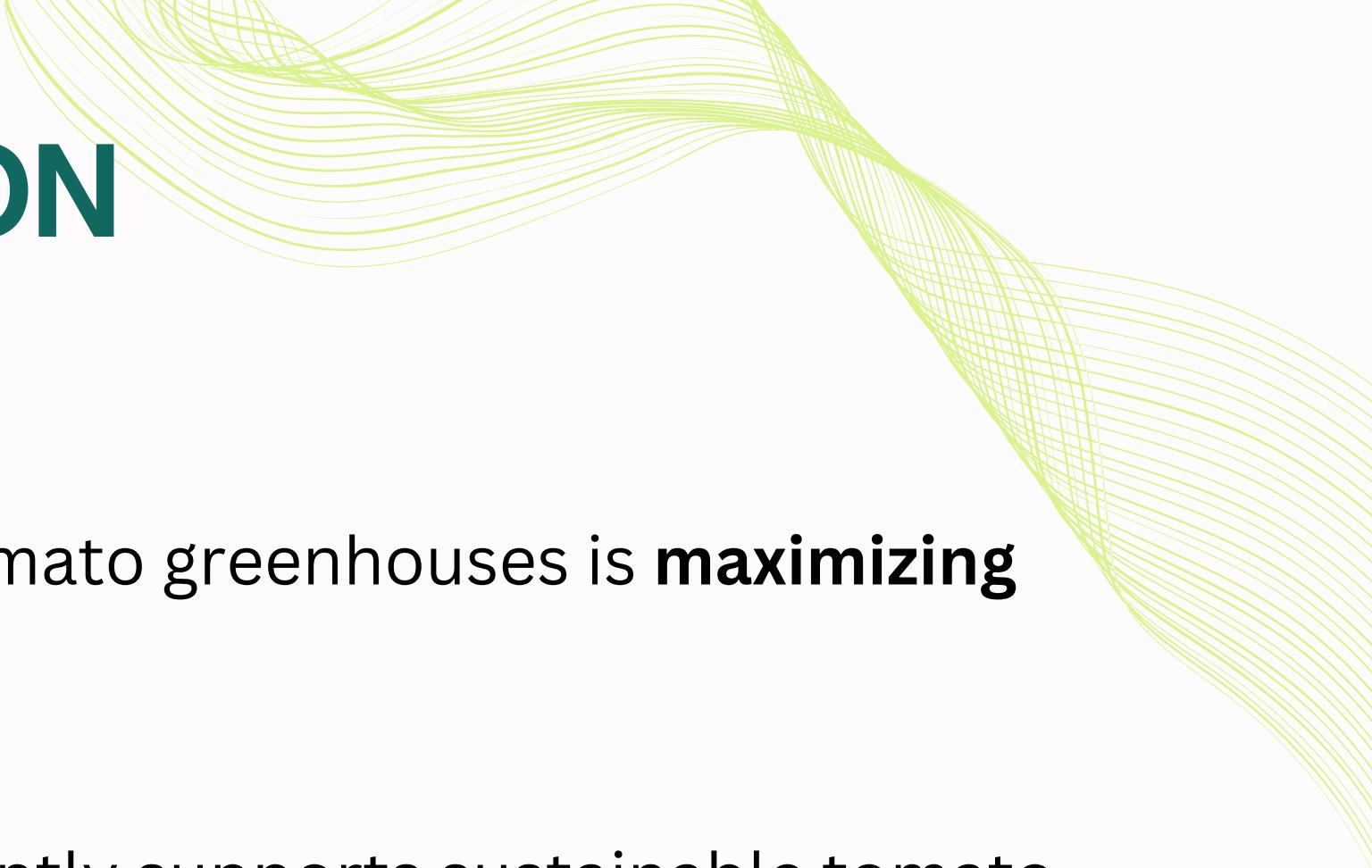


SMART GREENHOUSES DECISION SUPPORT SYSTEMS FOR TOMATO CULTIVATION

GROUP ID: 24-25J-064

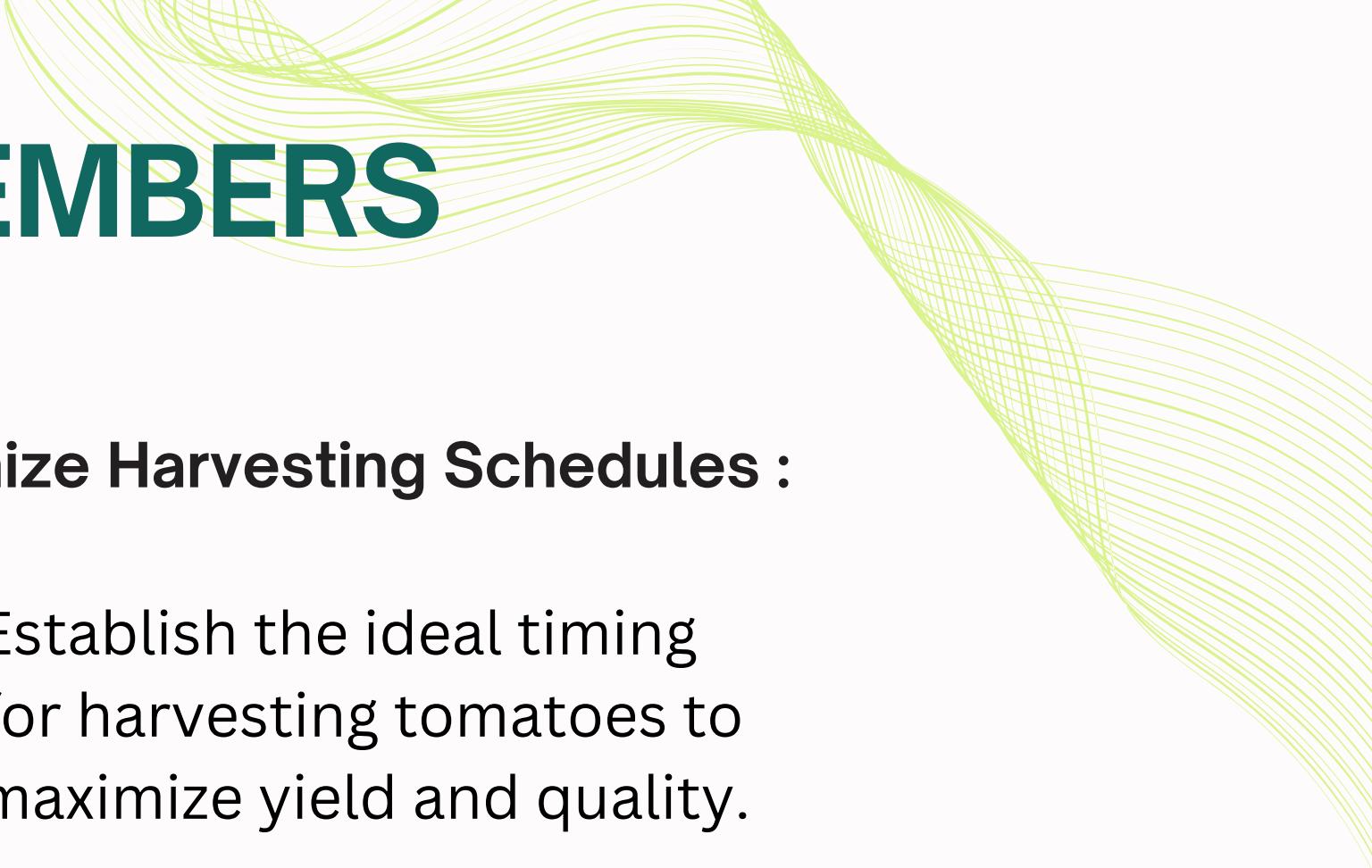


INTRODUCTION



- Maintaining optimal environmental conditions in tomato greenhouses is maximizing the yield and quality.
- Managing watering, fertilizing, and harvesting efficiently supports sustainable tomato farming.
- Machine learning can predict watering needs, fertilization, harvest times, disease identification and treatment recommendations.
- Combining IoT and ML, the project aims to make greenhouse management more efficient.

OBJECTIVES OF MEMBERS



Optimize Watering Requirements & IoT based Environmental monitoring:

- Develop a IoT Device and ML model decision support system to predict optimal watering requirements .

Optimize Harvesting Schedules :

- Establish the ideal timing for harvesting tomatoes to maximize yield and quality.

Optimize Fertilizing Schedules and Types :

- Identify the most effective fertilizing routines and products to enhance nutrient availability and promote robust tomato plants.

Disease identification and treatment recommendations

- Develop ml model to identify, prevent, and treat common tomato diseases and provide recommendations to maintain plant health.

