RP-24-25J-307

CUCUMBER *Sense*

The Evolution of Farming from Tradition to Innovation

RP-24-25J-307

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OVERVIEW

Our project focuses on developing a real-time monitoring system for salad cucumber farming in controlled environments. With cucumbers' fast growth cycle—harvest in 28 days—precise control of conditions like temperature, humidity, and water is key to maximizing yield. By leveraging modern sensor technology and data analysis, we aim to enhance crop management and support sustainable farming practices.

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RESEARCH QUESTION

How can a dynamic crop modeling approach be developed for controlled environments to optimize yield and ensure sustainable practices in modern agriculture, while reducing dependency on costly and error-prone contact sensors?

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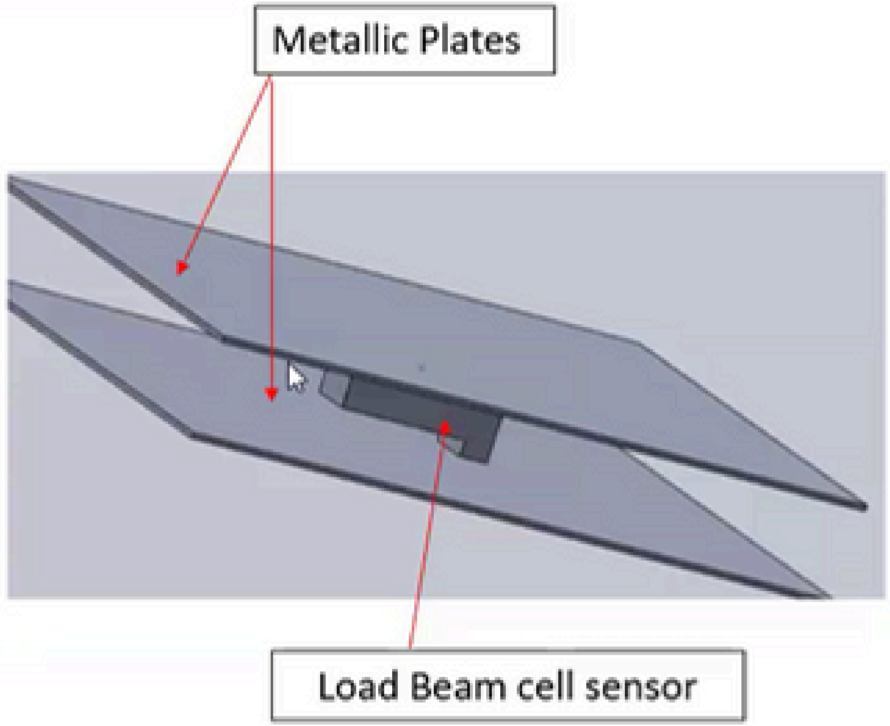
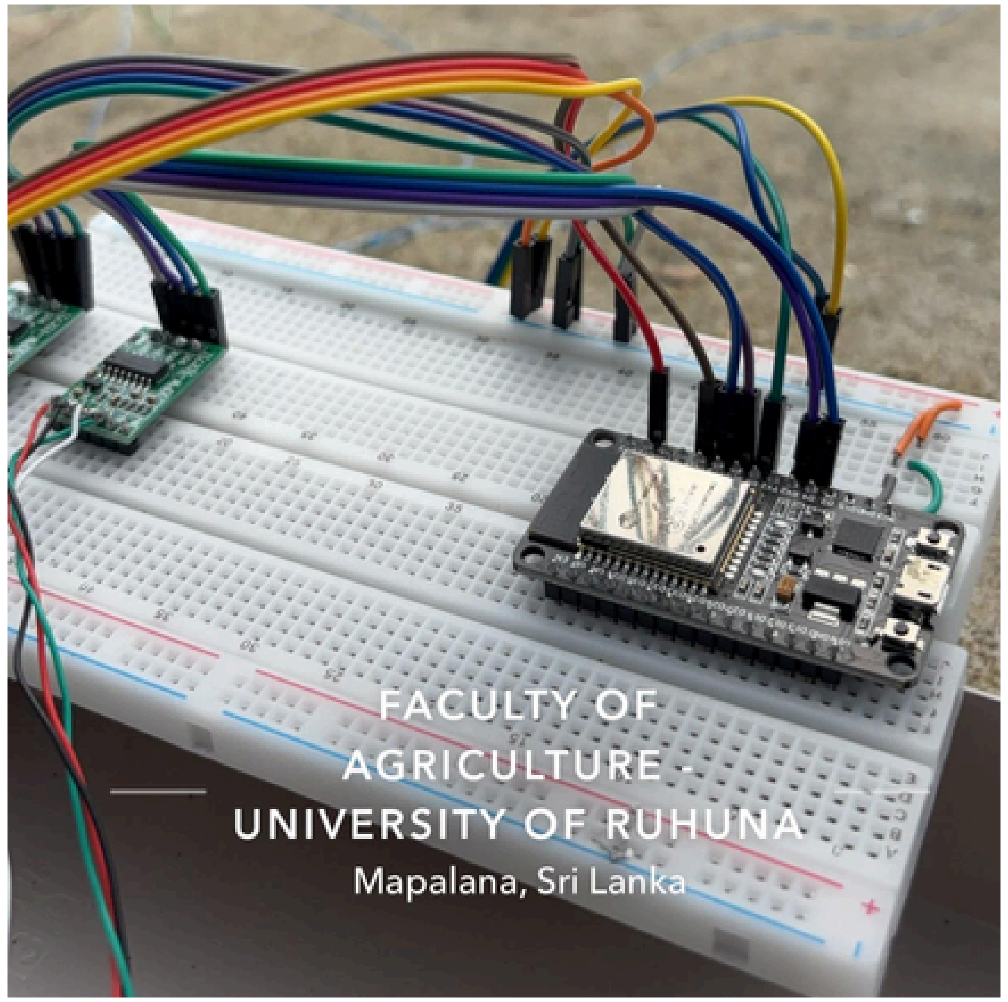
Research preparation





Plantation

salad -cucumber plantation inside the green house

DATA COLLECTION SETUP

Environmental Monitoring Sensors

DHT22 (AM2302): Captures both temperature and humidity inside and outside the greenhouse. It provides digital output with high accuracy (±0.5°C for temperature, ±2% for humidity).

Plant Weight Measurement

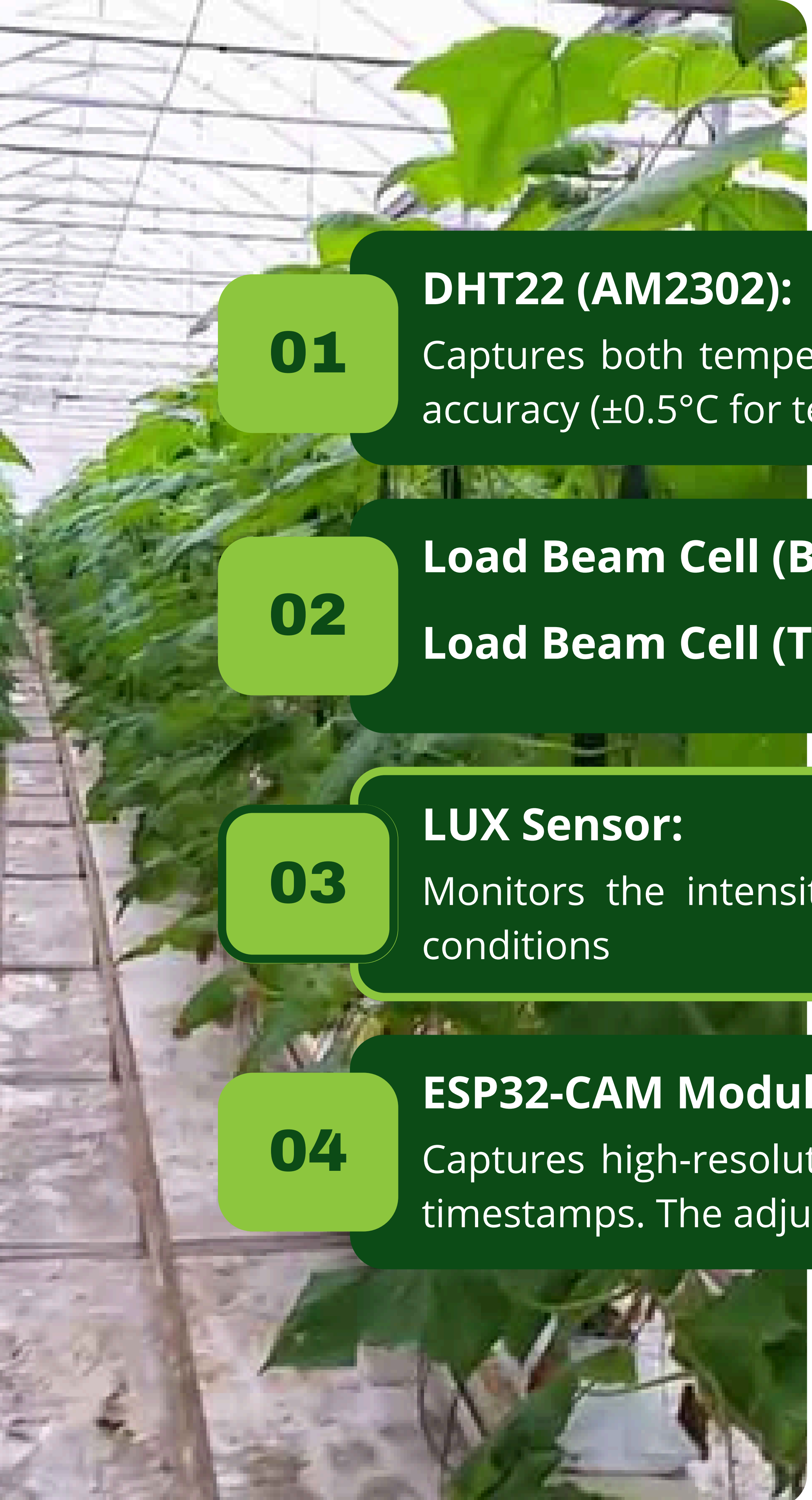
Load Beam Cell (Base): Measures the total weight of the plant and grow bag.
Load Beam Cell (Top): Specifically measures the plant weight, excluding the grow bag, for detailed growth analysis.

Light Intensity

LUX Sensor: Monitors the intensity of light exposure inside the greenhouse to assess optimal growth conditions.

Image Data Acquisition

ESP32-CAM Module: Captures high-resolution images of the cucumber plant, from the flowering stage to advanced fruiting stages, with timestamps. The adjustable stand ensures proper alignment as the plant grows.



Data Collection Setup

Sensors’ update

01

DHT22 (AM2302):

Captures both temperature and humidity inside and outside the greenhouse. It provides digital output with high accuracy (±0.5°C for temperature, ±2% for humidity).

02

Load Beam Cell (Base) Measures the total weight of the plant and grow bag.

Load Beam Cell (Top) Specifically measures the plant weight, excluding the grow bag, for detailed growth analysis.

03

LUX Sensor:

Monitors the intensity of light exposure inside the greenhouse to assess optimal growth conditions

04

ESP32-CAM Module

Captures high-resolution images of the cucumber plant, from the flowering stage to advanced fruiting stages, with timestamps. The adjustable stand ensures proper alignment as the plant grows

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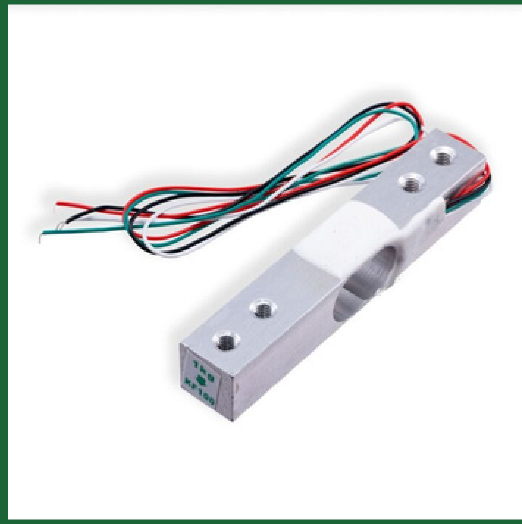
Data Collection Setup

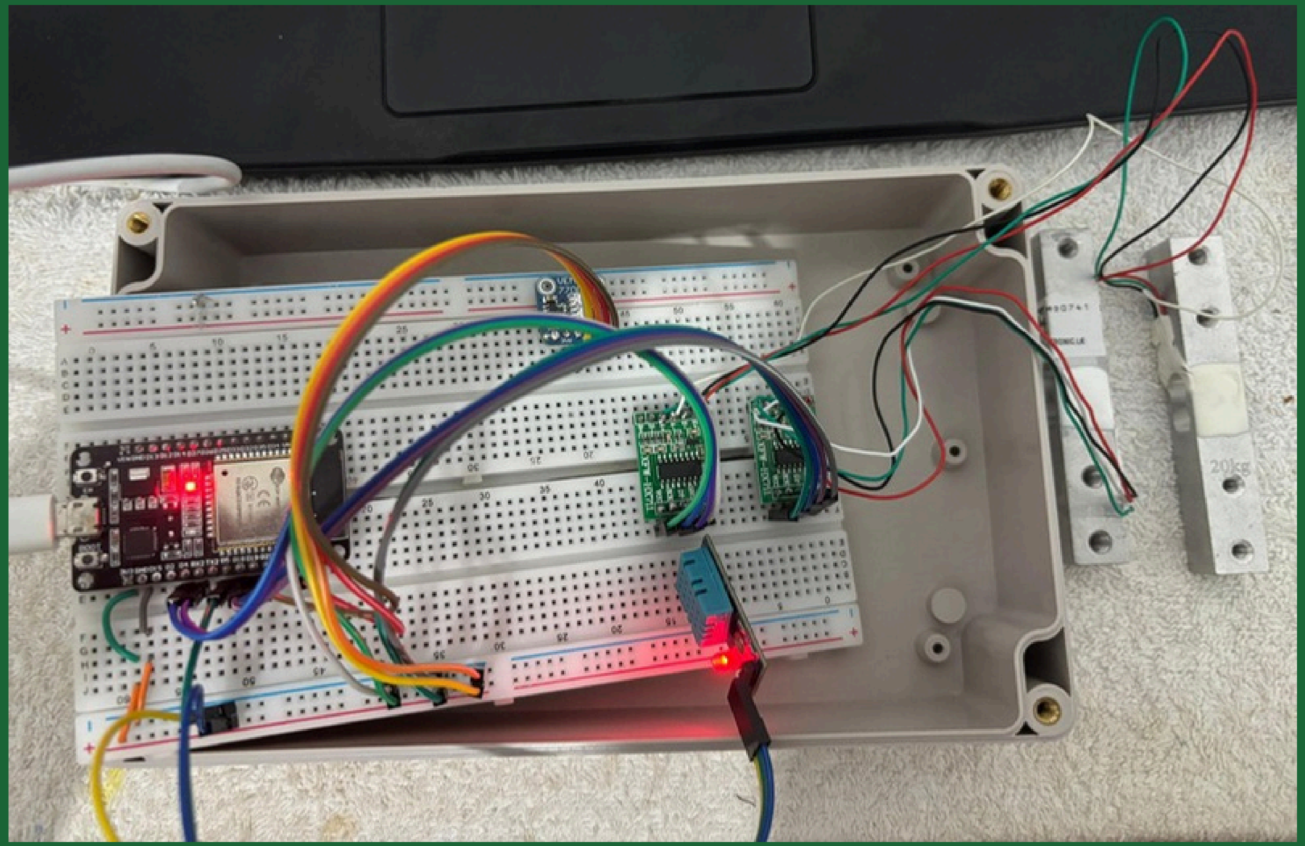
DHT22 (AM2302)



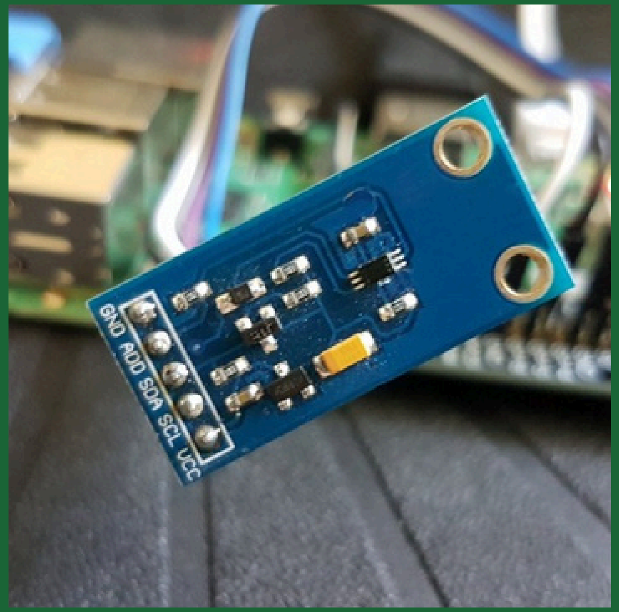
LOAD BEAM CELL (BASE)

OAD BEAM CELL (TOP)

ESP32-CAM MODULE



SYNCFUSION_FLUTTER_CHARTS: ^29.2.5



LUX SENSOR

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SP: DATA SCIENCE

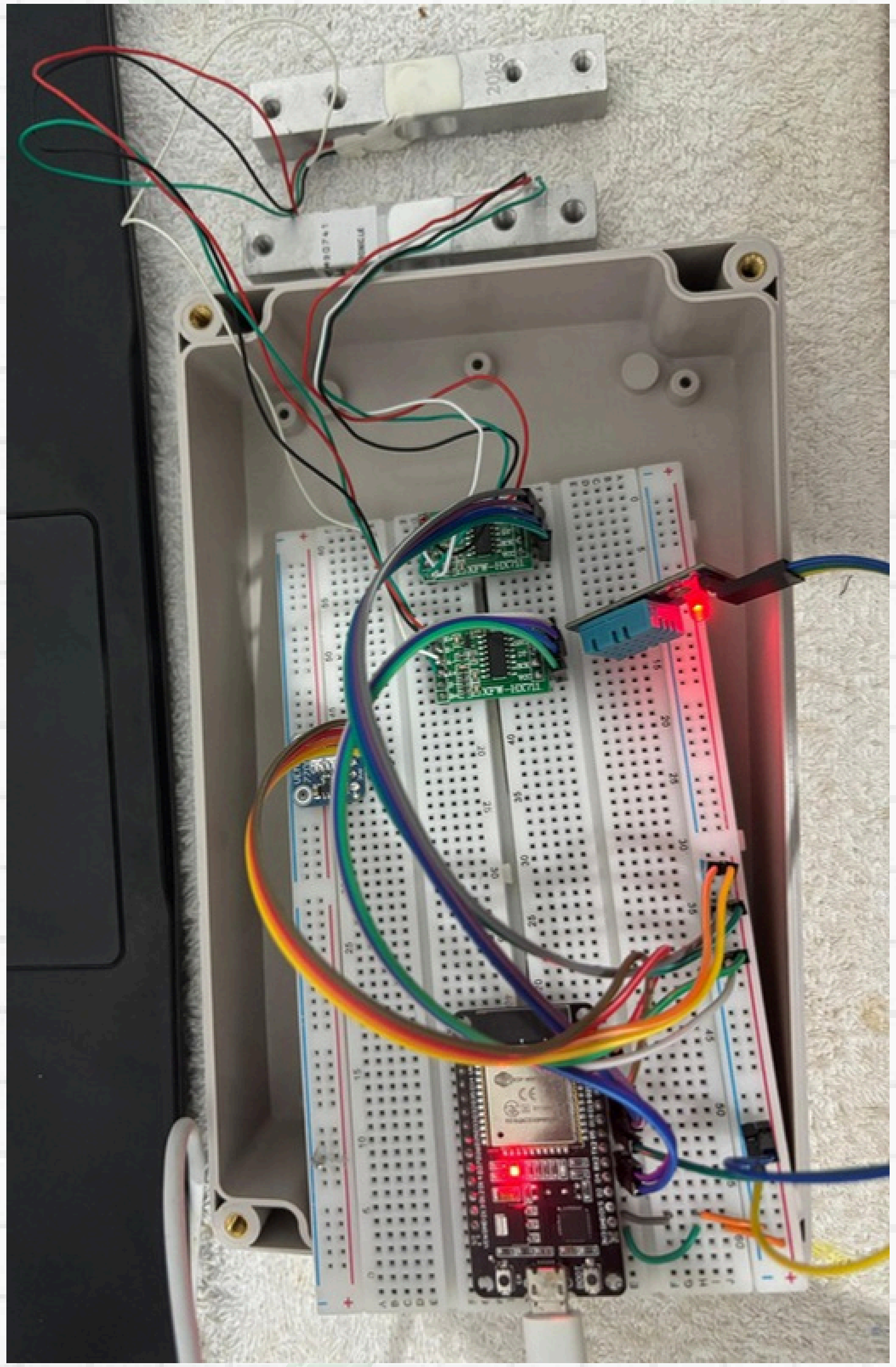
REAL-TIME YIELD PREDICTION USING SENSOR DATA

