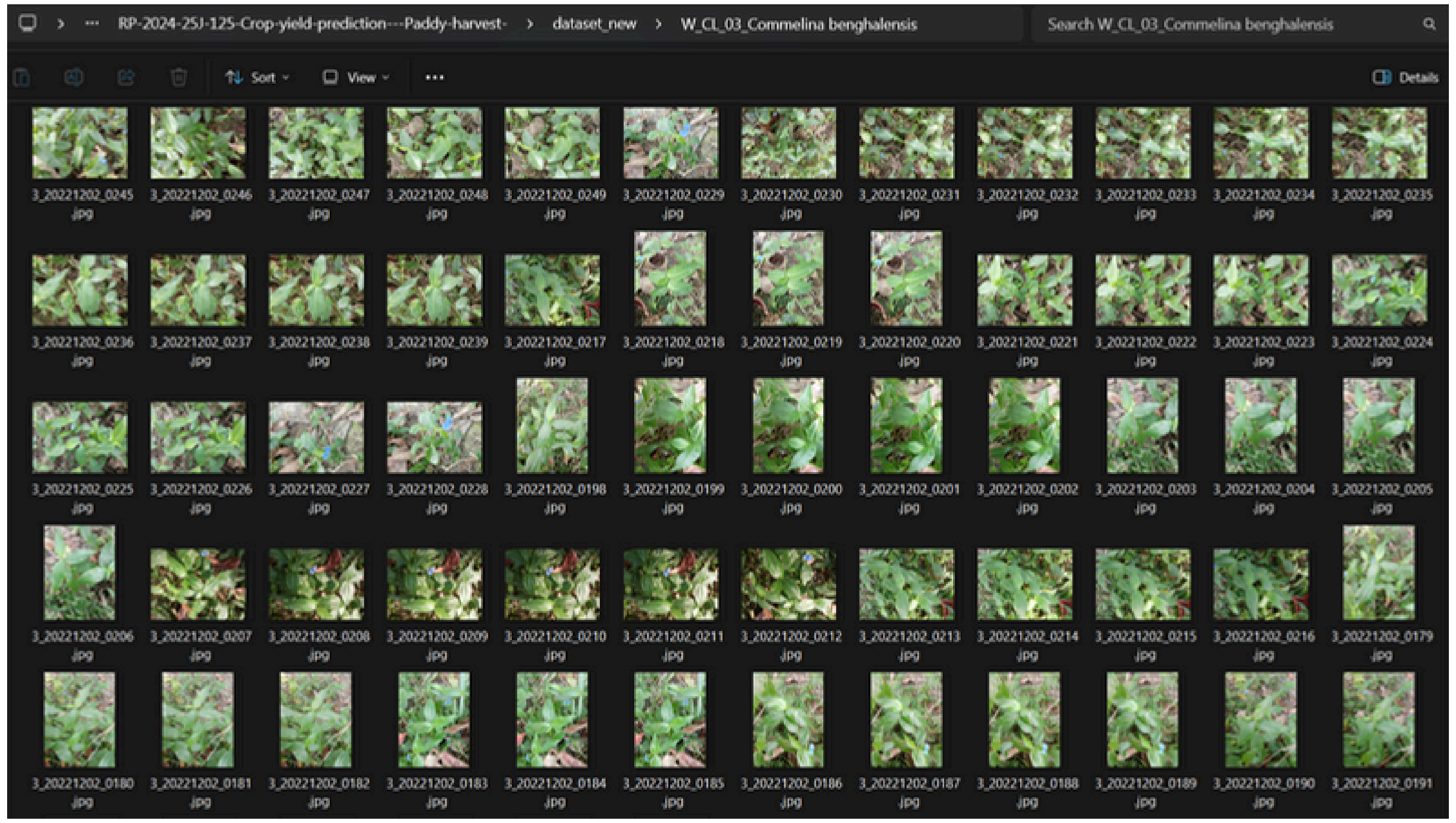
- **Dataset Collection and Preprocessing**
  - Collect Images
  - Preprocess Images

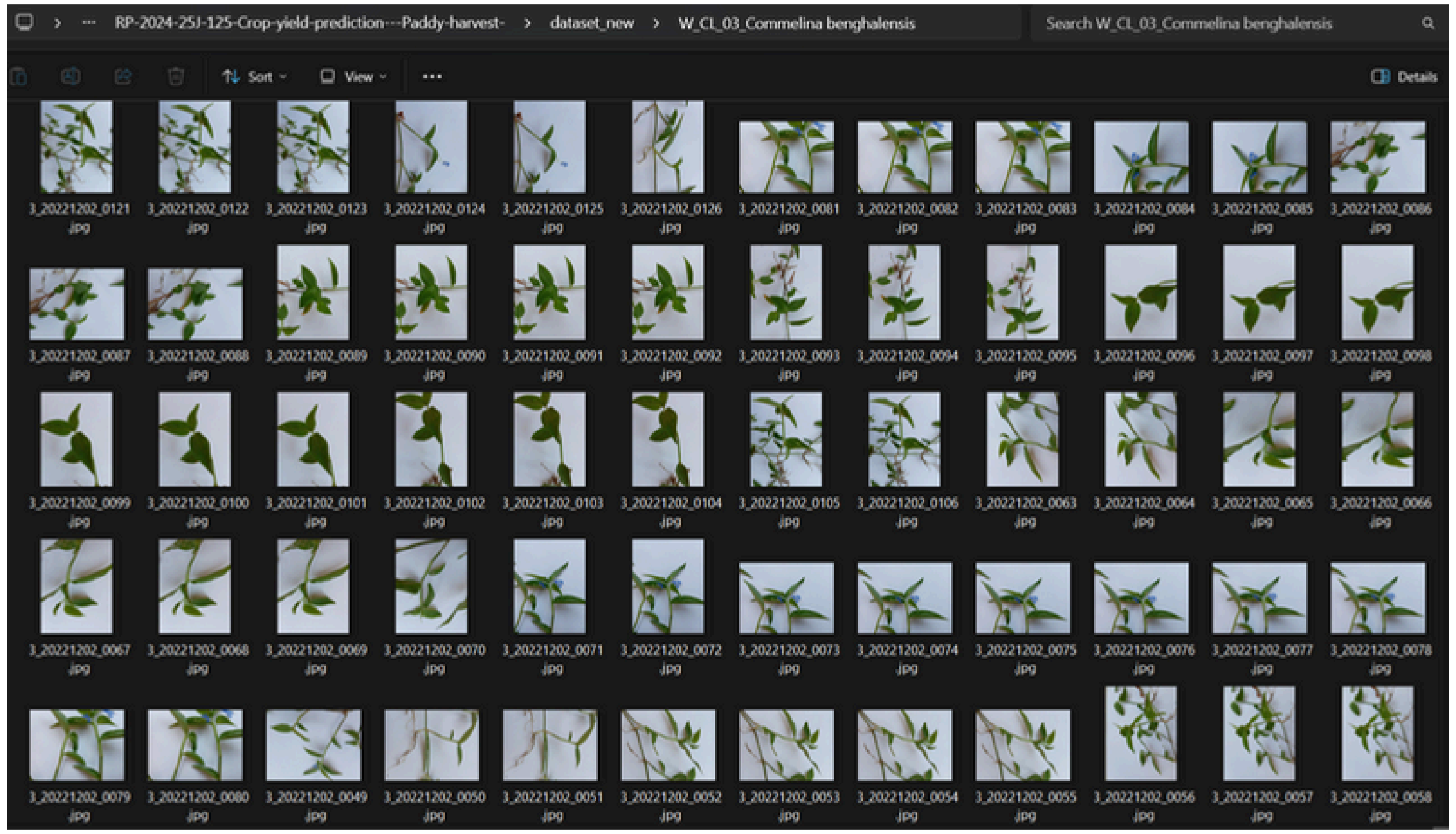
- **Model Training and Validation**
  - Split Dataset: Divide into training, validation, and test sets.
  - Choose Model: Select and train a CNN for image classification.
  - Evaluate Model: Assess performance