GROUP MEMBERS AND SUPERVISORS DETAILES

Group Leader - THRIMAVITHANA .V .D - IT21181160

1st Member - NAJAS .M .N .M - IT21186592

2nd Member - ASARDEEN .A - IT21231896

3rd Member - JAYANETHTHI .I .H .N .S - IT21231414

SUPERVISOR – Mrs. Geethanjali Wimalaratne

CO-SUPERVISOR – Mr. Samantha Thelijjagoda



IT21231896 | ASARDEEN .A

Information technology



INTRODUCTION BACKGROUND

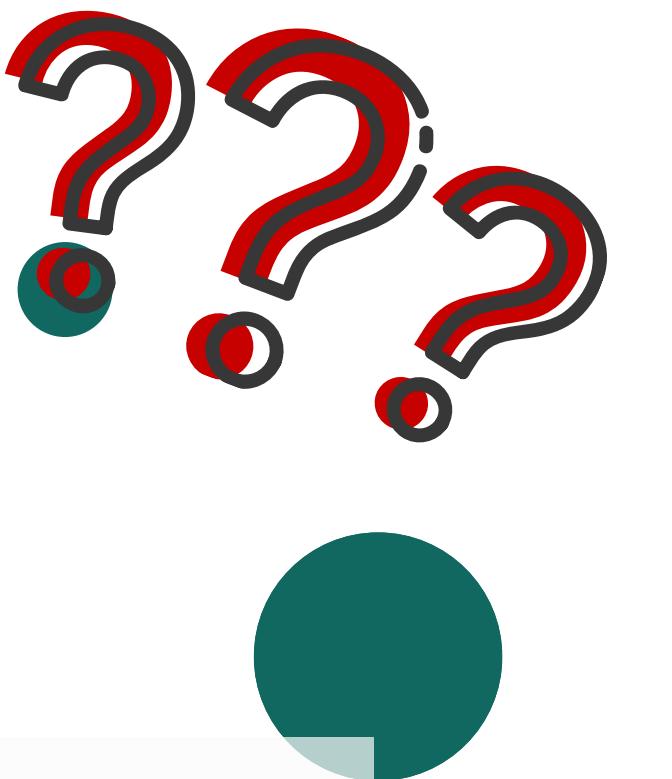
21°C - 27°C

- Water management is vital for tomato greenhouses.
- **Over-irrigation** and **under-irrigation** harm crop yield and health.
- Existing smart irrigation systems lack in predicting dynamic water needs.
- Environmental factors like **temperature** and **humidity** significantly **impact water needs**.
- **IoT** and **ML** model **improve irrigation** by **monitoring** the environmental factors.



RESEARCH QUESTIONS

How can we develop a decision support system that accurately predicts optimal water requirements and ensures water availability based on real-time environmental conditions?



RESEARCH GAP

Existing Products / Research	Features					
	Weather Condition Alerts	Soil Moisture, Light & Temperature Monitoring	Machine Learning Integration	Water level & Availability Monitoring	Predict Water Requirements (Quantity)	Real-Time Dashboard
IoT-Based Precision Irrigation System	✗	✓	✗	✓	✗	✗
Smart high-yield tomato cultivation System	✗	✗	✗	✓	✗	✓
Indoor Seedling Irrigation System	✓	✓	✗	✗	✗	✗
LoRaWAN based IoT system	✗	✓	✗	✗	✗	✓
Proposed System	✓	✓	✓	✓	✓	✓

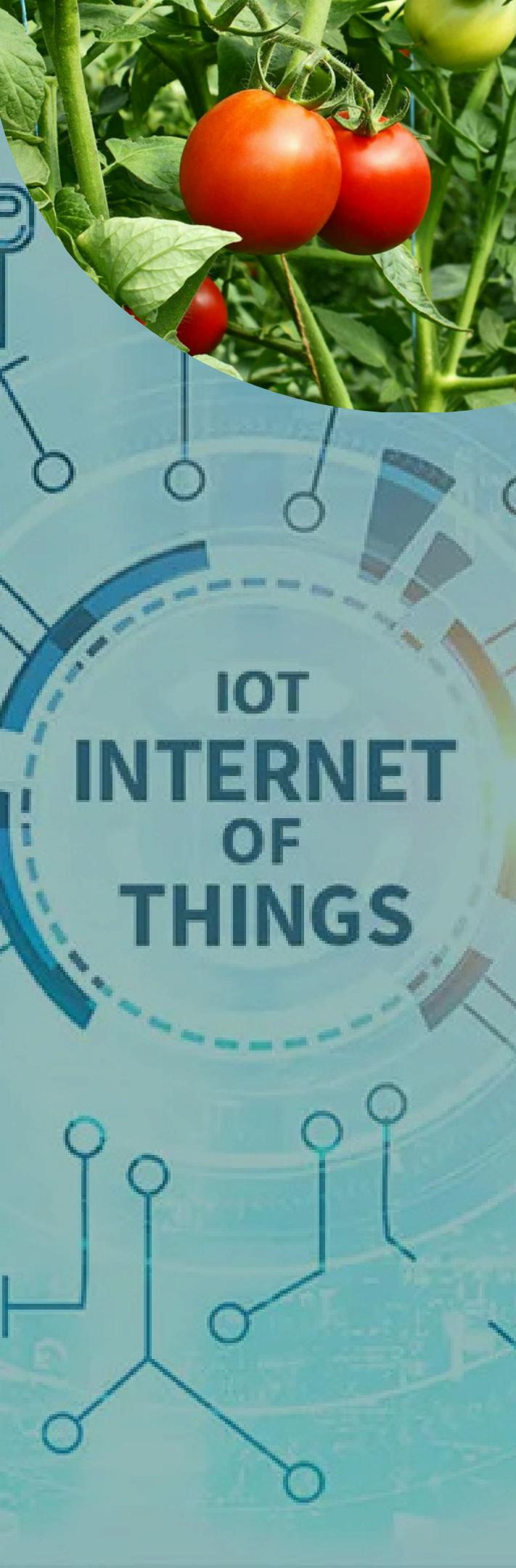
MAIN & SPECIFIC OBJECTS

Main objectives

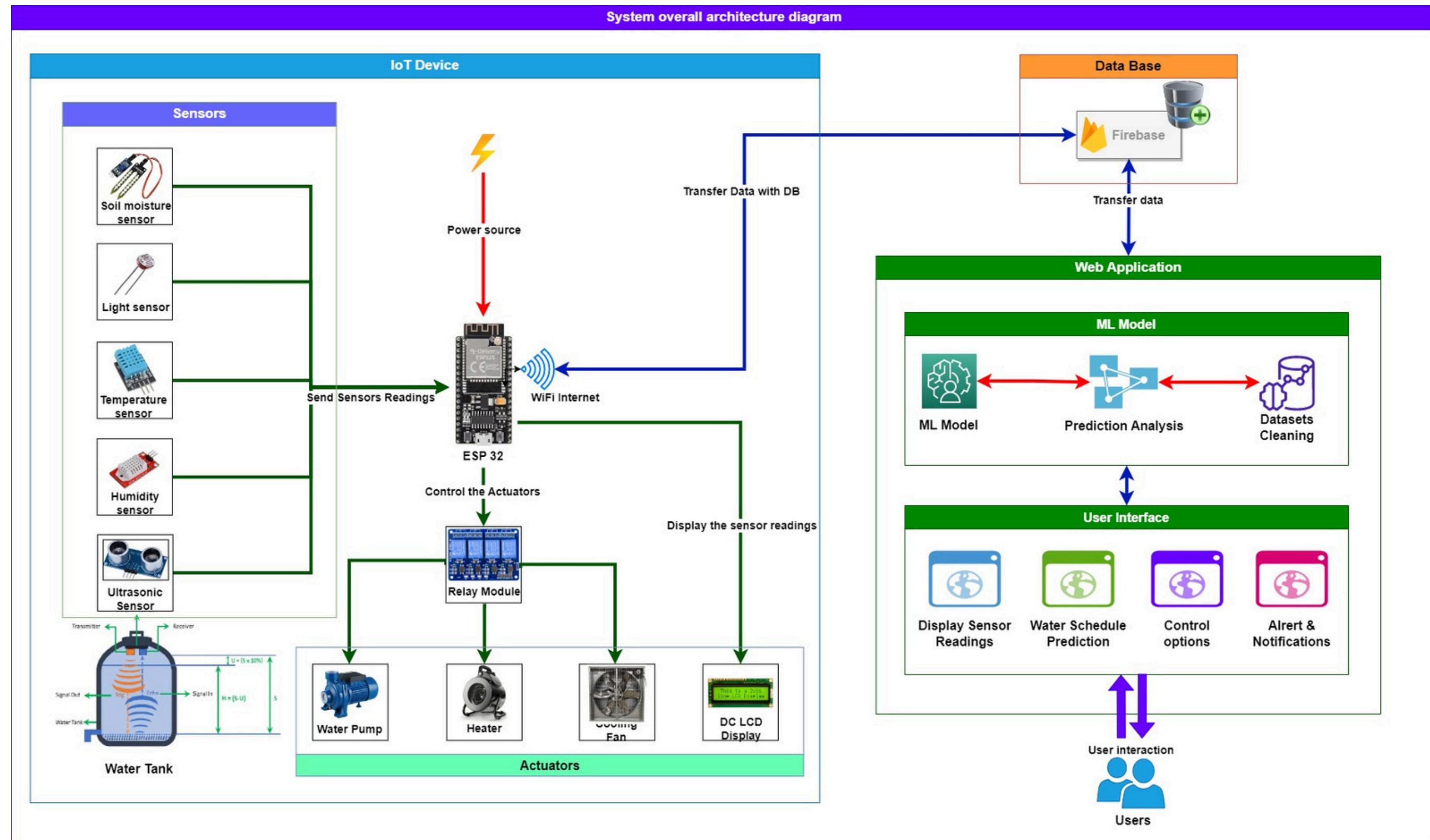
Develop a IoT Device and ML model decision support system to predict optimal watering requirements and ensure water availability in tomato greenhouse, leveraging real-time environmental data and user-friendly interfaces for monitoring and analysis.