HARVEST PREDICTION USING IOT SENSORS AND HYBRID MODELS

DATASET

Sensor Data Collection

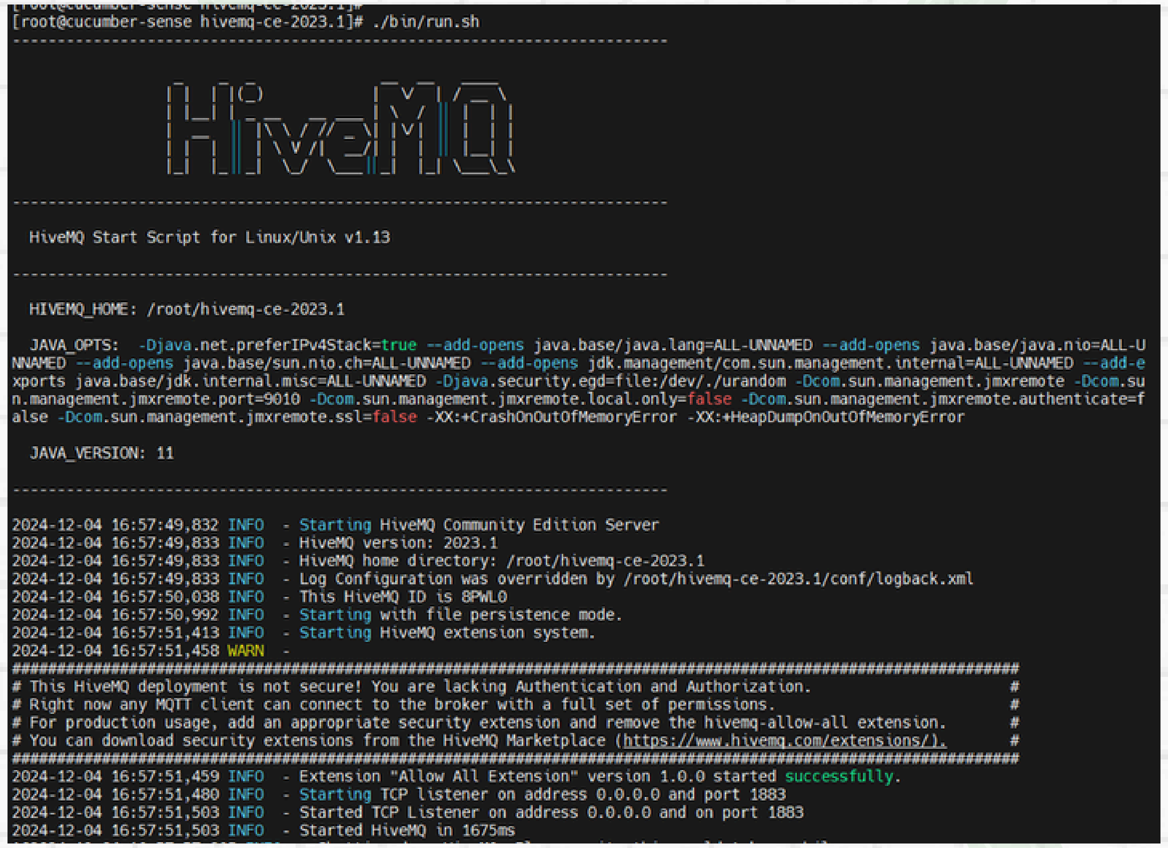
- Devices: ESP32 integrated with sensors (load cells for weight, DHT11 for temperature and humidity, and a lux sensor for light intensity).
- Data Volume: Continuous readings recorded over crop growth cycles.
- Data Format: Time-stamped JSON objects transmitted via MQTT.
- Source: Field-based IoT sensors deployed in varying environmental conditions.



INFRASTRUCTURE SETUP

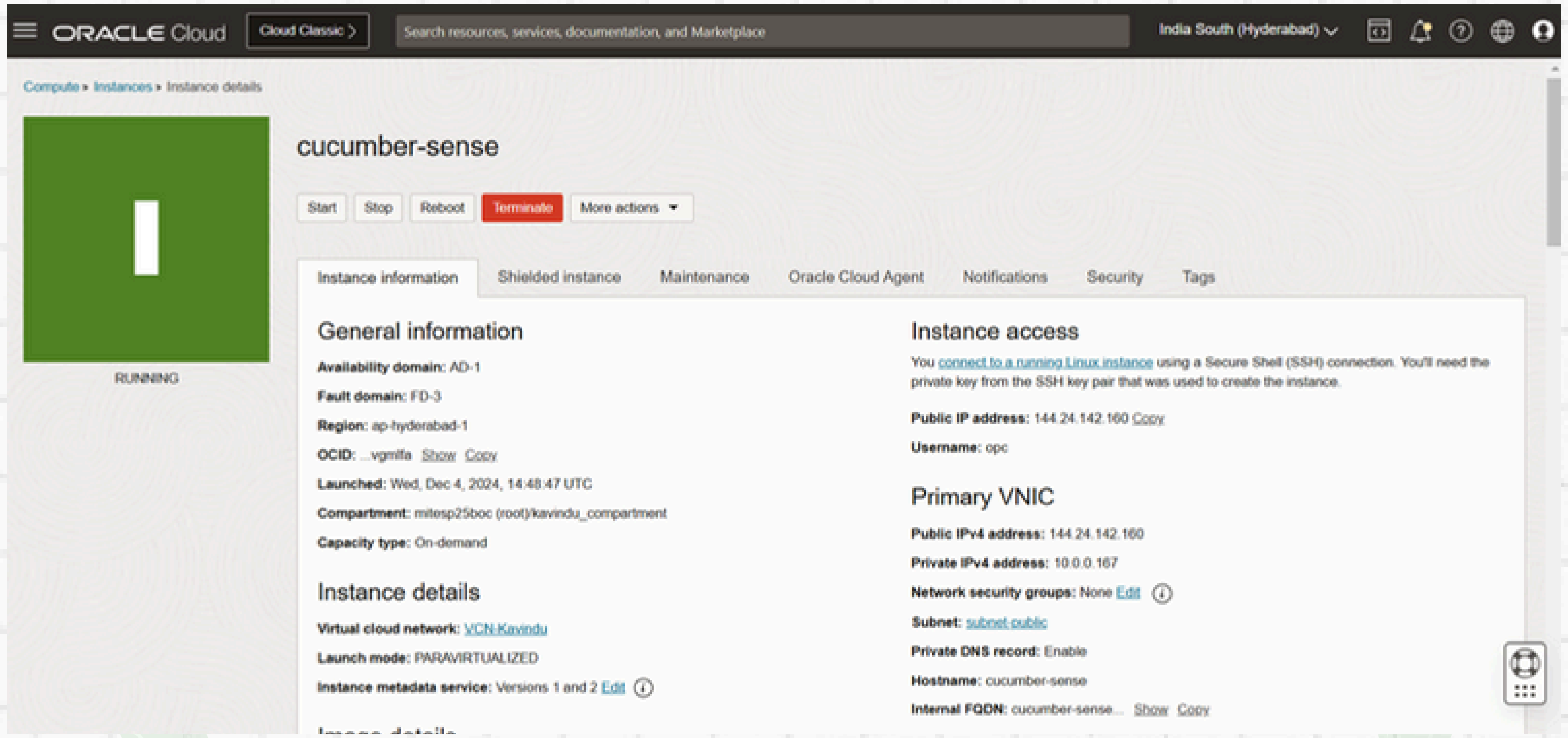
Hardware and Software:

1. Oracle Cloud VM: Configured with Python 3, Flask, and MQTT libraries.
2. MQTT Broker: HiveMQ/Mosquitto for communication between ESP32 and cloud.



IoT Device Configuration:

- ESP32 programmed to capture sensor data.
- Data published to MQTT topics for real-time transmission.



DATA COLLECTION & STORAGE

Source: IoT Sensors measuring:

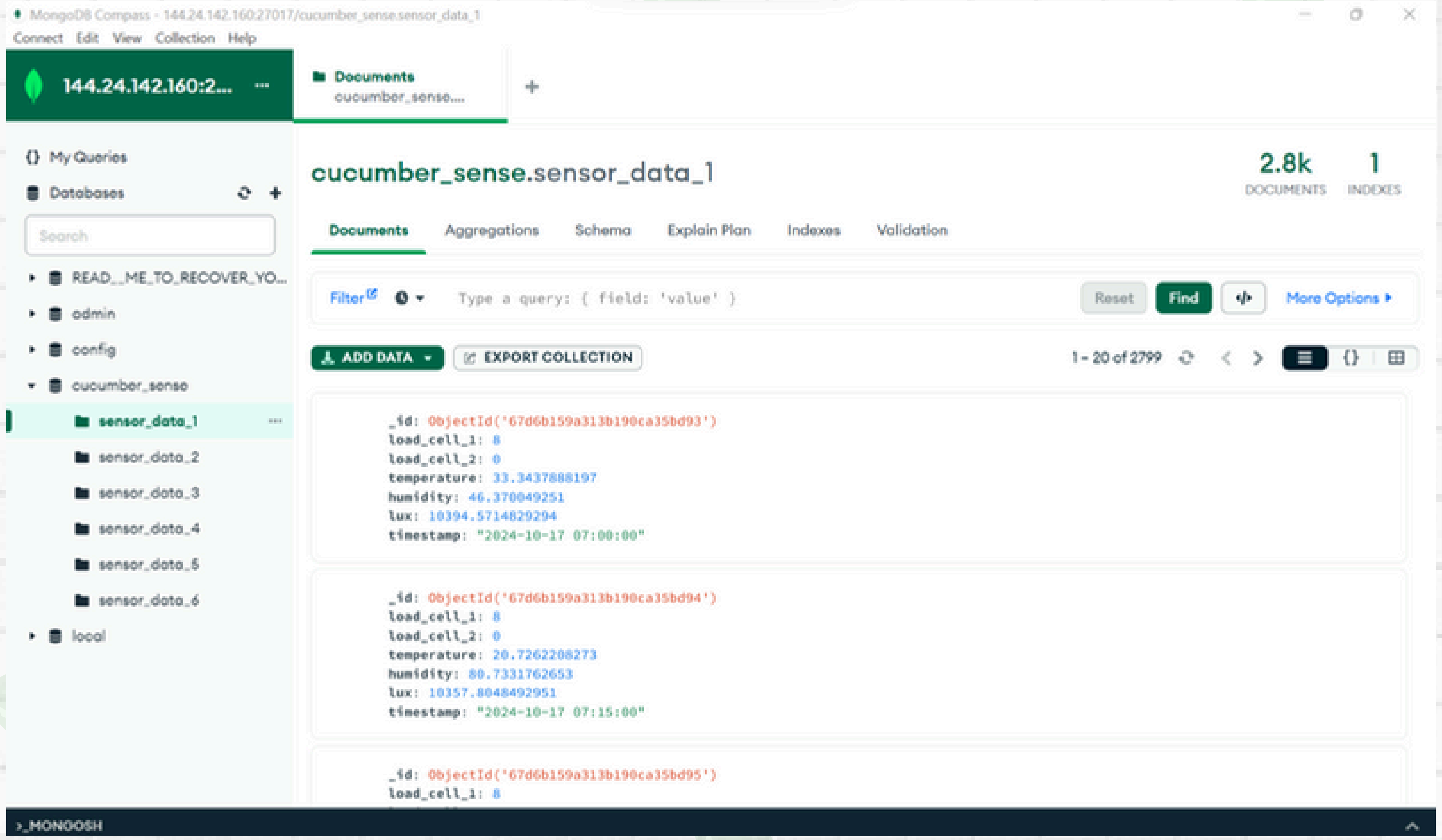
- Temperature
- Humidity
- Light Intensity (Lux)
- Load Cell (Weight) (Top and Bottom)

Storage:

- MongoDB stores real-time sensor readings.
- InfluxDB stores processed sensor data for visualization.

Why MongoDB?

- NoSQL database allows scalability and real-time data handling.



MODEL SELECTION

Why Random Forest (RF)?

- Handles non-linear relationships.
- Performs well on small datasets.
- Robust to missing data.
- Provides feature importance.

Why LSTM?

- Captures time-series dependencies.
- Works well for sequential forecasting.
- Learns patterns from past 10 sensor readings.

Hybrid Approach (RF + LSTM):

- RF captures complex relationships.
- LSTM detects time-based trends.
- Final prediction is an average of both.

```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error

# Define Features & Target
X = df[features]  # Input Features
y = df['harvest_ratio']  # Target Variable

# Train-Test Split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Train Random Forest Model
rf_model = RandomForestRegressor(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)

# Predict
rf_preds = rf_model.predict(X_test)
print("Random Forest MAE:", mean_absolute_error(y_test, rf_preds))
```

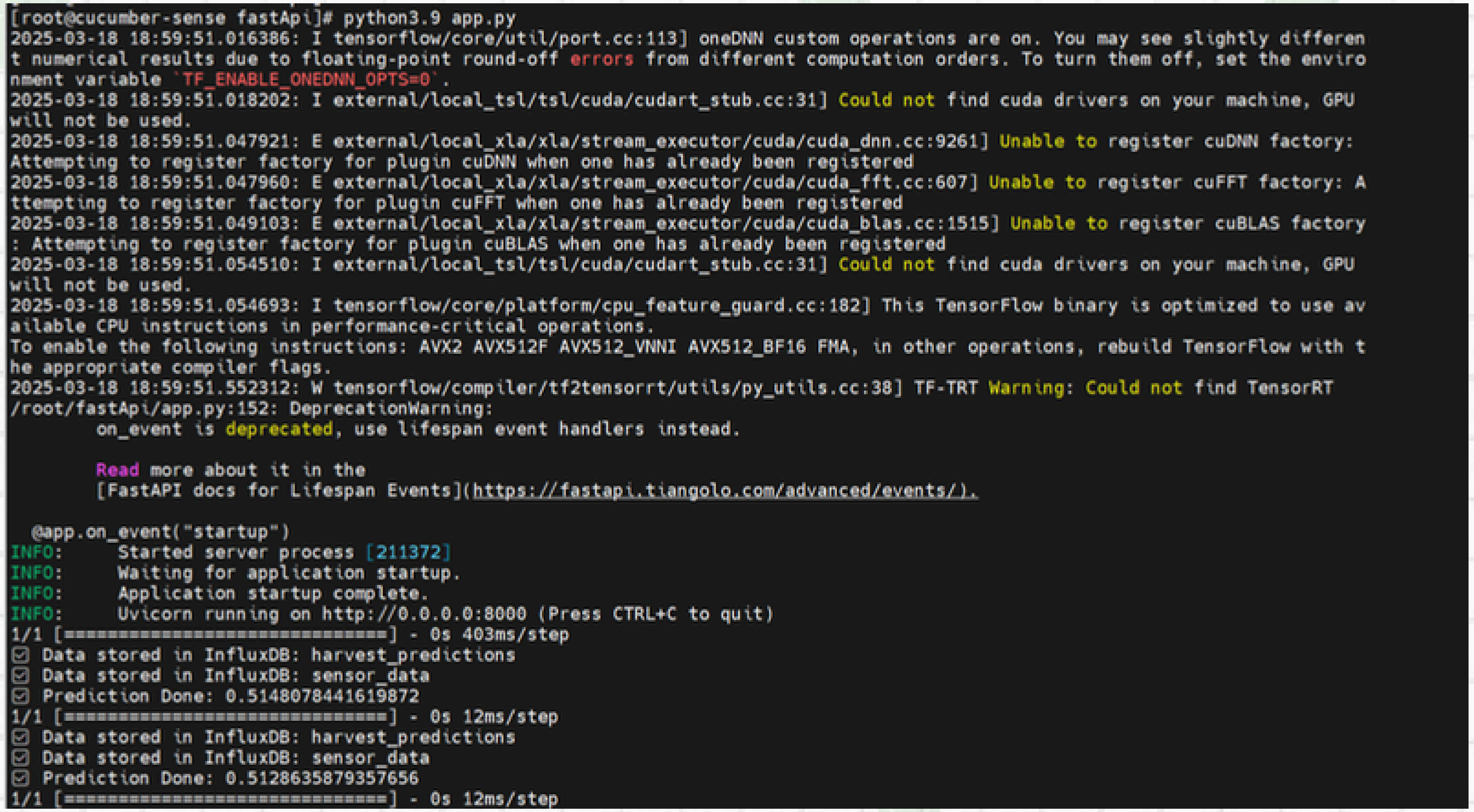
```
Random Forest MAE: 0.012741936984974696
```

```
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout

# Function to create time-series dataset for LSTM
def create_lstm_dataset(X, y, time_steps=10):
    Xs, ys = [], []
    for i in range(len(X) - time_steps):
        v = X.iloc[i:(i + time_steps)].values
        Xs.append(v)
        ys.append(y.iloc[i + time_steps])
    return np.array(Xs), np.array(ys)

# Convert Data to Sequential Format
time_steps = 10
X_lstm, y_lstm = create_lstm_dataset(df[features], df['harvest_ratio'], time_steps)

# Train-Test Split
split = int(0.8 * len(X_lstm))
X_train_lstm, X_test_lstm = X_lstm[:split], X_lstm[split:]
y_train_lstm, y_test_lstm = y_lstm[:split], y_lstm[split:]

# Define LSTM Model
lstm_model = Sequential()
lstm_model.add(LSTM(50, return_sequences=True, input_shape=(time_steps, len(features))))
lstm_model.add(LSTM(50, return_sequences=False))
lstm_model.add(Dropout(0.2))
lstm_model.add(Dense(25, activation='relu'))
lstm_model.add(Dense(1))

# Compile Model
lstm_model.compile(optimizer='adam', loss='mean_squared_error')

# Train LSTM Model
lstm_model.fit(X_train_lstm, y_train_lstm, epochs=50, batch_size=16, validation_data=(X_test_lstm, y_test_lstm))
```

