

AGRI DOC

A Multifunctional
Mobile Application for
Enhancing Paddy
Farming Efficiency

GROUP NO R25-057





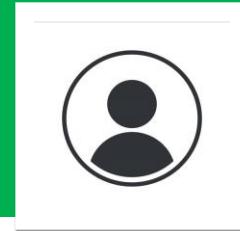
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Introduction to The Overall Project

How can an integrated digital platform address the challenges of irrigation management, weed identification, pest identification and control , and market analytics to improve the sustainability and productivity of paddy farming



Research Questions

1. How can AI-driven weed identification enhance precision agriculture and reduce herbicide dependency in paddy farming?
2. What measurable impact can cause pest identification & Effete
3. How does an IoT-based automated irrigation system impact paddy crop yield and water resource efficiency?
4. How can a user-friendly mobile platform improve accessibility and adoption of digital farming solutions among small-scale farmers?



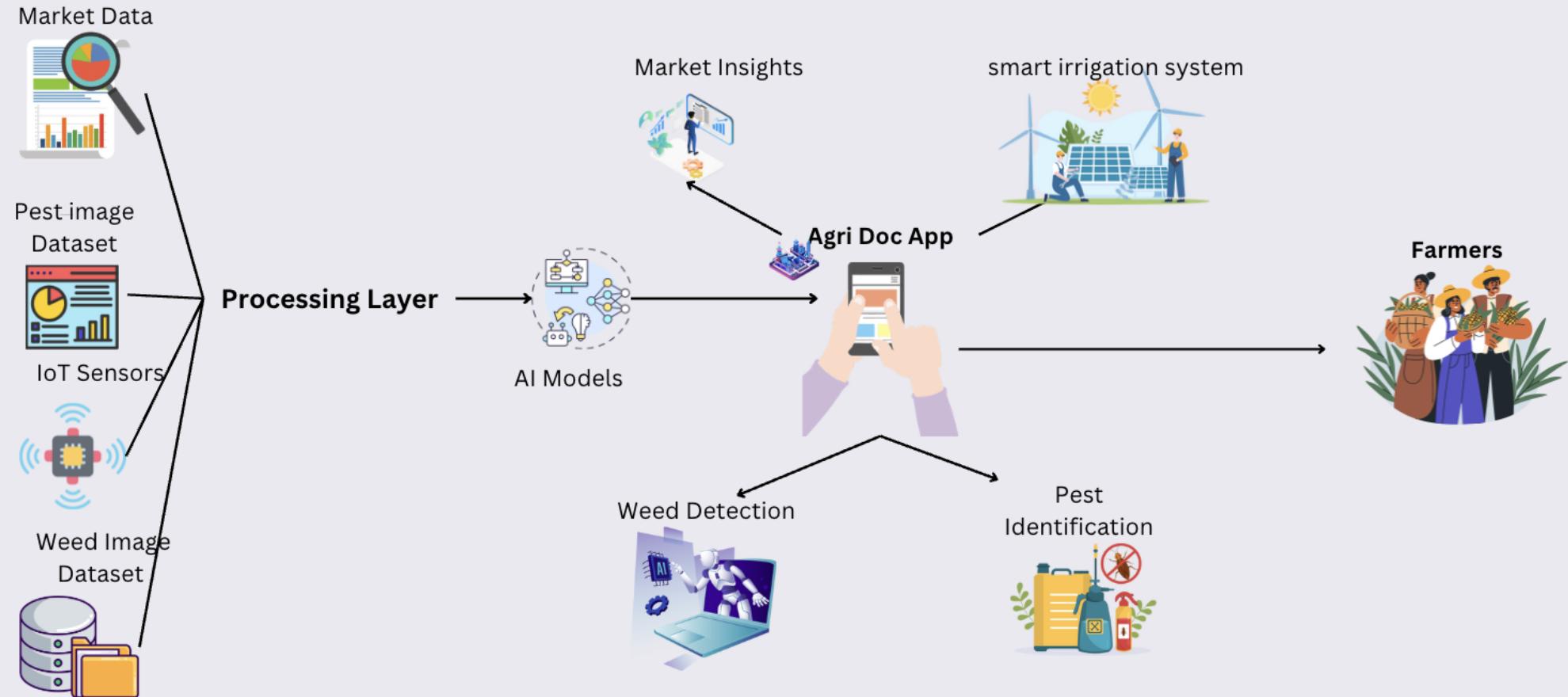
Research Objectives

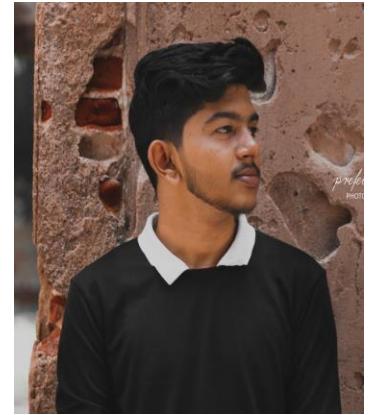


Develop *Agri Doc* app to empower paddy farmers with technology-driven solutions.

- Real-time irrigation monitoring using IoT sensors.
- AI-based weed identification for targeted control.
- Location-specific weather forecasts and alerts.
- Market insights with pricing and demand trends.

Diagram for Agri Doc





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Market Data Analysis



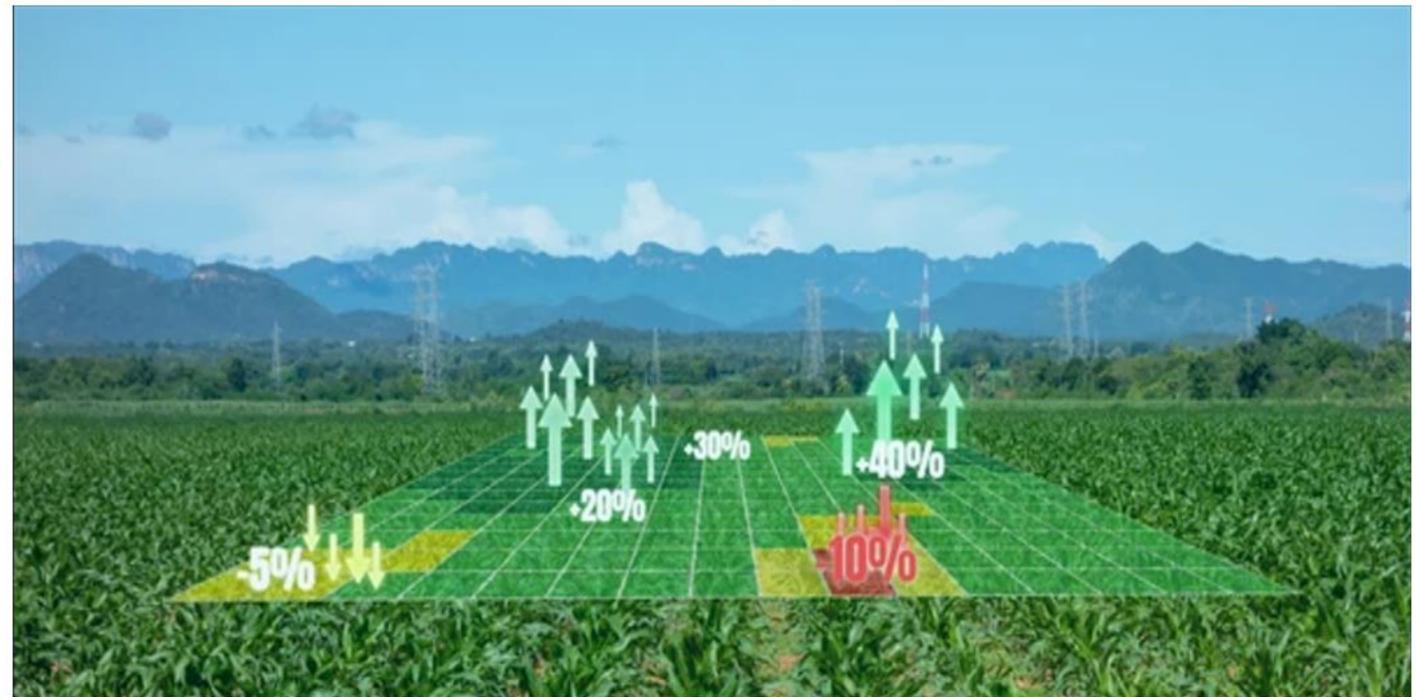
Introduction

Farmers often face challenges due to the lack of real-time market data, which leads to poor pricing decisions and financial losses. The market data analysis function addresses this issue by providing valuable insights into pricing trends and market demand. By leveraging data analytics, machine learning, and seamless market integration, this function equips farmers with accurate and timely information. These insights enable better decision-making, improve profitability, and contribute to enhanced financial stability for farmers.



Research Problem

- Farmers lack real-time, accurate market insights for pricing and sales decisions.
- This leads to economic instability and undervaluation of produce.
- Developing a predictable trend for price and demand can address these challenges effectively.



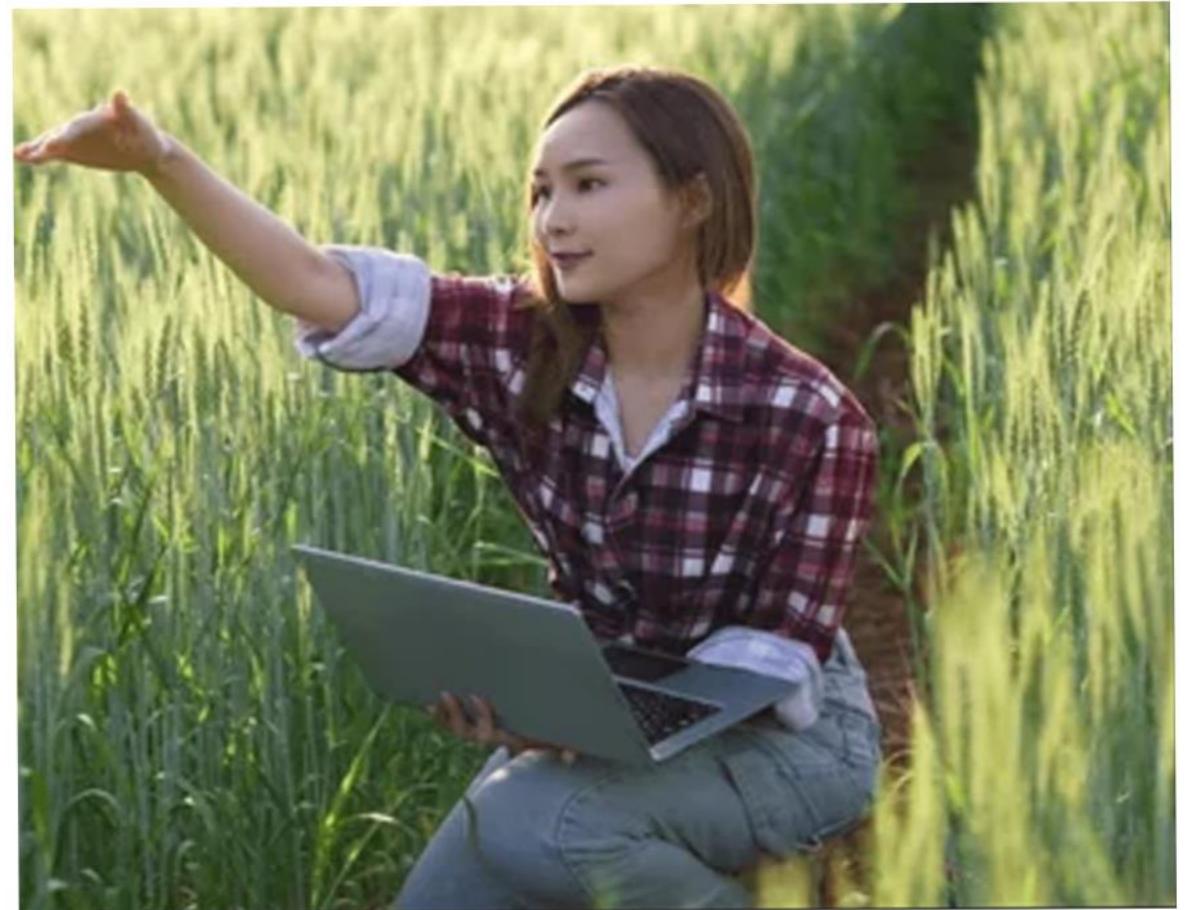
Research Gap



- Existing platforms focus primarily on crop cultivation, not market insights.
- No region-specific or predictive models tailored for paddy farmers.
- Previous apps and research have separate functions for prices or demands but lack a combined function integrating both price and demand.

Main Objective

To design a market data analysis module that equips farmers with actionable insights into pricing trends and optimal selling times.



Sub Objective

Collect and analyze

- Collect and analyze market data, including pricing and demand.