Sub objectives

- Develop a IoT device to collect and analyze real-time environmental data using sensors (soil moisture, temperature, humidity, and light).
- Develop ML models to predict optimal water requirements based on environmental data.
- Ensure water availability by based on water requirement predictions.
- Develop a web application for monitoring and analysis of greenhouse conditions
- Train, validate, and optimize the machine learning model using real datasets.



METHODOLOGY - DIAGRAM



90% COMPLETION OF THE PROJECT

Developed ,Trained and
Validated Machine
Learning Model



Developed IoT
Device and Deploy
with Firebase



Implemented Prediction UI
for Water Requirement
Calculation



Developed Web
Application with Real-
Time Dashboard



Conducted Initial
System Testing

ABOUT THE IOT DEVELOPMENT

IoT Code

```
// Pin definitions for sensors
#define DHTPIN 15
#define DHTTYPE DHT11
#define TRIG_PIN 27
#define ECHO_PIN 18
#define SIGNAL_PIN 34
#define LIGHT_SENSOR_PIN 33

// OLED display parameters
#define SCREEN_WIDTH 128
#define SCREEN_HEIGHT 64
#define OLED_RESET -1
#define OLED_I2C_ADDRESS 0x3C

// Initialize DHT sensor and OLED
DHT dht(DHTPIN, DHTTYPE);
Adafruit_SSD1306 display(SCREEN_WIDTH, SCREEN_HEIGHT, &OLED_I2C_ADDRESS);

// Read DHT sensor data
float temperature = dht.readTemperature();
float humidity = dht.readHumidity();

// Read ultrasonic sensor
digitalWrite(TRIG_PIN, LOW);
delayMicroseconds(2);
digitalWrite(TRIG_PIN, HIGH);
delayMicroseconds(10);
digitalWrite(TRIG_PIN, LOW);
long duration = pulseIn(ECHO_PIN, HIGH);
float distance = (duration * 0.034) / 2;

// Read soil moisture sensor
int soilMoisture = analogRead(SIGNAL_PIN);

// Read light sensor
int lightLevel = analogRead(LIGHT_SENSOR_PIN);

// Display data on OLED
display.clearDisplay();
display.setCursor(0, 0);
display.setTextSize(1);
display.setTextColor(SSD1306_WHITE);
display.print("Temp: ");
display.print(temperature);
display.println(" C");
display.print("Hum: ");
display.print(humidity);
display.println(" %");
display.print("Dist: ");
display.print(distance);
display.println(" cm");
display.print("Soil: ");
display.print(soilMoisture);
display.println();
display.print("Light: ");
display.print(lightLevel);
display.display();

// Log data to serial
Serial.print("Temperature: ");
Serial.print(temperature);
Serial.println("°C");
Serial.print("Humidity: ");
Serial.print(humidity);
Serial.println("%");
Serial.print("Distance: ");
Serial.print(distance);
Serial.println(" cm");
Serial.print("Soil Moisture: ");
Serial.print(soilMoisture);
Serial.println();
Serial.print("Light Level: ");
Serial.print(lightLevel);
Serial.println();
```

IoT Firebase Configurations

```
// Initialize Firebase
config.api_key = API_KEY;
config.database_url = DATABASE_URL;

if (Firebase.signup(&config, &auth, "", "")) {
    Serial.println("Firebase authentication succeeded");
    signupOK = true;
} else {
    Serial.printf("Firebase signup failed: %s\n", config.signer.s
}
Firebase.begin(&config, &auth);
```

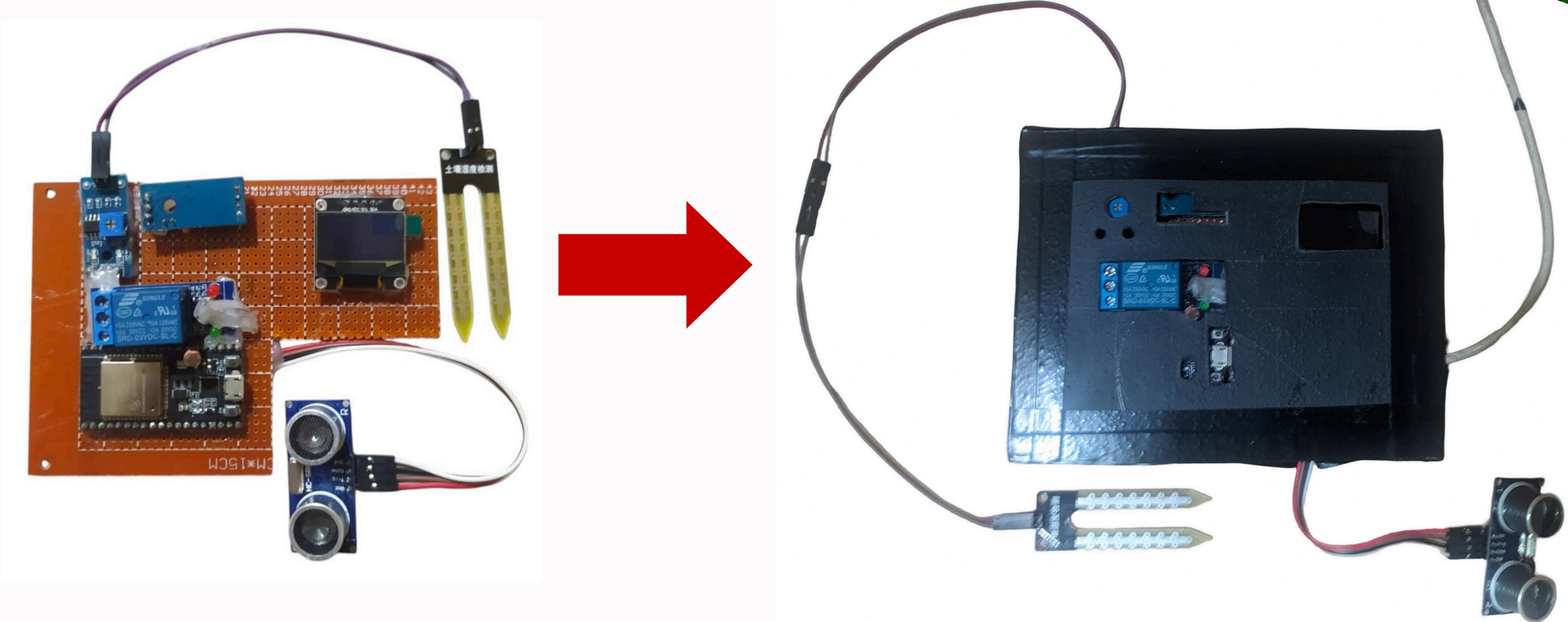
```
// Upload data to Firebase
if (Firebase.ready() && signupOK && millis() - sendDataPrevMillis > 2000) {
    sendDataPrevMillis = millis();

    Firebase.RTDB.setFloat(&fbdo, "/sensors/temperature", temperature);
    Firebase.RTDB.setFloat(&fbdo, "/sensors/humidity", humidity);
    Firebase.RTDB.setFloat(&fbdo, "/sensors/distance", distance);
    Firebase.RTDB.setInt(&fbdo, "/sensors/soilMoisture", soilMoisture);
    Firebase.RTDB.setInt(&fbdo, "/sensors/lightLevel", lightLevel);

    if (fbdo.httpCode() != 200) {
        Serial.print("Firebase failed: ");
        Serial.println(fbdo.errorReason());
    } else {
        Serial.println("Data uploaded to Firebase");
    }
}
```

IOT DEVICE

IoT device being successfully developed and covered with a casing for safety.



ABOUT THE DATASET

The dataset captures real-time environmental factors affecting tomato cultivation, including Timestamp, Temperature (°C), Humidity (%), Soil Moisture (%), Light Level (lux), and Water Needed (Liters), to optimize watering schedules in the Smart Greenhouse Decision Support System.