MODEL DEPLOYMENT

Real-time Predictions Workflow:

1. Data from MongoDB → Preprocessed.
2. Passed into RF & LSTM for prediction.
3. Final prediction stored in InfluxDB.
4. Displayed in Grafana Dashboard.



```
[root@cucumber-sense fastApi]# python3.9 app.py
2025-03-18 18:59:51.016386: I tensorflow/core/util/port.cc:113] oneDNN custom operations are on. You may see slightly differen
t numerical results due to floating-point round-off errors from different computation orders. To turn them off, set the enviro
nment variable `TF_ENABLE_ONEDNN_OPTS=0`.
2025-03-18 18:59:51.018202: I external/local_tsl/tsl/cuda/cudart_stub.cc:31] Could not find cuda drivers on your machine, GPU
will not be used.
2025-03-18 18:59:51.047921: E external/local_xla/xla/stream_executor/cuda/cuda_dnn.cc:9261] Unable to register cuDNN factory:
Attempting to register factory for plugin cuDNN when one has already been registered
2025-03-18 18:59:51.047960: E external/local_xla/xla/stream_executor/cuda/cuda_fft.cc:607] Unable to register cuFFT factory: A
ttempting to register factory for plugin cuFFT when one has already been registered
2025-03-18 18:59:51.049103: E external/local_xla/xla/stream_executor/cuda/cuda_blas.cc:1515] Unable to register cuBLAS factory
: Attempting to register factory for plugin cuBLAS when one has already been registered
2025-03-18 18:59:51.054510: I external/local_tsl/tsl/cuda/cudart_stub.cc:31] Could not find cuda drivers on your machine, GPU
will not be used.
2025-03-18 18:59:51.054693: I tensorflow/core/platform/cpu_feature_guard.cc:182] This TensorFlow binary is optimized to use av
ailable CPU instructions in performance-critical operations.
To enable the following instructions: AVX2 AVX512F AVX512_VNNI AVX512_BF16 FMA, in other operations, rebuild TensorFlow with t
he appropriate compiler flags.
2025-03-18 18:59:51.552312: W tensorflow/compiler/tf2tensorrt/utils/py_utils.cc:38] TF-TRT Warning: Could not find TensorRT
/root/fastApi/app.py:152: DeprecationWarning:
        on_event is deprecated, use lifespan event handlers instead.

        Read more about it in the
        [FastAPI docs for Lifespan Events](https://fastapi.tiangolo.com/advanced/events/).

  @app.on_event("startup")
INFO:     Started server process [211372]
INFO:     Waiting for application startup.
INFO:     Application startup complete.
INFO:     Uvicorn running on http://0.0.0.0:8000 (Press CTRL+C to quit)
1/1 [==============================] - 0s 403ms/step
☑ Data stored in InfluxDB: harvest_predictions
☑ Data stored in InfluxDB: sensor_data
☑ Prediction Done: 0.5148078441619872
1/1 [==============================] - 0s 12ms/step
☑ Data stored in InfluxDB: harvest_predictions
☑ Data stored in InfluxDB: sensor_data
☑ Prediction Done: 0.5128635879357656
1/1 [==============================] - 0s 12ms/step
```

API Integration (FastAPI)

- /predict_harvest endpoint updates InfluxDB.
- Grafana fetches latest values.

REAL-TIME VISUALIZATION

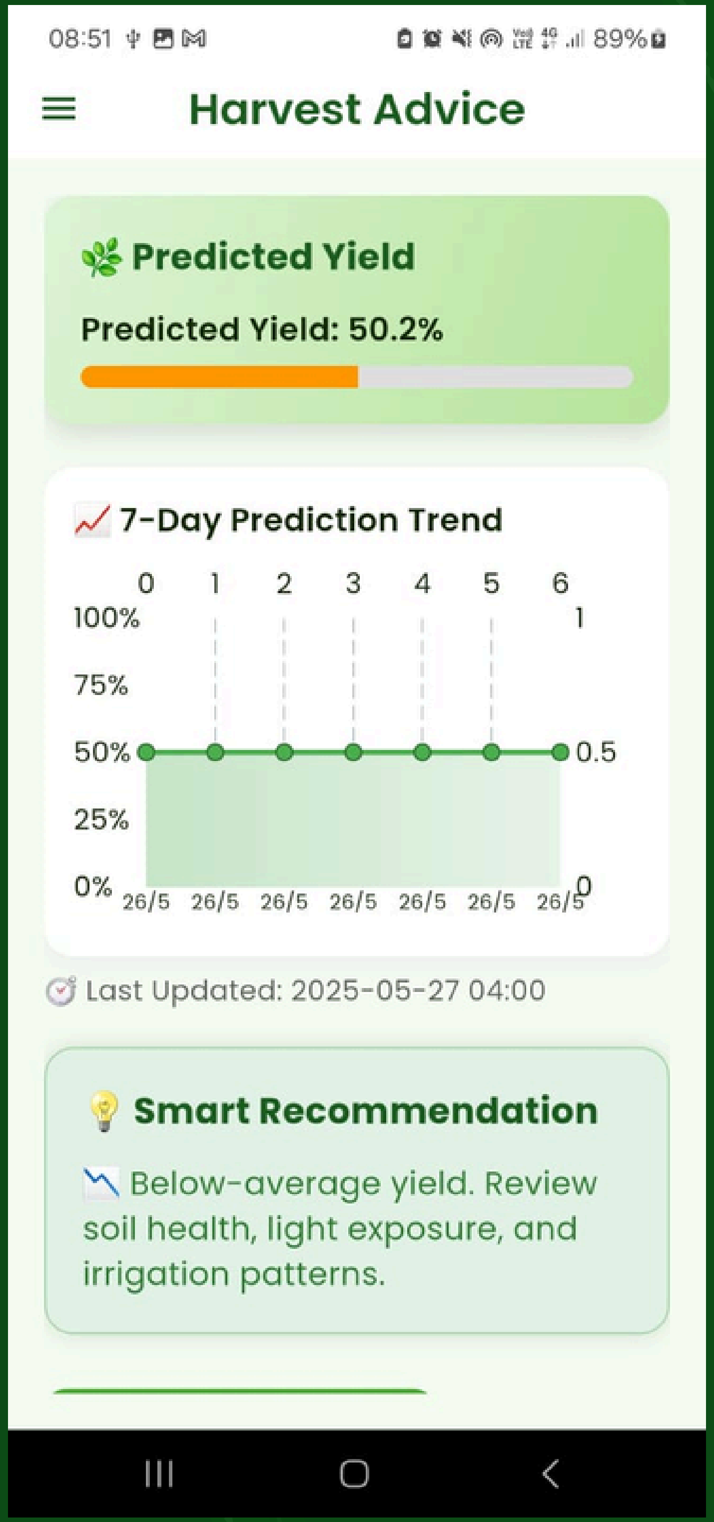
Grafana Dashboard:

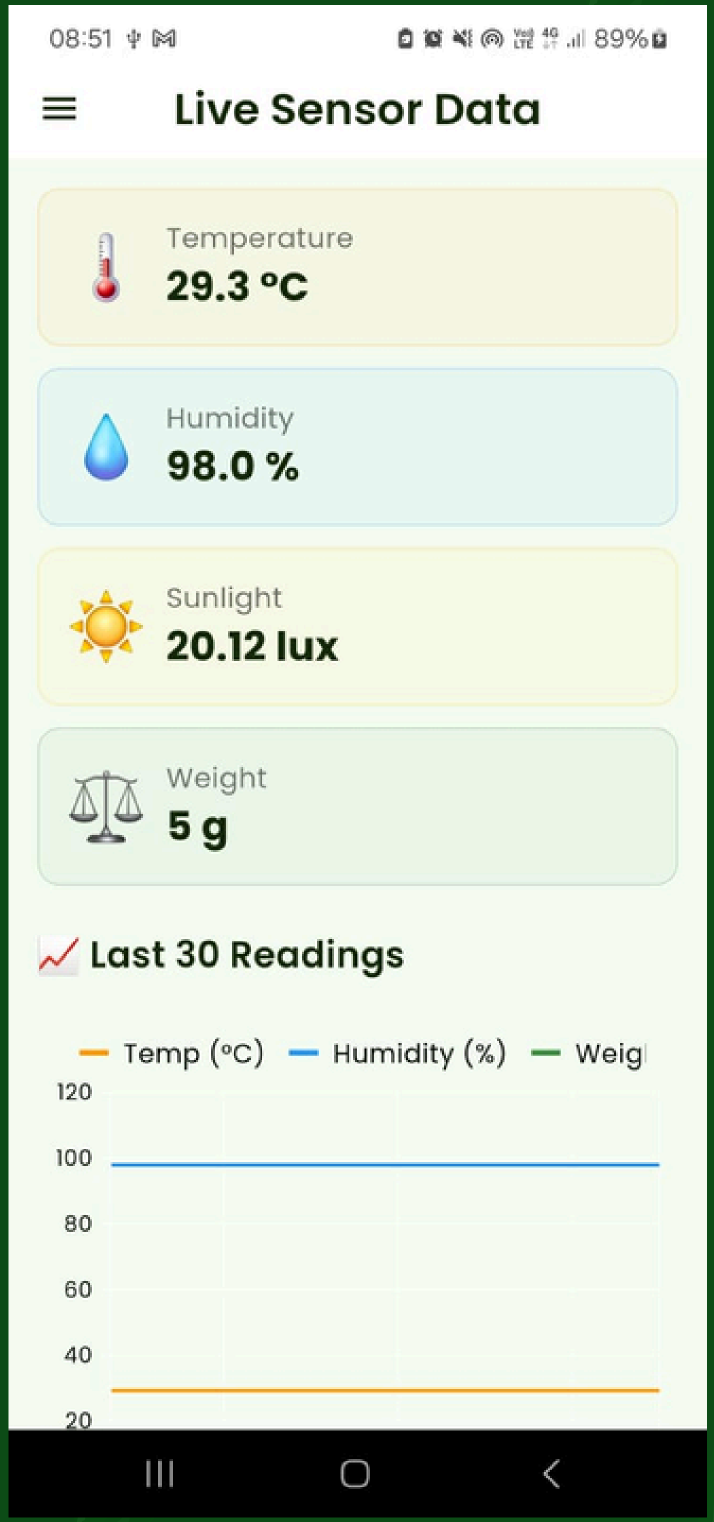
- Displays real-time sensor data + predictions.
- Supports alerts & notifications.

Why InfluxDB?

- Time-series database optimized for IoT data.
- High-performance reads & writes.

MOBILE APPLICATION





Live Data Page (Benefits for Farmers)

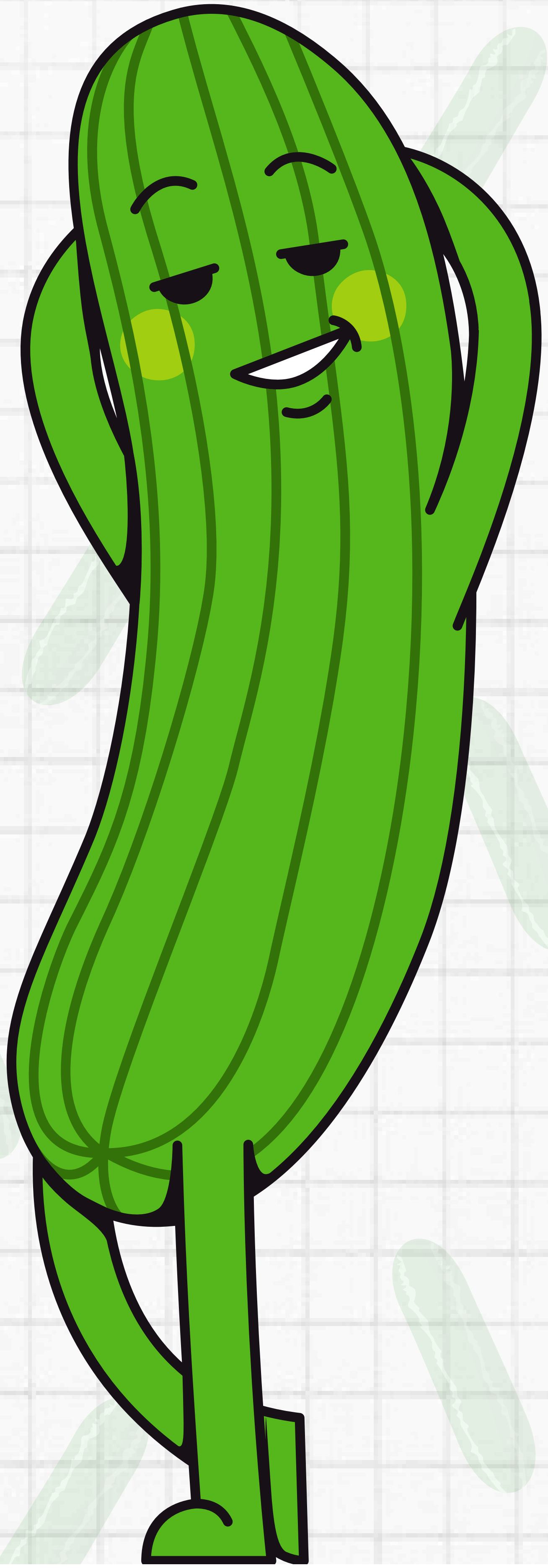
- Monitor real-time sensor data (temp, humidity, sunlight, weight).
- Helps in quick decisions for irrigation, shading, or fertilizing.
- Avoids manual field checks—saves time and effort.
- Detect issues early for crop protection.

Prediction Page (Benefits for Farmers)

- View AI-based harvest forecast (good, moderate, low).
- Get actionable advice (e.g., improve nutrients).
- Track progress with a 7-day yield trend.
- Supports planning & resource optimization.

REFERENCES

- Ramesh Medar, Vijay S. Rajpurohit, Shweta. "Crop Yield Prediction Using Machine Learning Techniques." International Journal of Engineering Research & Technology (IJERT). Available online.
- Mayank Champaneri, Darpan Chachpara, Chaitanya Chandvidkar, Mansing Rathod. "Crop Yield Prediction Using Machine Learning." IEEE Xplore, Available online.
- Anakha Venugopal, Aparna S, Jinsu Mani, Rima Mathew, Vinu Williams. "Crop Yield Prediction Using Machine Learning Algorithms." International Journal of Engineering Research & Technology (IJERT). Available online.



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SP: DATA SCIENCE

ON DEMAND IRRIGATION SYSTEM BASED ON BIO-MASS WEIGHT.

Salford & Co.

PROBLEM STATEMENT & OBJECTIVES

Inaccurate irrigation leads to water wastage and poor yield.
Soil moisture sensors are unreliable in long-term use.

Objectives:

- Develop weight-based irrigation system.
- Detect wilted leaves using image classification.
- Automate decision-making using ML models.

KEY FOCUS AREAS

SMART IRRIGATION SHEDULING

WILTED LEAF DETECTION AND IDENTIFICATION

SCOPE OF WORK

- Developed an intelligent irrigation system using real-time weight and environmental sensors.
- Designed and trained an Ml model for predictive irrigation scheduling.
- Integrated image-based wilt detection using a deep learning CNN model
- Deployed a full-stack IoT system with automated irrigation and Grafana-based dashboard and mobile App
- Validated system performance through cucumber crop cycles in a tunnel setup.

EXECUTION STRATEGY AND WORKFLOW

1

Data Collection
Real-time data was collected from cucumber plants using a combination of ESP32-CAMs for image capture and load cells and environmental sensors for tracking plant weight, temperature, humidity, and light intensity.

2

Data Preparation
Captured images were organized, cleaned, and prepared to ensure consistency and accuracy for analysis.

3

Model Development
Custom machine learning models were developed to analyze hydration trends and detect visible signs of plant stress. The system learned to recognize watering needs and leaf wilting conditions based on historical and real-time input data.