Develop

- Develop predictive models for future pricing trends and demand

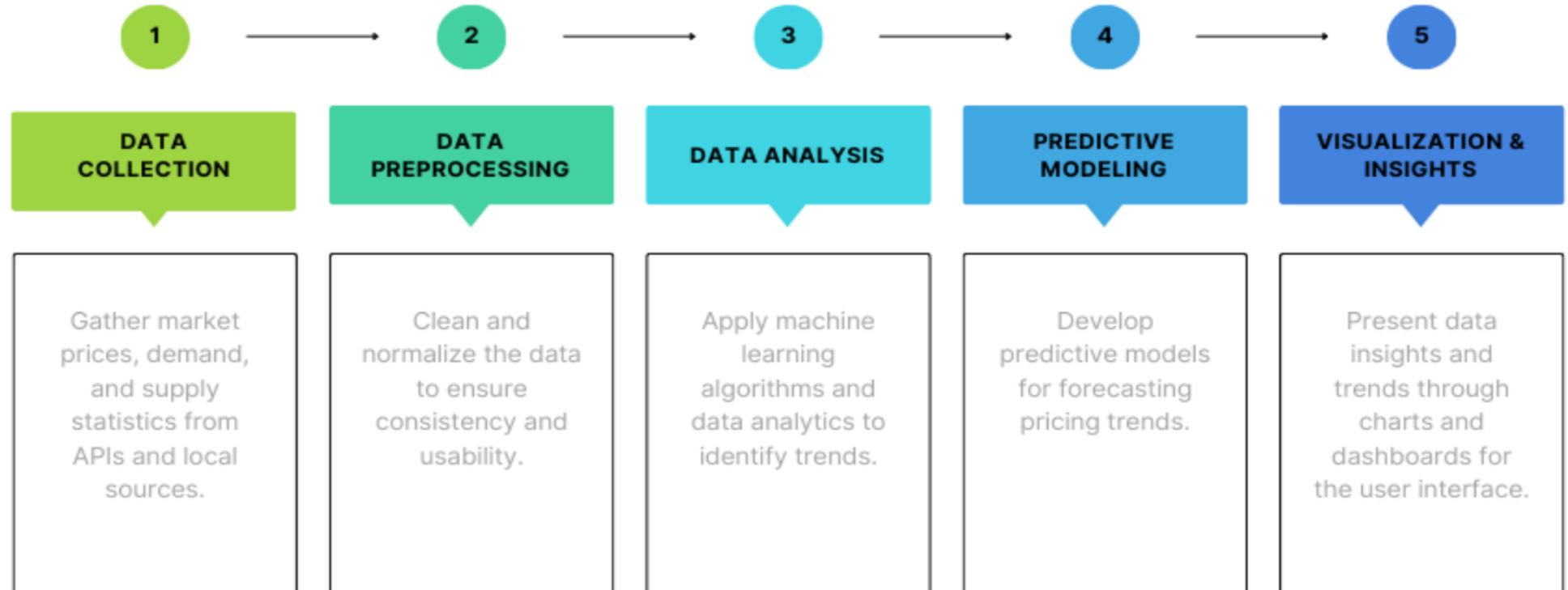
Provide

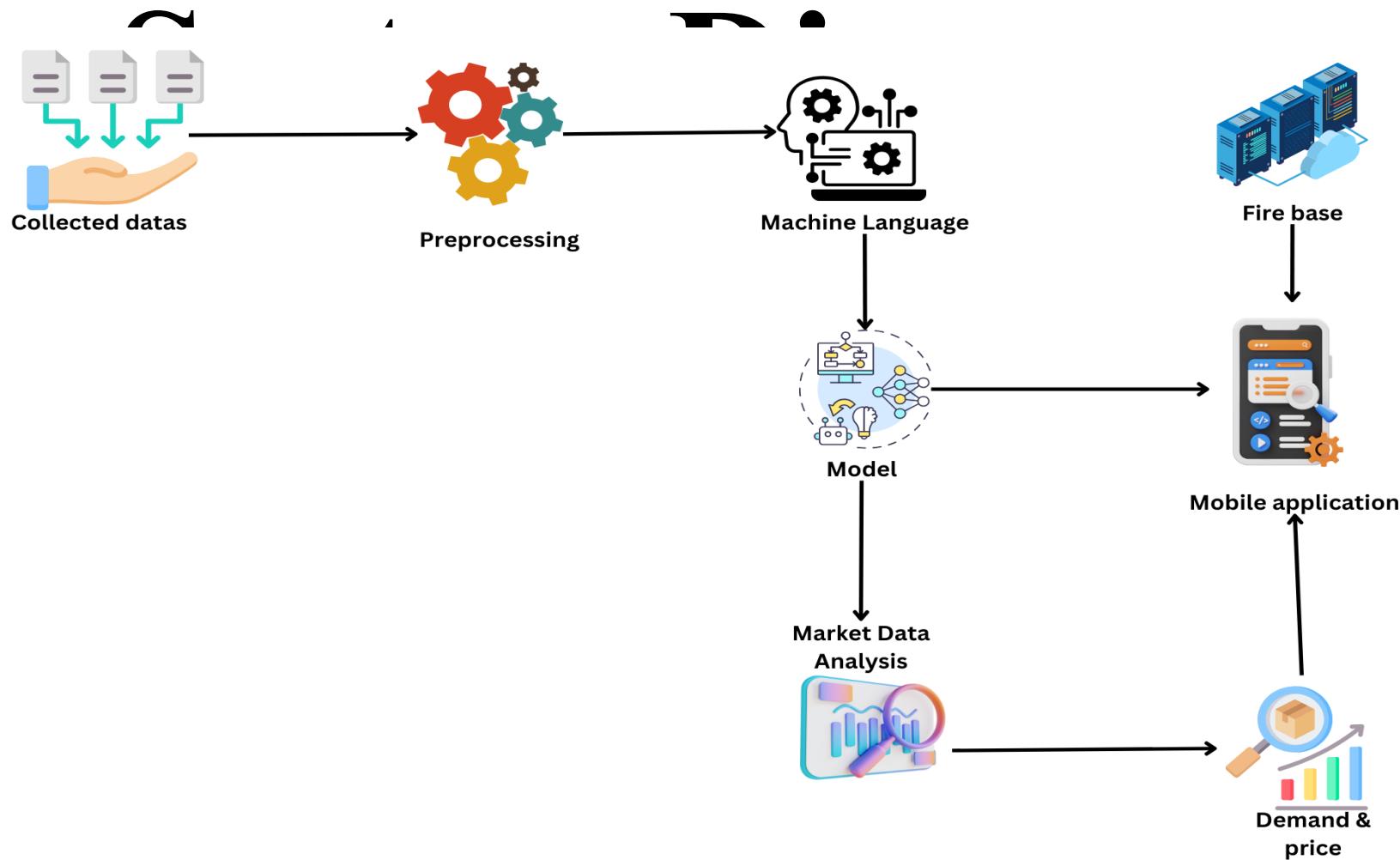
- Provide comparative insights into local and regional markets.

Enable

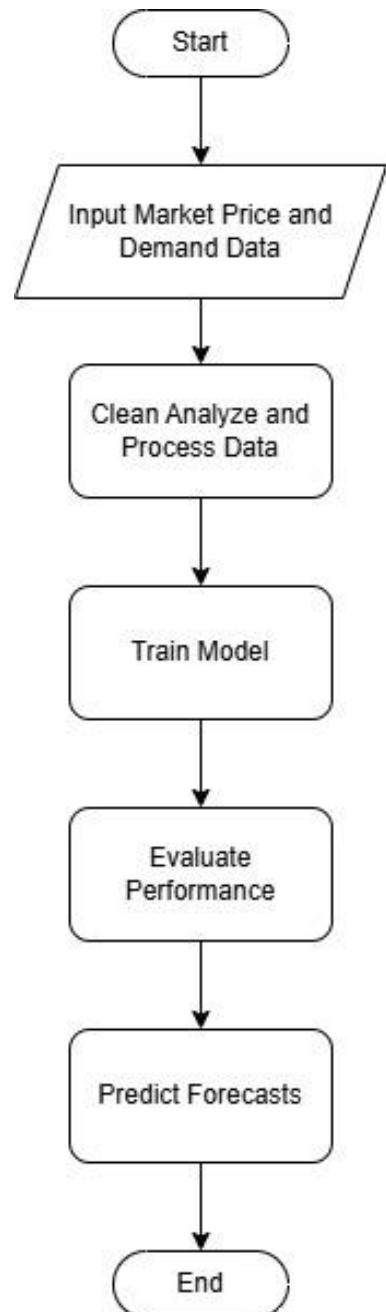
- Enable real-time tracking of market changes.

Methodology





Flow Chart Diagram



System Requirements



- **Hardware:**
Server: Intel Core i5, 8GB RAM, 500GB SSD, high-speed internet.
Mobile Devices: Android/iOS, 2GB RAM, 50MB storage.
- **Personal:**
System Administrator, Data Analyst, Software Developer.
- **Software:**
Development: Python, Dart, Firebase , Android Studio.
Machine Learning: Supervised Learning
Visualization: Flutter chart
API Integration: RESTful APIs for real-time data.

Technologies to Be Used



Programming Languages: Python (analytics), Dart (Flutter UI)



ML Frameworks: Supervised Learning



Database: Firebase



Dataset: Farmers



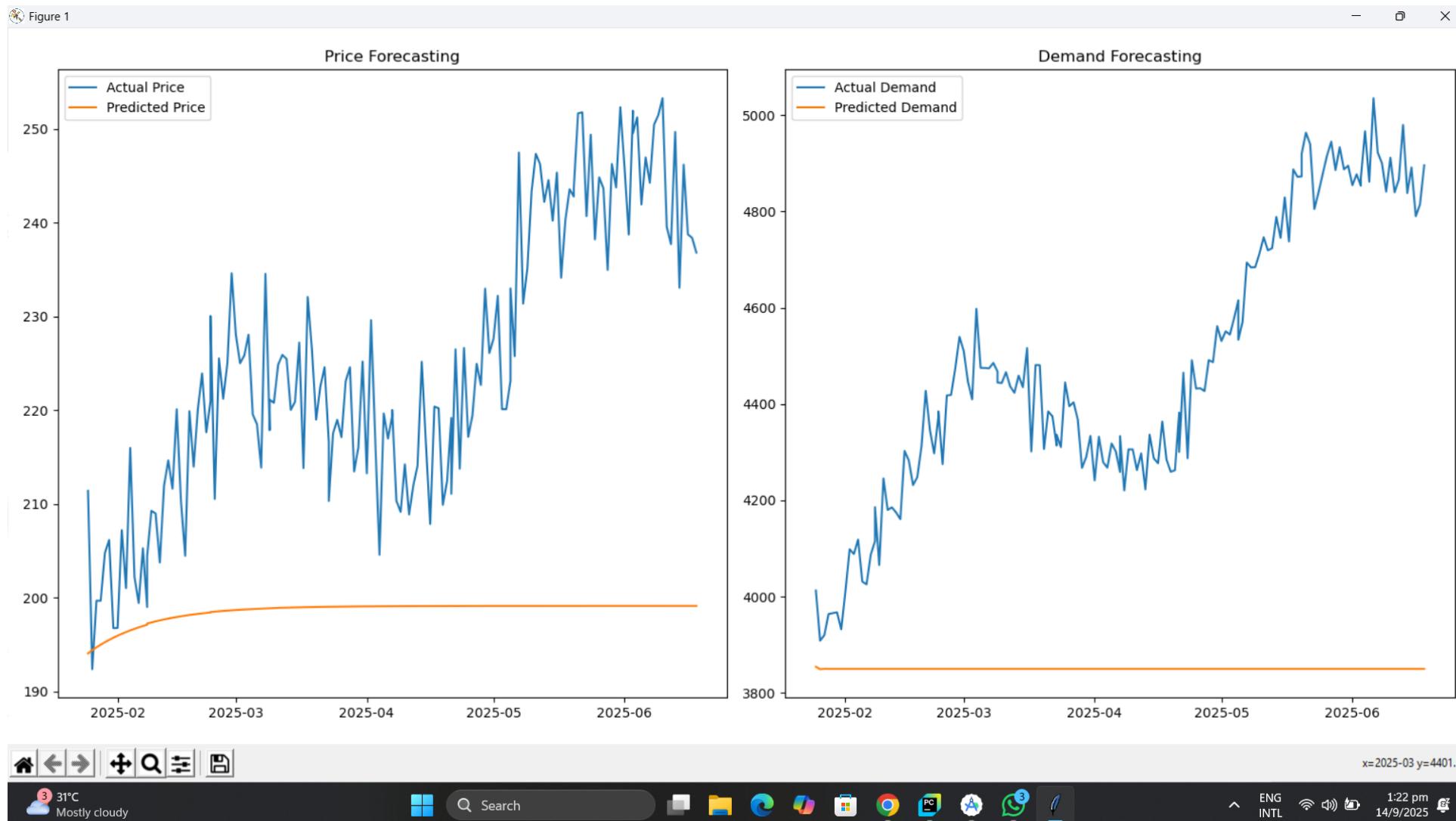
Visualization Tools: Flutter chart



Commercialization Strategy

- **Target Audience:** Small to medium-scale paddy farmers, agricultural cooperatives.
- **Revenue Model:**
 - Freemium (basic insights free, advanced analytics premium).
 - Partnerships with governments/NGOs for subsidies.
 - Advertisement revenue from agricultural products.
- **Distribution:**
 - Mobile app stores (Google Play, Apple App).
 - Partnerships with farming associations.
 - Workshops and awareness campaigns.
- **Growth:**
 - Localized market data and languages.
 - Expand to other crops/agriculture industries.
 - Integrate with e-commerce platforms.

Training Forecast



Prediction Forecast

The screenshot shows a Python development environment with the following details:

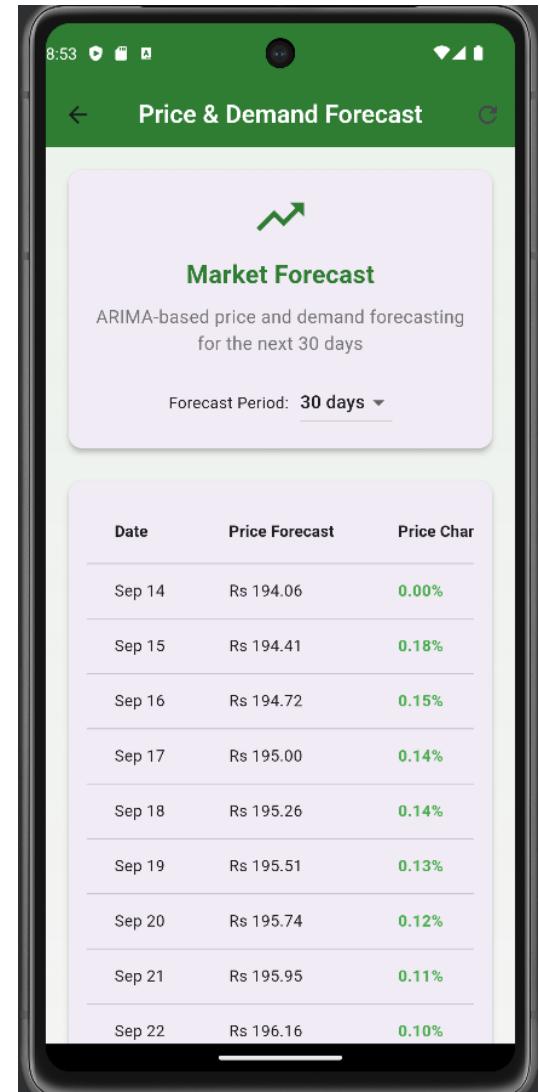
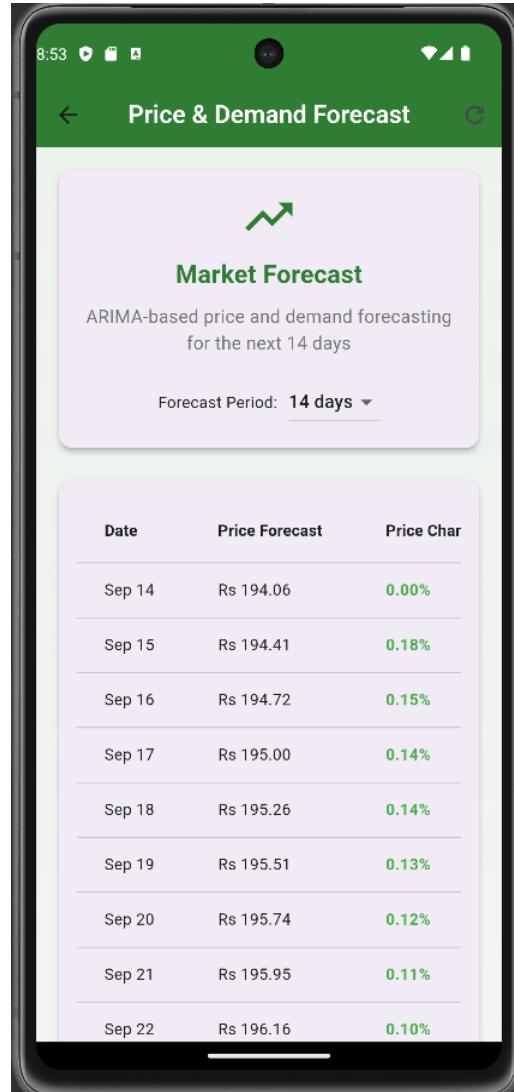
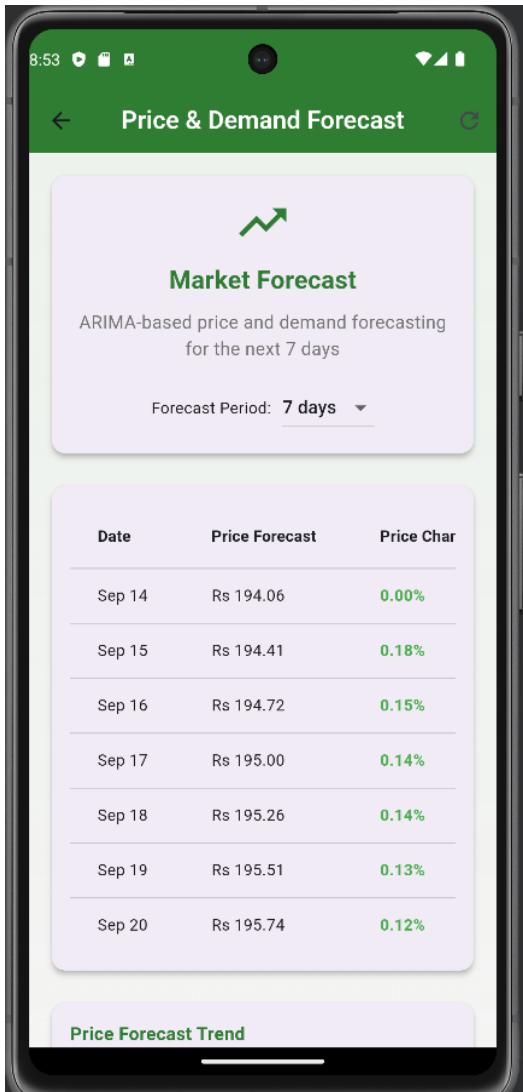
- Project Structure:** A folder named "My Final [Market Price & Demand Forecast]" contains files: "demand_forecast_model.pkl", "market_data.csv", and "predict_forecast.py".
- Code Editor:** The file "predict_forecast.py" is open, displaying code related to price and demand forecasting.
- Output Terminal:** The terminal window shows the execution results:
 - "Next 7 Days Forecast :" followed by a table of date, price_forecast, and demand_forecast values.
 - "Forecast with Percentage Changes:" followed by a table of date, price_forecast, price_change%, demand_forecast, and demand_change% values.
 - "Process finished with exit code 0"
- System Status Bar:** Shows the time (17:53), file path (My Final > predict_forecast.py), and system status (84°F, Mostly cloudy).