Timestamp	Temperature (°C)	Humidity (%)	Soil Moisture (%)	Light Level (lux)	Water Level Needed (Liters)
11/1/2024 8:00	27.5	69.6	10.5	903	4.8
11/1/2024 9:00	39	69.5	36.5	1696	11.2
11/1/2024 10:00	34.6	34.6	17.1	966	6.9
11/1/2024 11:00	32	54.7	48.4	1183	12.9
11/1/2024 11:00	23.1	32.9	15.9	517	5.5
11/1/2024 13:00	23.1	57.5	26.6	609	7.6
11/1/2024 14:00	21.2	52.1	13.4	1089	4.8
11/1/2024 15:00	37.3	74.4	49.9	1220	13.7
11/1/2024 16:00	32	47.5	30.1	1400	9.2
11/1/2024 17:00	34.2	35.9	33.8	937	10.2
11/1/2024 18:00	20.4	37.1	12.7	1542	4.6
11/1/2024 19:00	39.4	68.1	40	1790	11.9
11/1/2024 20:00	36.6	60.9	18.4	1670	7.3
11/1/2024 21:00	24.2	35.1	45.9	559	11.6
11/1/2024 22:00	23.6	34.2	18.2	1221	6
11/1/2024 23:00	23.7	65	17.6	657	5.9
11/2/2024 0:00	26.1	33.6	11.5	863	4.9
11/2/2024 1:00	30.5	71.1	28.9	1980	8.8

DATA PREPROCESSING & FEATURE ENGINEERING

```
15  
16     # Preprocess the data  
17     data['Timestamp'] = pd.to_datetime(data['Timestamp'])  
18  
19     # Feature Engineering  
20     data['Hour'] = data['Timestamp'].dt.hour  
21     data['DayOfWeek'] = data['Timestamp'].dt.dayofweek  
22     data['Month'] = data['Timestamp'].dt.month  
23     data['Year'] = data['Timestamp'].dt.year  
24
```

```
2     # Load dataset  
3     file_path = "irrigation_dataset.csv"  
4     data = pd.read_csv(file_path)  
5  
6     # Preprocess the data  
7     data['Timestamp'] = pd.to_datetime(data['Timestamp'])  
8  
9     # Feature Engineering  
10    data['Hour'] = data['Timestamp'].dt.hour  
11    data['DayOfWeek'] = data['Timestamp'].dt.dayofweek  
12    data['Month'] = data['Timestamp'].dt.month  
13    data['Year'] = data['Timestamp'].dt.year  
14  
15    # Handle missing values  
16    imputer = SimpleImputer(strategy='median')  
17    data[['Temperature (°C)', 'Humidity (%)', 'Soil Moisture (%)', 'Light Level (lux)']] = imputer.fit_transform(  
18        data[['Temperature (°C)', 'Humidity (%)', 'Soil Moisture (%)', 'Light Level (lux)']])  
19
```

```
61  
62     # Feature Scaling and Polynomial Expansion  
63     # Feature Scaling  
64     scaler = StandardScaler()  
65     features = ['Temperature (°C)', 'Humidity (%)', 'Soil Moisture (%)', 'Light Lev  
66     data[features] = scaler.fit_transform(data[features])  
67  
68     # Polynomial Feature Expansion  
69     poly = PolynomialFeatures(degree=2, include_bias=False)  
70     X_poly = poly.fit_transform(data[features])  
71
```

```
  Data columns (total 10 columns):  
   #   Column           Non-Null Count  Dtype     
   --  --     
   0   Timestamp       420 non-null    datetime64[ns]  
   1   Temperature (°C) 420 non-null    float64  
   2   Humidity (%)    420 non-null    float64  
   3   Soil Moisture (%) 420 non-null    float64  
   4   Light Level (lux) 420 non-null    float64  
   5   Water Level Needed (Liters) 420 non-null    float64  
   6   Hour            420 non-null    int64  
   7   DayOfWeek       420 non-null    int64  
   8   Month           420 non-null    int64  
   9   Year            420 non-null    int64  
   dtypes: datetime64[ns](1), float64(5), int64(4)  
   memory usage: 32.9 KB
```

MODEL TRAINING

```
1 # Split data into training
2 X = X_poly
3 y = data['Water Level Needed (Liters)']
4 X_train, X_temp, y_train, y_temp = train_test_split(*arrays: X, y, test_size=0.3, random_state=42)
5 X_val, X_test, y_val, y_test = train_test_split(*arrays: X_temp, y_temp, test_size=0.5, random_state=42)
6
7 # Hyperparameter Tuning
8 param_grid = {
9     'n_estimators': [100, 200, 300],
10    'max_depth': [10, 20, 30, None],
11    'min_samples_split': [2, 5, 10],
12    'min_samples_leaf': [1, 2, 4],
13    'bootstrap': [True, False]
14 }
15
16 grid_search = GridSearchCV(estimator=RandomForestRegressor(random_state=42),
17                             param_grid=param_grid,
18                             cv=5,
19                             n_jobs=-1,
20                             verbose=2,
21                             scoring='neg_mean_squared_error')
22
23 grid_search.fit(X_train, y_train)
```

```
# Best parameters
print("Best Hyperparameters found:", grid_search.best_params_)

# Train the model
best_model = grid_search.best_estimator_
y_val_pred = best_model.predict(X_val)

# performance metrics
val_rmse = mean_squared_error(y_val, y_val_pred, squared=False)
val_r2 = r2_score(y_val, y_val_pred)
val_mae = mean_absolute_error(y_val, y_val_pred)

print(f"Validation RMSE: {val_rmse:.2f}")
print(f"Validation R2 Score: {val_r2:.2f}")
print(f"Validation MAE: {val_mae:.2f}")
💡
```

```
134
135 # Save Models
136 joblib.dump(best_model, filename="irrigation_model.pkl")
137 joblib.dump(scaler, filename="scaler.pkl")
138 joblib.dump(poly, filename="poly.pkl")
139 print("Best model, scaler, and poly transformer saved successfully.")
140 💡
```

PERFORMANCE MATRIX ACCURECY :

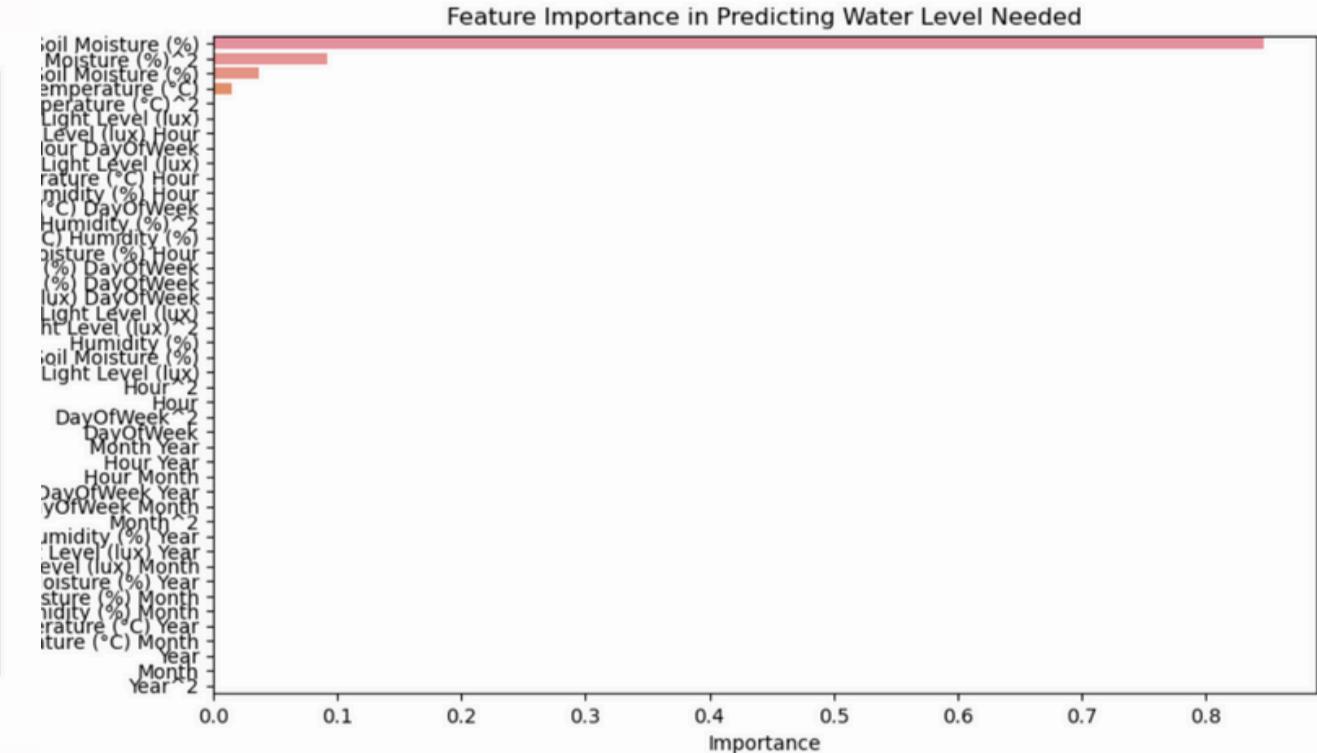
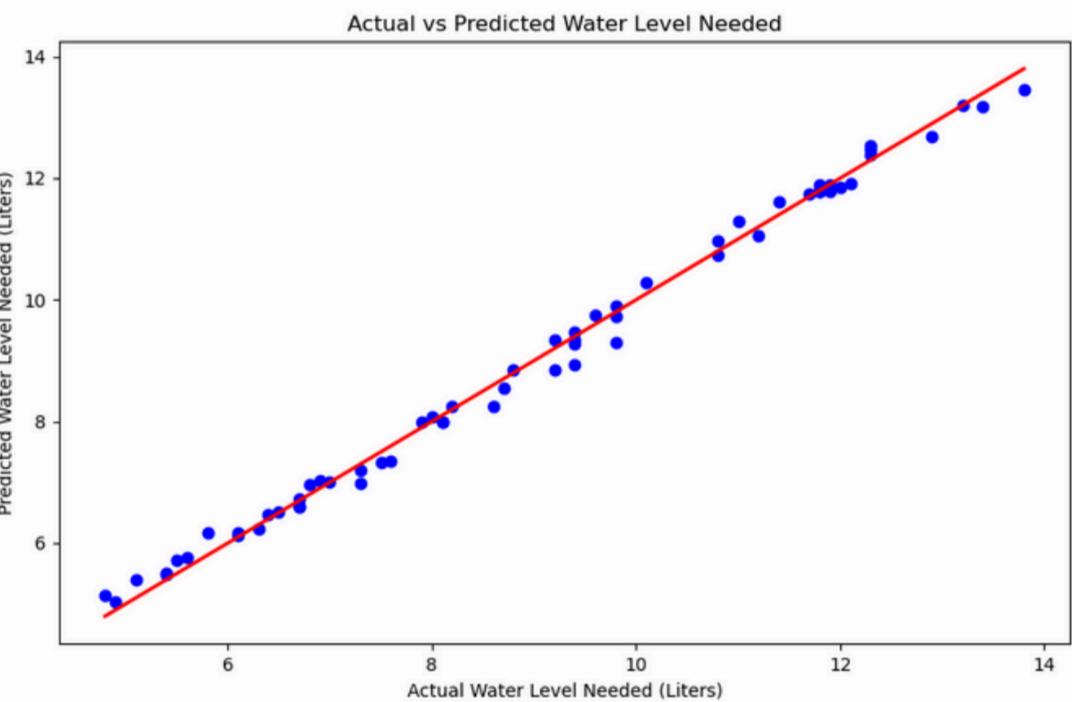
```
Validation RMSE: 0.19
Validation R2 Score: 0.99
Validation MAE: 0.15
```