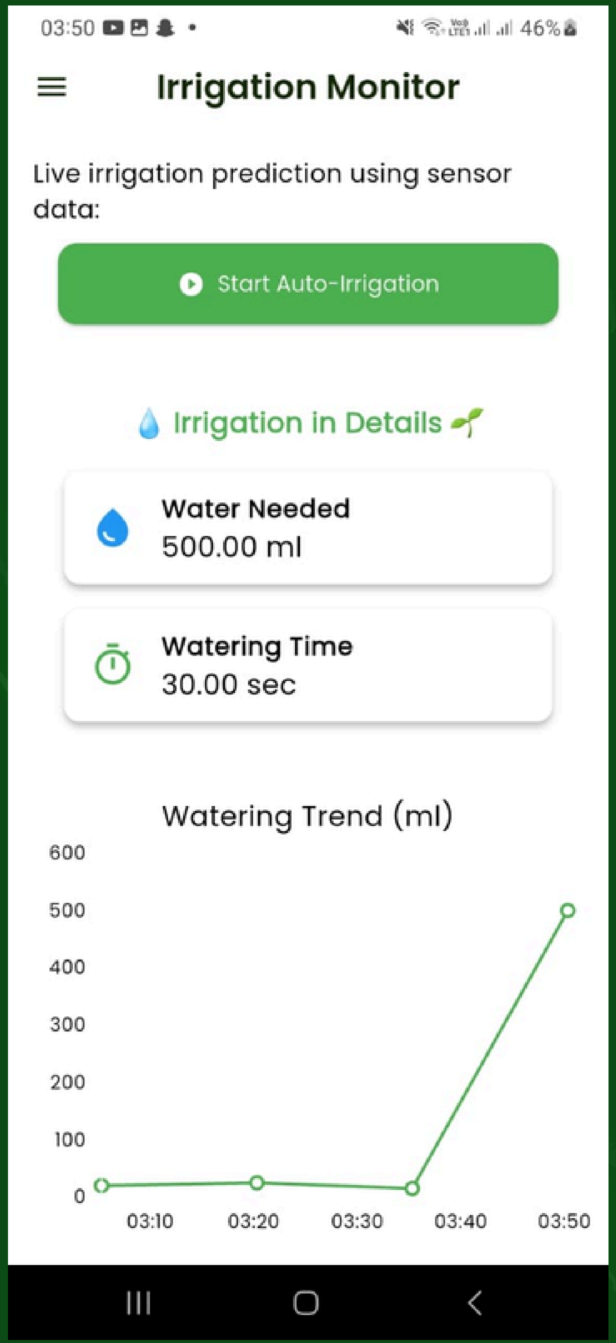
4

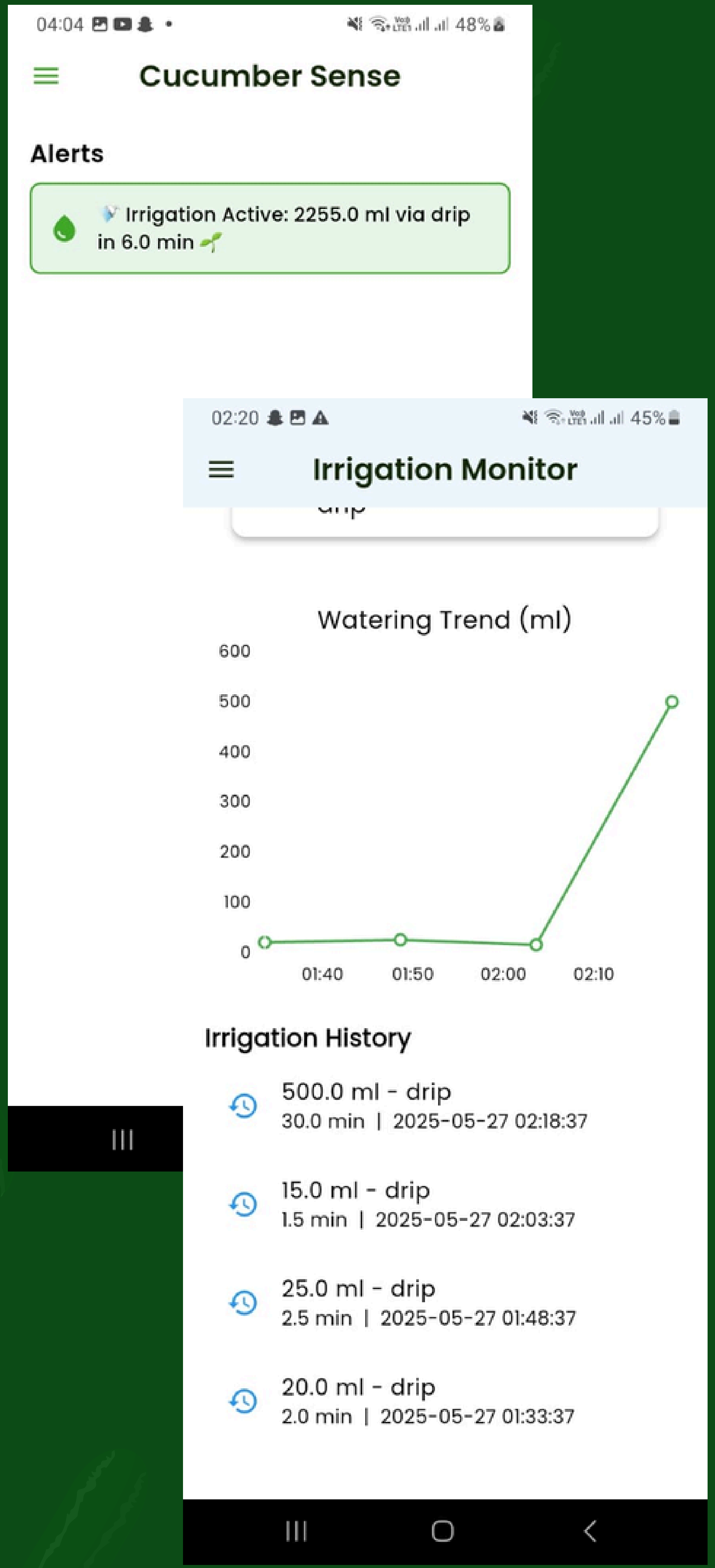
System Integration:
The trained models were deployed into a virtual environment and connected to a mobile app and dashboard for real-time monitoring and user interaction.

MOBILE APPLICATION

Irrigation Monitoring:

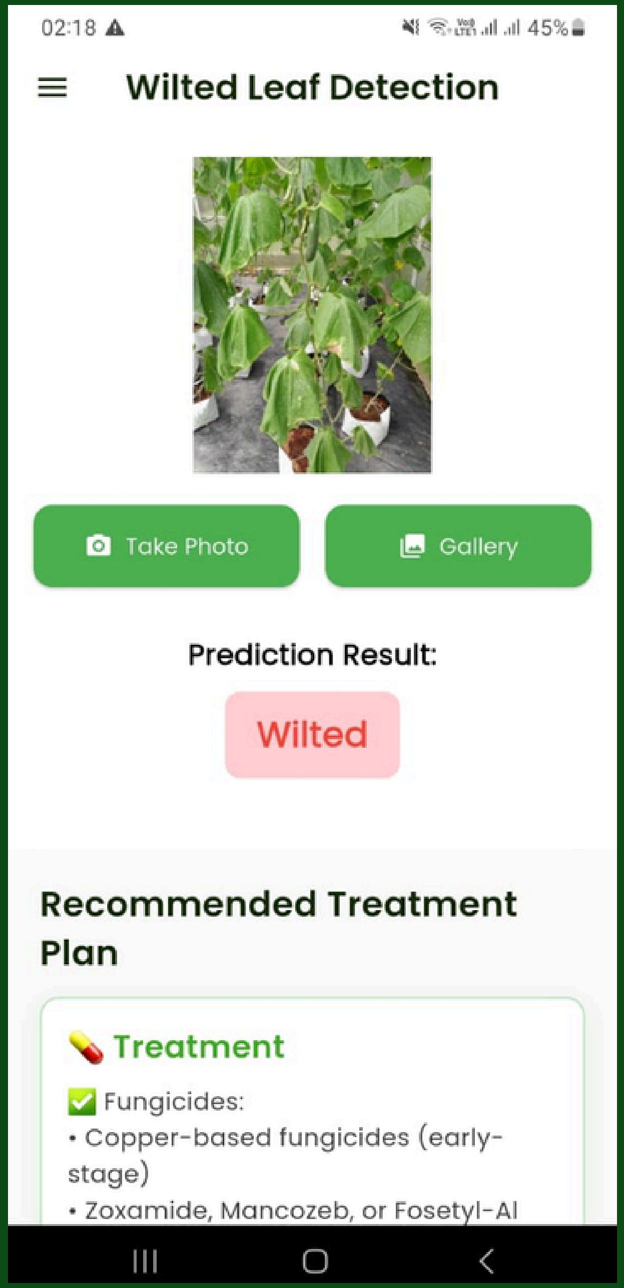
- Displays Irrigation details
- Also, farmers can manually control irrigation through an app
- History details of the irrigation and watering trend displaying
- The app sends a real-time alert to the user when watering happening

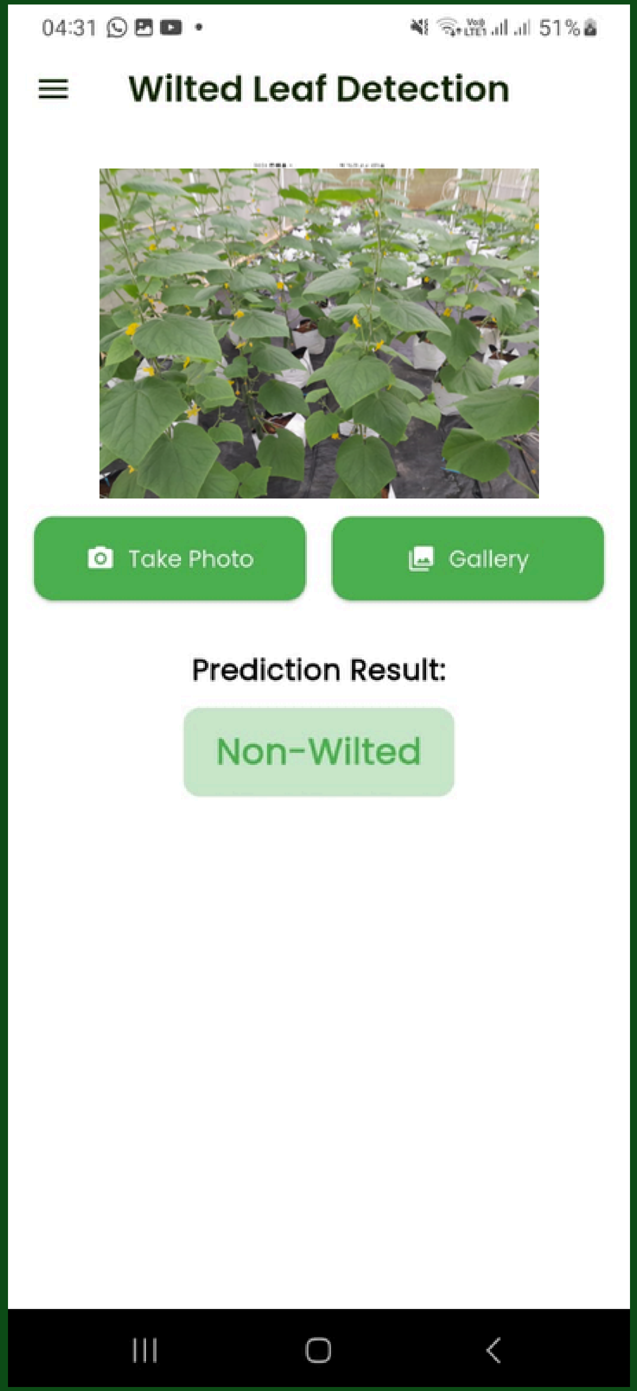




SLIIT FACULTY OF COMPUTING WIJESINGHE.W.E.S.P IT20418274 24-25J-307 27/05/2025

MOBILE APPLICATION





Wilted Leaf Detection and Identification:

- Farmers can upload leaf images via camera or gallery.
- The app predicts:
  - Whether the leaf is wilted or non-wilted.
  - Displays treatment and solution recommendations based on the diagnosis

AGRICULTURAL BENEFITS AND IMPACT

Importance of Sensor-Based Irrigation Prediction

- Provides real-time insight into plant hydration needs using weight and environmental data.
- Helps avoid over- or under-irrigation, improving water efficiency and plant health.
- Supports smart scheduling of irrigation based on actual plant demand.
- Enables continuous monitoring and adaptive responses to climate fluctuations.
- Reduces manual labor and human error through full automation.

Benefits of Real-Time Monitoring:

- Enhances decision-making by providing instant visual and analytical feedback.
- Reduces resource wastage and improves operational decision-making..
- Optimizes resource usage (water, fertilizers) and minimizes environmental impact.

Importance of Image-Based Wilt Detection (Leaf Analysis):

- Detects early signs of wilting before visible symptoms appear.
- Assists in timely corrective action to prevent irreversible crop stress.
- Distinguishes between water stress and disease-related symptoms.
- Improves plant care decisions with visual, data-backed alerts.

TECHNIQUES, TECHNOLOGIES, AND ALGORITHMS

TECHNIQUES

- Data Cleaning: Removal of outliers and erroneous measurements.
- Feature Engineering: Creation of additional relevant features from raw data.

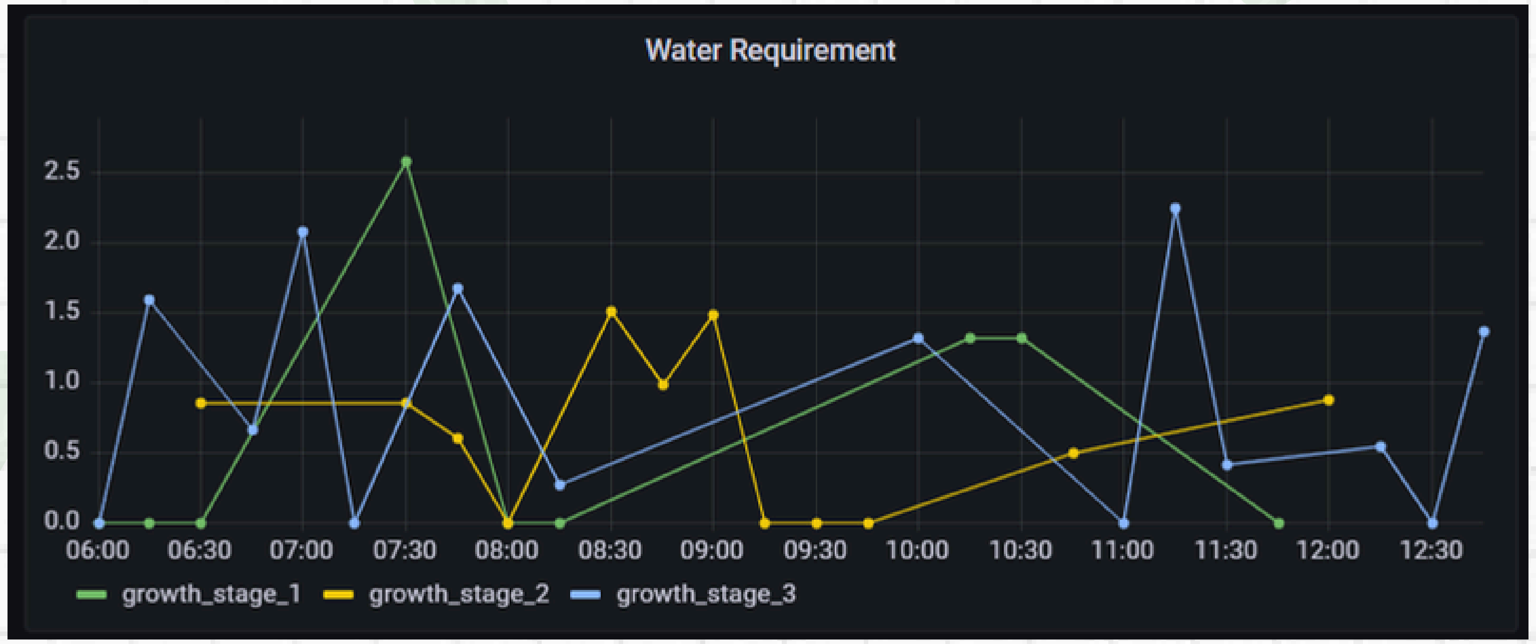
TECHNOLOGIES

- Hardware: Arduino/Raspberry Pi, sensors (biomass weight, temperature, humidity, soil moisture).
- Software: Python, Scikit-learn, TensorFlow/PyTorch

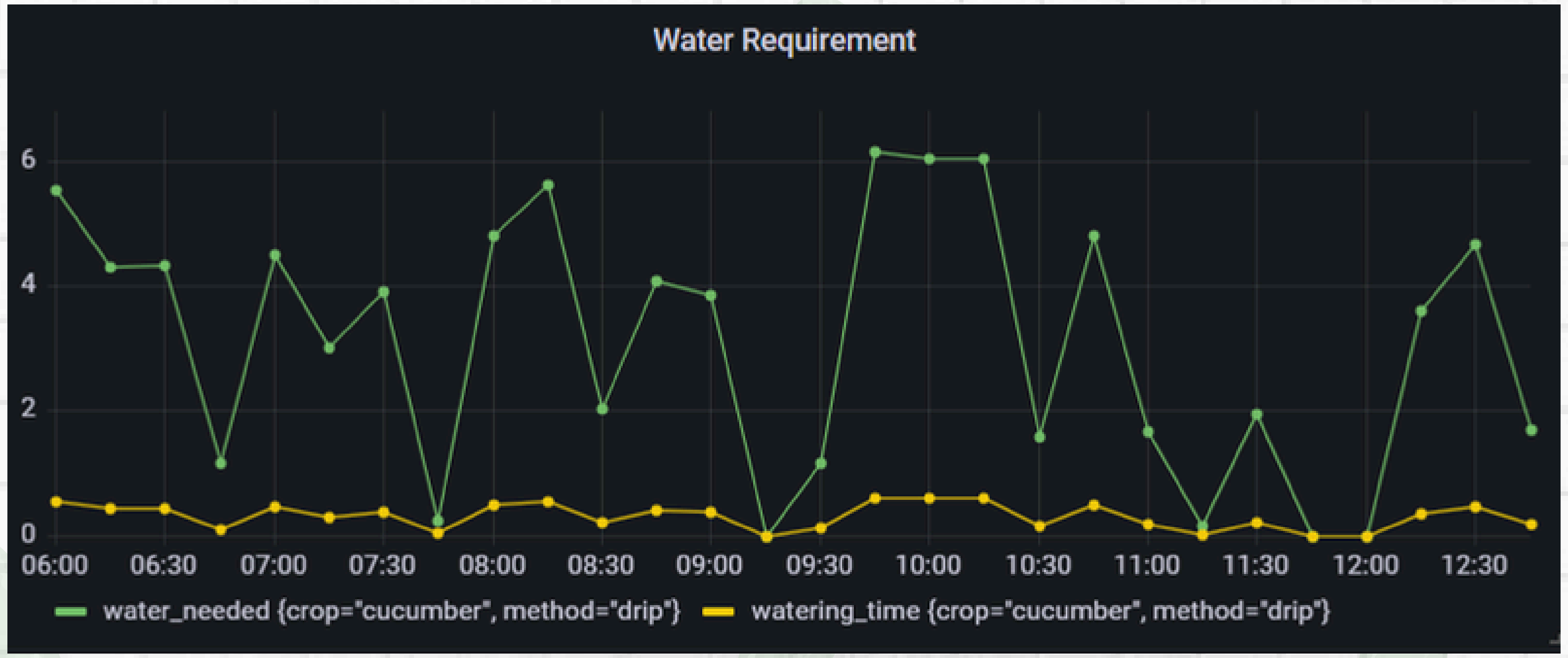
ALGORITHOMS

Machine learning models such as Random Forest, SVM, or Neural Networks for predicting irrigation needs.

DASHBOARD



Water consumption by stages



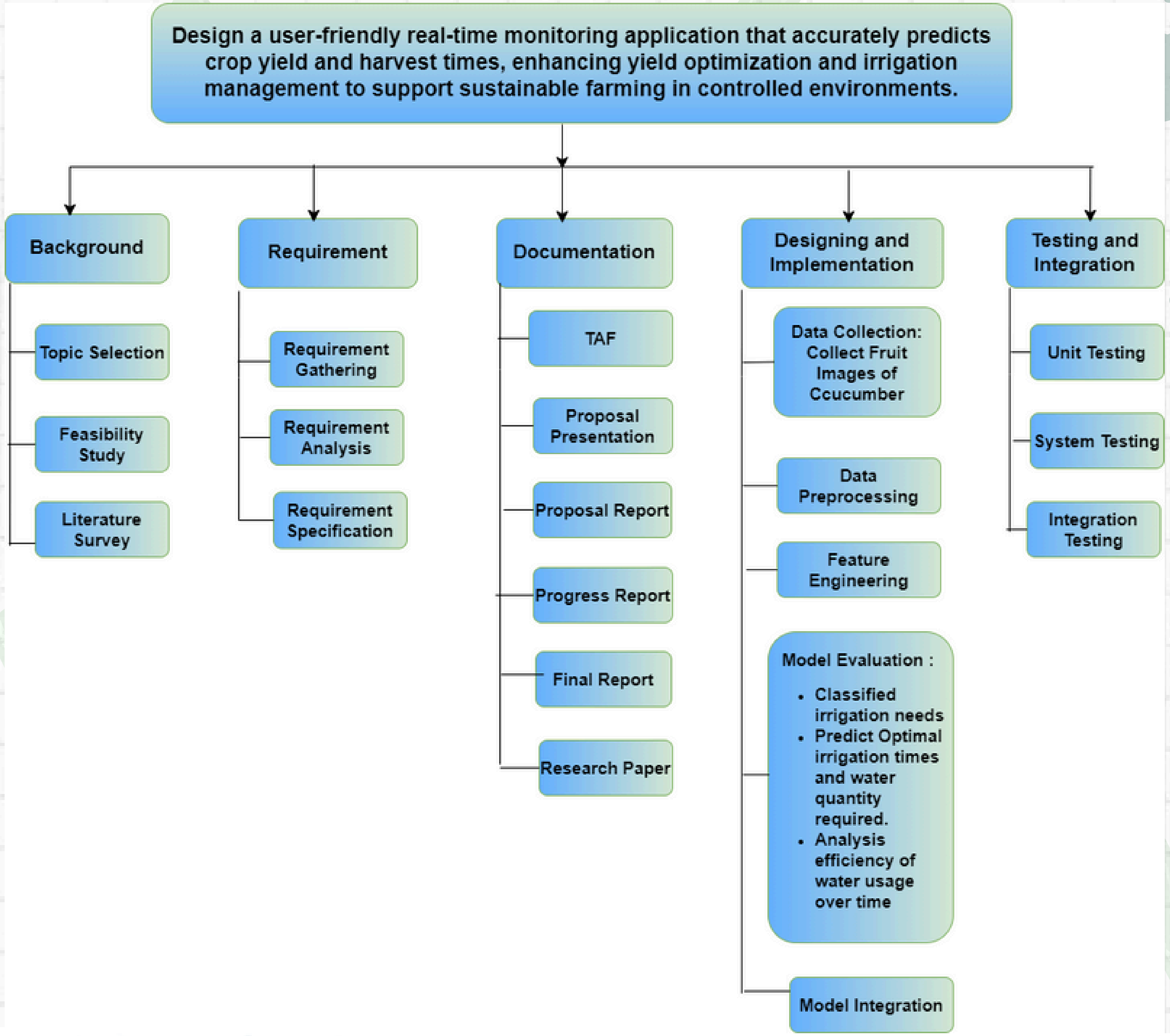
Water consumption per plant

wilted leaves detection count

DASHBOARD

This showed wilted leaves amount

WORK BREAKDOWN STRUCTURE



ON DEMAND IRRIGATION SYSTEM BASED ON IRRIGATION WEIGHT.