Debugging in Android Studio

The screenshot shows the Android Studio interface with the following details:

- Project Structure:** The left sidebar shows the project structure for "MobileApp". The "lib/pages" folder contains several Dart files: currentUser.dart, Registration.dart, dashboard_page.dart, and Price_Demand.dart (which is currently selected).
- Code Editor:** The main editor window displays the code for "Price_Demand.dart". The code performs an HTTP GET request to fetch forecast data from a local server and updates the UI with the results or error messages.
- Run Tab:** The top navigation bar shows the device configuration as "Pixel 7 API 34 (mobile)" and the current file as "Price_Demand.dart".
- Preview Window:** On the right, a preview window shows the mobile application's user interface. The screen title is "Price & Demand Forecast". It features a header with a green upward arrow icon and the text "Market Forecast". Below it, a message states "ARIMA-based price and demand forecasting for the next 7 days" and "Forecast Period: 7 days". A table lists the forecasted price and percentage change for each day from September 15 to 21. At the bottom, there is a section titled "Price Forecast Trend".
- Bottom Bar:** The footer includes standard Android Studio icons for Version Control, Run, TODO, Logcat, App Quality Insights, Services, App Inspection, and Dart Analysis. It also shows the current weather (30°C, Partly sunny), search, and system status indicators.

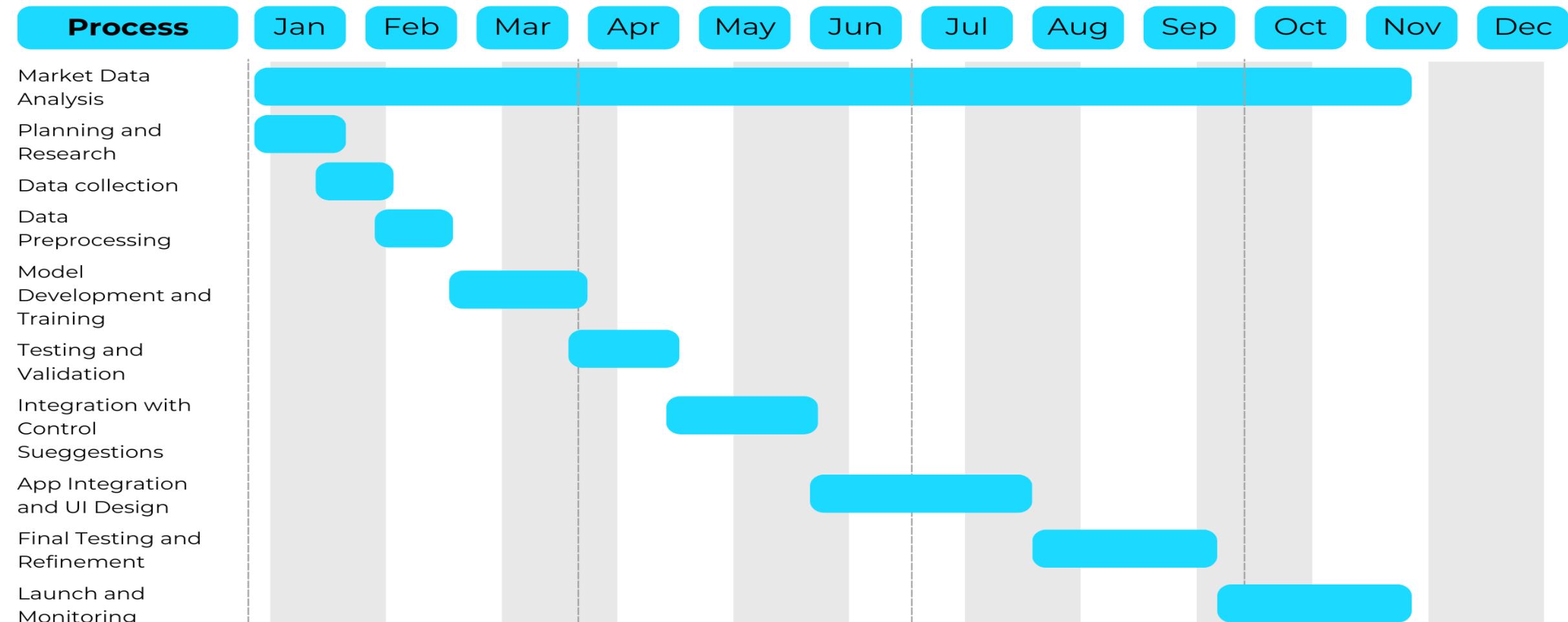
Emulator Screenshots





Gantt Chart

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References

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WEED IDENTIFICATION



Introduction

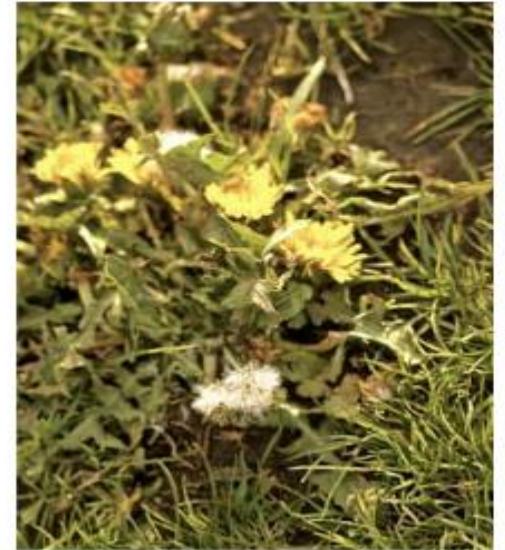
Background

- Weed management boosts crop yield by reducing competition for resources. Traditional methods are labor-intensive and inefficient for large-scale farming.
- Manual detection is often inaccurate, and excessive herbicide use harms the environment. Advanced tools for precision weed control are lacking.
- AI and ML enhance weed detection through image recognition, classify weeds efficiently, and provide tailored recommendations for effective control.
- AI systems reduce herbicide use, save time, promote sustainability, and improve crop yield.



Research problem

How can AI-based image recognition techniques be employed to develop an adaptive system that effectively identifies and classifies weeds in paddy fields, providing real-time recommendations for environmentally sustainable weed management?





Specific and Sub Objectives

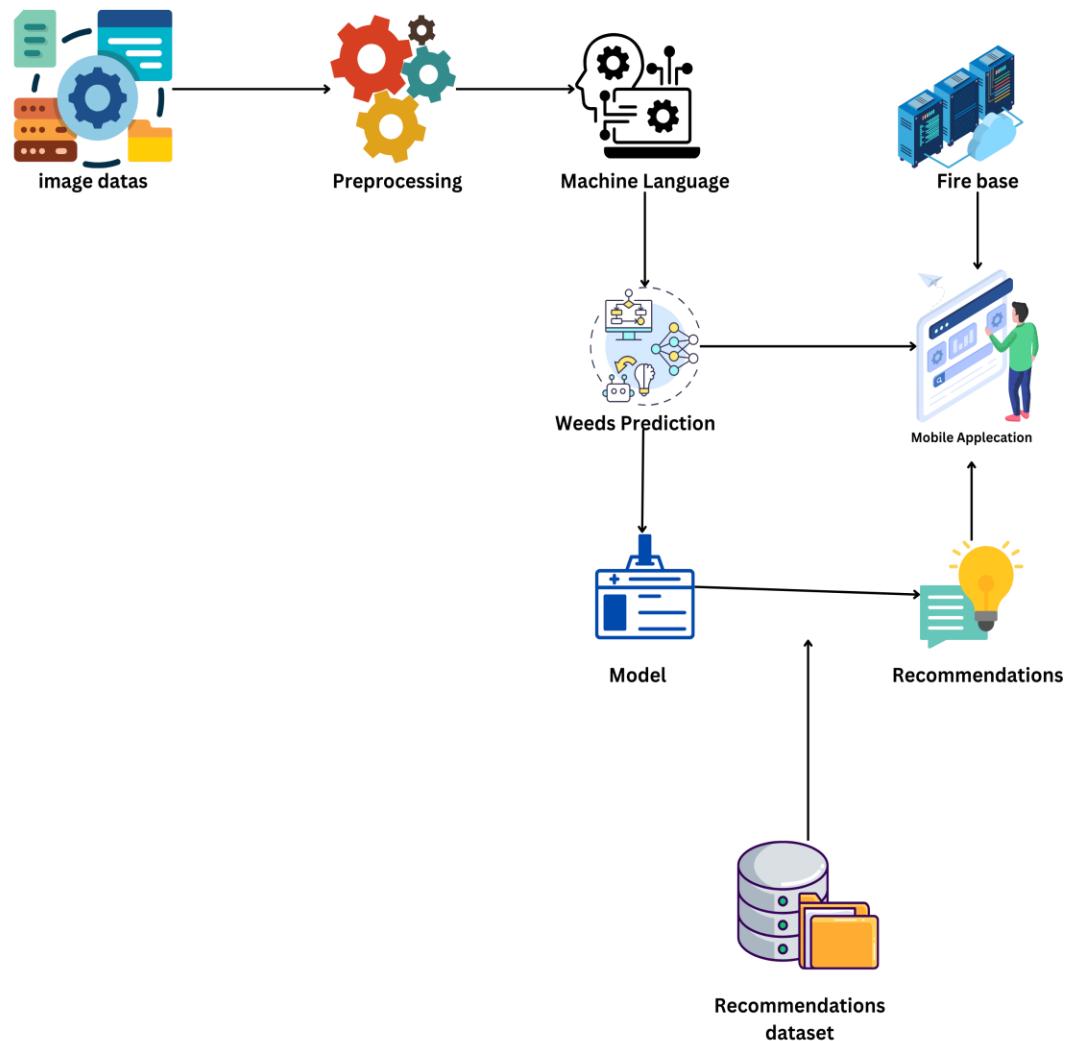
Specific Objectives

- Develop an Accurate Weed Identification Model
- Optimize for Real-Time Image Processing
- Provide Sustainable Weed Control Recommendations

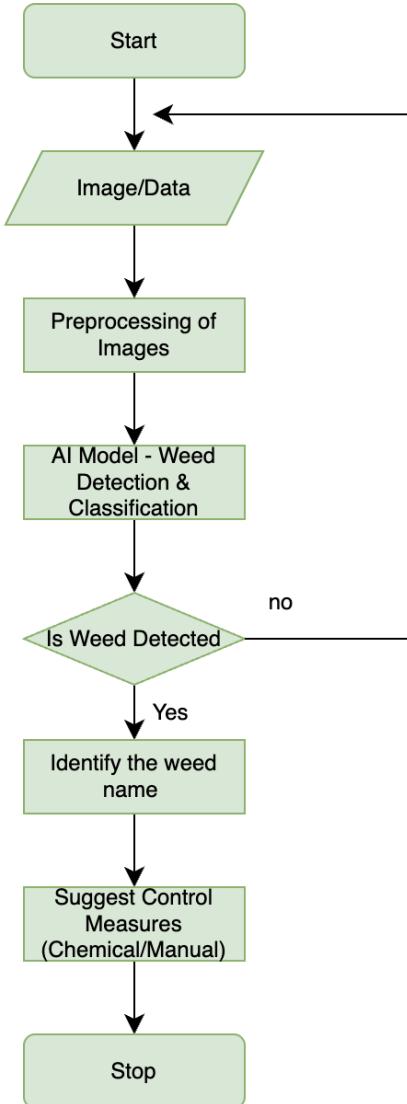
Sub-Objectives

- Data Collection & Labeling
- Model Training & Evaluation
- Cloud-Based Real-Time Alerts
- User Interface Design

System Diagram



Flow chart



Tools & Technologies



Technologies

- OpenCV, Flutter, Firebase, FastAPI , TensorFlow, VGG16

Storage

- Firebase Cloud Storage

Programming Languages

- Python (training the machine learning model)
- Dart

Functional

Identify and classify weed species from field images.

Notify farmers through the mobile app about detected weeds.

Provide real-time weed control recommendations.

Non-Functional

Fast processing

◦High availability

◦Multilingual support.



Weeds Identification System



Create an easy-to-use mobile or web app with accurate AI-based weed detection, integrating it with agricultural tools like drones or automated sprayers.

Develop the Product:



Identify target customers (farmers, agribusinesses, governments), analyze competitors, and tailor the product to meet market needs

Market Research



Offer subscription plans, freemium services, or B2B licensing to generate revenue.

Revenue Models



Collaborate with agricultural equipment manufacturers, research institutions, and government bodies.

Partnerships



Promote through case studies, digital marketing, trade shows, and referral programs.

Marketing



Scale globally with cloud technology, localize for different regions, and integrate with global agricultural data.

Global Expansion



Highlight environmental benefits by reducing herbicide use and promoting sustainable farming practices.

Sustainability

Accuracy 82.69%

The screenshot shows a code editor interface with a dark theme. The top bar displays the project name "Weeds Identification_Recommendation -- Tested -- ok" and a "Version control" dropdown. On the right, there are several icons for file operations and a "Start Free Trial" button.

The left sidebar shows a "Project" tree with the following structure:

- images
- dss.csv
- labels.csv
- temp_uploads
- augmentation.py
- Dastest.txt
- download.html
- Ludwigia parviflora502.jpg
- Ludwigia parviflora503.jpg
- Ludwigia parviflora514.jpeg

The main editor area contains the script `WeedModel_Train.py`:

```
134 # -----
135 # Save the label encoder
136 joblib.dump(label_encoder, filename: 'species_label_encoder.pkl')
137 # -----
138 # Evaluate the model
139 loss, accuracy = model.evaluate(validation_generator)
140 print(f"\nValidation Accuracy: {accuracy * 100:.2f}%")
141
142 # Print class mapping
```

The "Run" tab is selected, showing the output of the script:

```
Epoch 44: val_accuracy did not improve from 0.82692
14/14 31s 2s/step - accuracy: 0.8357 - loss: 0.4687 - val_accuracy: 0.7885 - val_loss: 0.6121
↓ Epoch 45/100
14/14 0s 2s/step - accuracy: 0.8259 - loss: 0.5305
Epoch 45: val_accuracy did not improve from 0.82692
14/14 31s 2s/step - accuracy: 0.8248 - loss: 0.5305 - val_accuracy: 0.7885 - val_loss: 0.6229
↓ Epoch 46/100
14/14 0s 2s/step - accuracy: 0.8197 - loss: 0.5199
Epoch 46: val_accuracy did not improve from 0.82692
14/14 31s 2s/step - accuracy: 0.8205 - loss: 0.5182 - val_accuracy: 0.7308 - val_loss: 0.6176
4/4 6s 1s/step - accuracy: 0.8214 - loss: 0.5619

Validation Accuracy: 82.69%
```