MODEL PERFORMANCE EVALUATION

```
#plot the model Performance
plt.figure(figsize=(10, 6))
plt.scatter(y_val, y_val_pred, color='blue')
plt.plot(*args: [min(y_val), max(y_val)], [min(y_val), max(y_val)], color='red')
plt.title('Actual vs Predicted Water Level Needed')
plt.xlabel('Actual Water Level Needed (Liters)')
plt.ylabel('Predicted Water Level Needed (Liters)')
plt.show()

# Find the Important feature(x data) for water need prediction
feature_importances = best_model.feature_importances_
features_list = poly.get_feature_names_out(features)
importance_df = pd.DataFrame({
    'Feature': features_list,
    'Importance': feature_importances
})
importance_df = importance_df.sort_values(by='Importance', ascending=False)

plt.figure(figsize=(10, 6))
sns.barplot(x='Importance', y='Feature', data=importance_df)
plt.title('Feature Importance in Predicting Water Level Needed')
plt.show()
```



```
# predict watering needs
def predict_watering(temperature, humidity, soil_moisture, light_level, timestamp):
    timestamp = pd.to_datetime(timestamp)
    hour = timestamp.hour
    day_of_week = timestamp.dayofweek
    month = timestamp.month
    year = timestamp.year

    # DataFrame input
    input_data = pd.DataFrame(data=[[temperature, humidity, soil_moisture, light_level, hour, day_of_week, month, year]],
                               columns=['Temperature (°C)', 'Humidity (%)', 'Soil Moisture (%)', 'Light Level (lux)', 'Hour', 'DayOfWeek', 'Month', 'Year'])

    # Normalize the input
    input_data_scaled = scaler.transform(input_data)

    # Apply polynomial
    input_data_poly = poly.transform(input_data_scaled)

    # prediction
    predicted_water_level = model.predict(input_data_poly)

    return predicted_water_level[0]
```

```
# prediction
predicted_water_level = model.predict(input_data_poly)

return predicted_water_level[0]

# data live
temperature = 25.5
humidity = 65.0
soil_moisture = 25.3
light_level = 1500
timestamp = "2024-11-01 10:00:00"

predicted_water_level = predict_watering(temperature, humidity, soil_moisture, light_level, timestamp)
print(f"Predicted Water Level Needed: {predicted_water_level:.2f} Liters")
```

Run Preidct_watering ×

C:\Users\moham\Downloads\Compressed\Python38_01

C:\Users\moham\Downloads\Compressed\Python38_01

warnings.warn()

Predicted Water Level Needed: 7.62 Liters

Process finished with exit code 0

REAL-TIME MONITORING DASHBOARD

WATER REQUIREMENT PREDICTION

Dashboard Predict



Water Level
182.291



Humidity
79



Light Level
459



Soil Moisture
1104



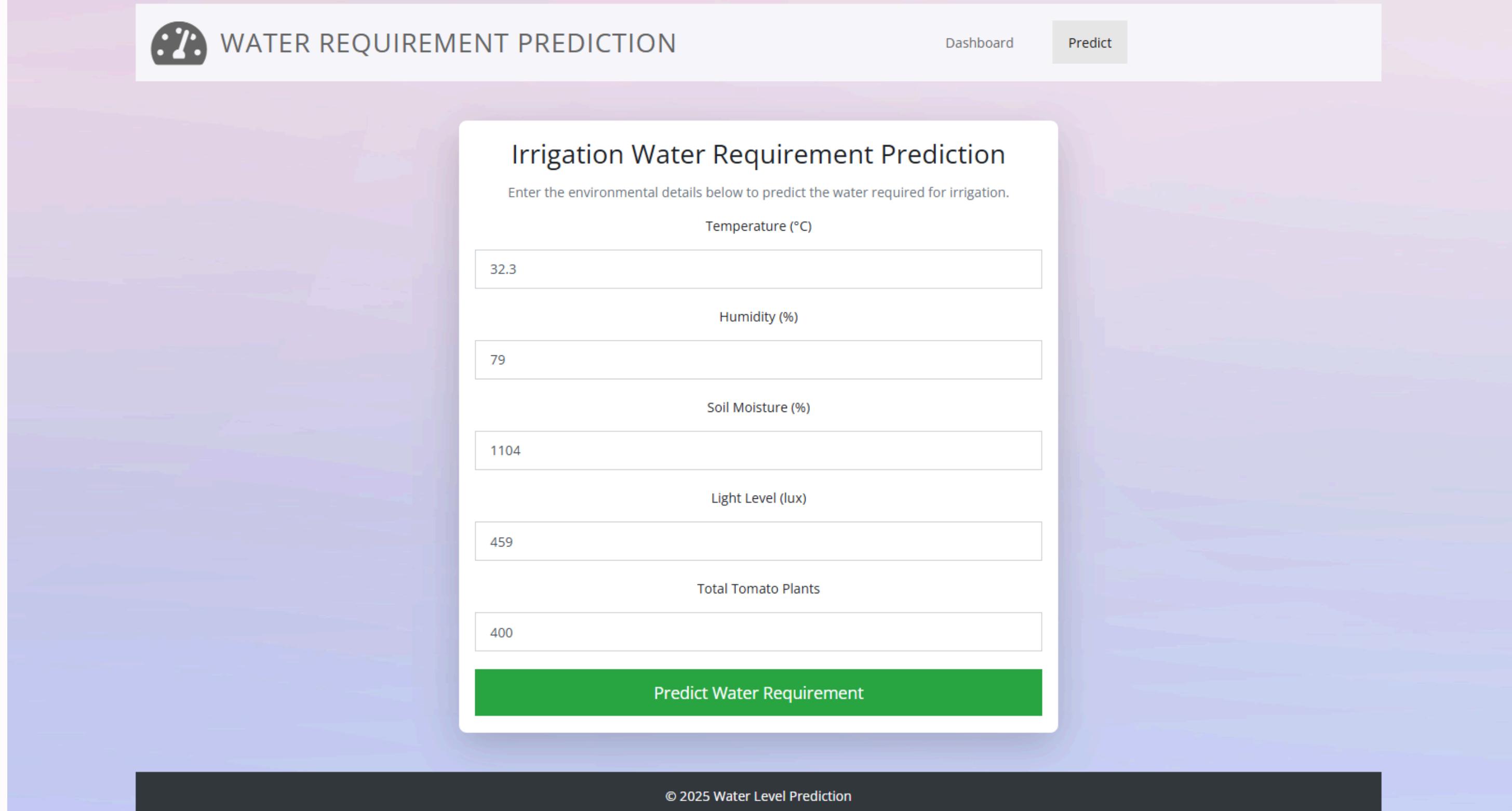
Temperature
32.3

Watering System
System Status:
Current Status: OFF

Refresh Data

© 2025 Water Level Prediction

WATER REQUIREMENT PREDICTION UI



The screenshot shows a web-based irrigation water requirement prediction application. The interface includes a header with a logo, navigation links for 'Dashboard' and 'Predict', and a central form titled 'Irrigation Water Requirement Prediction'. The form contains five input fields: 'Temperature (°C)' with value '32.3', 'Humidity (%)' with value '79', 'Soil Moisture (%)' with value '1104', 'Light Level (lux)' with value '459', and 'Total Tomato Plants' with value '400'. A green button at the bottom labeled 'Predict Water Requirement' is used to submit the data. The footer of the page displays the copyright notice '© 2025 Water Level Prediction'.