GANTT CHART

	Semester 1						Semester 2						
task	July	August	Sep	Oct	Nov	Dec	Jan	Feb	Mar	April	May	June	Jul
Project Planning & Setup													
Define project scope and objectives	■												
Identify resources and stakeholders	■												
Develop project plan and timeline	■												
Data Collection													
Set up sensors and data collection systems		■	■	■									
Collect biomass, temperature, humidity, and soil moisture data		■	■	■									
Clean and preprocess the data for analysis		■	■	■									
Feature Engineering & Data Preparation													
Normalize and engineer features from collected data				■	■								
Create labels for irrigation needs				■	■								
Split data into training, validation, and test sets				■	■								
Model Development													
Implement machine learning models (LSTM, Random Forest, SVM)					■	■	■	■					
Train models on the prepared dataset					■	■	■	■					
Perform cross-validation and hyperparameter tuning					■	■	■	■					
System Integration													
Integrate the trained model with the irrigation system							■	■					
Develop a user interface for system control							■	■					
Ensure real-time data flow between sensors and model							■	■					
Testing & Validation													
Test the system in controlled environments									■	■	■		
Validate the model's performance on new data									■	■	■		
Iterate and improve the model/system based on feedback									■	■	■		
Deployment & Monitoring													
Deploy the system in a real agricultural setting											■	■	
Monitor system performance and water usage efficiency											■	■	
Collect feedback and make necessary adjustments											■	■	
Documentation & Reporting													
Prepare project documentation													■
Create a final report detailing outcomes and findings													■
Present the project to stakeholders													■

ON DEMAND IRRIGATION SYSTEM BASED ON IRRIGATION WEIGHT.

REFERANCES

[1] J. Smith, A. Doe, and L. Johnson, "Soil Moisture and Weather Data in Automated Irrigation Systems," Journal of Agricultural Technology, vol. 45, no. 3, pp. 567-583, 2020.

[2] X. Zhang, Q. Li, and Y. Yang, "Machine Learning Models for Precision Agriculture: A Review," Computers and Electronics in Agriculture, vol. 176, p. 105647, 2021.

[3]J. Ramos, A. Cunha, J. Oliveira, and J. Soares, "An IoT-Based Smart Irrigation System for Precision Agriculture," IEEE Access, vol. 7, pp. 167155-167170, 2019, doi: 10.1109/ACCESS.2019.2953980.

DINANDI SOMARATHNE

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SP: DATA SCIENCE

CROP GROWTH ANALYSIS USING PICTORIAL DATA

KEY FOCUS AREAS

GROWTH STAGE MONITORING AND PREDICTION

LEAF DISEASE DETECTION AND IDENTIFICATION

SCOPE OF WORK

Created a system that observes cucumber plants, identifies their current growth stage, and predicts how they will progress.

Developed a solution that checks if a cucumber leaf is healthy or affected by one of the most common diseases.

Created a system that observes cucumber plants, identifies their current growth stage, and predicts how they will progress.

AGRICULTURAL BENEFITS AND IMPACT

Importance of Crop Growth Stage Classification:

- Provides real-time insights into the current growth stage of the cucumber plant.
- Helps farmers apply the right type and amount of fertilizers specific to each stage.
- Suggests timely agricultural treatments like pruning, pollination assistance, or nutrient adjustments.
- Enables early detection of anomalies in plant development through continuous monitoring.

Benefits of Real-Time Monitoring:

- Enhances decision-making by providing instant visual and analytical feedback.
- Reduces guesswork in crop management and improves yield quality and quantity.
- Optimizes resource usage (water, fertilizers) and minimizes environmental impact.

Importance of Leaf Disease Detection and Identification:

- Allows farmers to determine if a leaf is healthy or diseased.
- If diseased, the model identifies the specific disease from the most prevalent types.
- Each diagnosis is accompanied by recommended treatments and solutions.

EXECUTION STRATEGY AND WORKFLOW

1
Data Collection
Images of cucumber plants and leaves were regularly captured using a camera setup to monitor growth and health conditions.

2
Data Preparation
Captured images were organized, cleaned, and prepared to ensure consistency and accuracy for analysis.

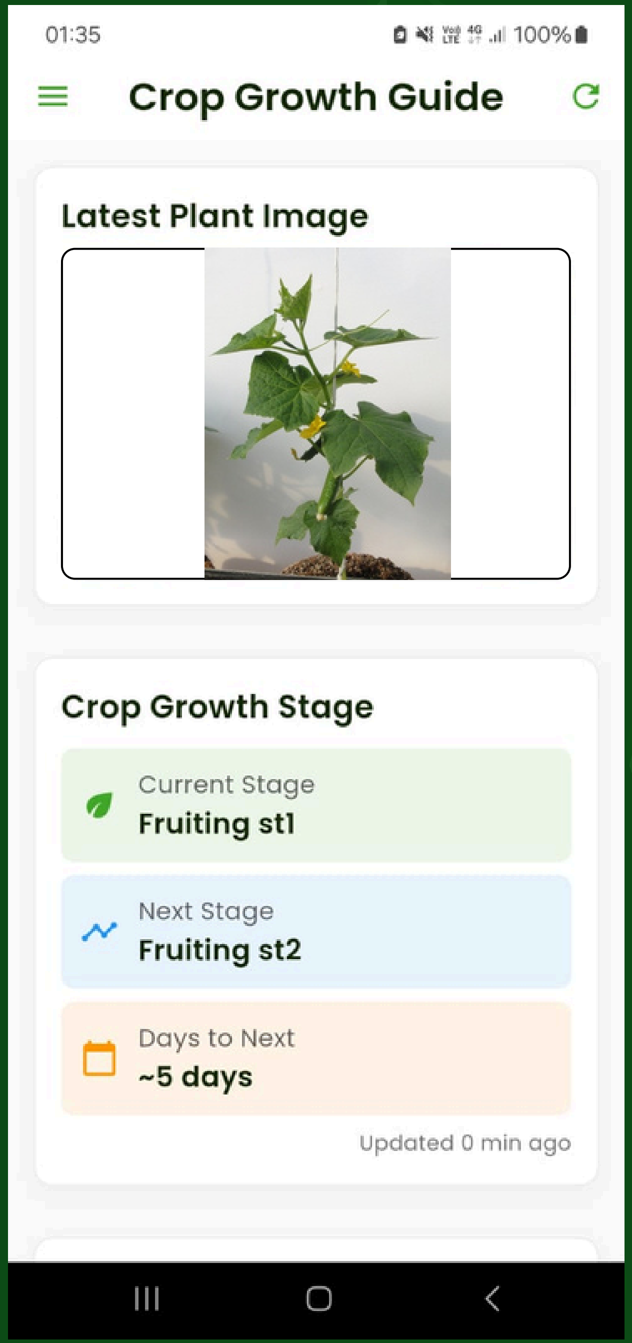
3
Model Development
Custom models were trained to recognize plant growth stages and identify common leaf diseases from the prepared image data.

4
System Integration:
The trained models were deployed into a virtual environment and connected to a mobile app and dashboard for real-time monitoring and user interaction.

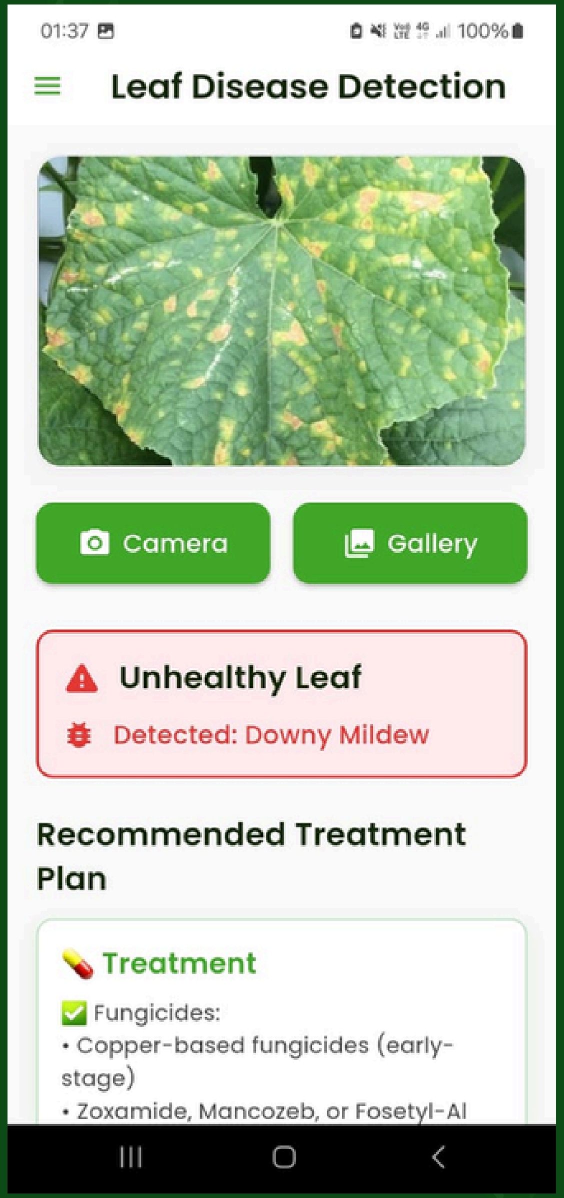
MOBILE APPLICATION

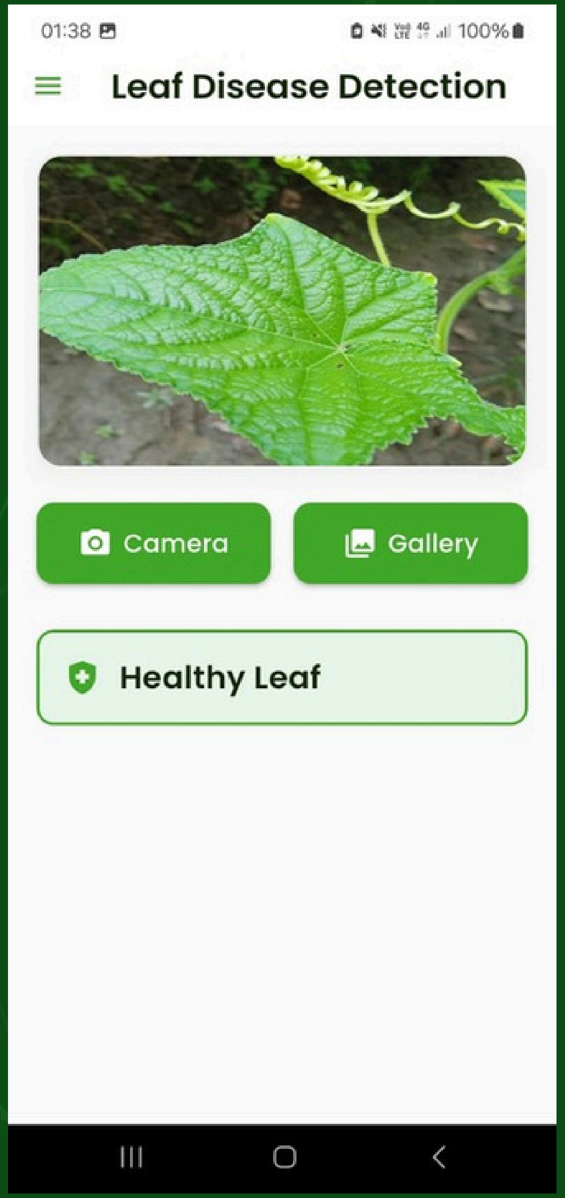
Crop Growth Stage Monitoring:

- Displays real-time image of each plant.
- Shows the predicted growth stage.
- Recommends fertilizers and treatments appropriate to the detected stage.



MOBILE APPLICATION





Leaf Disease Detection and Identification:

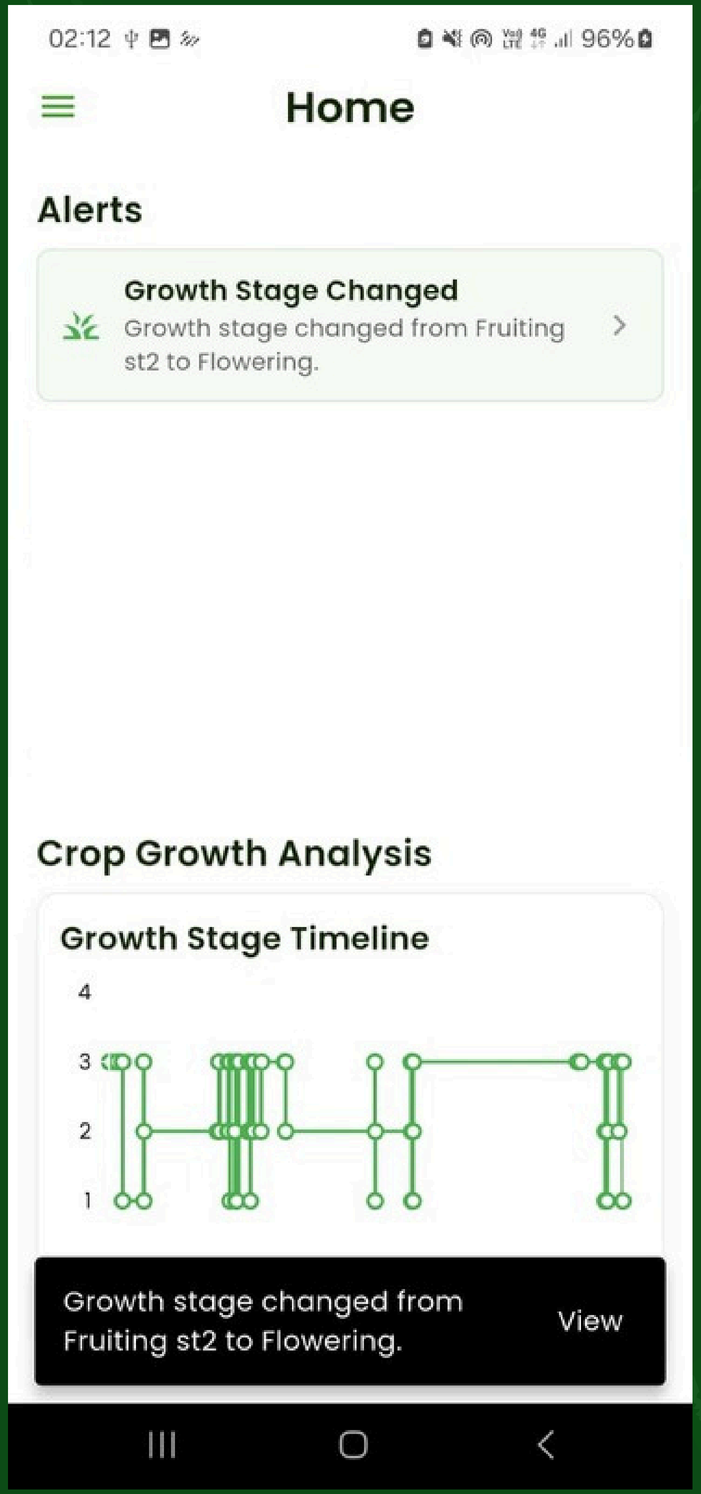
- Farmers can upload leaf images via camera or gallery.