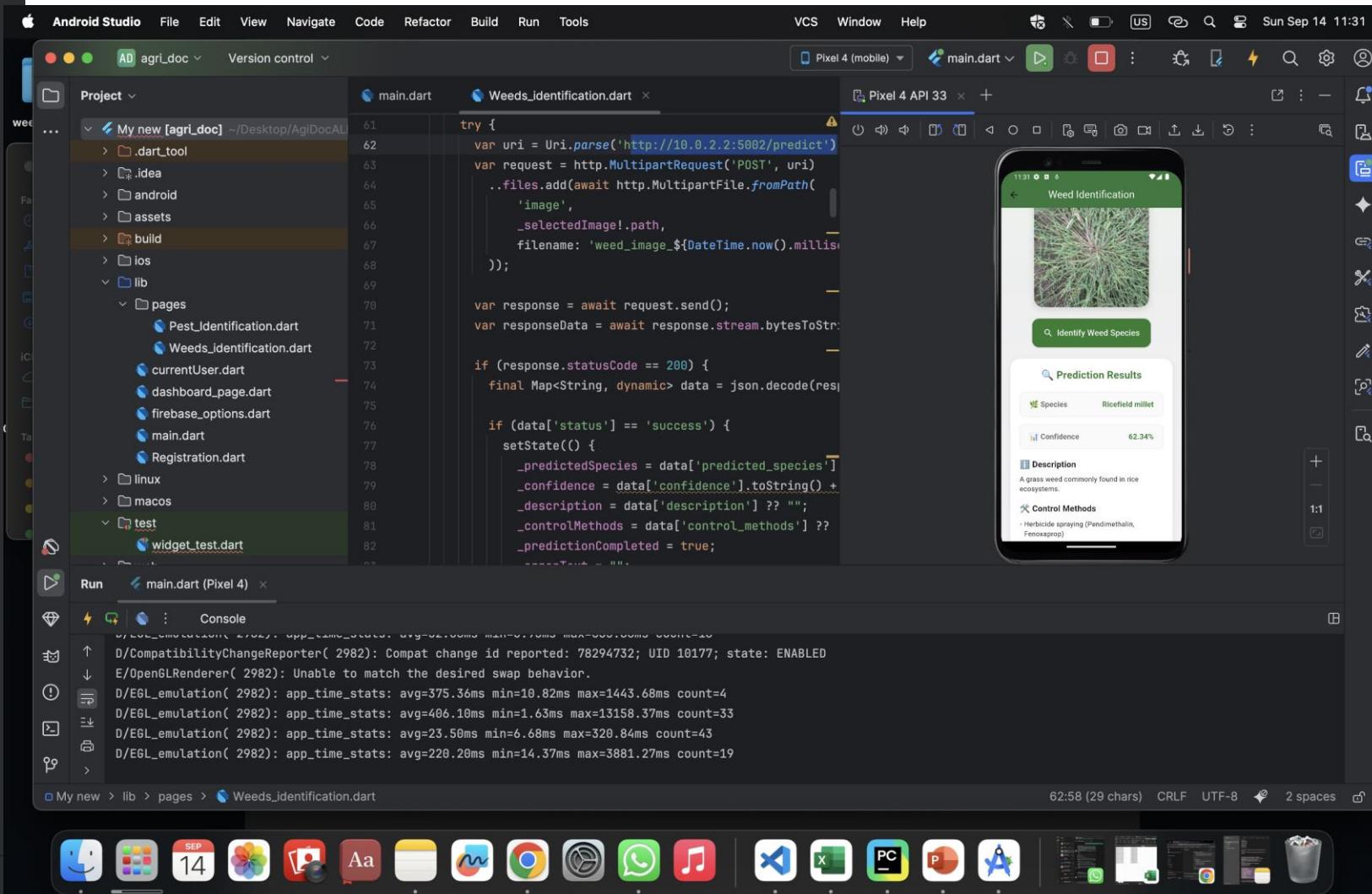
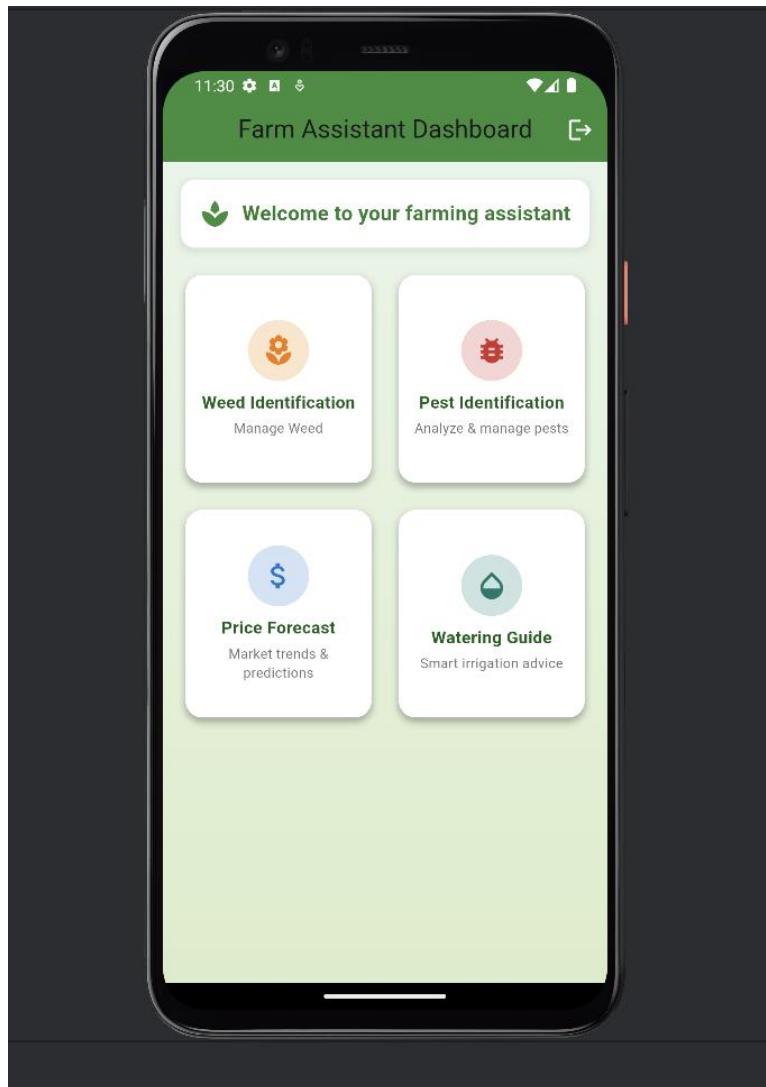
The output concludes with a "Class mapping:" section:

- 0: Barnyard grass
- 1: Bearded sprangletop
- 2: Fimbristylis miliacea
- 3: Leptochloa filiformis
- 4: Ludwigia parviflora
- 5: Negative
- 6: Ricefield millet
- 7: Smallflower umbrella sedge

At the bottom, a "Traceback (most recent call last):" section is present, though no specific error details are visible.

The status bar at the bottom shows the path "Weeds Identification_Recommendation -- Tested -- ok > WeedModel_Train.py", the current time "129:15", and the file encoding "UTF-8".

UI



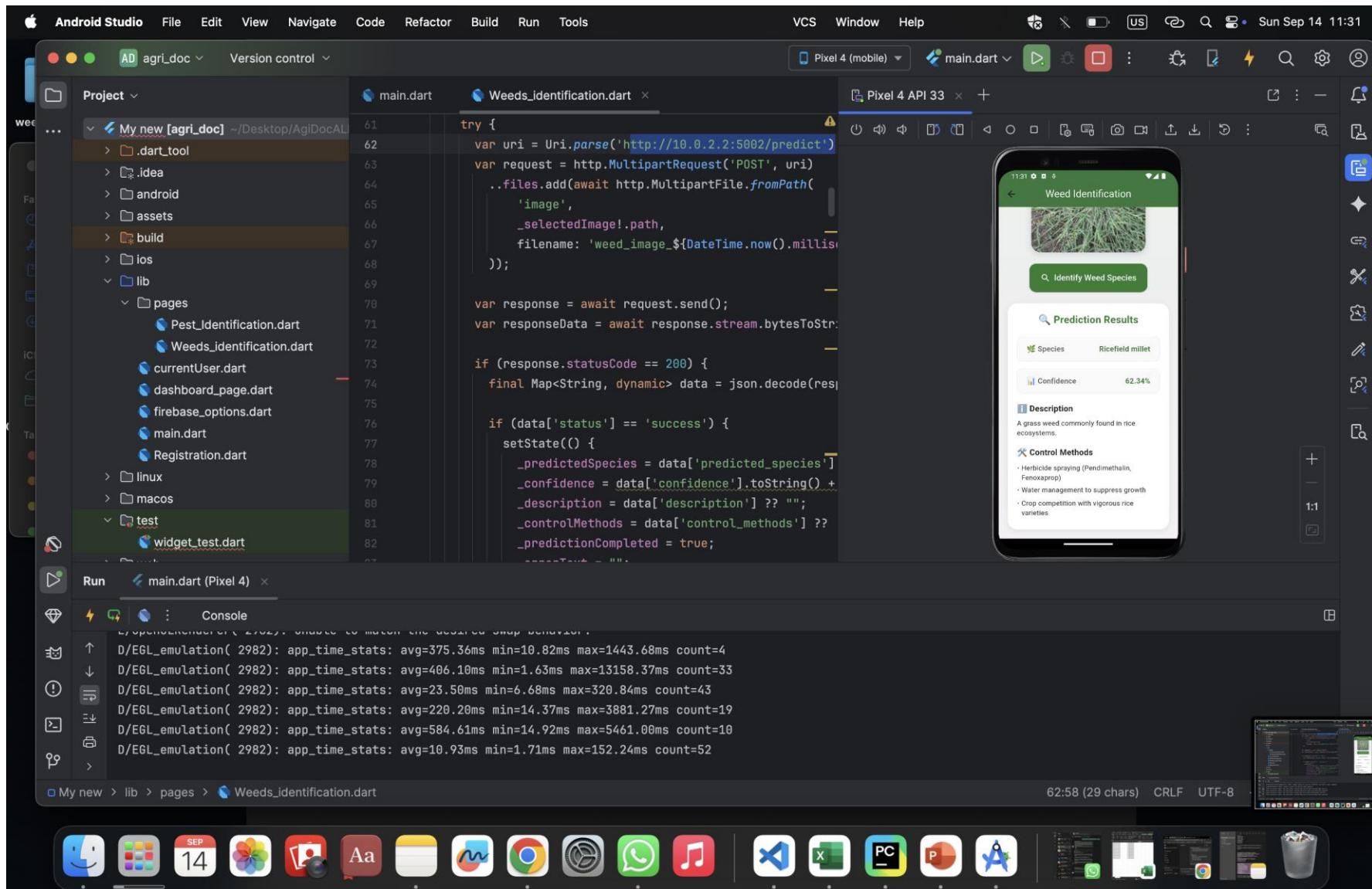
The image shows the Android Studio interface. On the left, the project structure for "My new [agri_doc]" is visible, including files like main.dart, Weeds_identification.dart, and currentUser.dart. The main.dart file is open in the center, showing Dart code for weed identification. On the right, a preview window shows a mobile application titled "Weed Identification" displaying a photograph of a plant and a "Identify Weed Species" button. Below the preview, the Android Studio toolbar and docked tools are visible.

```
try {
    var uri = Uri.parse('http://10.0.2.2:5002/predict')
    var request = http.MultipartRequest('POST', uri)
        .files.add(await http.MultipartFile.fromPath(
            'image',
            _selectedImage!.path,
            filename: 'weed_image_${DateTime.now().millisecondsSinceEpoch}');
}

var response = await request.send();
var responseData = await response.stream.bytesToString();

if (response.statusCode == 200) {
    final Map<String, dynamic> data = json.decode(responseData);
    if (data['status'] == 'success') {
        setState(() {
            _predictedSpecies = data['predicted_species'];
            _confidence = data['confidence'].toString();
            _description = data['description'] ?? '';
            _controlMethods = data['control_methods'] ?? '';
            _predictionCompleted = true;
        });
    }
}
```

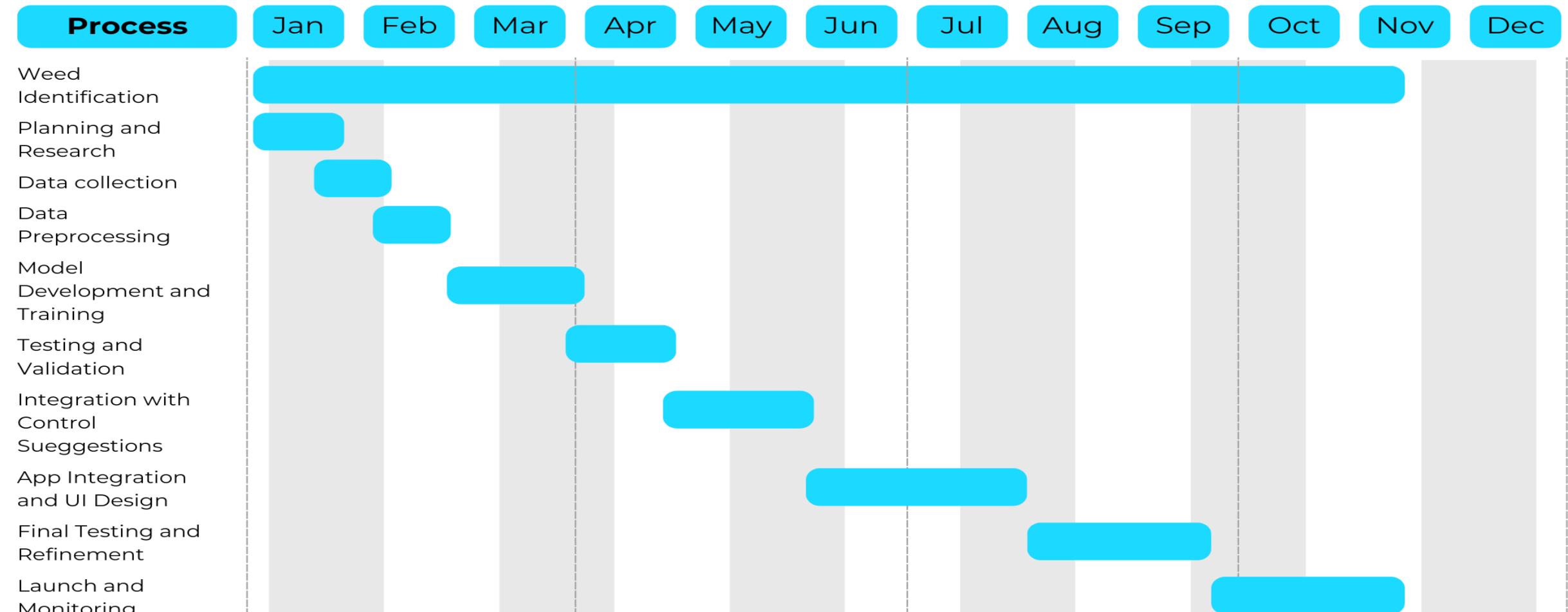
Relative Topic Suggestion





Gantt Chart

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Smart Irrigation System



"SMART" Irrigation

INTRODUCTION

- Agriculture is a cornerstone of Sri Lanka's economy, with paddy farming being one of the primary crops cultivated.
- Irrigation is essential for paddy farming, but traditional methods are often inefficient, relying on fixed schedules rather than real-time water needs.
- Global efforts in smart agriculture have demonstrated the potential of IoT and machine learning in optimizing irrigation systems, yet these technologies are underutilized in Sri Lanka.





Research gaps

Technological Gaps

- Current systems lack real-time monitoring of environmental and soil conditions.
- Limited use of machine learning models to predict irrigation needs based on data trends and environmental factors.