- **Development and Integration**
  - Document Details(DB) : Include methods, techniques, and dosages.
  - Develop Algorithm: Link detected weeds to mitigation strategies.
  - User Interface Development: Design an interface to upload images and receive mitigation methods.

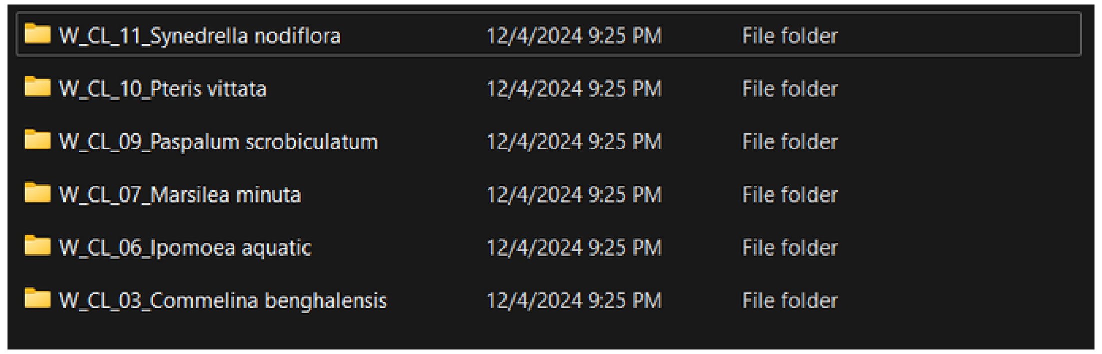
- **Field Testing and Feedback Collection**

DATA COLLECTION





- 3000 images for six most common paddy weed classes (without augmented images)
- Natural and controlled enviroments



W_CL_11_Synedrella nodiflora	12/4/2024 9:25 PM	File folder
W_CL_10_Pteris vittata	12/4/2024 9:25 PM	File folder
W_CL_09_Paspalum scrobiculatum	12/4/2024 9:25 PM	File folder
W_CL_07_Marsilea minuta	12/4/2024 9:25 PM	File folder
W_CL_06_Ipomoea aquatic	12/4/2024 9:25 PM	File folder
W_CL_03_Commelina benghalensis	12/4/2024 9:25 PM	File folder

MODEL SELECTION

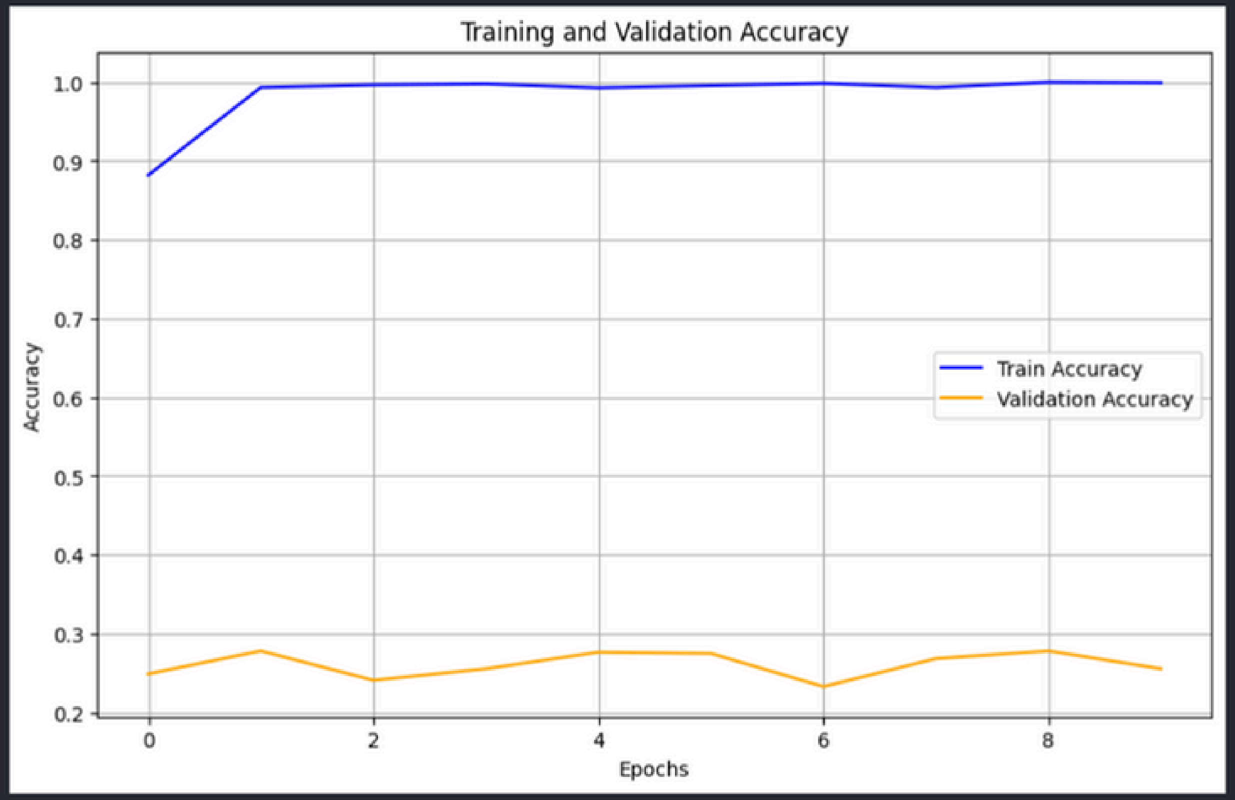
```
test_loss, test_accuracy = model.evaluate(test_generator)
print(f"Test Accuracy: {test_accuracy * 100:.2f}%")
```

[10]

```
20/20 ━━━━━━━━━━━━━━━━━━━━ 4s 189ms/step - accuracy: 0.2576 - loss: 24.8933
Test Accuracy: 25.57%
```

```
plt.grid(True)
plt.show()
```