WATER REQUIREMENT PREDICTION

Dashboard Predict

Irrigation Water Requirement Prediction

Enter the environmental details below to predict the water required for irrigation.

Temperature (°C)

32.3

Humidity (%)

79

Soil Moisture (%)

1104

Light Level (lux)

459

Total Tomato Plants

400

Predict Water Requirement

© 2025 Water Level Prediction

WATER REQUIREMENT PREDICTION OUTPUT

Predicted Water Requirement For a Single Plant

1.59 Liters

Total Water Requirement For All Plants

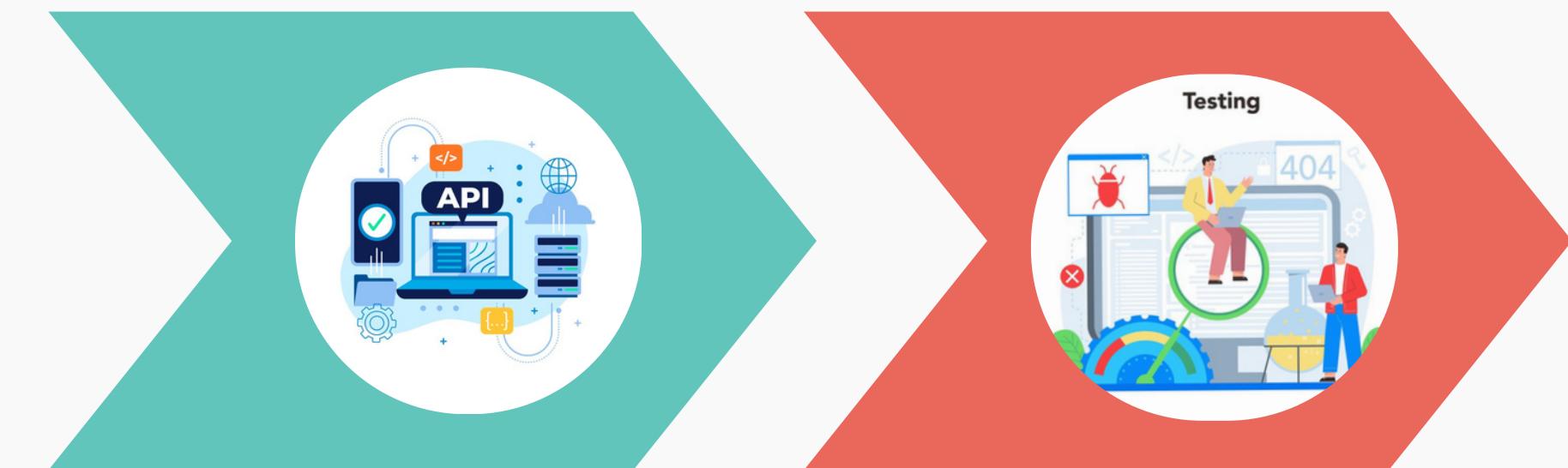
636.79 Liters

Reason for Prediction

Alert: Elevated temperature detected. Consider providing shade and increasing watering frequency.