Farmer Adoption Challenges

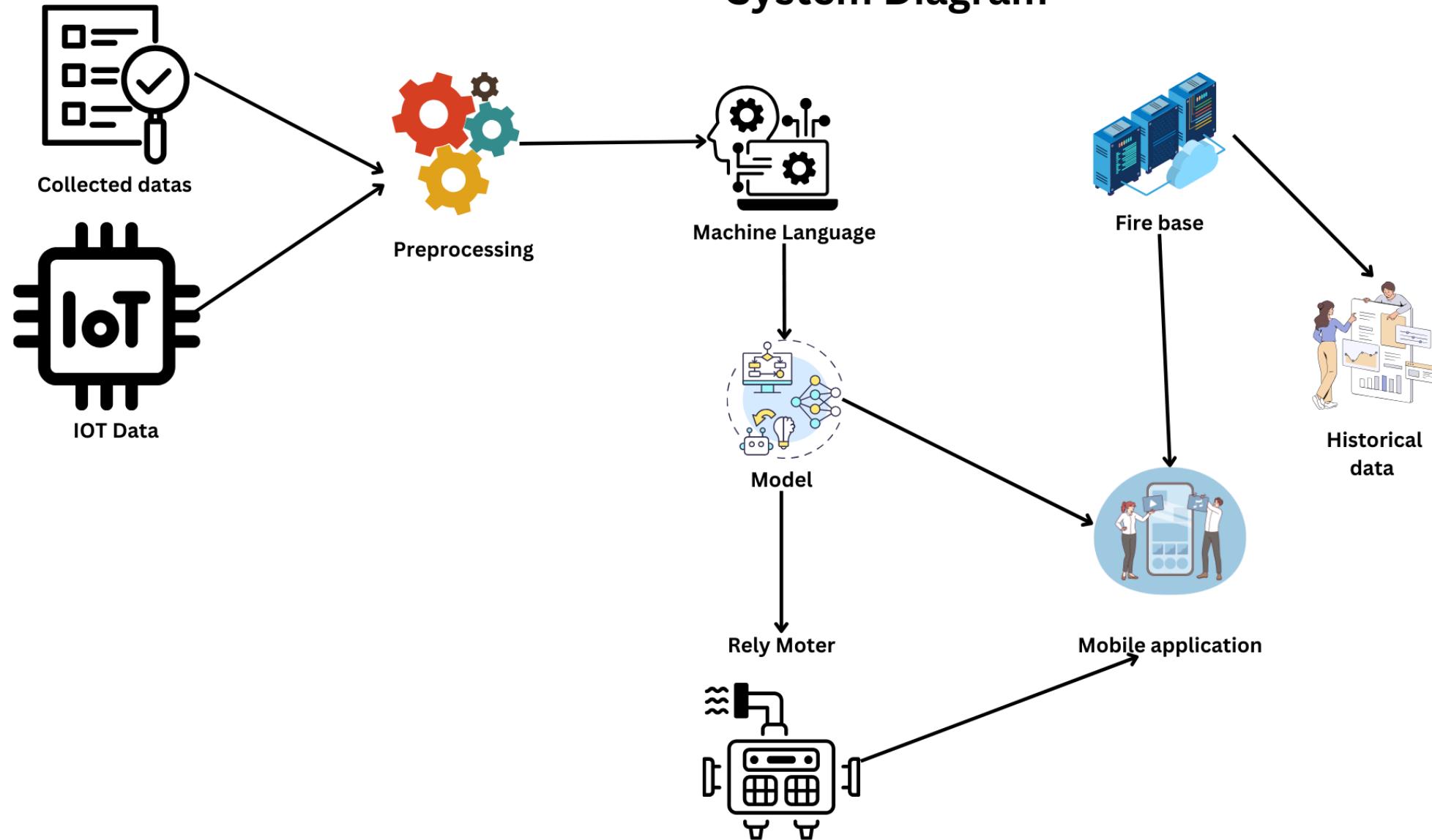
- Most existing solutions are either too complex or expensive for local farmers to adopt.
- Lack of mobile-friendly platforms tailored to Sri Lankan farmers' needs and literacy levels.

Localized Solutions

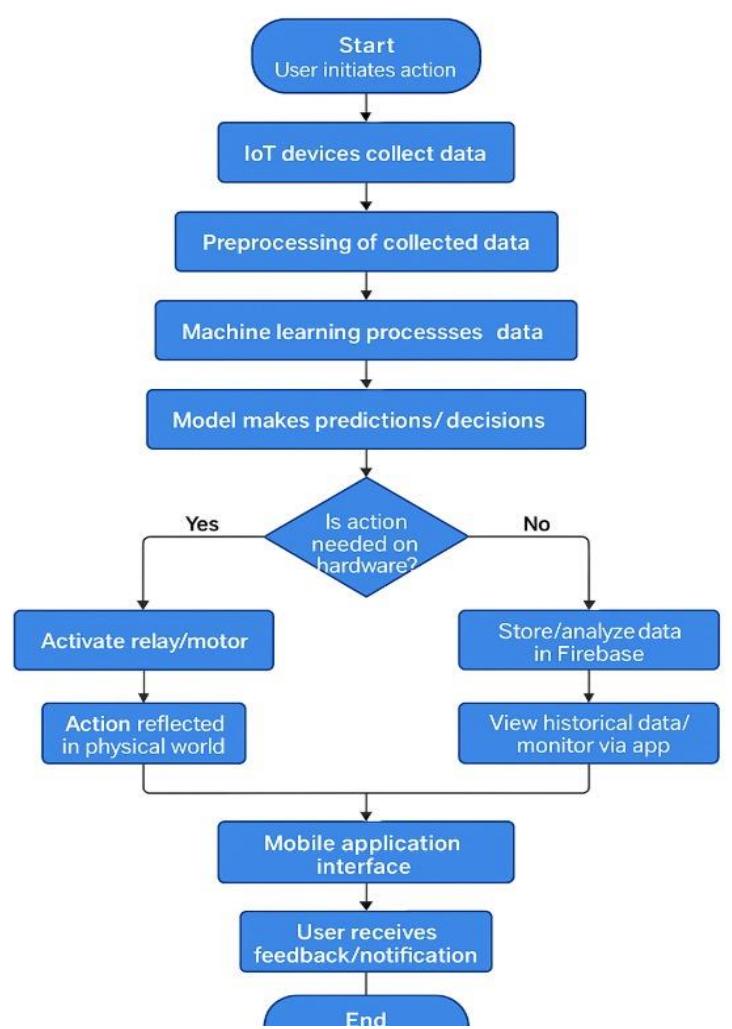
- Few solutions address the unique environmental and socio-economic conditions of Sri Lankan paddy fields, such as tank irrigation systems and irregular rainfall



System Diagram



Flow chart



System Requirements



Hardware

Server: Intel Core i5, 8GB RAM, 500GB SSD, high-speed internet.

Mobile Devices:
Android/iOS, 2GB RAM,
50MB storage



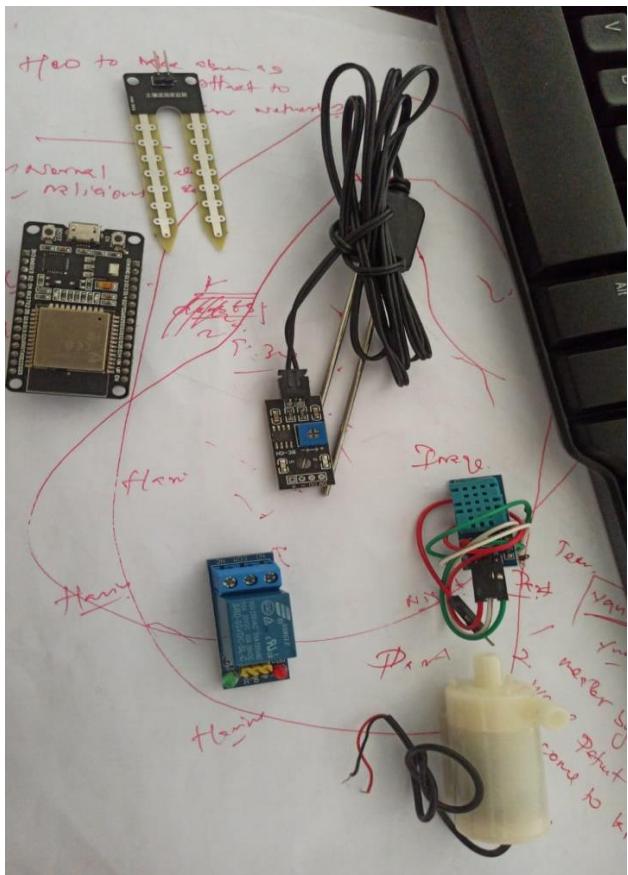
System Administrator,
Data Analyst, Software
Developer.



Development: Python, Dart, MySQL, Android Studio.
Machine Learning:
Supervised Learning
Visualization: Chart.js.
API Integration: RESTful APIs for real-time data.



Key Technologies



Internet of Things (IoT)

Utilizes wireless sensor networks for continuous monitoring of soil moisture and other environmental parameters.

Machine Learning

Develops predictive models to analyze data and provide accurate irrigation recommendations.

Using python

Cloud Computing

Enables secure data storage, analysis, and communication between system components.

Mobile App

Provides farmers with a user-friendly interface to access real-time data, irrigation schedules, and system alerts.

Using flutter

Commercialization Strategy



1 Target Audience

Paddy farmers, agricultural cooperatives, and government agencies involved in promoting sustainable farming practices.



2 Value Proposition

Reduced water consumption, increased crop yields, and improved profitability for farmers, while promoting sustainable agriculture.



3 Marketing & Sales

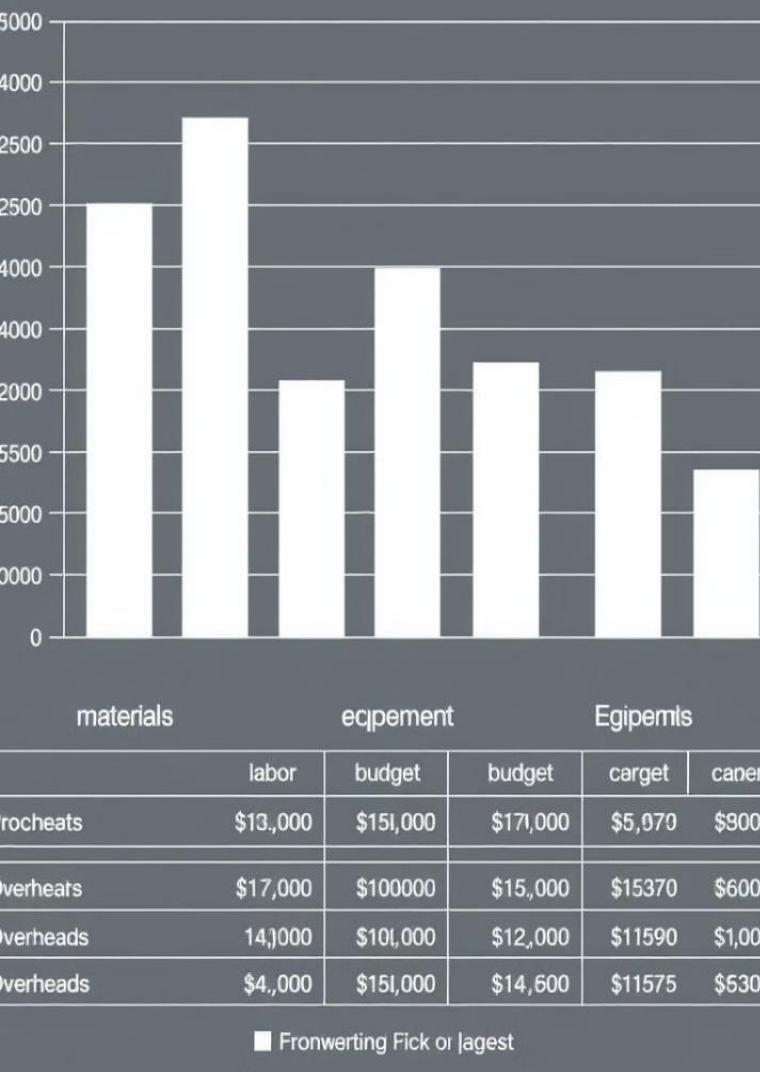
Targeted marketing campaigns, partnerships with agricultural organizations, and demonstrations in pilot paddy fields.



4 Pricing Strategy

Subscription-based model with flexible pricing plans tailored to the specific needs of different farmer groups.





Budget & Funding

35k

Development Costs

Hardware, software,
and development
team expenses.

500K

Marketing & Sales

Marketing
campaigns,
partnerships, and
training programs.

25k

Pilot Deployment
System deployment
costs and farmer
training.

Prediction screen shot

The screenshot shows the PyCharm IDE interface with the following details:

- Project:** my project [IoT-Based Automated System] C:\Users\V.Asvika
- Files:** Train.py, Predict.py, soil_watering_data.csv, watering_duration_model.pkl, watering_scaler.pkl
- Panels:**
 - Editor:** Displays the Predict.py script. The code defines a predict_watering function that loads a model and scaler, handles FileNotFoundError, creates features, scales them, and makes predictions based on soil moisture, temperature, and humidity.
 - Run:** Shows the output of the Predict.py run, which includes a list of predictions for different soil conditions.
- Terminal:** Shows the command used to run the script and the resulting output.
- Status Bar:** Shows the current time (28:48), encoding (CRLF), file encoding (UTF-8), indentation (4 spaces), Python version (Python 3.8), and a copy icon.

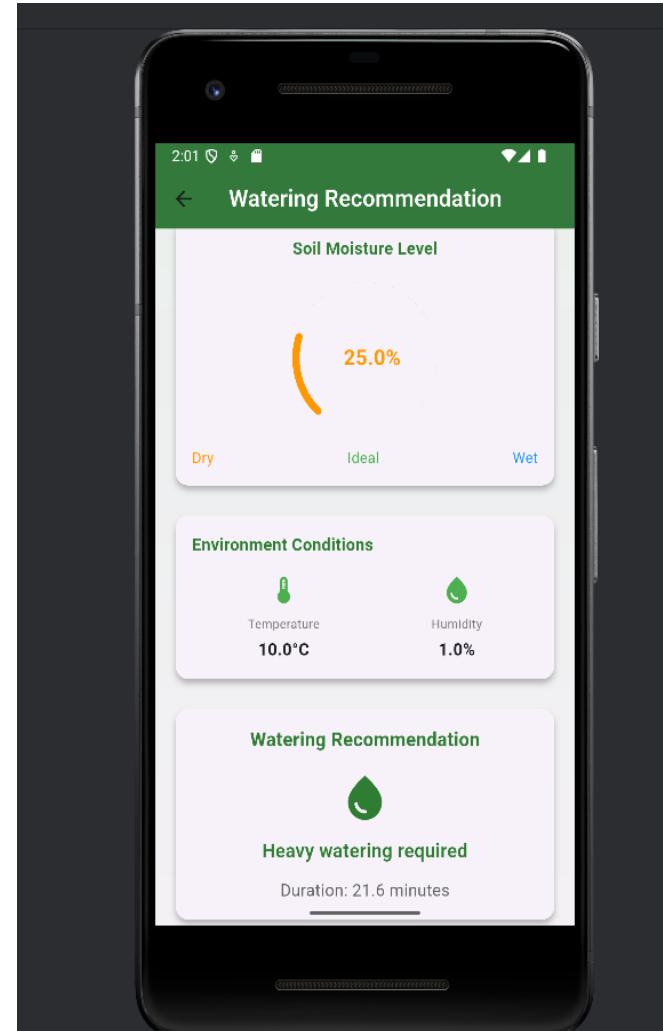
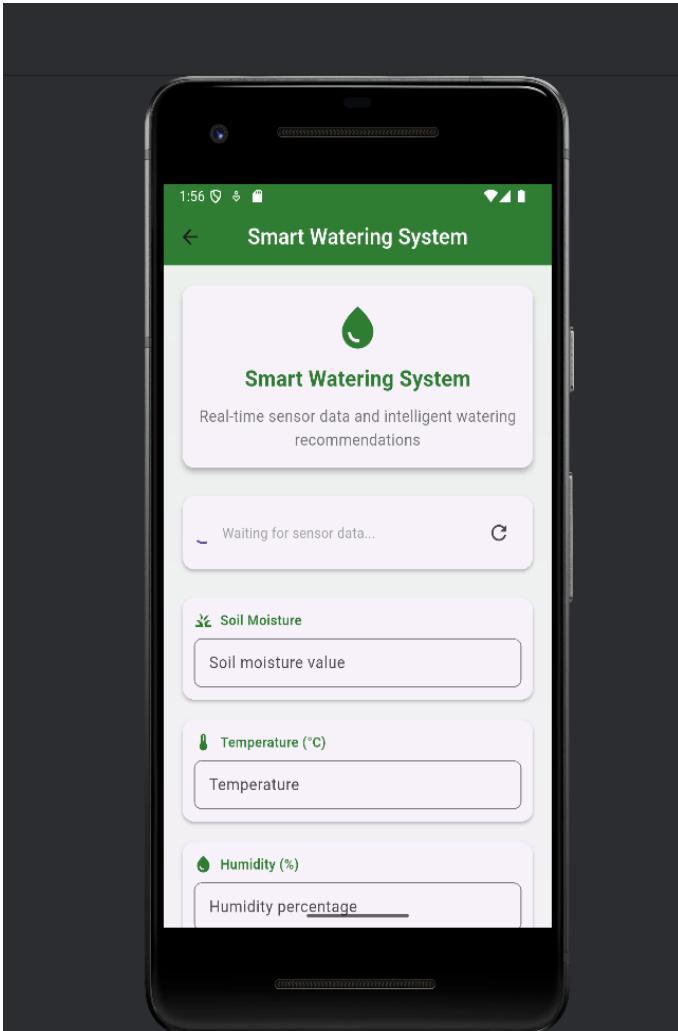
Arduino readings