[11]



- Trained few models with different accuracy levels
- Fixed the imbalance in the classes of the dataset
- Increased the image count by image augmentation

MODEL SELECTION

```python
train_data_dir = augmented_dir
test_data_dir = test_dir

train_datagen = ImageDataGenerator(rescale=1.0/255)
test_datagen = ImageDataGenerator(rescale=1.0/255)

train_generator = train_datagen.flow_from_directory(
    train_data_dir, target_size=(150, 150), batch_size=32, class_mode='categorical'
)
test_generator = test_datagen.flow_from_directory(
    test_data_dir, target_size=(150, 150), batch_size=32, class_mode='categorical'
)
```

[5]

```
Found 9363 images belonging to 6 classes.
Found 464 images belonging to 6 classes.
```

```python
test_loss, test_accuracy = model.evaluate(test_generator)
print(f"Test Accuracy: {test_accuracy * 100:.2f}%")
```

[9]

```
15/15 ──────────────────── 3s 177ms/step - accuracy: 0.4620 - loss: 4.1965
Test Accuracy: 46.98%
```

```python
base_model = VGG16(weights='imagenet', include_top=False, input_shape=(150, 150, 3))

model = Sequential([
    base_model,
    Flatten(),
    Dense(128, activation='relu'),
    Dropout(0.5),
    Dense(train_generator.num_classes, activation='softmax')
])

base_model.trainable = False
model.compile(optimizer=Adam(learning_rate=0.0001), loss='categorical_crossentropy', metrics=['accuracy'])

history = model.fit(train_generator, epochs=20, validation_data=test_generator)
```

[7]

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/vgg16/vgg16_weights_tf_dim_ordering_tf_kernels_notop.h5
58889256/58889256 ──────────────────── 0s 0us/step