© 2025 Water Level Prediction

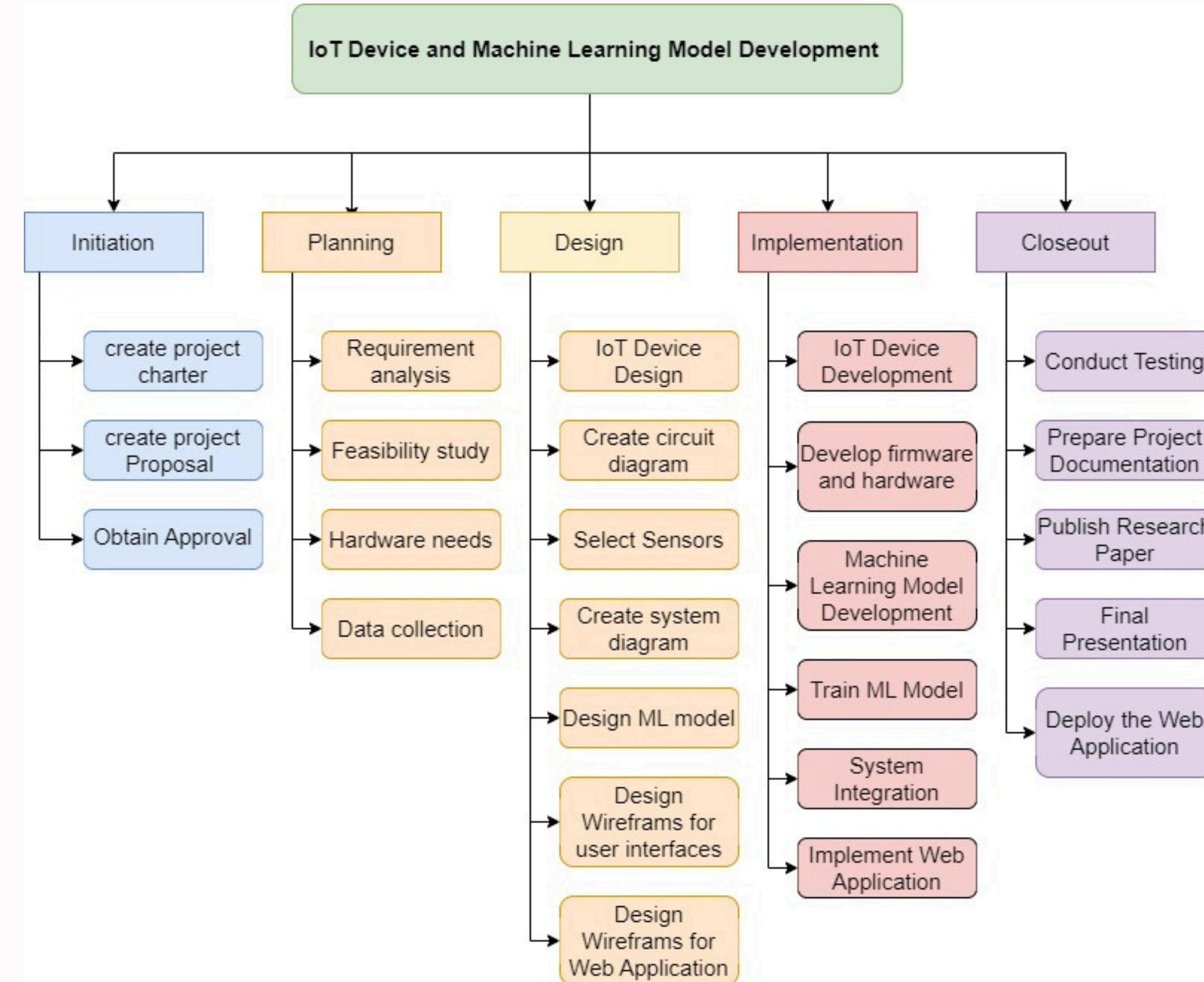
FUTURE CHECKLIST



**System Integration
and Deployment**

**Conduct final Testing
and validation**

WORK BREAKDOWN CHART



REFERENCES

- [1] Tao, W., Zhao, L., Wang, G. & Liang, R. (2021). Review of the internet of things communication technologies in smart agriculture and challenges, *Computers and Electronics in Agriculture*, Vol. 189, 2021, 106352, ISSN0168-1699, <https://doi.org/10.1016/j.compag.2021.106352>.
- [2] Food and Agriculture Organization of the United Nations, Global agriculture towards 2050, https://www.fao.org/fileadmin/templates/wsfs/docs/Issues_papers/HLEF2050_Global_Agriculture.pdf.
- [3] Saggi, M.K. & Jain, S. A. (2022). Survey Towards Decision Support System on Smart Irrigation Scheduling Using Machine Learning approaches. *Archives of Computational Methods in Engineering*, 29, 4455–4478. <https://doi.org/10.1007/s11831-022-09746-3>.
- [4] Salim, O., Fouad, K. & Hassan, B. (2022). Dual-Level Sensor Selection with Adaptive Sensor Recovery to Extend WSNs' Lifetime, *Human-centric Computing and Information Sciences*, Vol. 12, Article number: 18, <https://doi.org/10.22967/HCIS.2022.12.018>.
- [5] Goap, A., Sharma, D., Shukla, A.K. & Krishna, R. (2018). An IoT based smart irrigation management system using Machine learning and open source technologies, *Computers and Electronics in Agriculture*, Vol. 155, PP: 41-49, ISSN0168-1699, <https://doi.org/10.1016/j.compag.2018.09.040>.
- [6] Fouad, K. & Elbably, D. (2020). Intelligent approach for large-scale data mining. *Int. J. Computer Applications in Technology*, Vol. 63, Nos. 1/2, PP: 93-112.
- [7] Fouad, K., Hassan, B. & Salim, O. (2022). Hybrid Sensor Selection Technique for Lifetime Extension of Wireless Sensor Networks. *Computers, Materials & Continua* 2022, 70(3), 4965-4985. <https://doi.org/10.32604/cmc.2022.020926>.



IT21181160 | Thrimavithana V. D.

Information technology



INTRODUCTION TO PREDICTING FERTILIZING SCHEDULES

Tomatoes are a vital crop, but their cultivation is challenged by climate change, which affects soil nutrients.

Proper fertilization is essential to ensure healthy growth, but mismanagement can harm plants and the environment.



KEY CHALLENGES

- **Over-Fertilization:** Causes nutrient leaching, pollution, and plant toxicity.
- **Under-Fertilization:** Leads to poor growth and low yields.



ENVIRONMENTAL FACTORS

- **High temperatures** increase nutrient demand but risk imbalances.
- **Low temperatures** slow nutrient uptake, risking deficiencies.

RESEARCH QUESTION

How can we develop a decision support system for tomato greenhouses that optimizes fertilizing schedules and types that ensures nutrient balance based on real-time plant and environmental conditions?

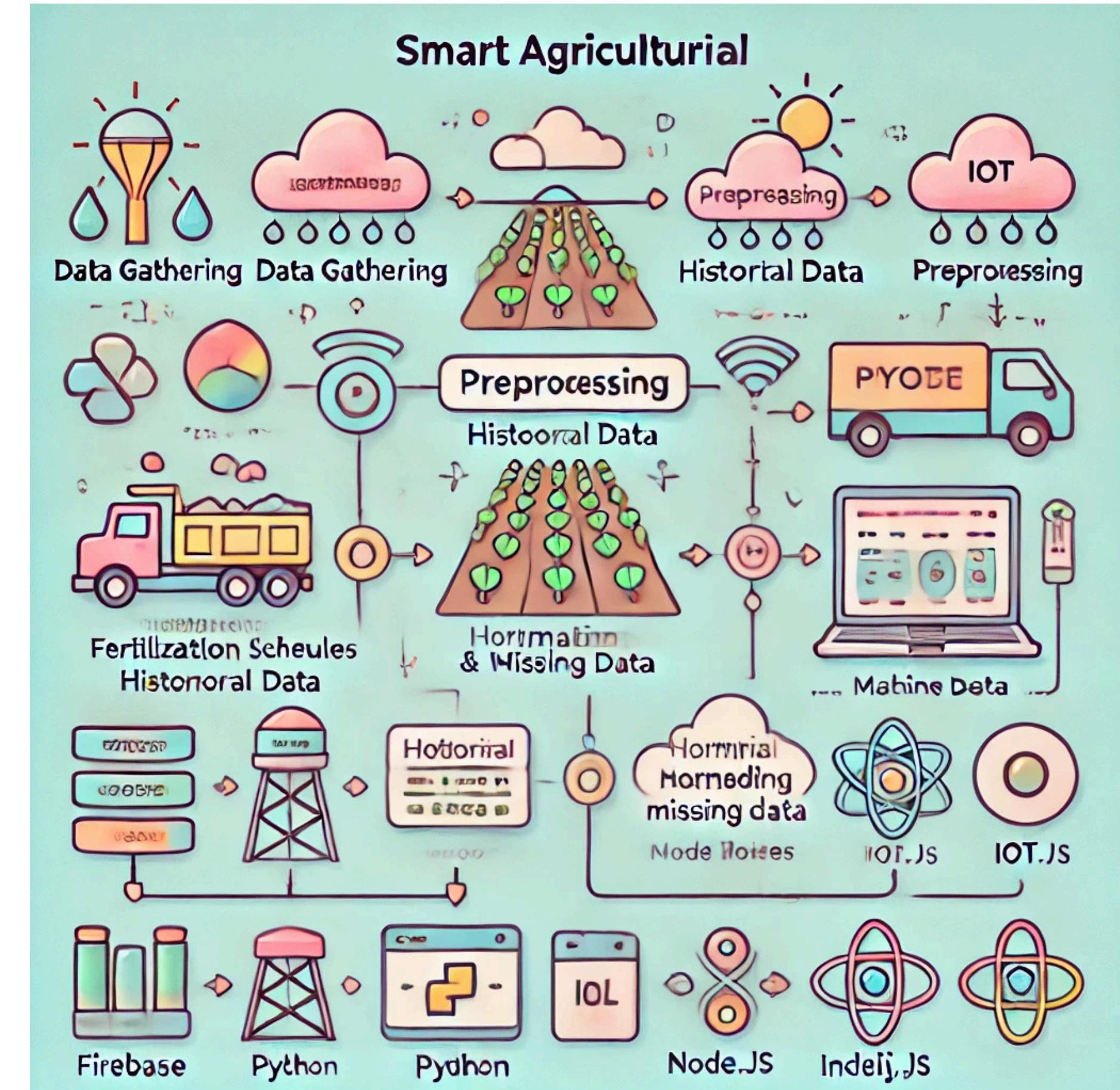


RESEARCH GAP

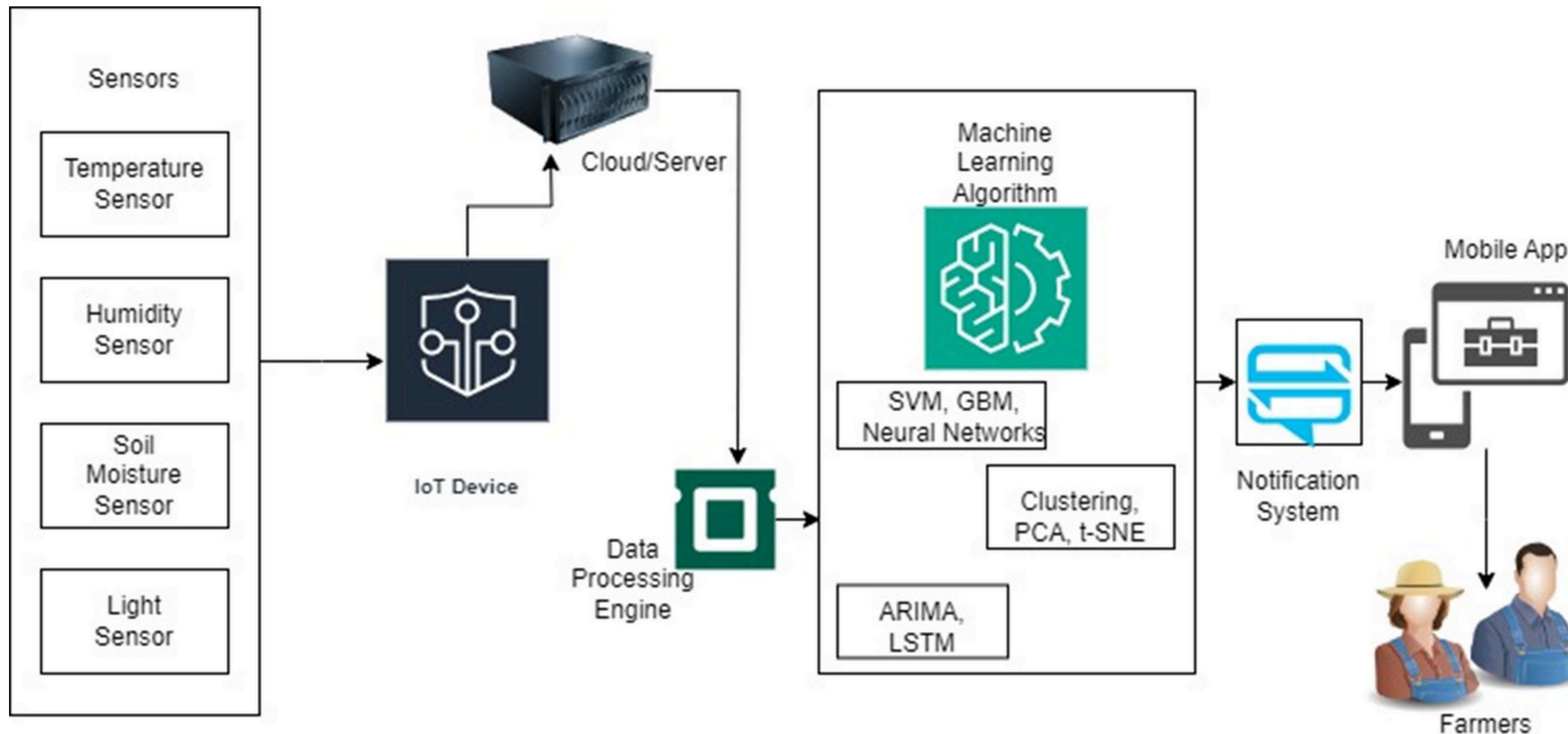
Existing Products / Research	Features						
	Automated Fertilizer Application	Real-Time Nutrient Monitoring	Precision Nutrient Delivery	Environmental & Sustainable Practices	Integration with IoT and Sensors	Impact on Fruit Quality	Predictive Analytics for Nutrient Needs
IoT-Based Precision Fertilization System	✓	✗	✓	✗	✓	✗	✗
Smart Fertigation Management System	✓	✓	✗	✗	✗	✓	✗
Integrated Hydroponic Nutrient Solution	✗	✓	✓	✓	✗	✗	✓
Proposed System	✓	✓	✓	✓	✓	✓	✓