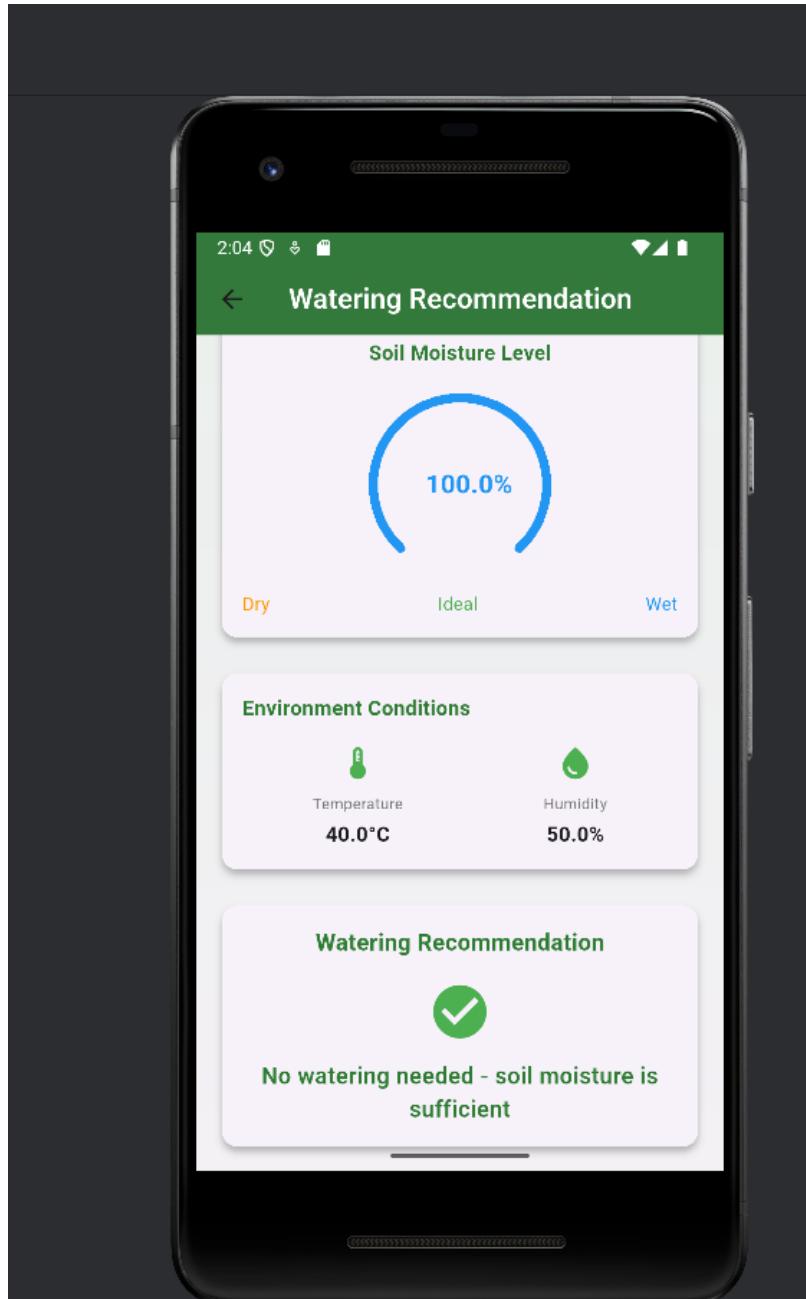
The screenshot shows the Arduino IDE interface with a dark theme. The top menu bar includes File, Edit, Sketch, Tools, and Help. A toolbar below the menu contains icons for saving, running, and connecting. The sketch name is "sketch_apr7a.ino". The code reads environment temperature and humidity from DHT sensors and soil moisture from an analog pin, printing the results to the Serial Monitor. The Serial Monitor window shows the output of the code, including sensor values and a progress bar for package download.

```
sketch_apr7a | Arduino IDE 2.0.4-nightly-20230216
File Edit Sketch Tools Help
✓ → ⚙️ ESP32 Dev Module
sketch_apr7a.ino
51     } else {
52         Serial.println("Error: Failed to read from DHT sensor");
53     } else {
54         Serial.print("Environment Temperature: ");
55         Serial.print(envTemperature);
56         Serial.println(" °C");
57         Serial.print("Environment Humidity: ");
58         Serial.print(humidity);
59         Serial.println(" %");
60     }
61
62     // Read soil moisture value
63     int soilMoistureValue = analogRead(soilSensorPin);
64     Serial.print("Soil Moisture Level: ");
65     Serial.println(soilMoistureValue);
66
67     Serial.println("-----");
68
69
70     delay(2000);
71 }

Output Serial Monitor ×
Message (Enter to send message to 'ESP32 Dev Module' on 'COM3')
Soil Temperature: 28.30 °C
Environment Temperature: 28.30 °C
Environment Humidity: 68.00 %
Soil Moisture Level: 4095
-----
Soil Temperature: 28.44 °C
Environment Temperature: 28.30 °C
Environment Humidity: 68.00 %
Soil Moisture Level: 4095
-----
Soil Temperature: 28.44 °C
New Line 115200 baud
Downloading index: package_esp8266com_index.json
Ln 47, Col 37 ESP32 Dev Module on COM3 21:01 07/04/2025
28°C Mostly cloudy Search 🐥 Google Folder Spotify WhatsApp PDF 🚧 10/21/2025 54
```

Mobile application user Interface

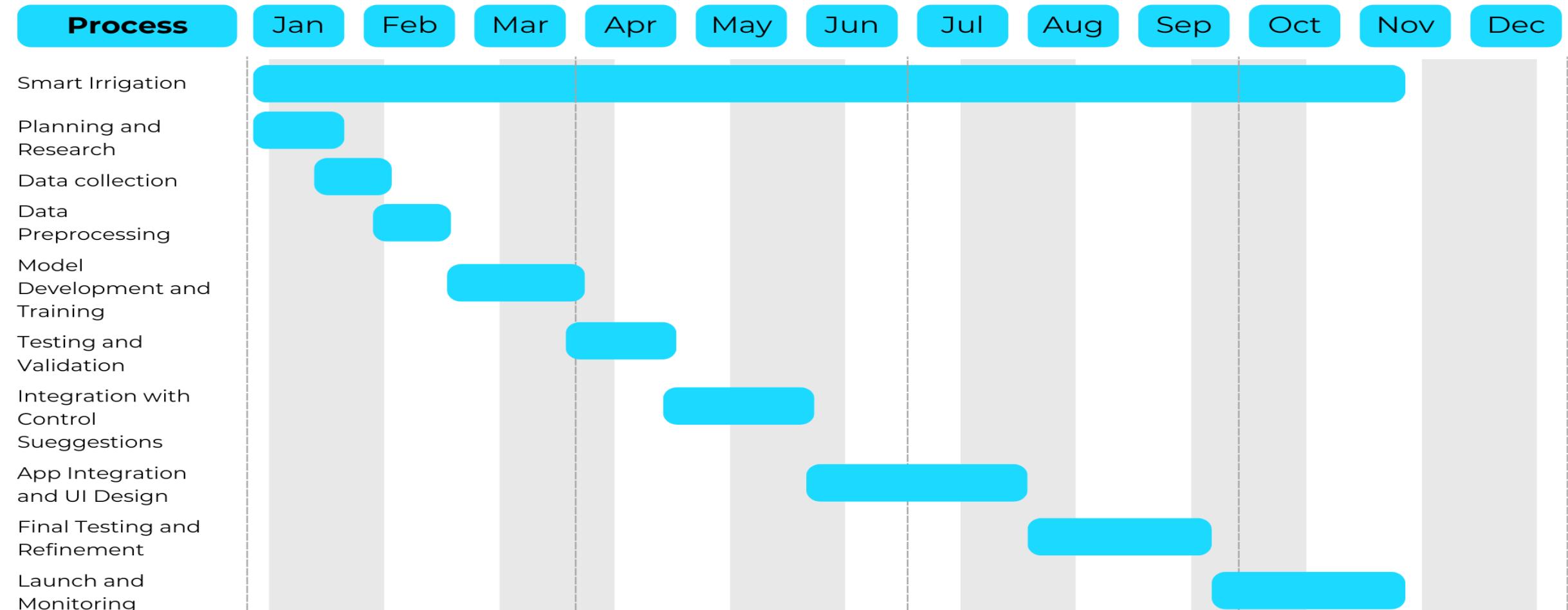






Gantt Chart

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IT21813320 | A.SHIVAPHIRIYAN

BSc (Hons) Information Technology Specializing in Information Technology

PEST IDENTIFICATION & CONTROL



Introduction

This research project focuses on developing a pest identification and control system for paddy farmers. It leverages image processing and machine learning to identify pests, determine severity, and recommend suitable fertilizers. The system is designed to support sustainable farming through timely and accurate decision-making.



Research Problem

Paddy cultivation in Sri Lanka is heavily impacted by pest infestations, yet most small-scale farmers lack access to timely and accurate pest identification methods. Traditional approaches are manual, depend on expert knowledge, and often result in delays in diagnosis and improper use of fertilizers. This leads to reduced crop yield, overuse of chemicals, and long-term soil degradation.





Research Gap

Current agricultural advisory systems lack automation in pest detection, struggle with accuracy in rural field conditions, and provide generalized recommendations. This project addresses these issues using AI and image analysis for tailored, real-time insights.



Objectives



Main Objective



To develop an AI-powered pest identification and control system using image processing to improve paddy farming productivity.

Sub-Objectives



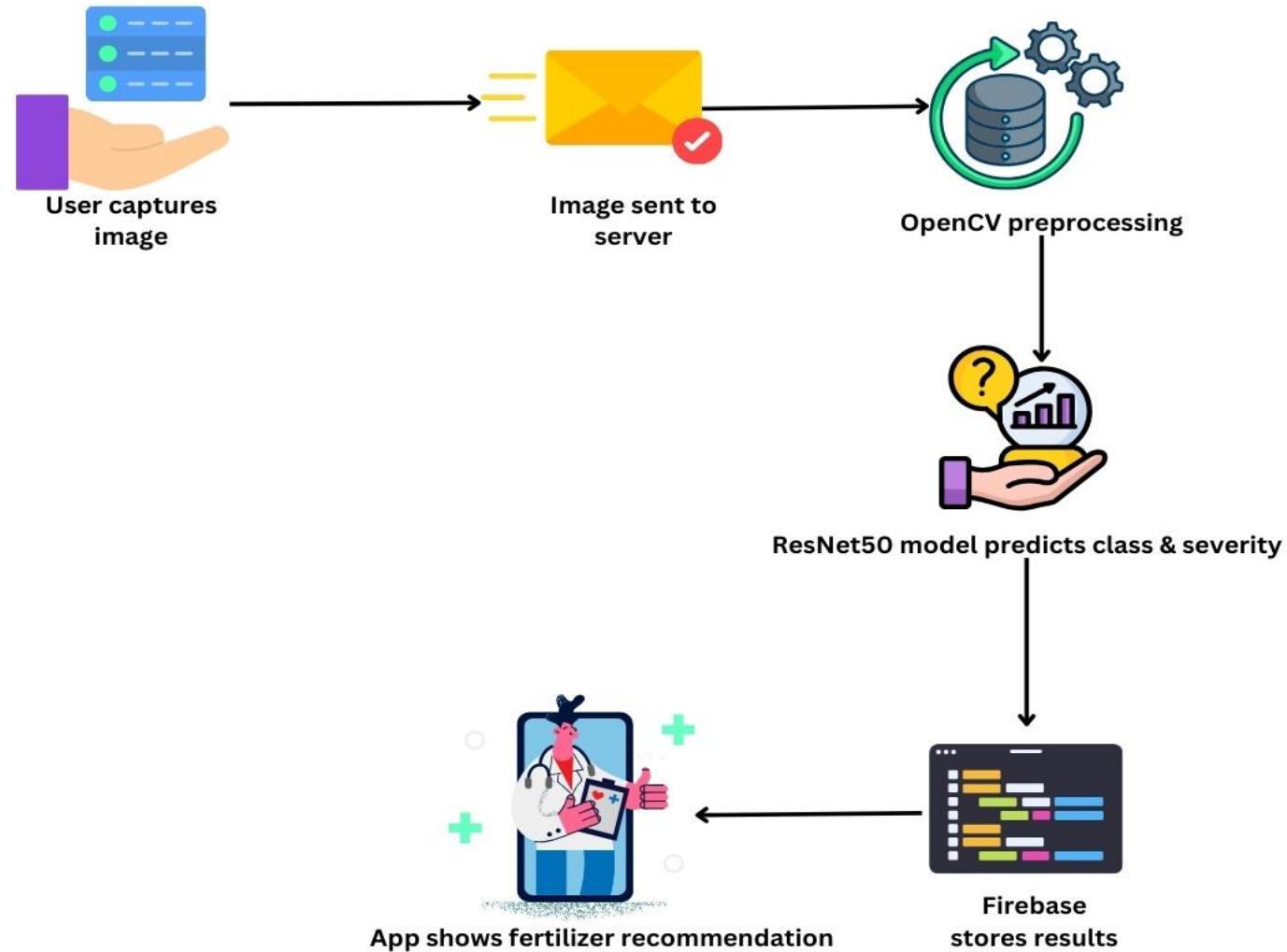
1. Identify pests and classify them as harmful or harmless.
2. Determine severity of infestation (low, mild, severe).
3. Recommend suitable fertilizers (organic or artificial).
4. Analyze leaf affliction severity for further treatment.

Project Methodology

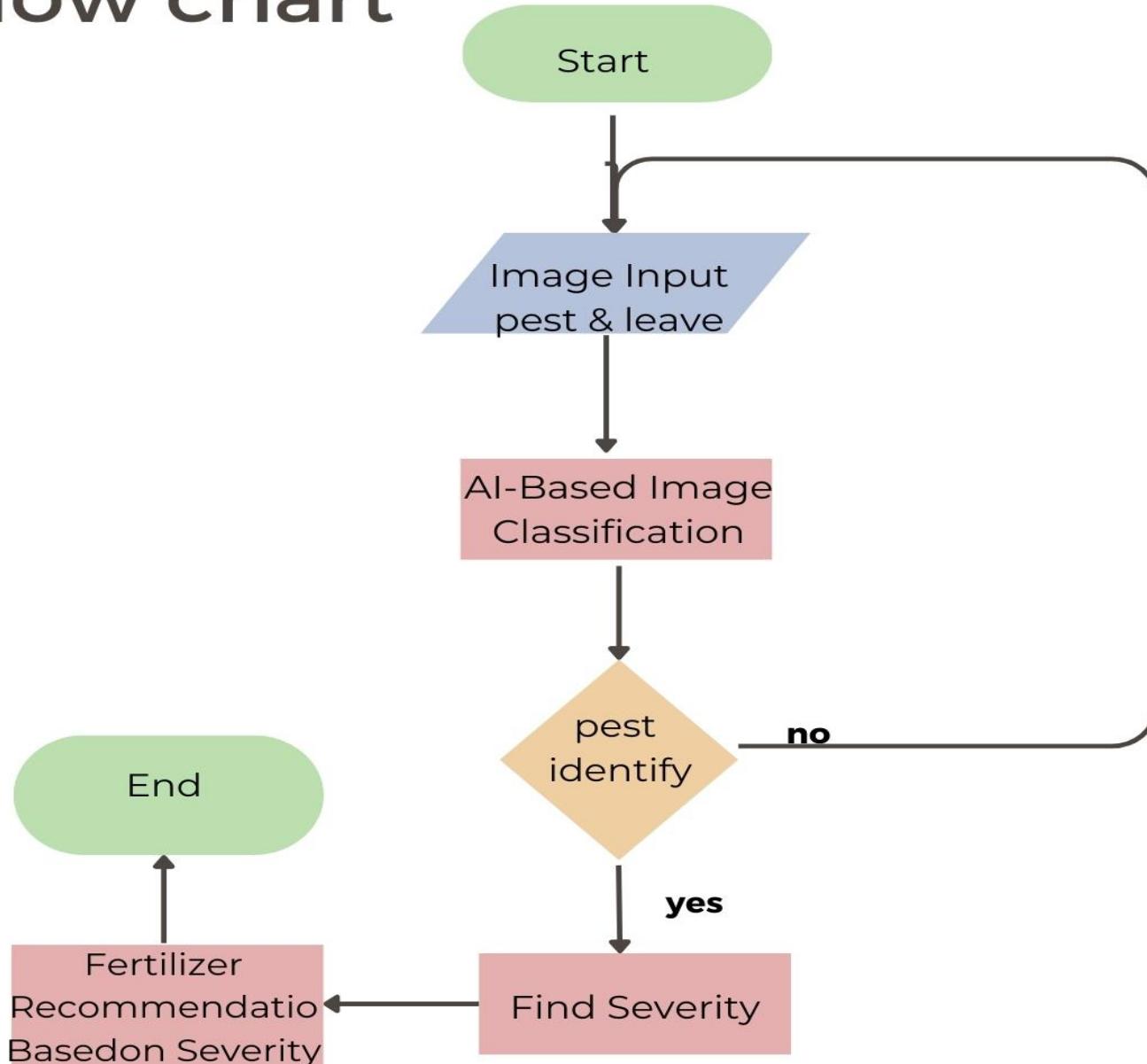
- Phase 1: Data Collection - Gather pest and leaf images from field and datasets.
- Phase 2: Image Processing - Use OpenCV for image preprocessing (resizing, noise removal).
- Phase 3: Model Training - Train ResNet50 for pest classification and severity detection.
- Phase 4: Integration - Connect trained model with a mobile-friendly backend using Python and Firebase.
- Phase 5: Evaluation - Test system accuracy and usability.