Epoch 1/20
/usr/local/lib/python3.10/dist-packages/keras/src/trainers/data_adapters/py_dataset_adapter.py:122: UserWarning: Your `PyDataset` class should call `super().
  self._warn_if_super_not_called()
293/293 ──────────────────── 61s 168ms/step - accuracy: 0.8712 - loss: 0.4363 - val_accuracy: 0.4483 - val_loss: 2.3112
Epoch 2/20
293/293 ──────────────────── 37s 125ms/step - accuracy: 1.0000 - loss: 0.0082 - val_accuracy: 0.4504 - val_loss: 2.6057
```

MODEL SELECTION

```
model = models.Sequential([
    layers.Conv2D(32, (3, 3), activation='relu', input_shape=(150, 150, 3)),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(128, (3, 3), activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Flatten(),
    layers.Dense(128, activation='relu'),
    layers.Dense(len(class_names), activation='softmax')  # Output layer for 6 classes
])
```

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 148, 148, 32)	896
max_pooling2d (MaxPooling2D)	(None, 74, 74, 32)	0
conv2d_1 (Conv2D)	(None, 72, 72, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 36, 36, 64)	0
conv2d_2 (Conv2D)	(None, 34, 34, 128)	73,856
max_pooling2d_2 (MaxPooling2D)	(None, 17, 17, 128)	0
flatten (Flatten)	(None, 36992)	0
dense (Dense)	(None, 128)	4,735,104
dense_1 (Dense)	(None, 6)	774

Total params: 4,829,126 (18.42 MB)

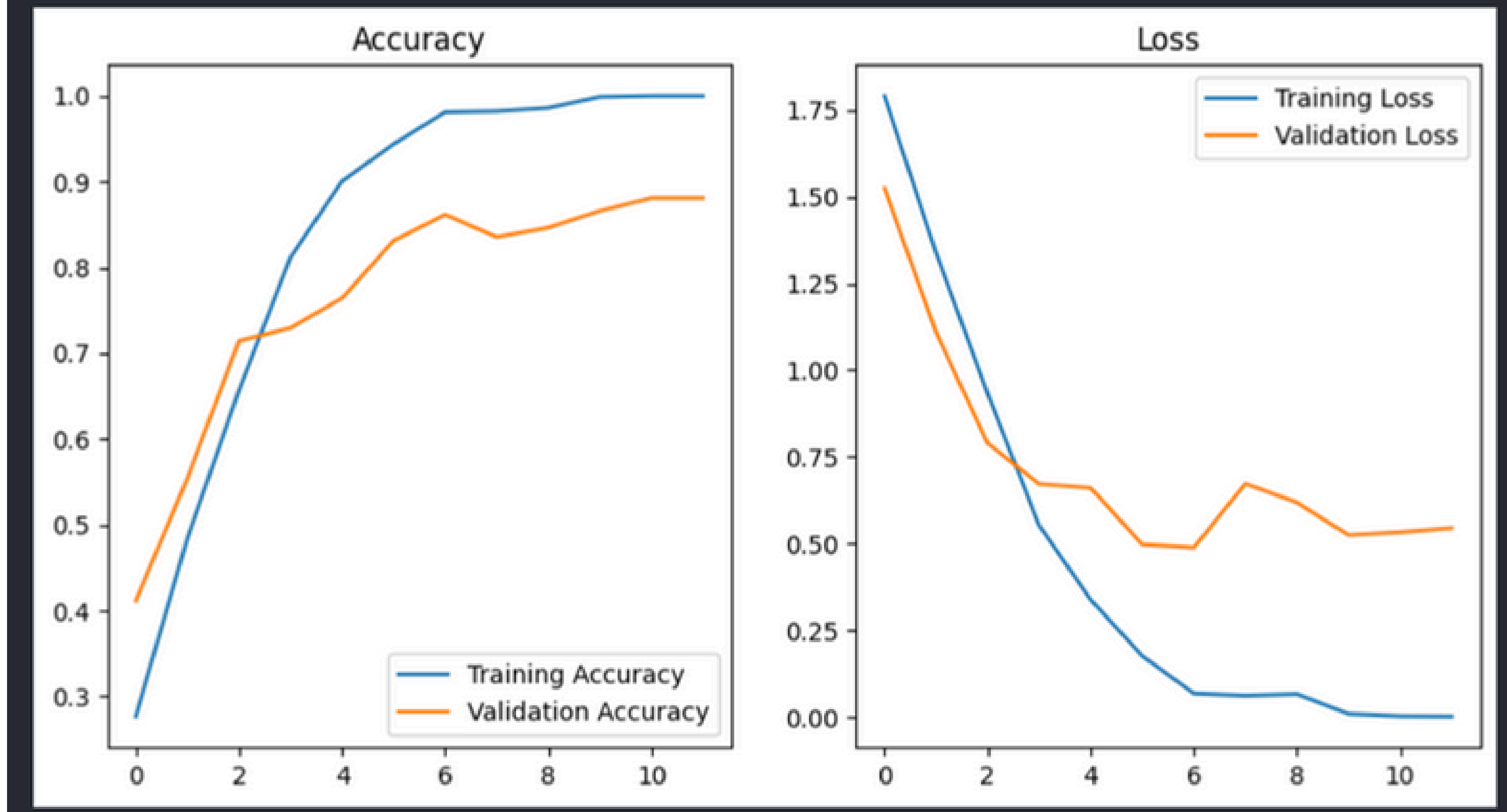
Trainable params: 4,829,126 (18.42 MB)

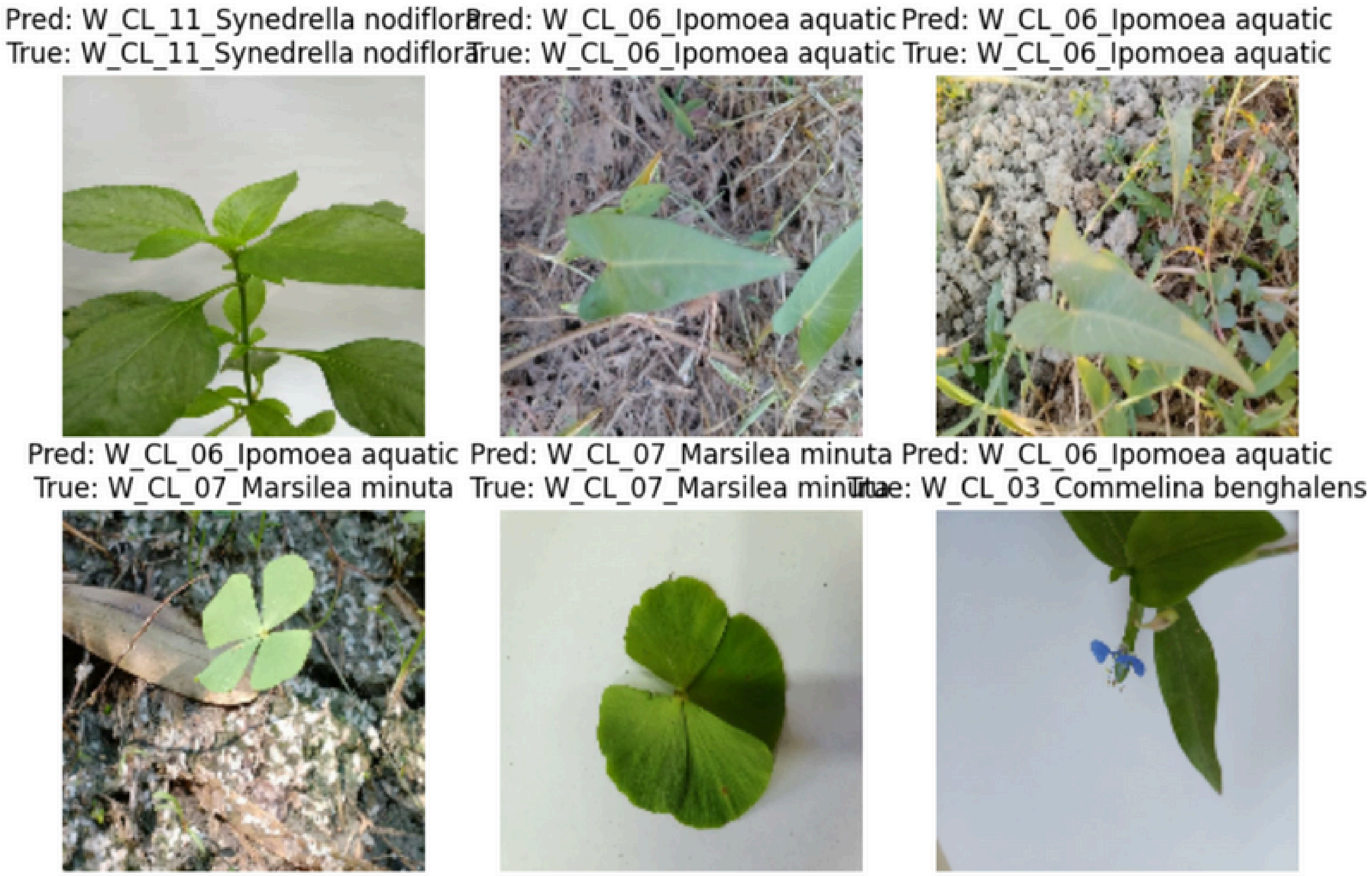
Non-trainable params: 0 (0.00 B)

- Selected a Custom CNN model built using the Sequential API
- Accuracy level - 86%

MODEL SELECTION