- The app predicts:
  - Whether the leaf is healthy or unhealthy.
  - If unhealthy, the specific disease name.
  - Displays treatment and solution recommendations based on the diagnosis

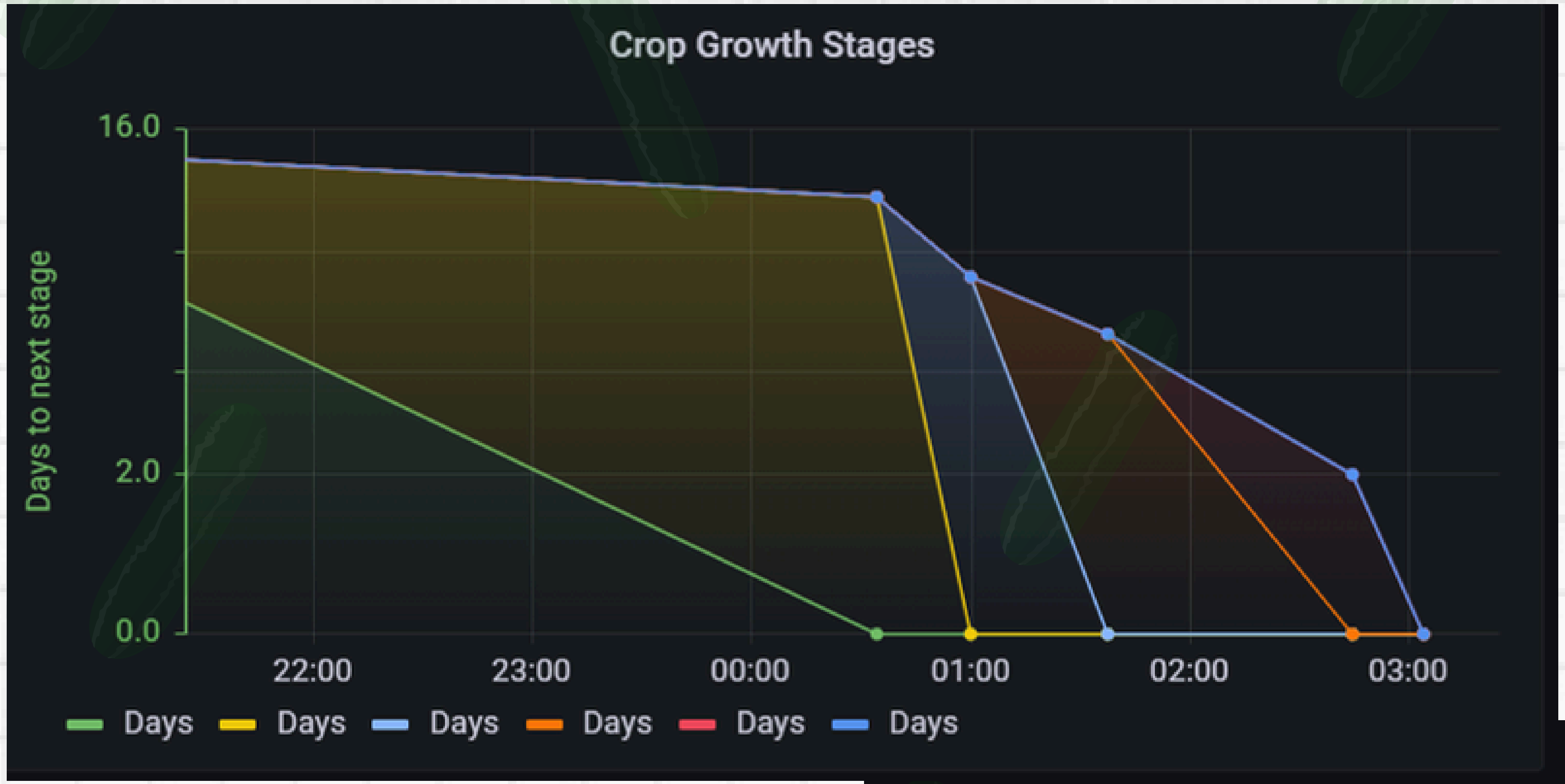
MOBILE APPLICATION

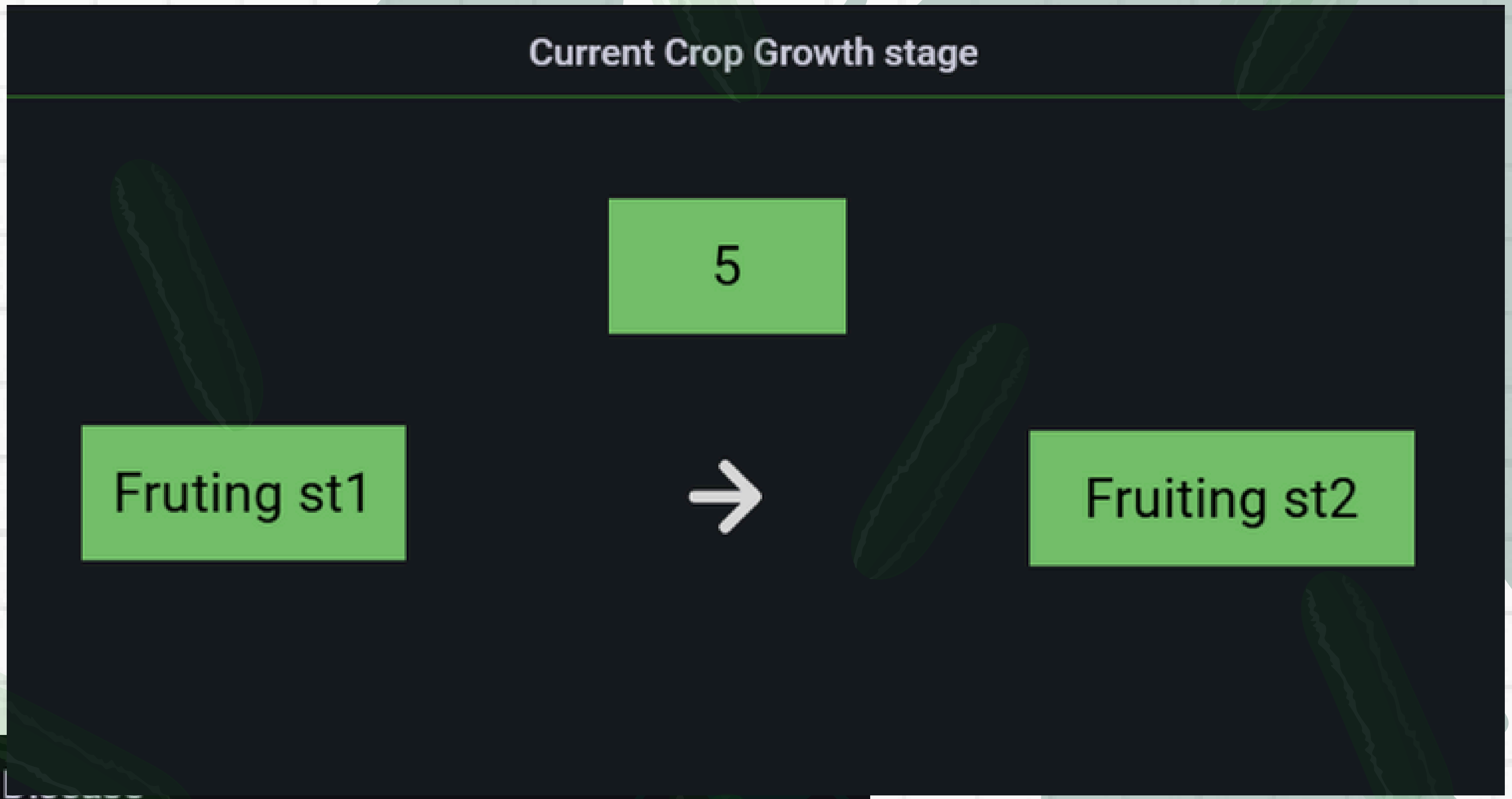
Alerting and Notifications:

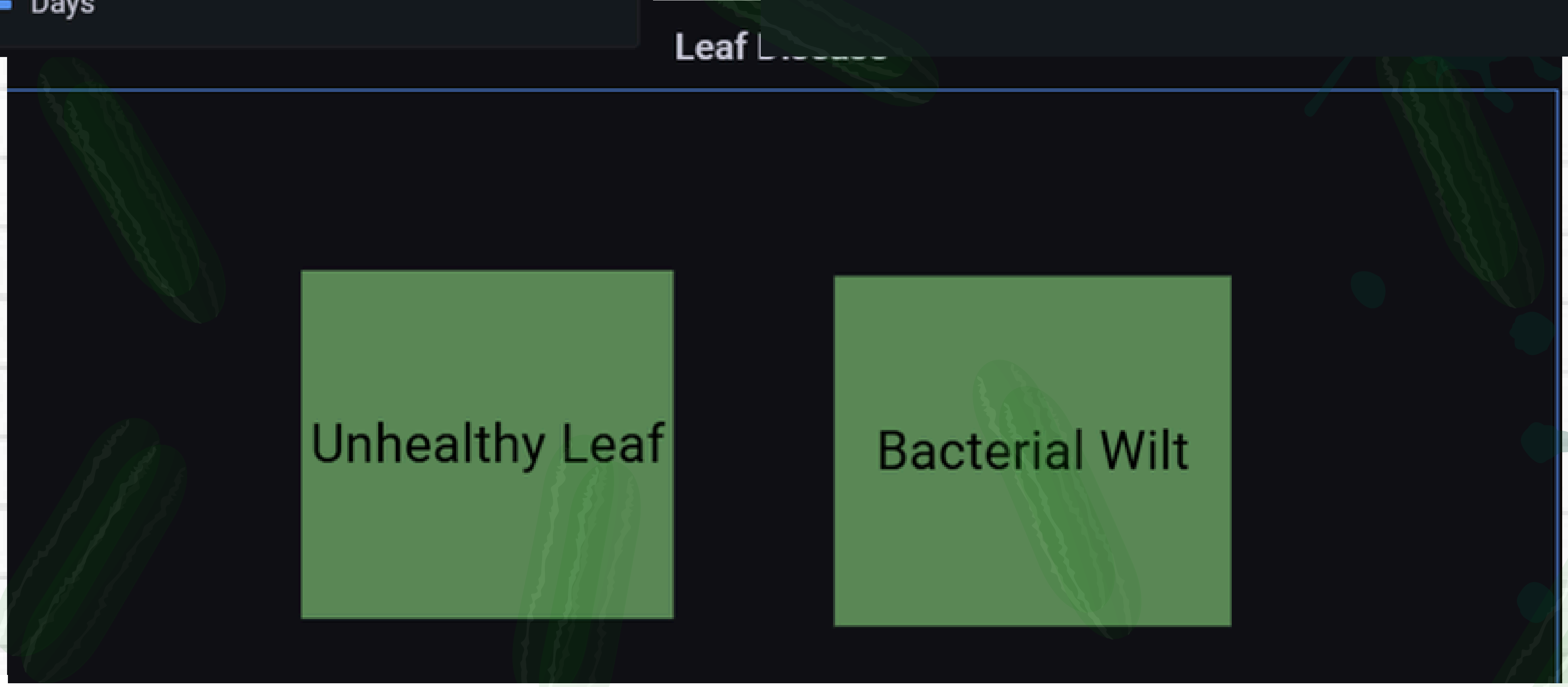
- The app sends a real-time alert to the user when a plant's growth stage changes from one stage to another.
- This enables timely interventions, helping farmers act quickly with stage-specific care practices.



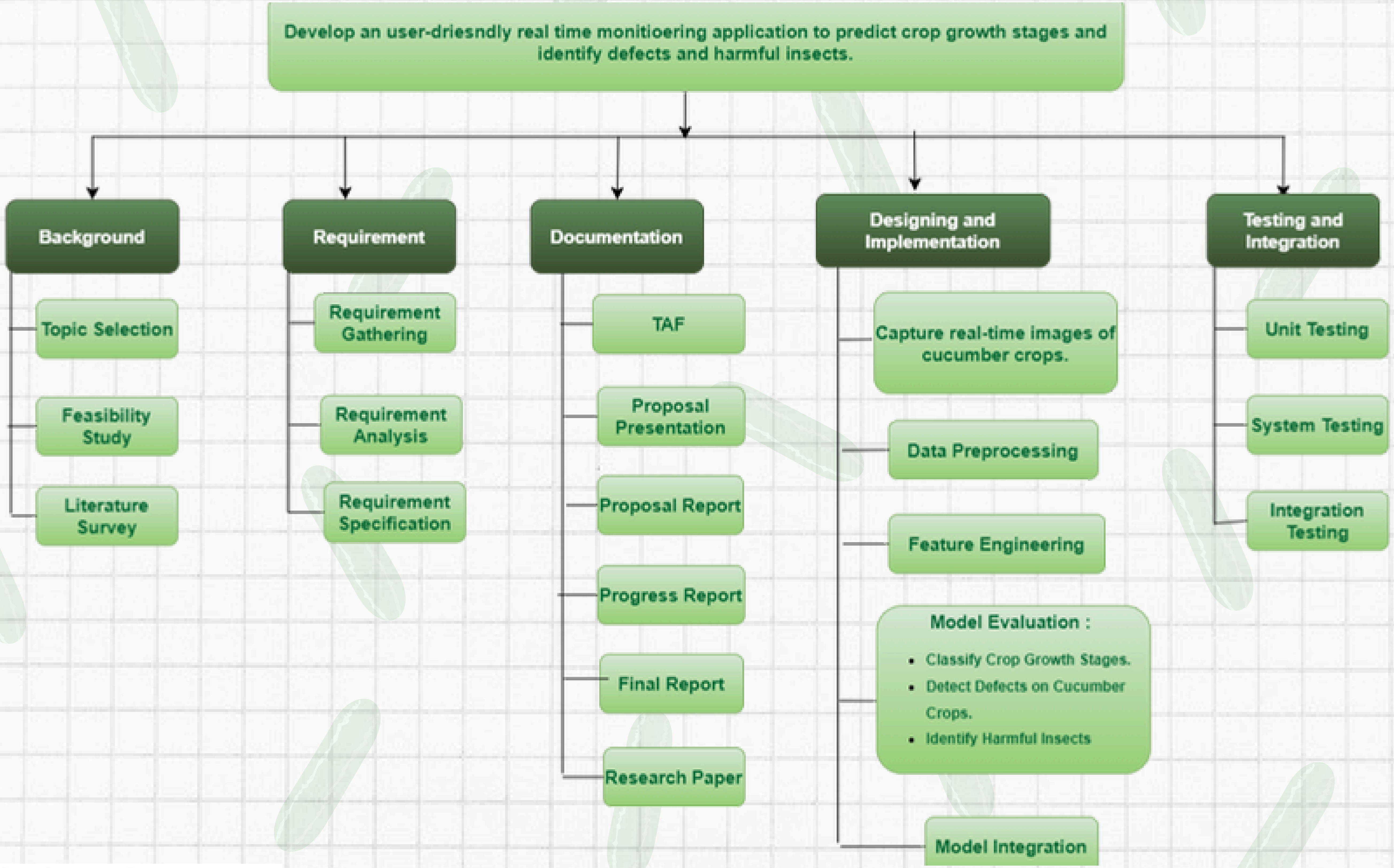
GRAFANA DASHBOARD INTEGRATION



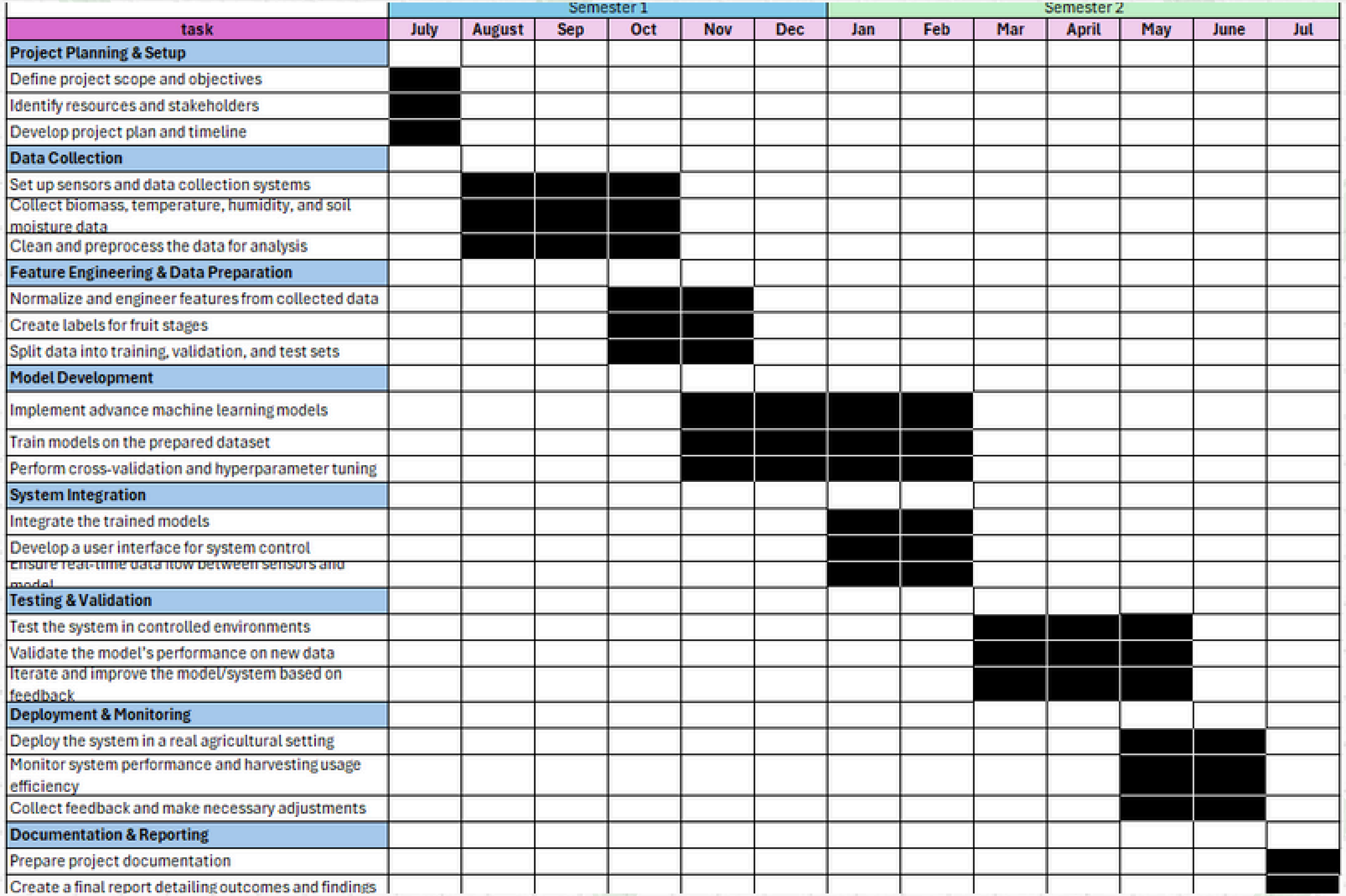




WORK BREAKDOWN CHART



GRANTT CHART



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[1] X. Liu, D. Zhao, W. Jia, W. Ji, C. Ruan, and Y. Sun, “Cucumber Fruits Detection in Greenhouses Based on Instance Segmentation,” IEEE Access, vol. 7, pp. 139635–139642, 2019, doi: https://doi.org/10.1109/ACCESS.2019.2942144.

[11] S. Kum, S. Oh, Y. Kim, J. Moon, Alejandro Barrera Carvajal, and Francisco Andres Perez, “Design of Crop Growth Analysis Platform with Image and Time Series Analysis,” Nov. 2023, doi: https://doi.org/10.1109/metroagrifor58484.2023.10424382.

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BINURI THILAKARATHNE

IT21267222

THILAKARATHNE M.B.N

SP: DATA SCIENCE

REAL-TIME IMAGE ANALYSIS FOR OPTIMAL FRUIT HARVEST TIMING AND STAGE IDENTIFICATION.

KEY FOCUS AREAS

MATHURITY PREDICTION

QUALITY ASSESSMET

&

DEFEAT IDENTIFICATION

SCOPE OF WORK

Created a system that observes cucumber fruits to identify their current growth stages from bus to maturity.

Developed a solution that checks if a cucumber is in good quality or affected by one of the most common diseases.

Created a system to predict the best harvest time to pick each cucumber fruit and how they will progress.

AGRICULTURAL BENEFITS AND IMPACT

Importance of Crop Growth Stage Classification:

- Accurately predicting the maturity stage of cucumber fruits helps ensure they are harvested at the optimal time for best size, taste, and texture.
- It prevents losses caused by early harvesting (underdeveloped fruits) or delayed harvesting (overripe or spoiled fruits).
- Timely harvest improves market quality, increases profitability, and supports better planning for post-harvest handling and distribution.

Benefits of Real-Time Monitoring:

- Enhances decision-making by providing instant visual and analytical feedback.
- Reduces guesswork in crop management and improves yield quality and quantity.
- Optimizes resource usage (water, fertilizers) and minimizes environmental impact.

Importance of Leaf Disease Detection and Identification:

- Detecting defects early prevents damaged cucumbers from being packed or sold.
- It helps farmers take quick action to reduce further crop losss.
- Each diagnosis is accompanied by recommended treatments and solutions.

EXECUTION STRATEGY AND WORKFLOW

1

Data Collection

Images of cucumber fruits stages and cucumber fruits were regularly captured using a camera setup to monitor growth and quality

2

Data Preparation

Captured images were organized, cleaned, and prepared to ensure consistency and accuracy for analysis.

3

Model Development

Custom models were trained to predict the harvest time and identify quality and suggestions from the prepared image data.