System Diagram



Flow chart



System Overview

Mobile app (Flutter) for uploading images and receiving recommendations.



Python backend handles logic and model integration.

Firebase stores images, user data, and model outputs.



System Requirements

Hardware:

- Android/iOS phone with camera
- Server: 8GB RAM, 100GB SSD, Python environment

Software:

- OpenCV for image processing
- TensorFlow with ResNet50
- Firebase for data storage and model output



Key Technologies

Frontend:

Flutter

Image Processing:

OpenCV

Model:

ResNet50 (Pretrained CNN
for classification)

Backend:

Python

Database:

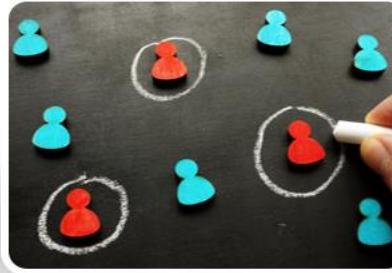
Firebase Realtime DB

ML Approach:

Supervised Learning (Image classification)



Commercialization Strategy



Target Audience:
Paddy farmers, agricultural extension officers



Value Proposition:
Fast, accurate pest detection and tailored fertilizer guidance



Marketing:
Farmer workshops, extension programs, digital outreach



Pricing:
Freemium app with paid tier for detailed analytics and offline features

ResNet50 Model (accuracy-15%-30%)

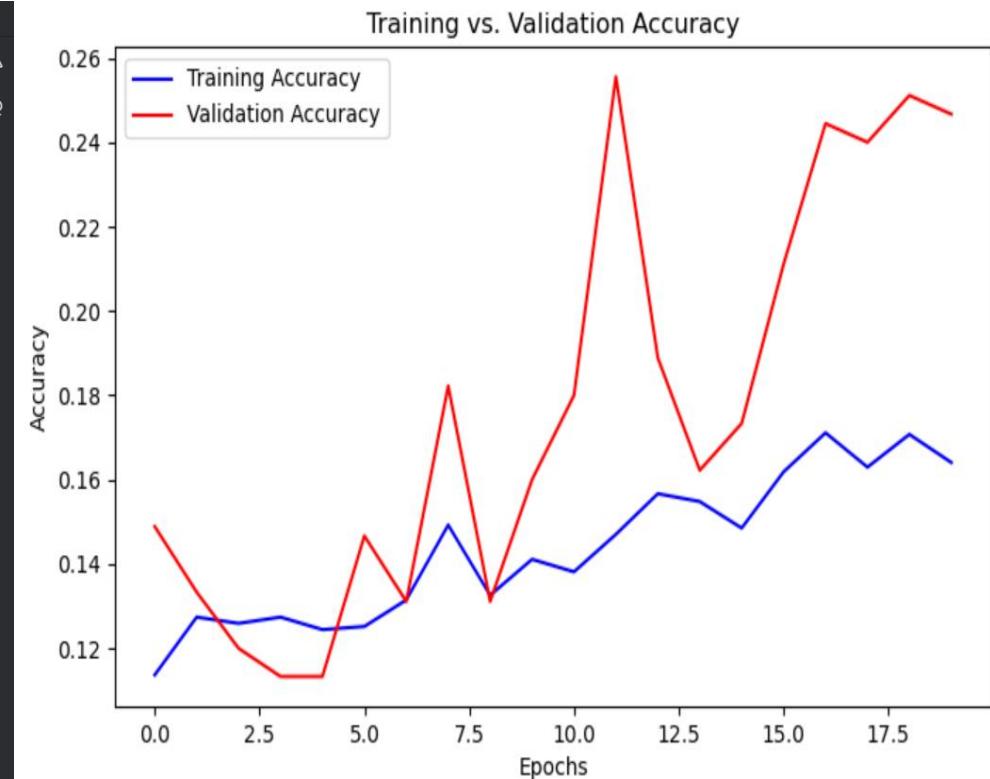
The screenshot shows the PyCharm IDE interface. The project is named 'MyFYP [Pest Identification_Fertilizer Recommendation]'. The 'predict_image.py' file is open, containing the following code:

```
def predict_image(img_path):    # Rescale image    img_array = img_array / 255.0    predictions = pre.model.predict(img_array)    # Get the predicted    predicted_class_idx = np.argmax(predictions, axis=1)[0]    confidence_score = np.max(predictions, axis=1)[0]    return predicted_class_idx, confidence_score
```

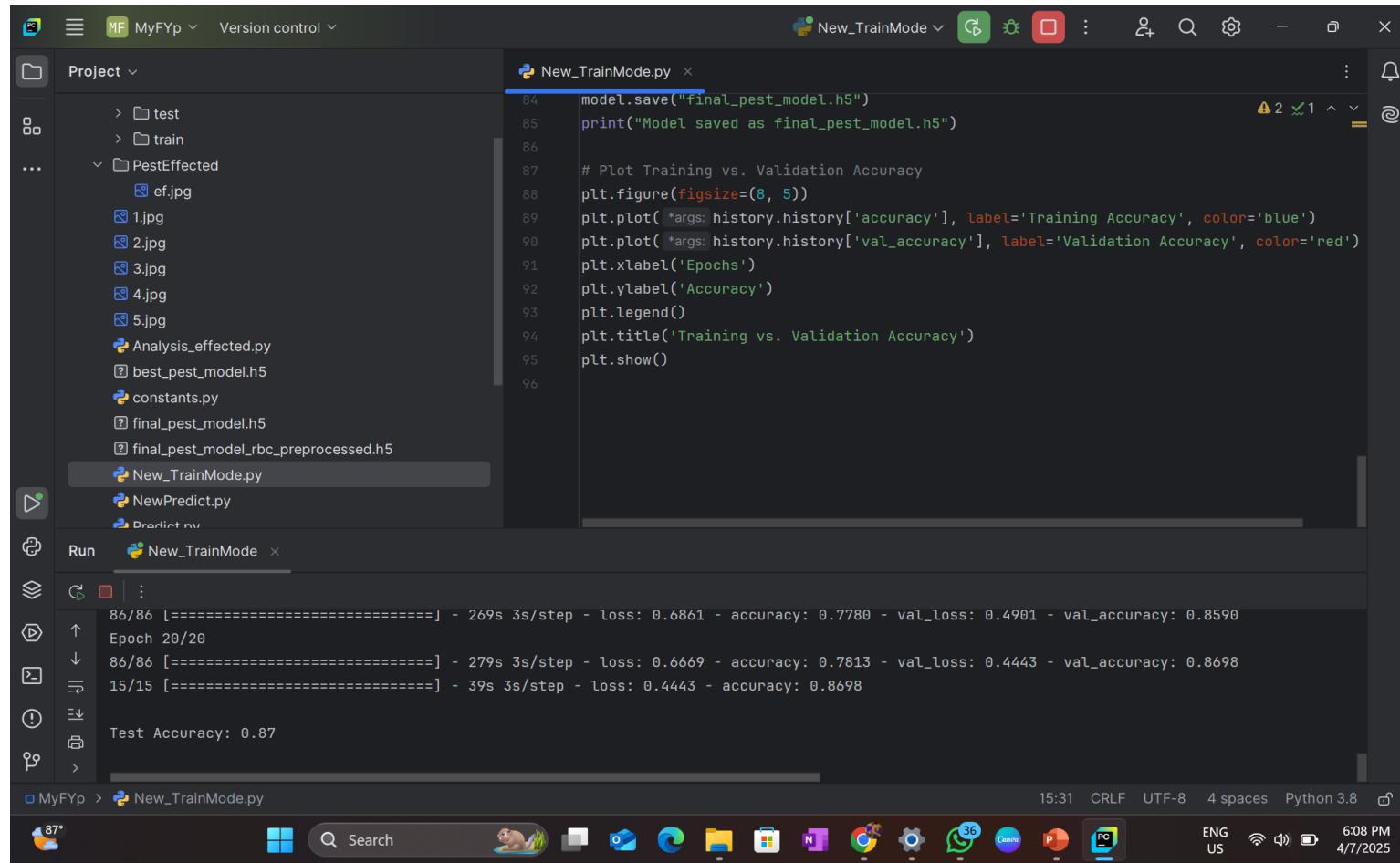
The 'Run' tab shows the command 'TrainMode_Pest' and the output window displays training logs:

```
Epoch 27/150  
7/7 [=====] - 10s 1s/step - loss: 2.3801 - accuracy: 0.1000 - val_loss: 2.3628 - val_accuracy: 0.1273  
2/2 [=====] - 2s 827ms/step - loss: 2.3491 - accuracy: 0.1455  
Test Accuracy: 0.15  
Model saved as final_pest_model.h5
```

The status bar at the bottom shows the time as 18:34, date as 4/6/2025, and Python version as 3.8.



VGG16 Model(accuracy-87%)



The screenshot shows a code editor window with a Python script named `New_TrainMode.py`. The script includes code to save a model and plot training and validation accuracy. The terminal below shows the execution of the script, displaying training and validation metrics across 20 epochs. The status bar at the bottom indicates the system is running at 87% CPU usage.

```
model.save("final_pest_model.h5")
print("Model saved as final_pest_model.h5")

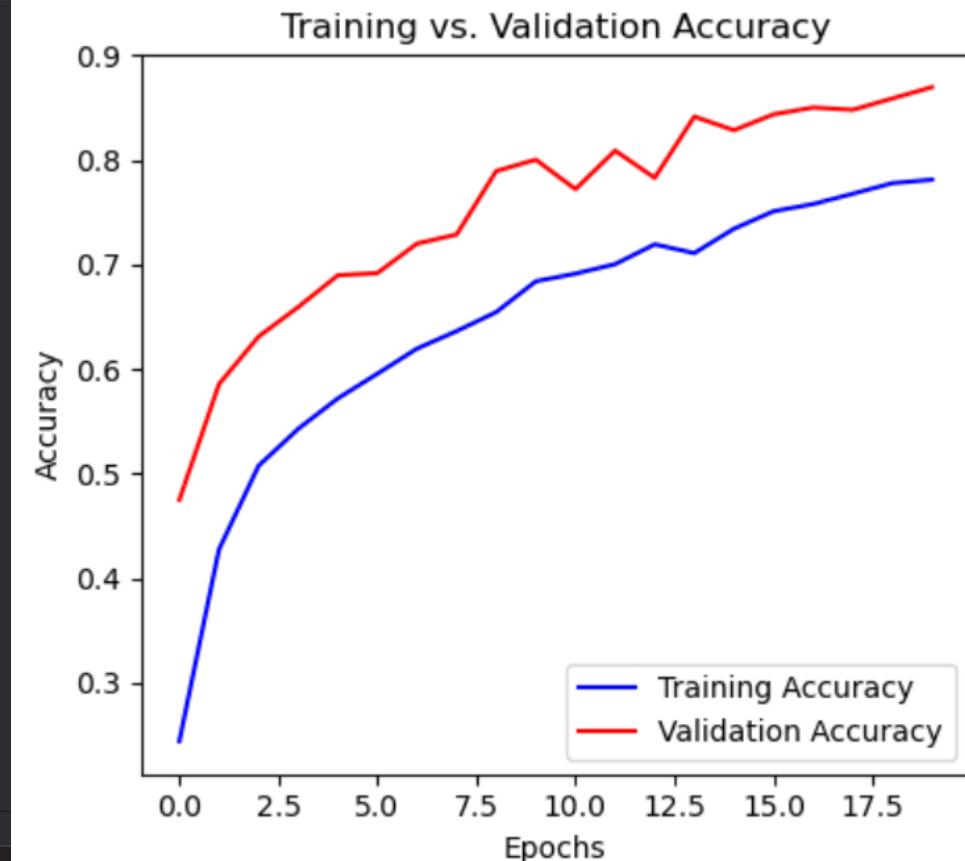
# Plot Training vs. Validation Accuracy
plt.figure(figsize=(8, 5))
plt.plot(args.history.history['accuracy'], label='Training Accuracy', color='blue')
plt.plot(args.history.history['val_accuracy'], label='Validation Accuracy', color='red')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.title('Training vs. Validation Accuracy')
plt.show()
```

```
86/86 [=====] - 269s 3s/step - loss: 0.6861 - accuracy: 0.7780 - val_loss: 0.4901 - val_accuracy: 0.8590
Epoch 20/20
86/86 [=====] - 279s 3s/step - loss: 0.6669 - accuracy: 0.7813 - val_loss: 0.4443 - val_accuracy: 0.8698
15/15 [=====] - 39s 3s/step - loss: 0.4443 - accuracy: 0.8698
Test Accuracy: 0.87
```

87%

15:31 CRLF UTF-8 4 spaces Python 3.8

6:08 PM 4/7/2025



Pest Identification Result

The screenshot shows a Windows desktop environment with a dark-themed IDE (PyCharm) and a terminal window.