```
plt.plot(val_loss, label='Validation Loss')
plt.legend(loc='upper right')
plt.title('Loss')
plt.show()
```






```
test_loss, test_acc = model.evaluate(val_dataset)
print(f"Test Accuracy: {test_acc:.2f}")
```

[18]

```
15/15 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - accuracy: 0.8345 - loss: 0.5735
Test Accuracy: 0.86
```

INTEGRATED SOLUTION


```
API Final Response: {
  "weed_class": "W_CL_09_Paspalum scrobiculatum",
  "mitigation": {
    "Cultural Control": [
      "Crop rotation with broadleaf crops such as legumes or mustard to disrupt growth.",
      "Dense planting of desired crops to reduce competitiveness.",
      "Mulching with organic residues to suppress germination."
    ],
    "Mechanical Control": [
      "Frequent shallow tillage to uproot seedlings before they establish.",
      "Hand weeding before seed setting to prevent future infestations."
    ],
    "Chemical Control": [
      "Use pre-emergent herbicides such as Pendimethalin, Atrazine, and Oxadiazon.",
      "Apply post-emergent herbicides like Glyphosate, Clethodim, or Fluazifop-p-butyl for selective grass control."
    ],
    "Biological Control": [
      "Use of fungal pathogens like Pyricularia grisea has been explored for controlling grassy weeds.",
      "Certain insects that feed on grass weeds may provide additional suppression."
    ]
  }
}
INFO:     127.0.0.1:50550 - "POST /weed/predict/ HTTP/1.1" 200 OK
```


Request URL

`http://127.0.0.1:8000/weed/predict/`

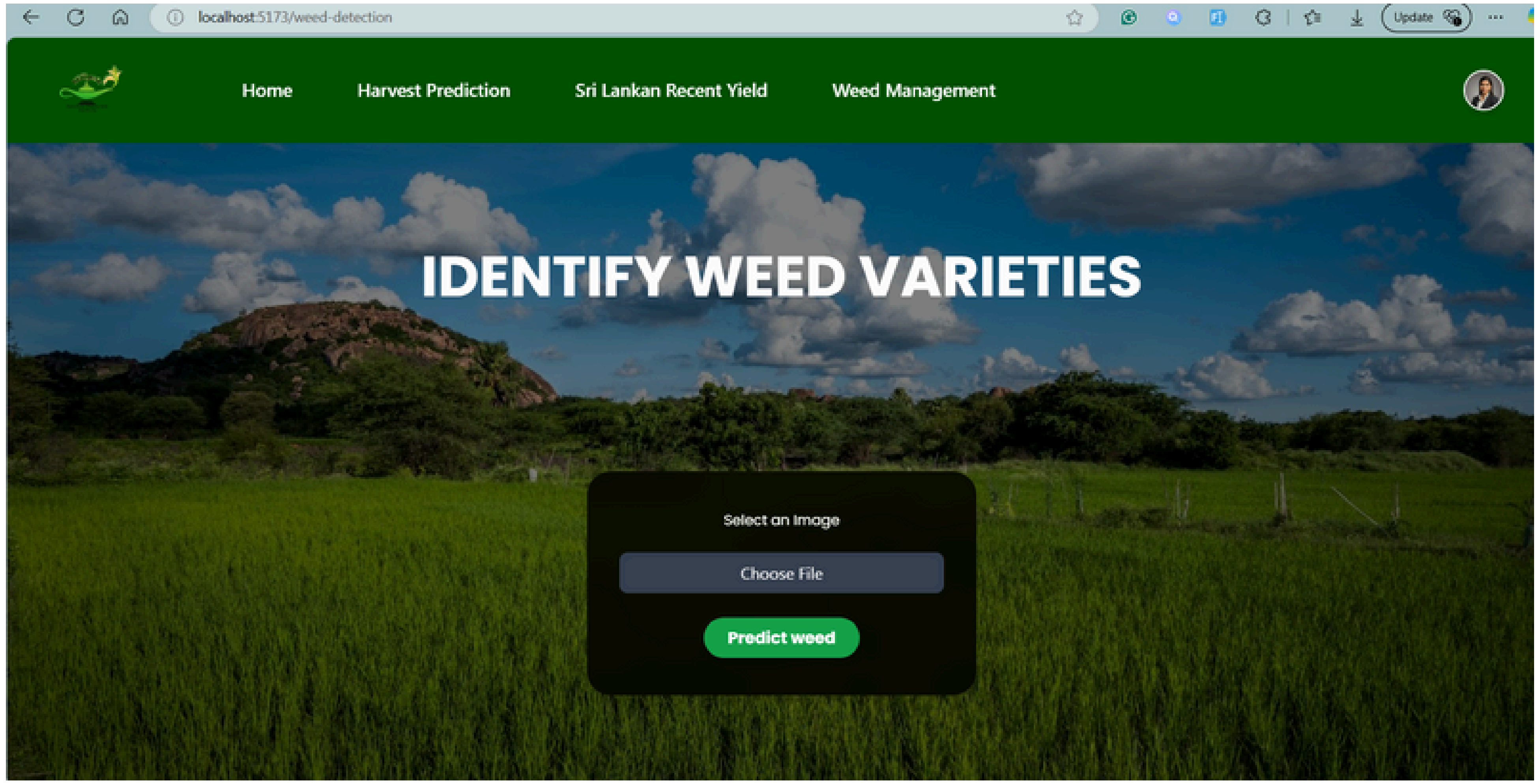
Server response

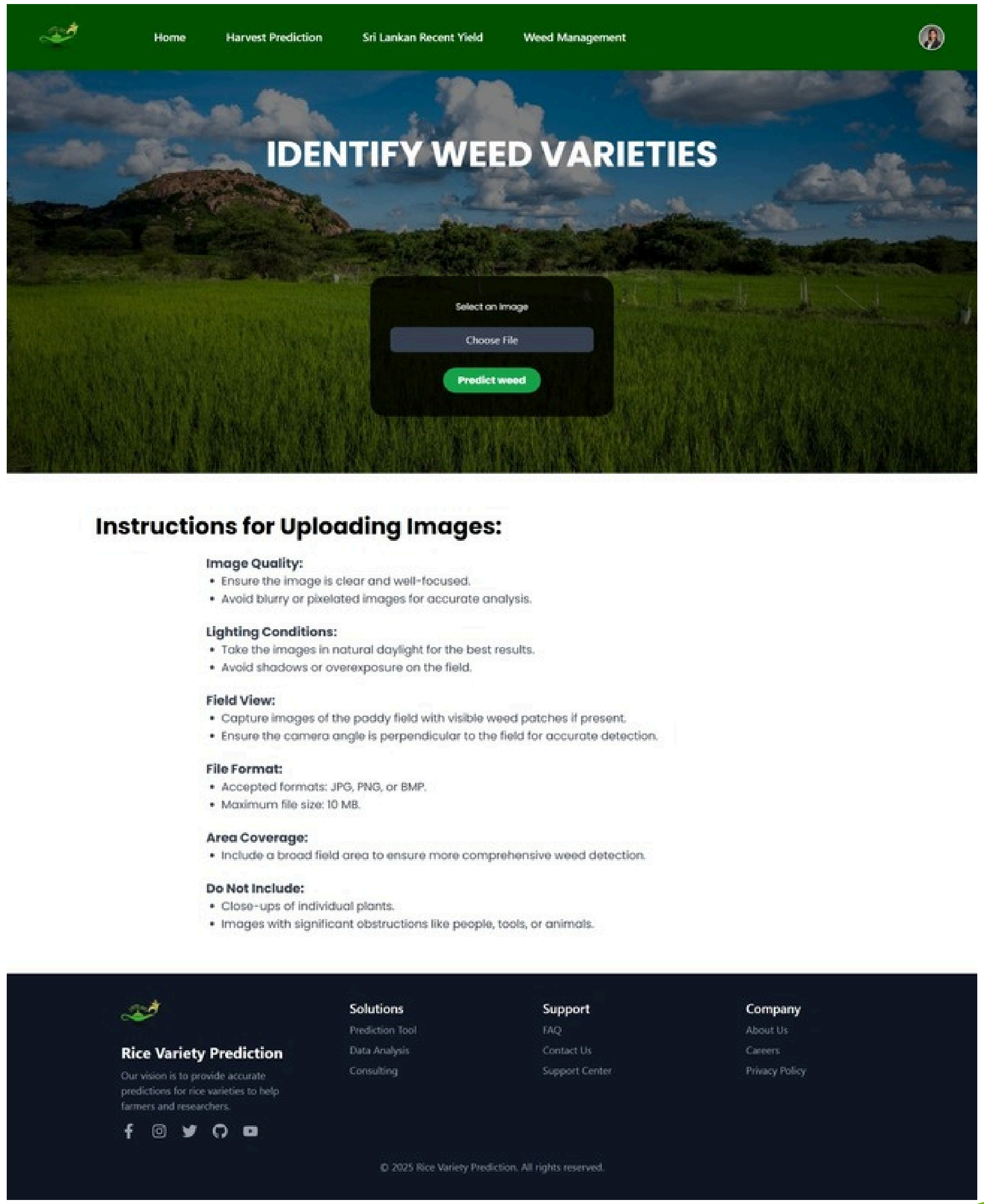
Code	Details
200	Response body