4

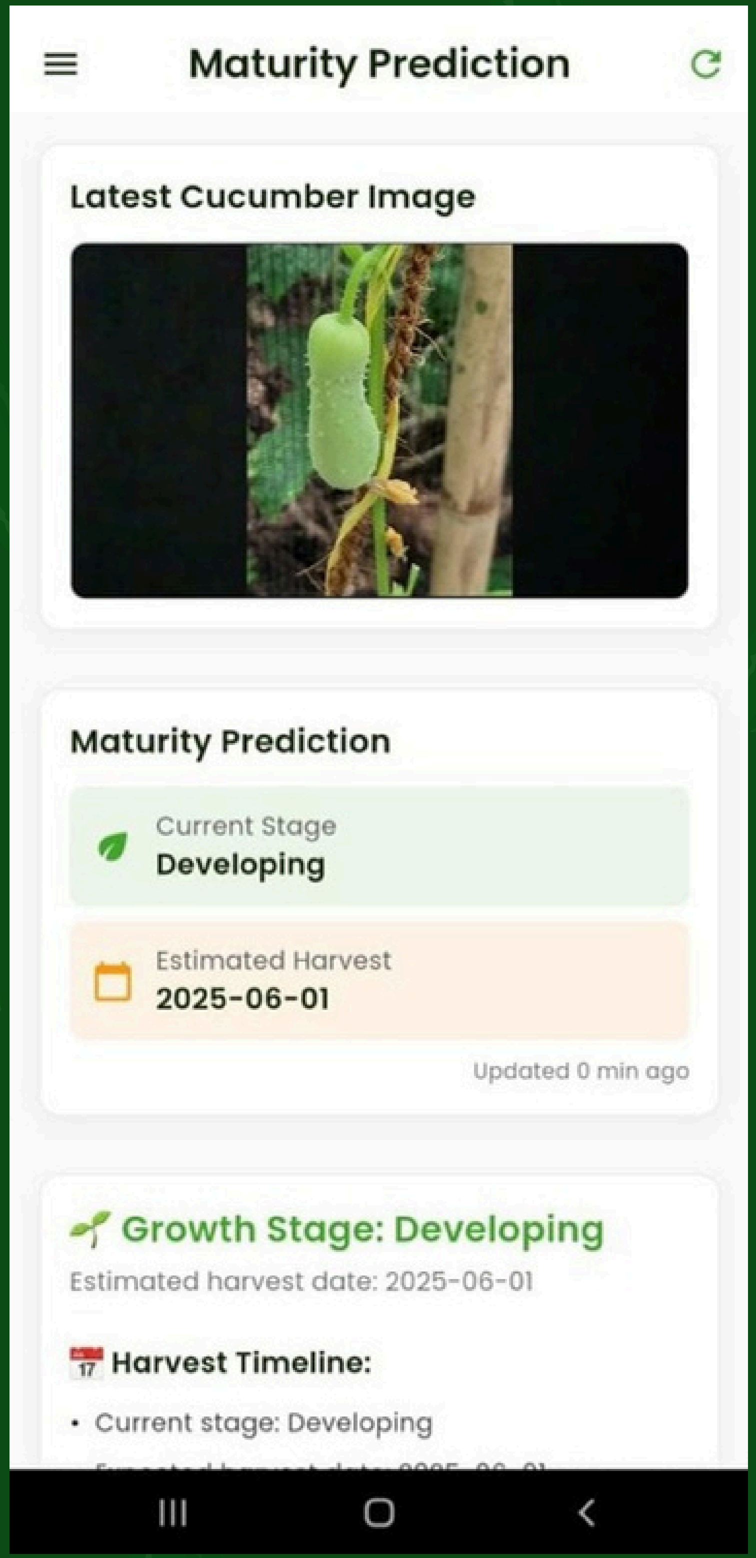
System Integration:

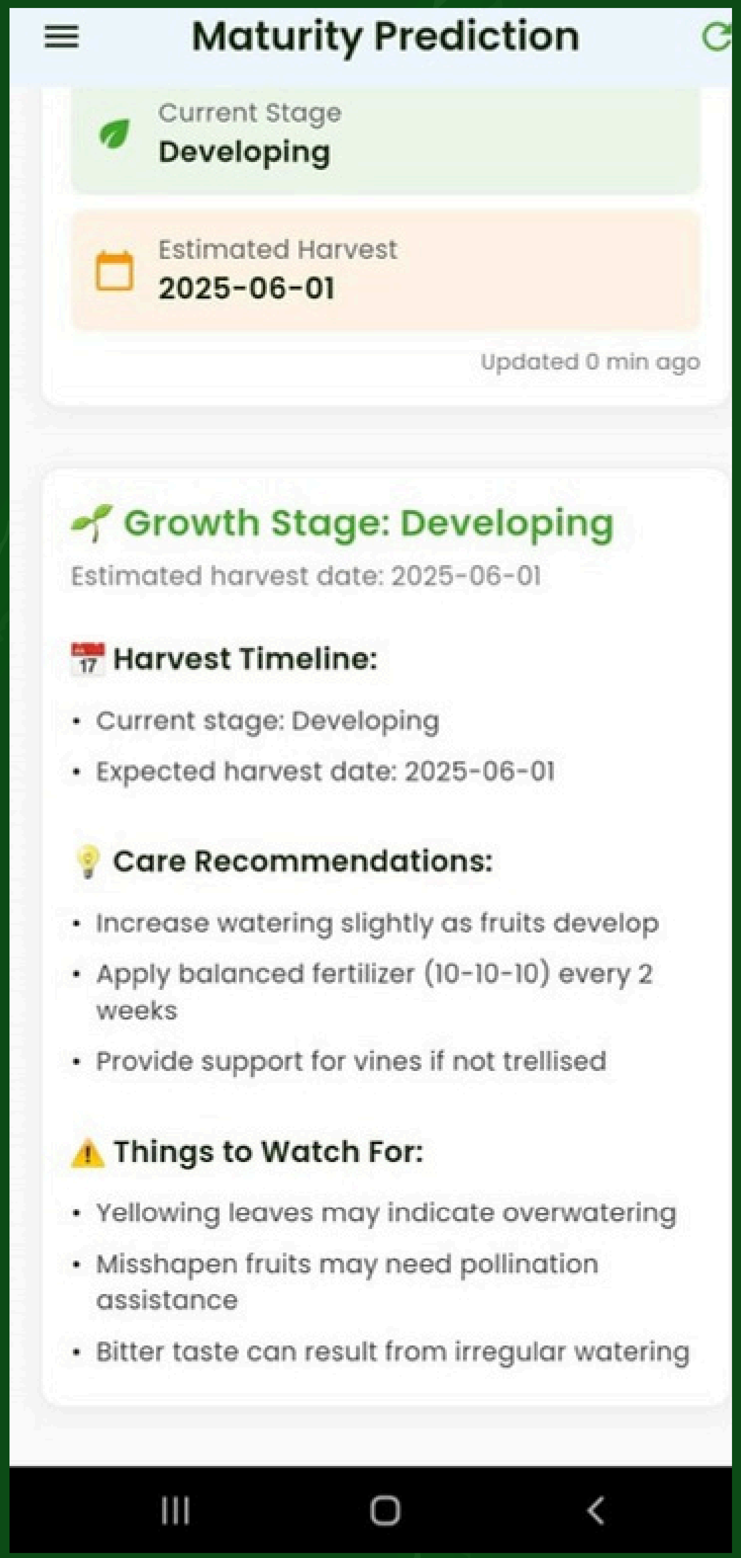
The trained models were deployed into a virtual environment and connected to a mobile app and dashboard for real-time monitoring and user interaction.

MOBILE APPLICATION

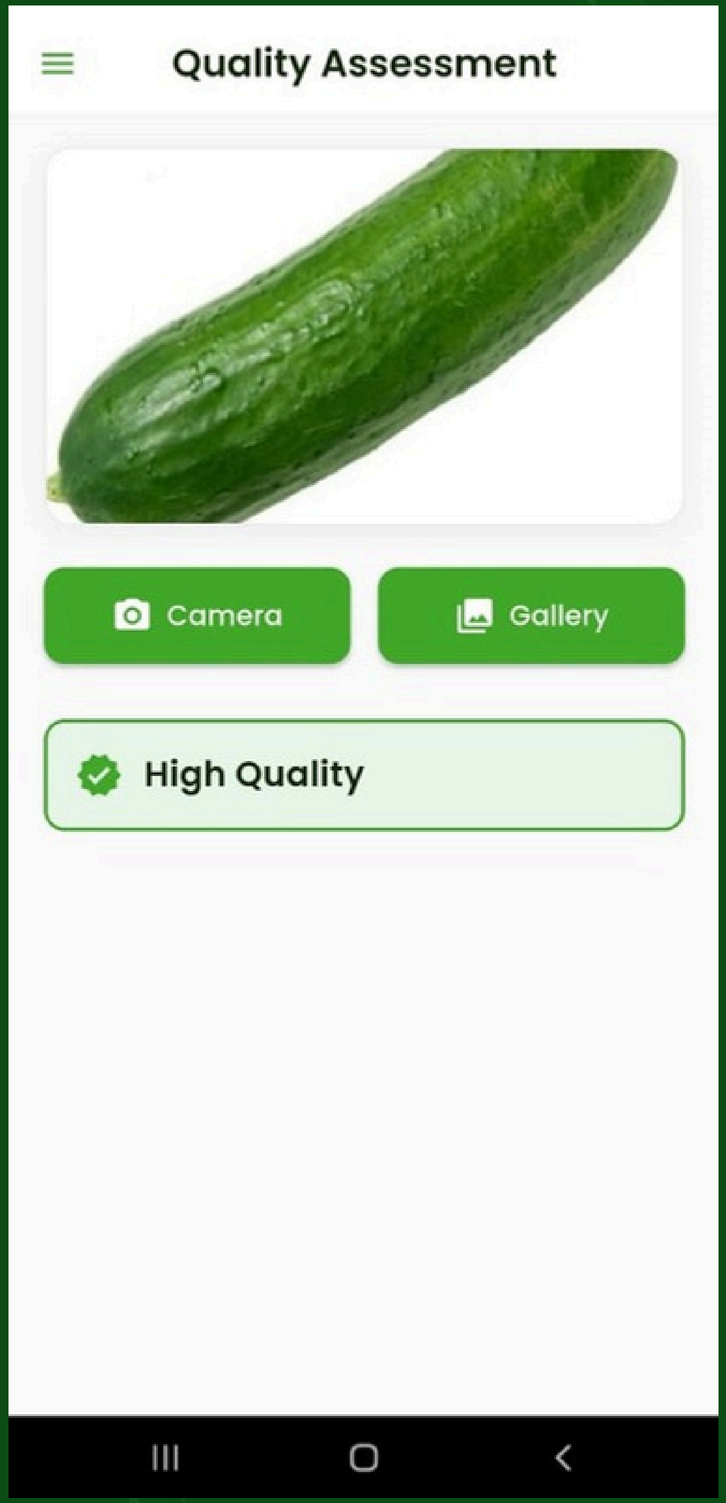
Maturity identification:

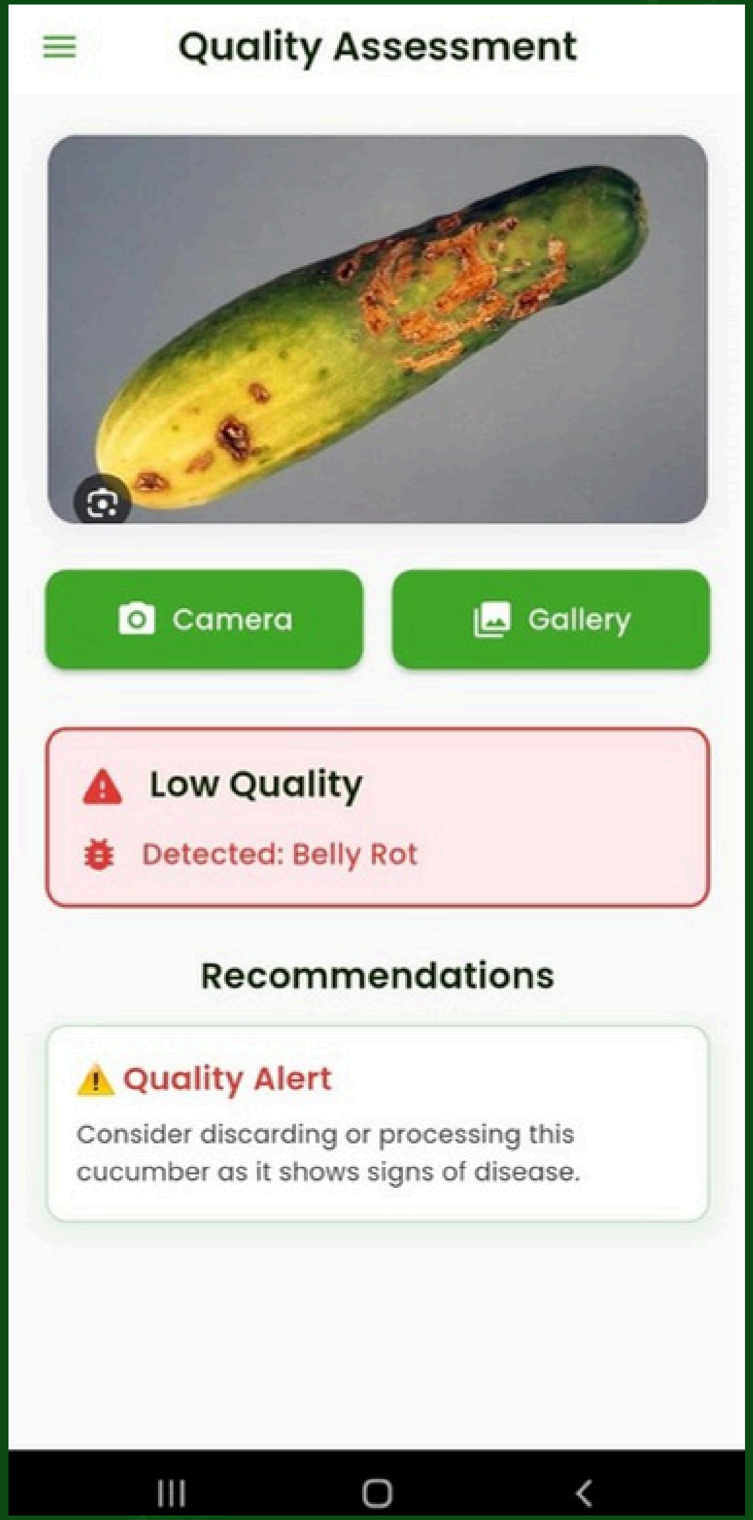
- Displays the real-time image of each plant with the cucumber fruits.
- Shows the estimated harvest Date.
- Displays the recommendation to appropriate cucumber fruit.





MOBILE APPLICATION





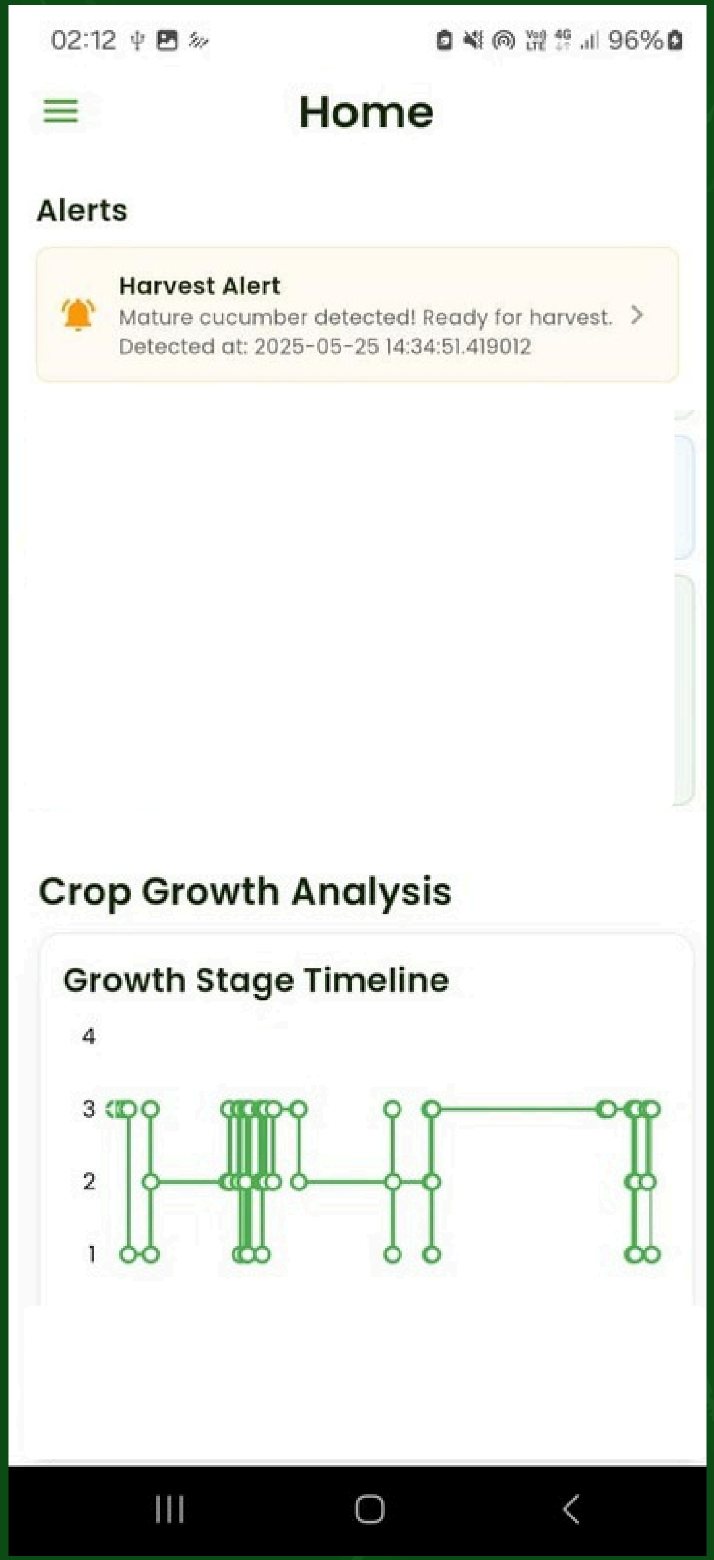
Quality Assessment and Defect Identification:

- Farmers can upload cucumber fruit images via camera or gallery.
- The app predicts:
  - Whether the cucumber is good quality or low quality.
  - If low quality, the specific defeact name.
  - Displays the recommendations based on the diagnosis