Project Structure:

- MyFYP
- Version control
- Project
- test
- train
- PestEffected
 - ef.jpg
 - 1.jpg
 - 2.jpg
 - 3.jpg
 - 4.jpg
 - 5.jpg
- Analysis_effected.py
- best_pest_model.h5
- constants.py
- final_pest_model.h5
- final_pest_model_rbc_preprocessed.h5
- New_TrainMode.py
- NewPredict.py
- Predict.py

NewPredict.py (Code Editor):

```
1 > import ...
2
3 # Constants
4 MODEL_PATH = "final_pest_model.h5"
5 IMG_PATH = "3.jpg"
6 IMG_SIZE = (224, 224)
7 TEST_PATH = "PestDataset/test"
8
9 # Load model
10 model = tf.keras.models.load_model(MODEL_PATH)
11 print("Model loaded successfully.")
12
13 # Get class names from folder structure
14 class_names = sorted(os.listdir(TEST_PATH))
15 class_names = [folder for folder in class_names if folder != "test"]
16 print(f"Classes detected: {class_names}")
17
18 # Load and preprocess the image
19
20
21
22
```

Terminal Output:

```
2025-04-07 18:11:45.413597: I tensorflow/stream_executor/cuda/cuda_diagnostics.cc:176] host
2025-04-07 18:11:45.414074: I tensorflow/core/platform/cpu_feature_guard.cc:151] This Tensor
To enable them in other operations, rebuild TensorFlow with the appropriate compiler flags.
Model loaded successfully.
Classes detected: ['aphids', 'armyworm', 'beetle', 'bollworm', 'grasshopper', 'mites', 'mosquito', 'sawfly', 'stem_borer']
Predicted Class: armyworm
```

Figure 1 (Prediction Window):

Prediction: armyworm

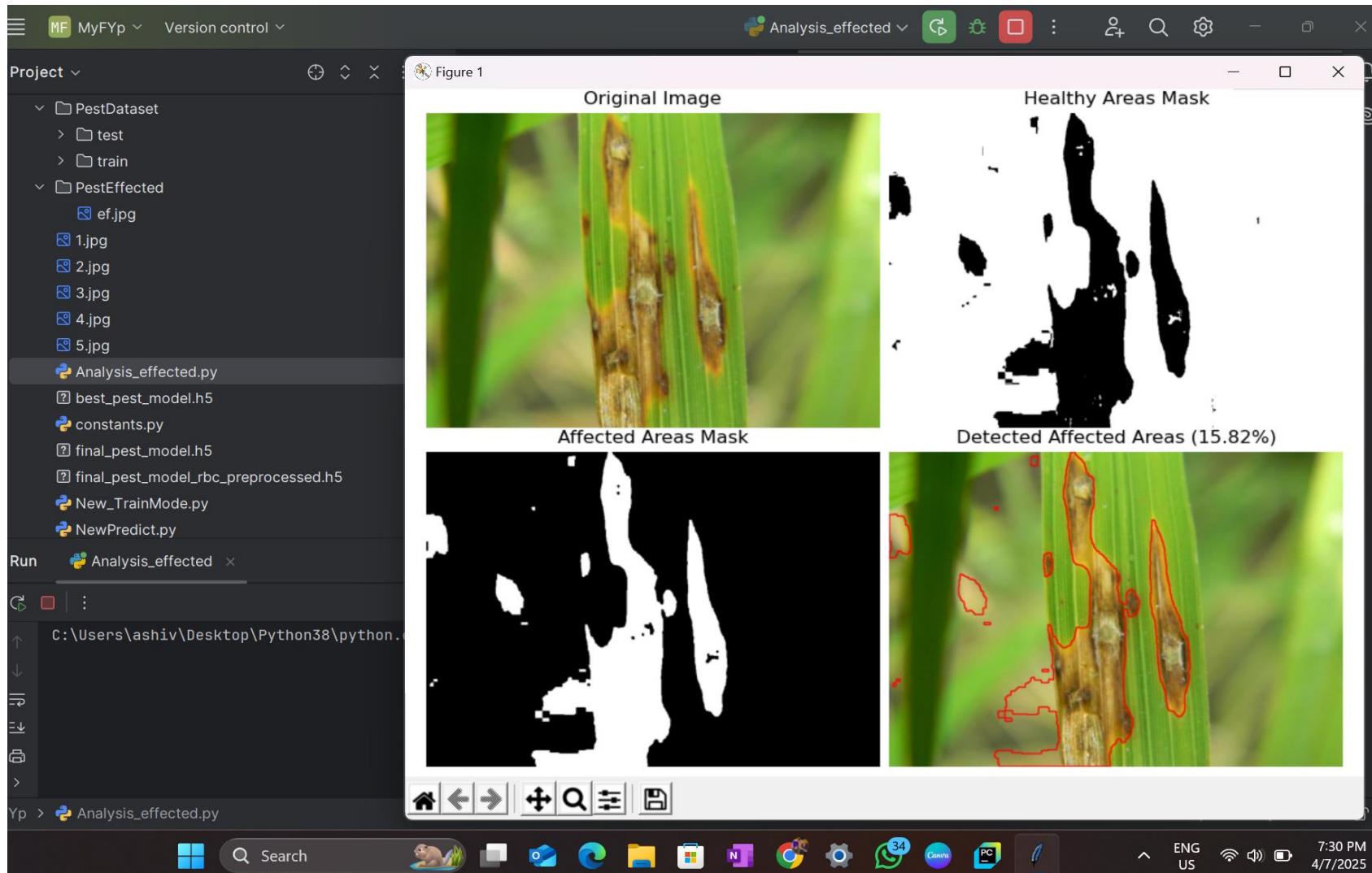


The figure shows a caterpillar with a segmented body, greenish-yellow with darker stripes, crawling on a green plant stem against a blurred background.

```
Model loaded successfully.

Classes detected: ['aphids', 'armyworm', 'beetle', 'bollworm',
Predicted Class: armyworm )
```

Effected Leaves Results (with Severity Level)



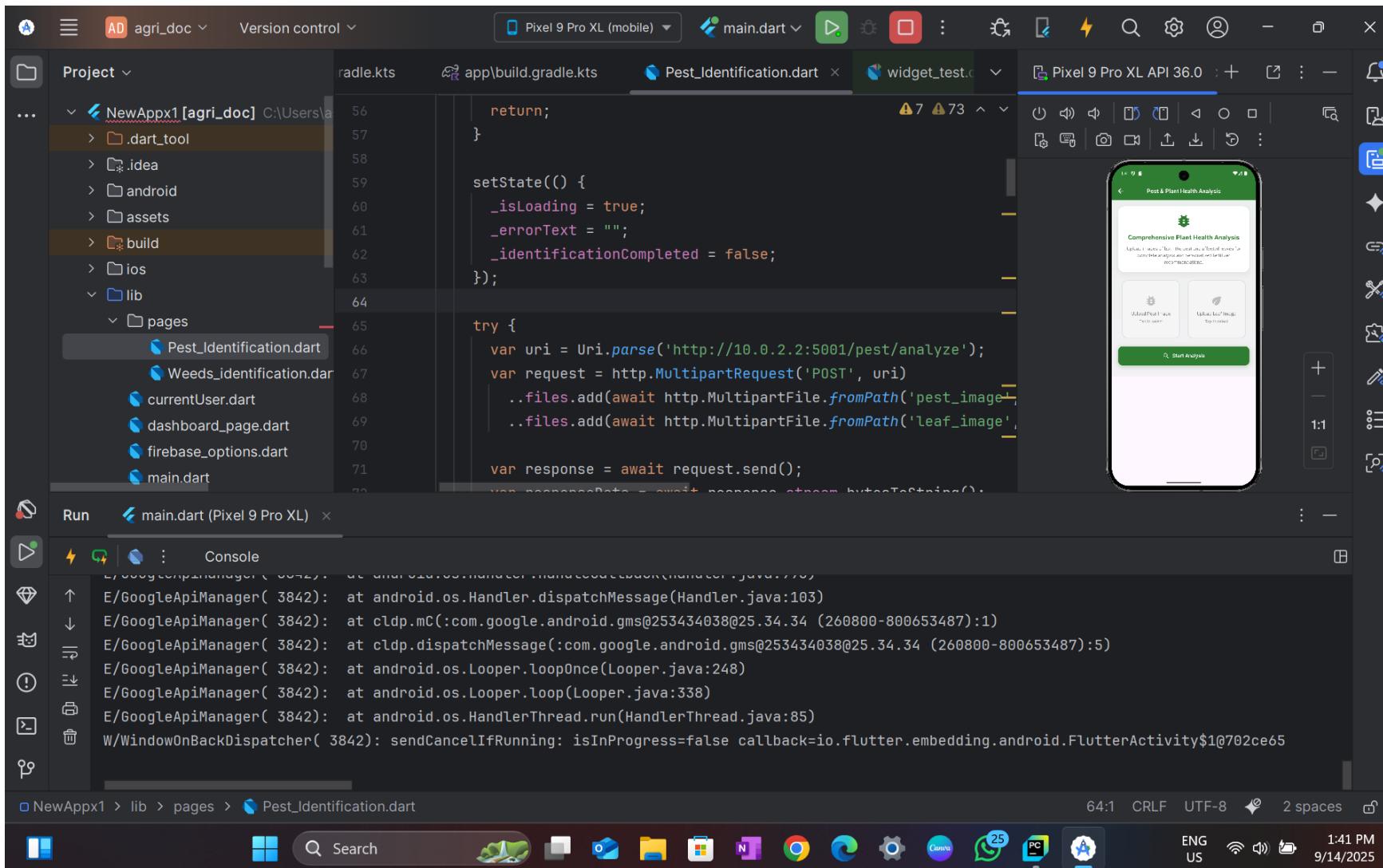
1. OpenCV preprocessing

Used to identify and segment affected areas on leaves

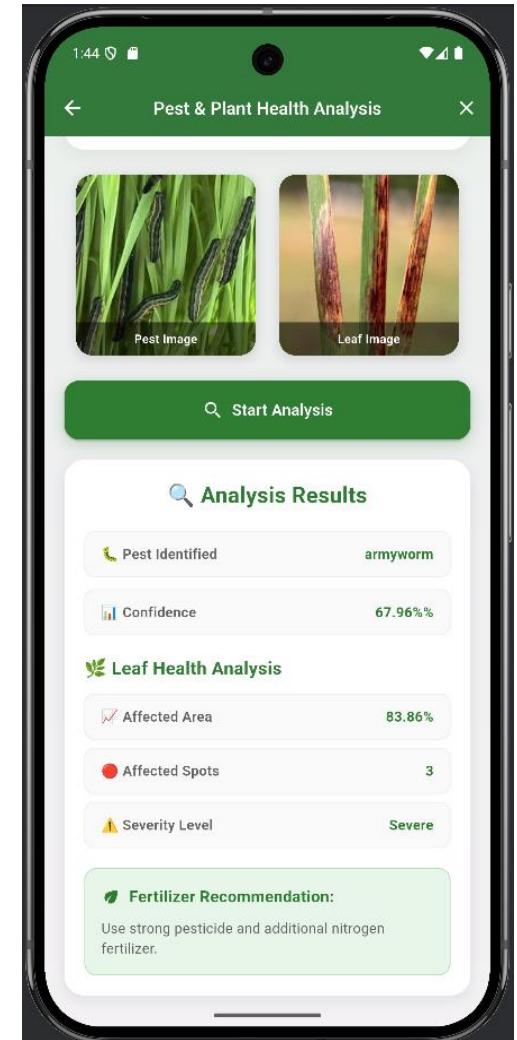
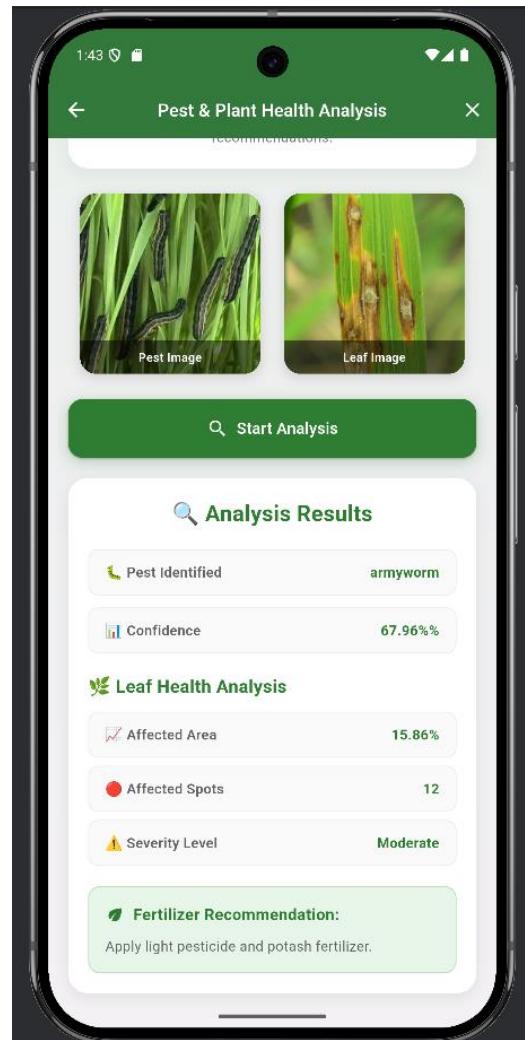
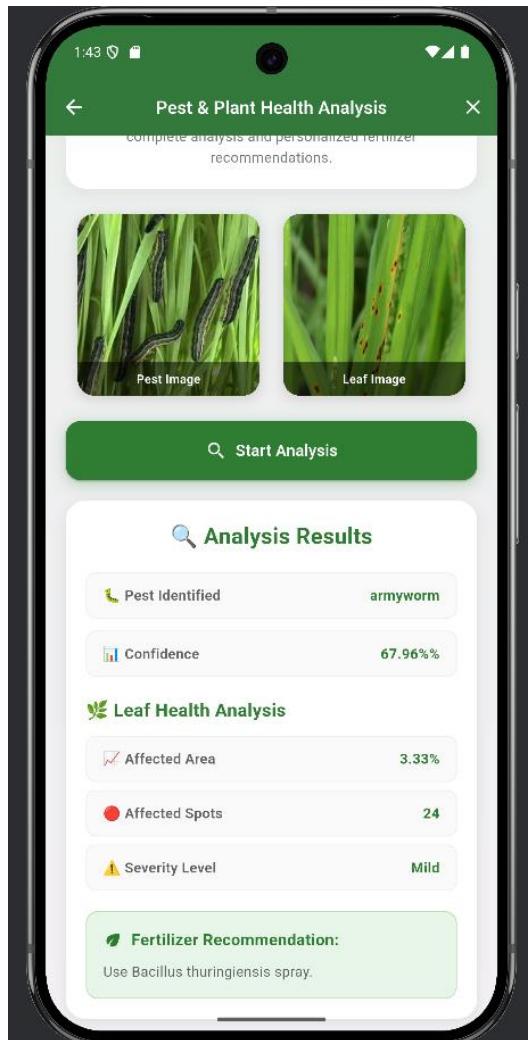
2. Calculates affected percentage (mild(<10%) , moderate(10-30%), severe(>30%)

```
C:\Users\ashiv\Desktop\Python38\python
Percentage of affected area: 15.82%
Number of affected spots: 11
Severity: Moderate
```

Mobile App Development: Debugging

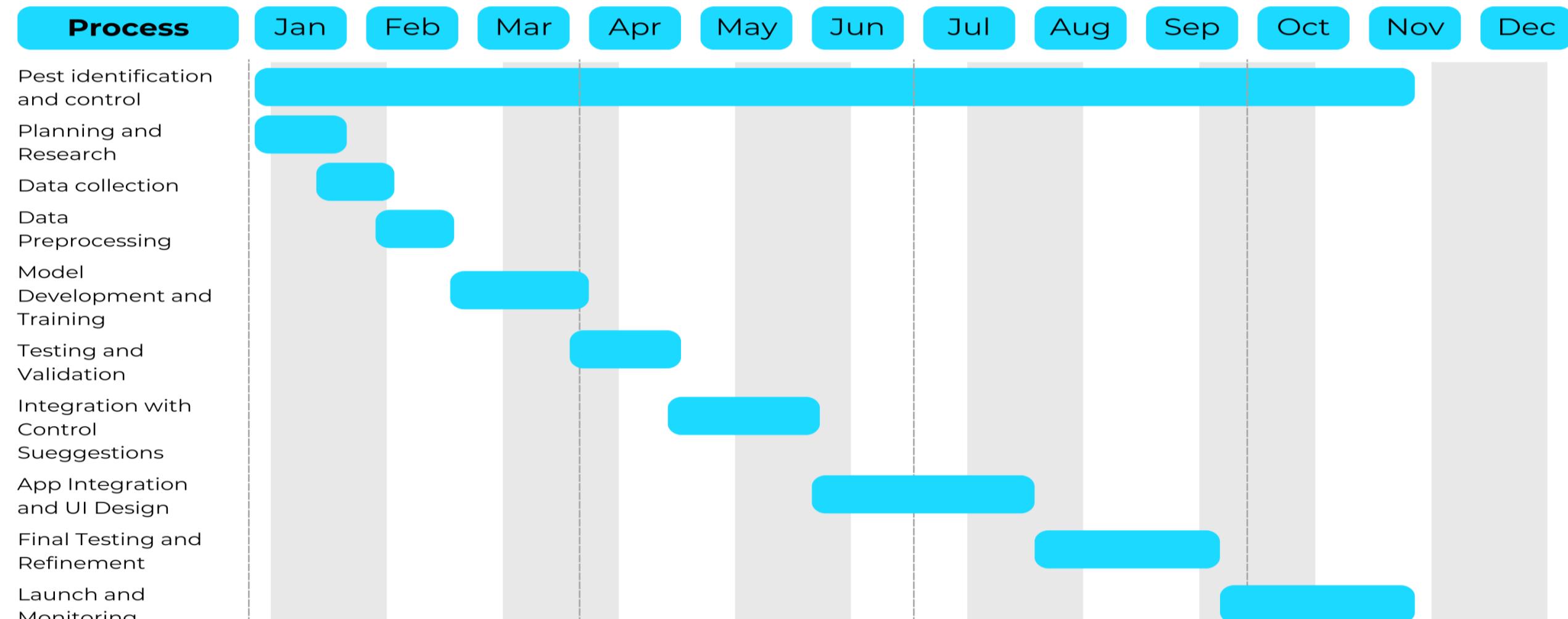


Final Result



Gantt Chart

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Thank For
Your Attention

End Presentation

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