```
{
  "weed_class": "W_CL_09_Paspalum scrobiculatum",
  "mitigation": {
    "Cultural Control": [
      "Crop rotation with broadleaf crops such as legumes or mustard to disrupt growth.",
      "Dense planting of desired crops to reduce competitiveness.",
      "Mulching with organic residues to suppress germination."
    ],
    "Mechanical Control": [
      "Frequent shallow tillage to uproot seedlings before they establish.",
      "Hand weeding before seed setting to prevent future infestations."
    ],
    "Chemical Control": [
      "Use pre-emergent herbicides such as Pendimethalin, Atrazine, and Oxadiazon.",
      "Apply post-emergent herbicides like Glyphosate, Clethodim, or Fluazifop-p-butyl for se
    ],
    "Biological Control": [
      "Use of fungal pathogens like Pyricularia grisea has been explored for controlling gras
      "Certain insects that feed on grass weeds may provide additional suppression."
    ]
  }
}
```


- API Response -> Weed Class + Mitigation methods
- Using
    - Softmax (Argmax)
    - Hash Map (Dictionary) Lookup & String Cleaning

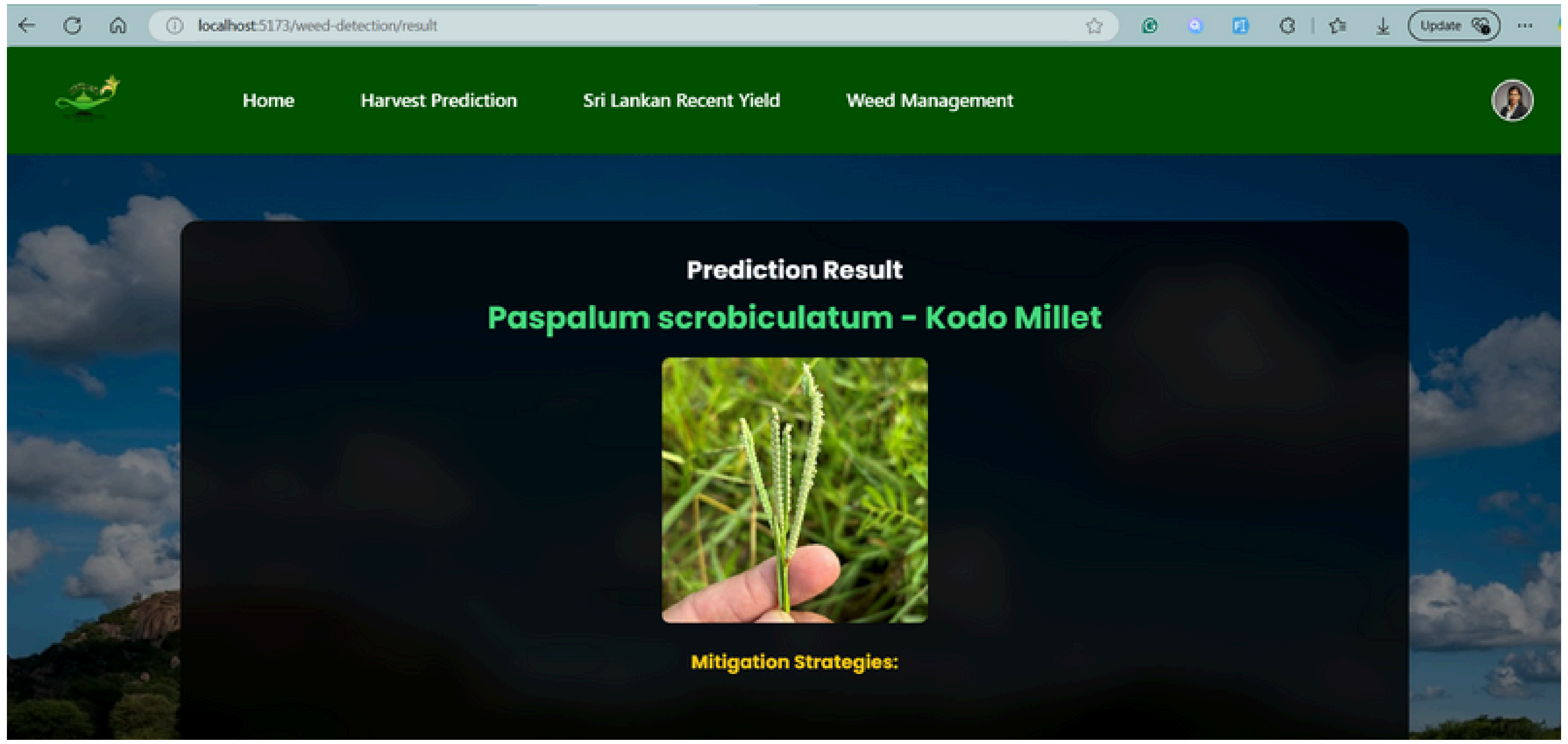
INTEGRATED SOLUTION

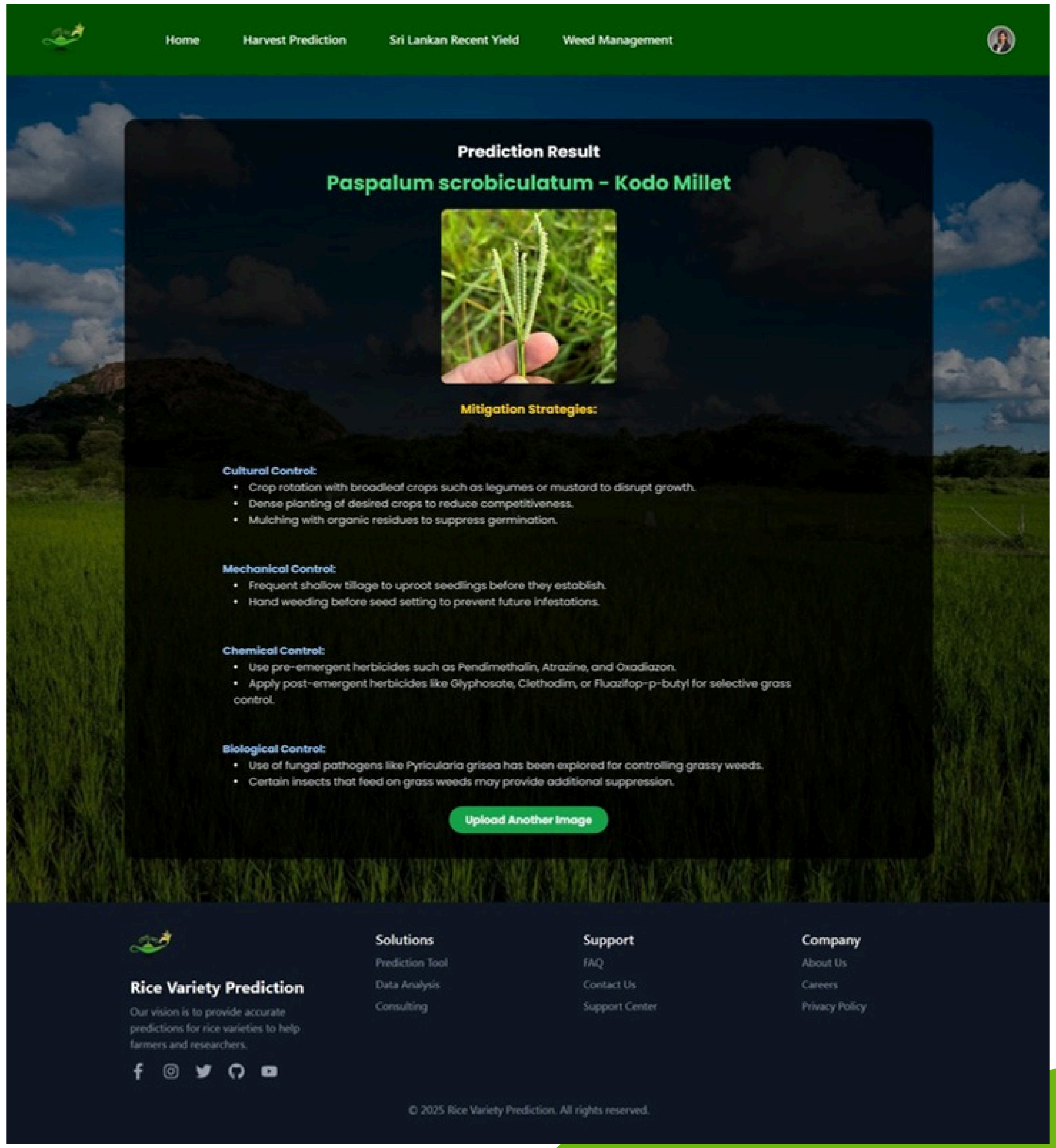




- Image upload with instructions to follow on

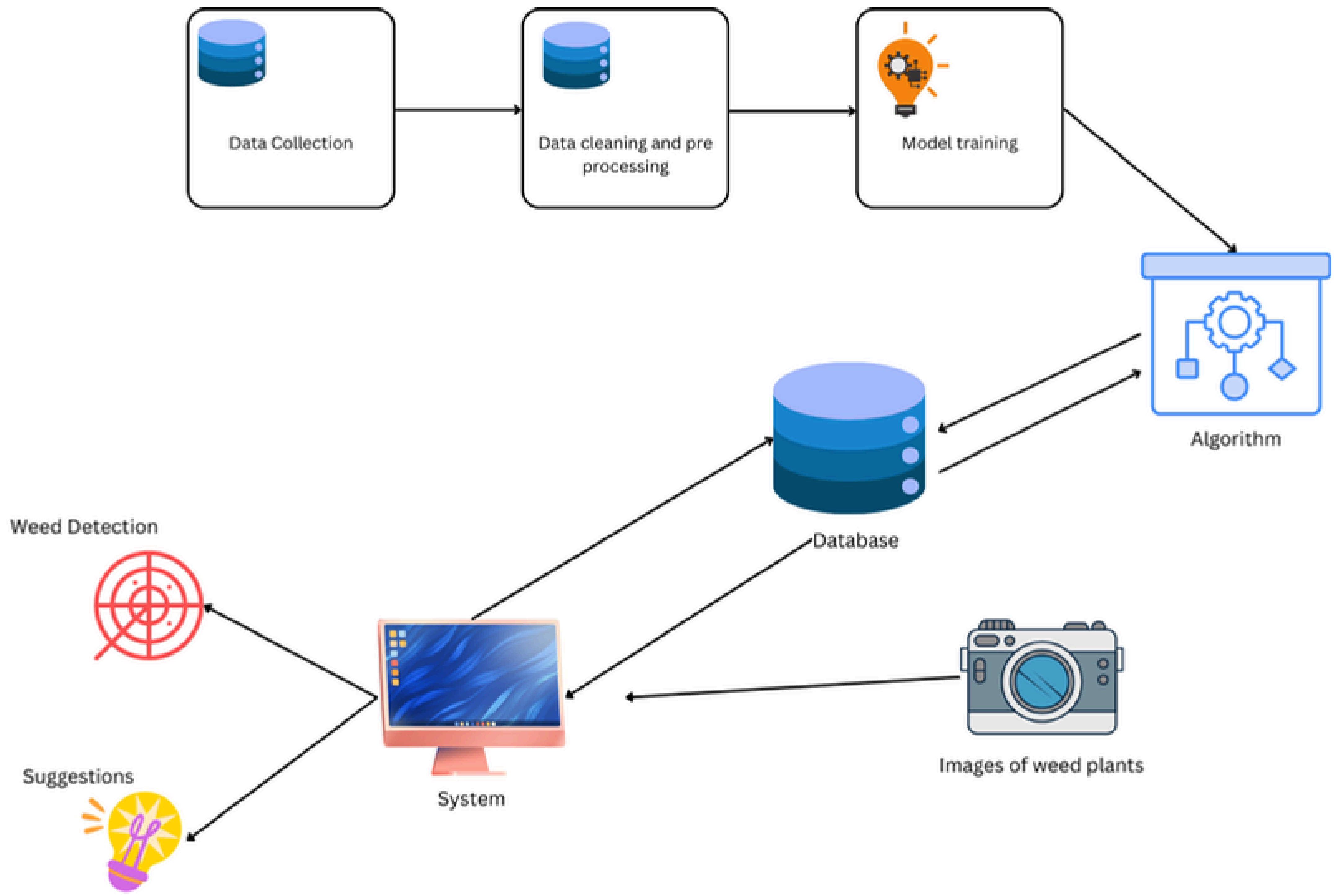
INTEGRATED SOLUTION





- Predicted weed variety with mitigation strategies

SYSTEM DIAGRAM



TECHNOLOGIES

- Python (Back end)
- ML (CNN)
- ReactJS (Front end)
- Tailwind (for styles)
- Fast API
- Google Colab
- MySql
- Git Hub (Version control system)
- Trello(Project Management)

Requirements

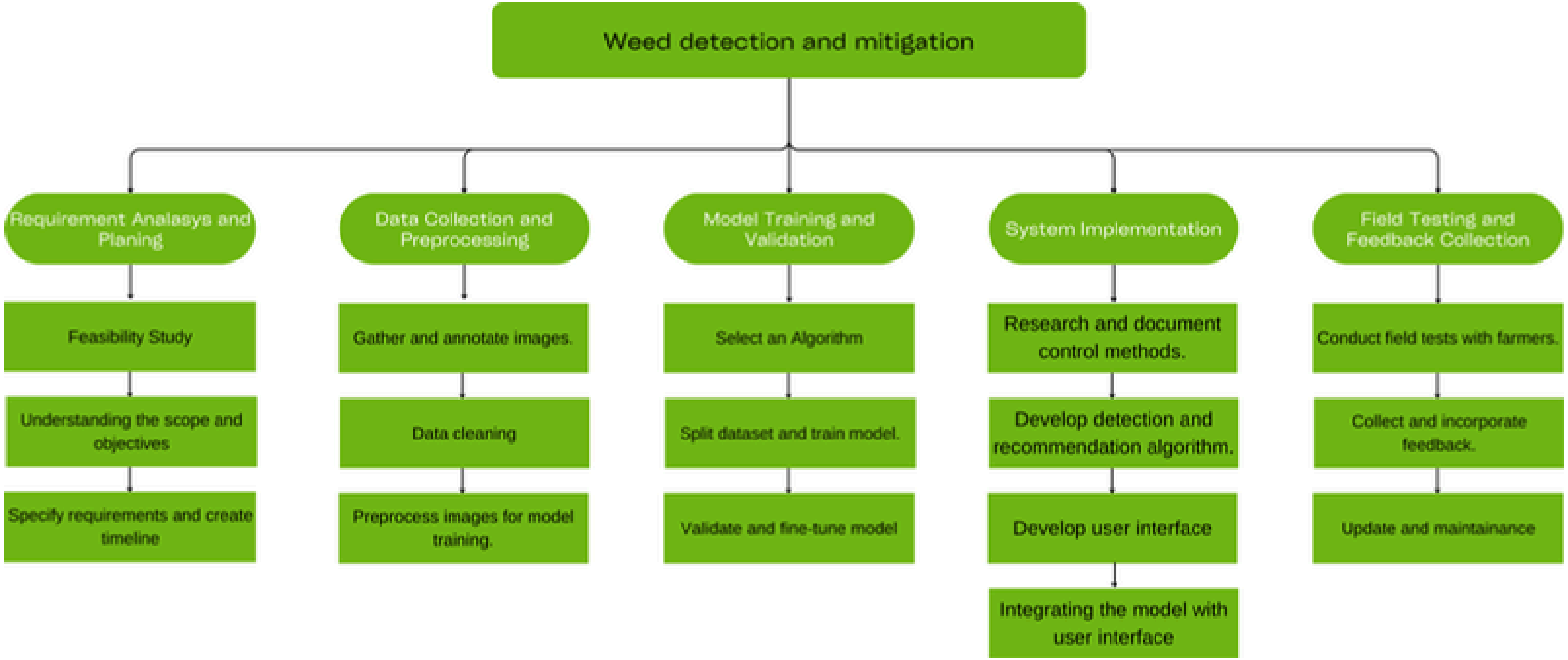
Non-functional requirements

- Availability
- Reliability
- Performance
- Usability

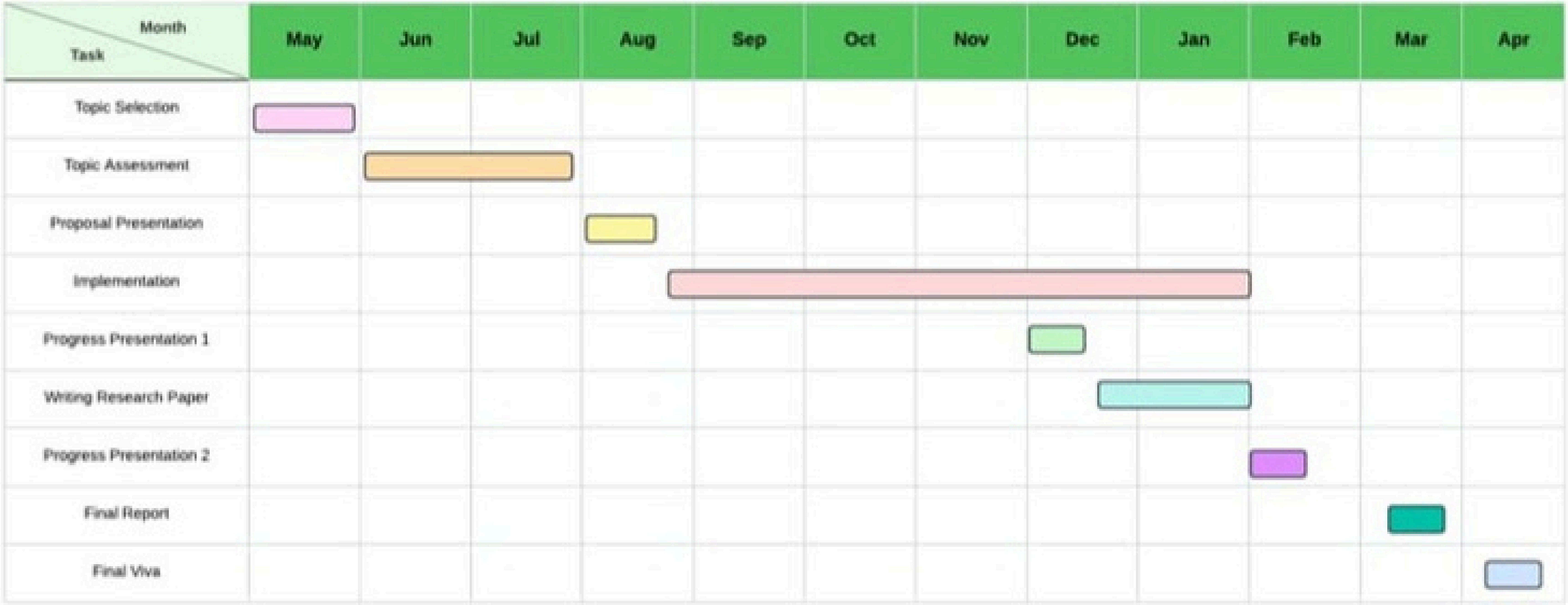
Functional requirements

- Ability to identify weed varieties
- Ability to suggest treatments to mitigate weed plants

Work Breakdown Structure



Gantt chart


Month
Task
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Jan
Feb
Mar
Apr
Topic Selection
Topic Assessment
Proposal Presentation
Implementation
Progress Presentation 1
Writing Research Paper
Progress Presentation 2
Final Report
Final Viva

References

[1]Elakya, R. & Vignesh, U. & Valarmathi, P. & Chithra, N. & Sigappi, S.. (2022). A Novel Approach for Identification of Weeds in Paddy By using Deep Learning Techniques. International Journal of Electrical and Electronics Research. https://www.researchgate.net/publication/366698172_A_Novel_Approach_for_Identification_of_Weeds_in_Paddy_By_using_Deep_Learning_Techniques

[2] Kamath, Radhika & Balachandra, Mamatha & Prabhu, Srikanth. (2020). Paddy Crop and Weed Discrimination: A Multiple Classifier System Approach. International Journal of Agronomy. 2020. 1-14. 10.1155/2020/6474536.
Available at: https://doi.org/10.1155/2022/3287561 (Accessed: August 3, 2024).

[3] Radhika Kamath, Mamatha Balachandra, Amodini Vardhan & Ujjwal Maheshwari | (2022) Classification of paddy crop and weeds using semantic segmentation,
https://doi.org/10.1080/23311916.2021.2018791

THANK YOU FOR

Your Attention