MOBILE APPLICATION

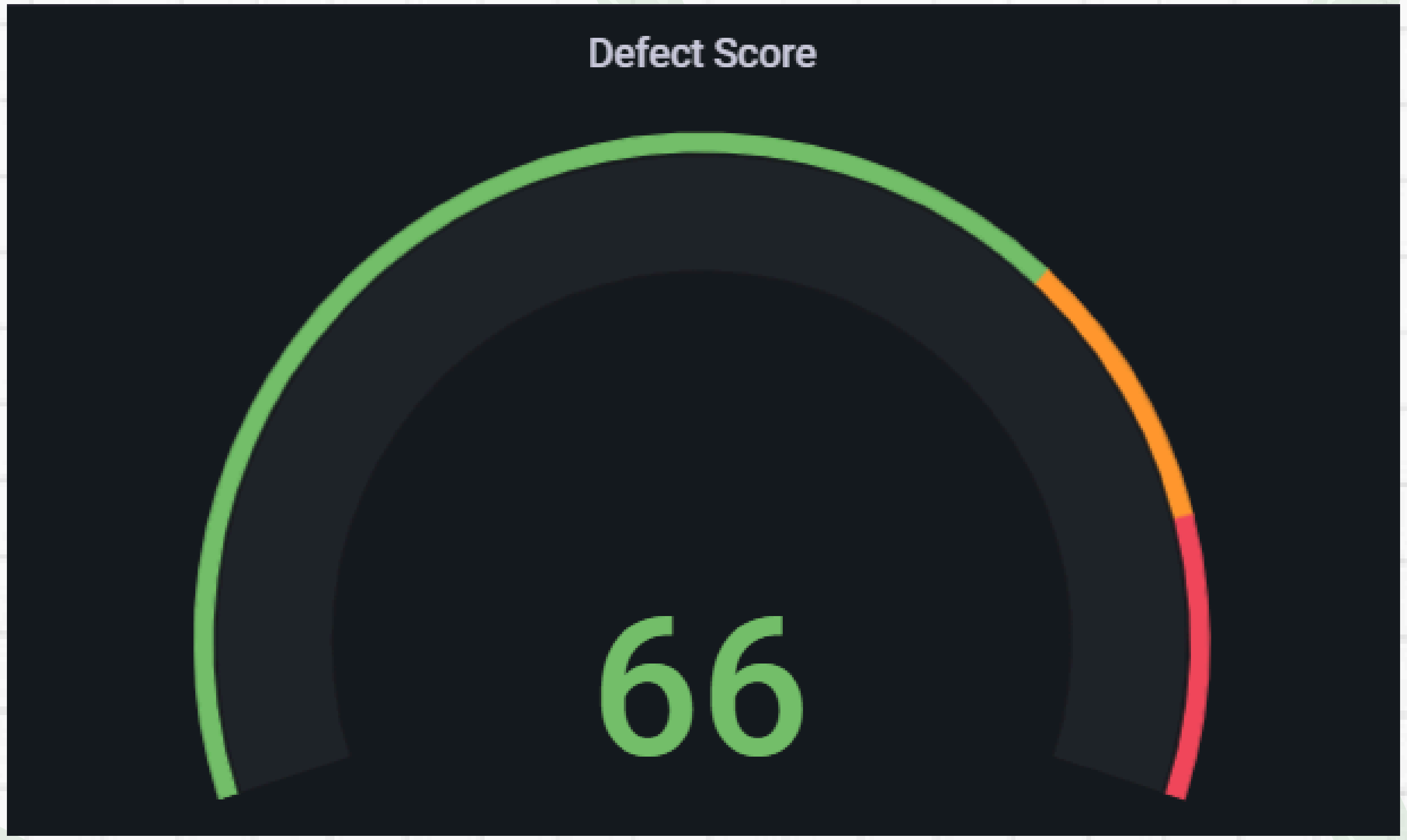
Alerting and Notifications:

- The app sends a real-time alert to the user when detect the mature cucumber fruit.
- It prevents losses caused by early harvesting (underdeveloped fruits) or delayed harvesting (overripe or spoiled fruits).

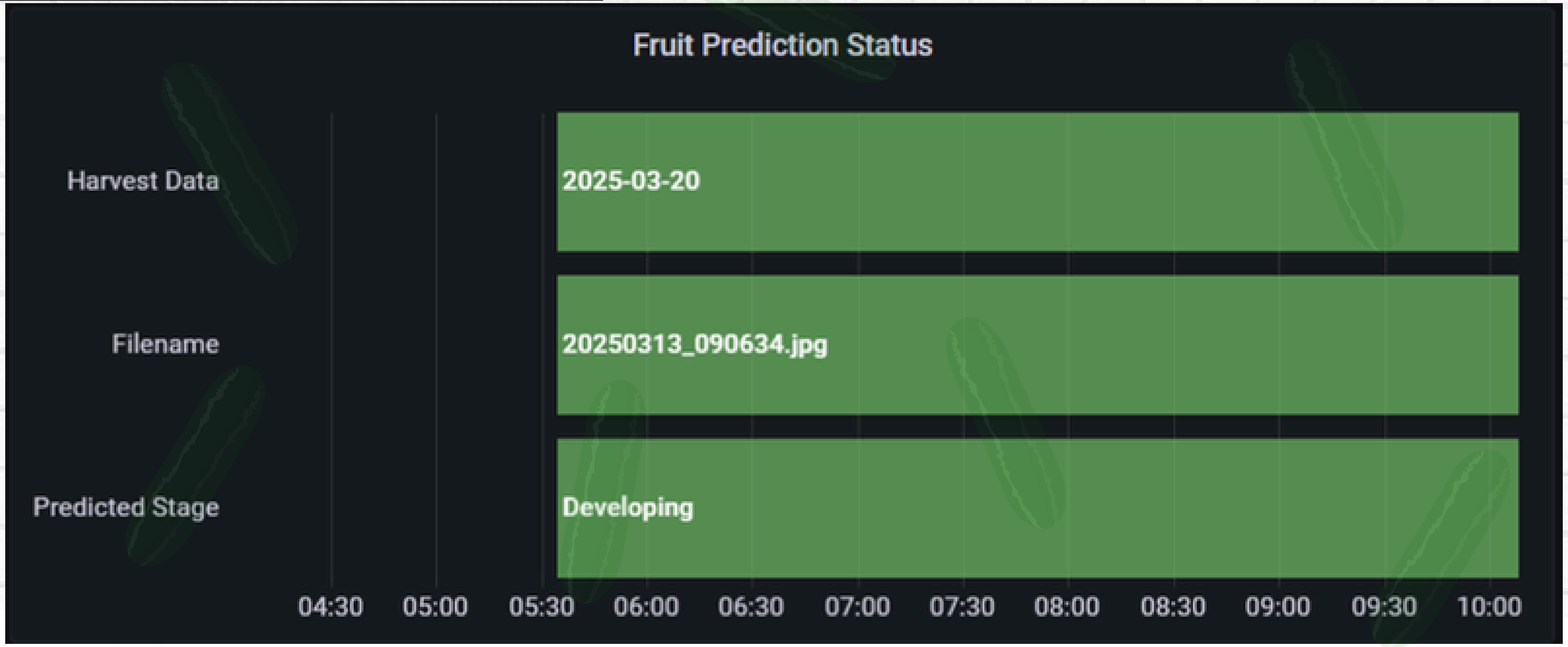


DASHBOARD

Fruit Quality Score
22



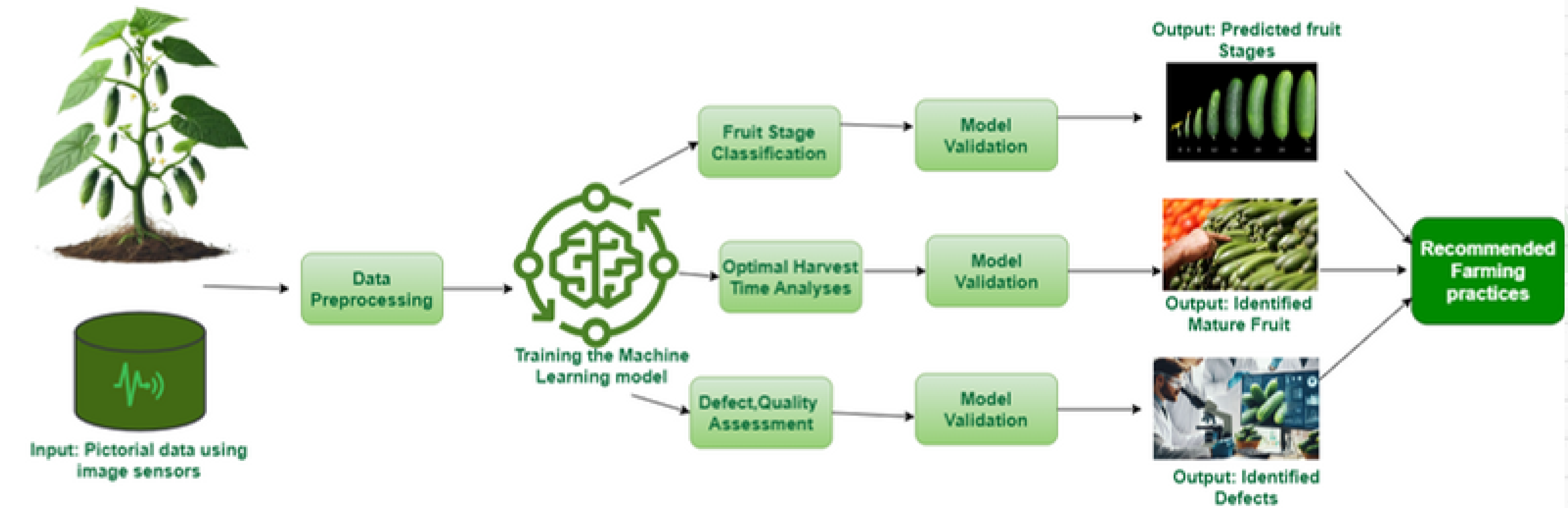
Defect Score
66



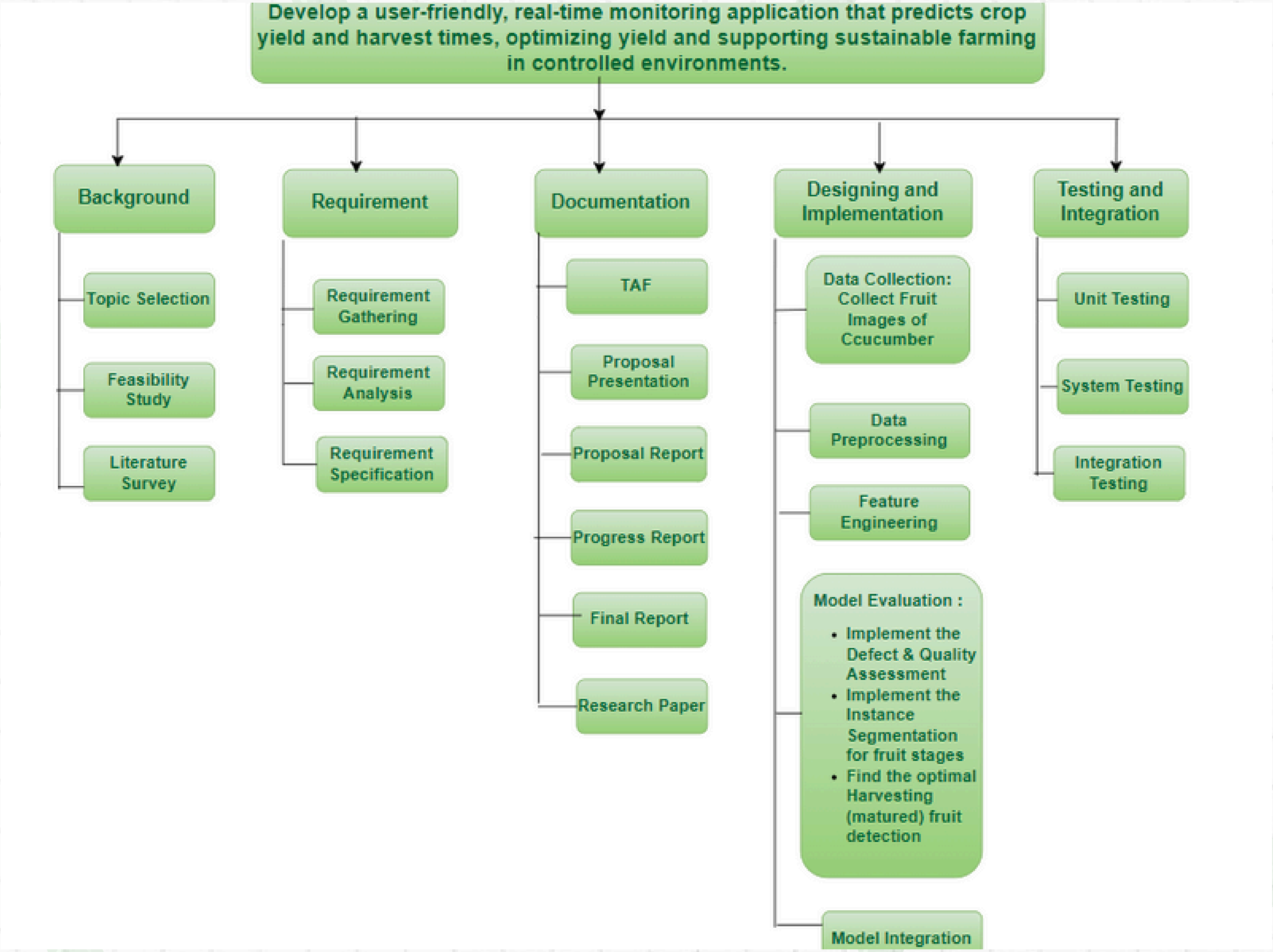
Fruit Prediction Status
Harvest Data
2025-03-20
Filename
20250313_090634.jpg
Predicted Stage
Developing
04:30
05:00
05:30
06:00
06:30
07:00
07:30
08:00
08:30
09:00
09:30
10:00

METHODOLOGY

SYSTEM - DIAGRAM

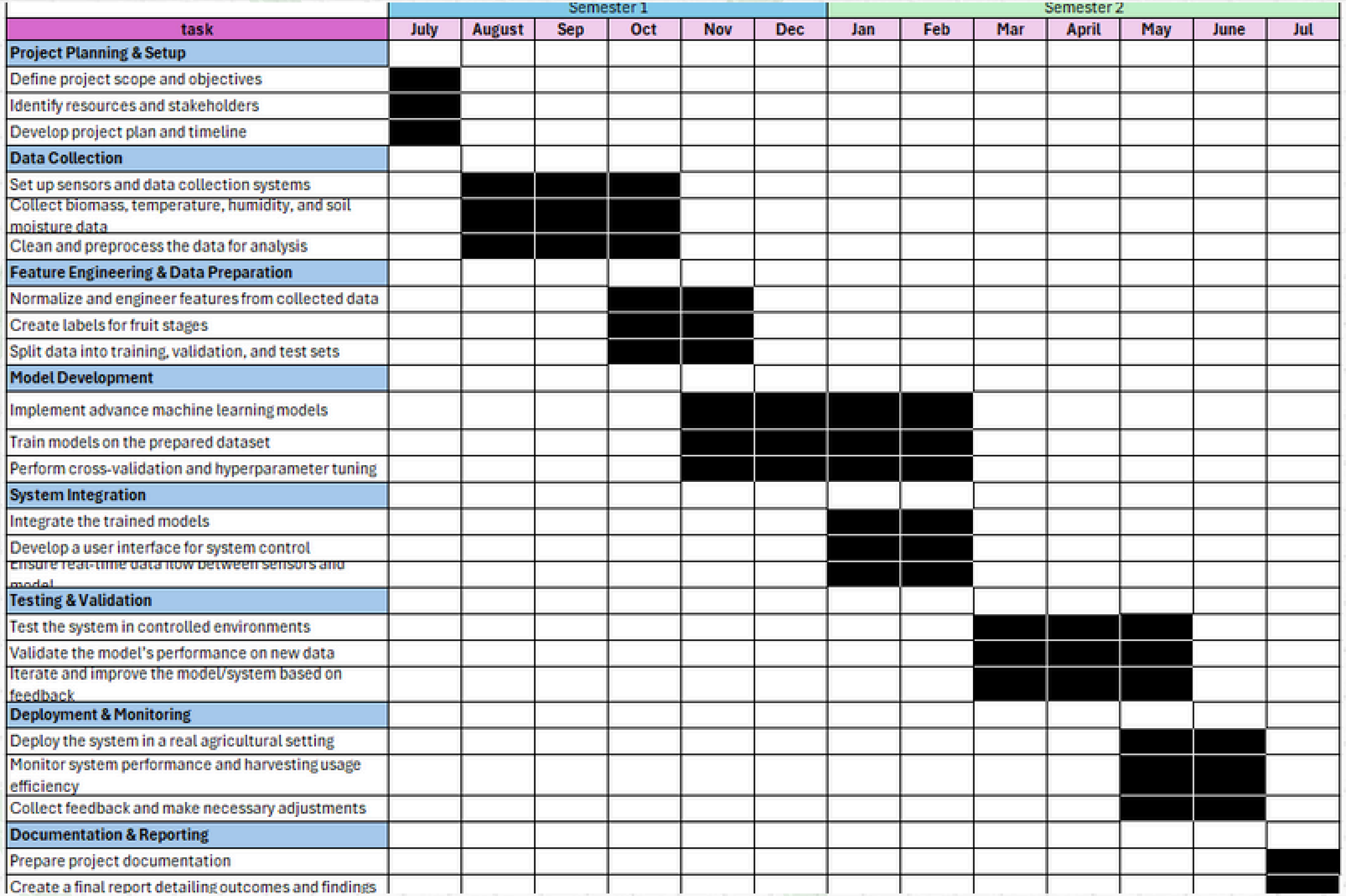


WORK-BREAKDOWN CHART



REAL-TIME IMAGE CAPTURING AND ANALYSIS BASED ON FRUIT GROWTH STAGES

GANT CHART



Semester 1
Semester 2
task
July
August
Sep
Oct
Nov
Dec
Jan
Feb
Mar
April
May
June
Jul
Project Planning & Setup
Define project scope and objectives
Identify resources and stakeholders
Develop project plan and timeline
Data Collection
Set up sensors and data collection systems
Collect biomass, temperature, humidity, and soil moisture data
Clean and preprocess the data for analysis
Feature Engineering & Data Preparation
Normalize and engineer features from collected data
Create labels for fruit stages
Split data into training, validation, and test sets
Model Development
Implement advance machine learning models
Train models on the prepared dataset
Perform cross-validation and hyperparameter tuning
System Integration
Integrate the trained models
Develop a user interface for system control
Ensure real-time data flow between sensors and model
Testing & Validation
Test the system in controlled environments
Validate the model's performance on new data
Iterate and improve the model/system based on feedback
Deployment & Monitoring
Deploy the system in a real agricultural setting
Monitor system performance and harvesting usage efficiency
Collect feedback and make necessary adjustments
Documentation & Reporting
Prepare project documentation
Create a final report detailing outcomes and findings

CHALLENGES

REFERENCES

(1) X. LIU, D. ZHAO, W. JIA, W. JI, C. RUAN, AND Y. SUN, "CUCUMBER FRUITS DETECTION IN GREENHOUSES BASED ON INSTANCE SEGMENTATION," IEEE ACCESS, VOL. 7, PP. 139635-139642, 2019, DOI: HTTPS://DOI.ORG/10.1109/ACCESS.2019.2942144.

(2) "NEURAL NETWORK MODELLING OF FRUIT COLOUR AND CROP VARIABLES TO PREDICT HARVEST DATES OF GREENHOUSE-GROWN SWEET PEPPERS W. C. LIN1 AND B. D. HILL2 1PACIFIC AGRI-FOOD RESEARCH CENTRE, AGRICULTURE AND AGRI-FOOD CANADA, BOX 1000, AGASSIZ, BRITISH COLUMBIA, CANADA V0M 1A0 (E-MAIL: LINW@AGR.GC.CA); 2LETHBRIDGE RESEARCH CENTRE, AGRICULTURE AND AGRI-FOOD CANADA," P.O. BOX, VOL. 3000, NO. 38705072, 2005.

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THANK YOU!