METHODOLOGY

- 1.Gather soil, nutrient data and environmental conditions.
- 2.Collect historical fertilization schedules and crop yield data.
- 3.Preprocess the data to handle missing values and normalize it.
- 4.Choose appropriate hybrid ML models.
- 5.Train the models using the preprocessed data to optimize fertilization schedules.



SYSTEM DIAGRAM



DATASET

	A	B	C	D	E	F	G	H
1	Organic Matter	Humidity (%)	Temperature (°C)	Fertilizer Type	Fertilizer Quantity (kg/ha)	Fertilizer Timing (Week)	Crop Yield (tons/ha)	Historical Yield (tons/ha)
2	2.749080238	75.83158087	20.13094457	Potash	180.4636872	8	4.675482342	7.215243009
3	3.901428613	75.79236286	26.63537372	Ammonium Nitrate	176.9410612	7	8.222115865	4.788313252
4	3.463987884	61.82412206	21.78035967	DAP	218.7758391	11	7.24419086	3.632189534
5	3.197316968	69.88840609	29.61070317	Potash	97.97520052	6	4.579206821	7.69094318
6	2.312037281	61.1511752	21.48662728	Urea	94.57535091	7	5.45136297	6.864895329
7	2.311989041	70.99057765	24.14624124	Potash	181.4074344	5	4.074424218	3.289116074
8	2.116167224	68.83061003	20.85349668	Ammonium Nitrate	160.9741684	5	6.812607793	5.160302795
9	3.732352292	77.75408366	29.96874252	Ammonium Nitrate	118.3824933	6	5.807591565	8.740798893
10	3.202230023	67.01830025	25.0219501	DAP	91.11871166	4	7.590144906	6.002406874
11	3.416145156	62.34134033	25.95385017	Potash	91.99215494	8	5.783426846	5.596374816
12	2.041168989	62.85983364	20.67076477	Urea	205.1867225	7	5.799514669	5.746197631
13	3.939819704	75.23021263	27.4996047	Urea	106.8614255	5	8.459159192	4.253296344
14	3.664885282	72.36436127	22.09905593	NPK	125.2720187	4	4.288857016	5.212243025
15	2.424678221	62.02245352	28.98054289	Urea	111.7318963	6	9.417369971	5.218879536
16	2.363649934	61.68213612	22.0513964	DAP	129.6994828	10	9.113583246	3.314130121
17	2.36680902	74.01938263	21.90687721	DAP	89.71933798	9	8.006828099	7.605405771
18	2.608484486	61.45526013	20.36549668	Urea	152.6683707	10	7.559329421	5.499026591
19	3.049512863	76.43720119	24.72066945	Urea	89.4657589	10	9.353814989	7.933079321
20	2.863890037	74.12484454	25.64841133	NPK	192.0499111	5	5.111981077	8.102088007
21	2.58245828	61.62697561	20.65708639	Urea	112.7196915	11	4.473814973	4.271964328
22	3.223705789	61.69675428	27.75527617	NPK	155.601668	11	5.437061019	6.944120893
23	2.278987721	79.73279157	24.53288835	NPK	203.2110723	6	8.767469672	5.833690825
24	2.584289297	67.48541592	25.24390269	Urea	171.1228317	7	4.2080216	8.280940428
25	2.732723687	67.41284294	24.40762747	Ammonium Nitrate	154.6140901	11	7.496841011	4.294444075
26	2.912139968	76.25599135	24.00763061	Ammonium Nitrate	125.4067254	10	9.972625097	7.066879202
27	3.570351923	78.94497155	25.59640331	NPK	126.6202678	11	9.134176563	6.646512734
28	2.399347564	79.72002128	21.55240246	Urea	173.7281737	10	7.128674134	4.771808865

< > fertilization_data +

DATA PREPROCESSING

```
9     # Load the dataset
10    file_path = "fertilization_data.csv"
11    df = pd.read_csv(file_path)
12
13    # Preprocess
14    df = pd.get_dummies(df, columns=['Fertilizer Type'], drop_first=True)
15
16    # Split data
17    X = df.drop(['Fertilizer Quantity (kg/ha)', 'Fertilizer Timing (Week)'], axis=1) # Features
18    y = df[['Fertilizer Quantity (kg/ha)', 'Fertilizer Timing (Week)']] # Targets
19
20    # Train-test split
21    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
22
23    # Normalize
24    scaler = StandardScaler()
25    X_train_scaled = scaler.fit_transform(X_train)
26    X_test_scaled = scaler.transform(X_test)
27
```

MODEL TRAINING

```
28 # Train the models
29 rf_model = RandomForestRegressor(n_estimators=100, random_state=42)
30 gb_model = GradientBoostingRegressor(n_estimators=100, random_state=42)
31 rf_model.fit(X_train_scaled, y_train['Fertilizer Quantity (kg/ha)'])
32 gb_model.fit(X_train_scaled, y_train['Fertilizer Timing (Week)'])
33 rf_predictions = rf_model.predict(X_test_scaled)
34 gb_predictions = gb_model.predict(X_test_scaled)
35
36 # Evaluate
37 rf_mae = mean_absolute_error(y_test['Fertilizer Quantity (kg/ha)'], rf_predictions)
38 rf_mse = mean_squared_error(y_test['Fertilizer Quantity (kg/ha)'], rf_predictions)
39 rf_r2 = r2_score(y_test['Fertilizer Quantity (kg/ha)'], rf_predictions)
40
41 gb_mae = mean_absolute_error(y_test['Fertilizer Timing (Week)'], gb_predictions)
42 gb_mse = mean_squared_error(y_test['Fertilizer Timing (Week)'], gb_predictions)
43 gb_r2 = r2_score(y_test['Fertilizer Timing (Week)'], gb_predictions)
44 rf_cv_scores = cross_val_score(rf_model, X_train_scaled, y_train['Fertilizer Quantity (kg/ha)'], cv=5, scoring='neg_mean_absolute_error')
45 gb_cv_scores = cross_val_score(gb_model, X_train_scaled, y_train['Fertilizer Timing (Week)'], cv=5, scoring='neg_mean_absolute_error')
```

SENSOR DATA - FUNCTION

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

- Project:** MylastFyp (C:\Users\user\Desktop\MylastFyp)
- File Structure:** static, css, img, js, uploads, webfonts, templates (containing index.html, main.html), API.py, App.py, fertilization_data.csv, rf_model.pkl, Predict_Fertilization.py, Train_Fertilization.py, waterering-7b4c7-firebase-adminsdk-ntnzb-ee048fb927.json.
- Code Editor:** App.py (selected tab) showing Python code for sensor data and prediction functions.
- Code Content:**

```
8
9     # Load models
10    rf_model = joblib.load('rf_model.pkl')
11    gb_model = joblib.load('gb_model.pkl')
12    scaler = joblib.load('scaler.pkl')
13    # Initialize Firebase Admin SDK
14    if not firebase_admin._apps:
15        cred = credentials.Certificate("watering-7b4c7-firebase-adminsdk-ntnzb-ee048fb927.json")
16        firebase_admin.initialize_app(cred, options={
17            'databaseURL': 'https://watering-7b4c7-default.firebaseio.com/'
18        })
19
20    # Realtime Database path
21    sensor_ref = db.reference('/sensors')
22
23    # Sensor data function
24    def get_sensor_data(): 1 usage
25        ref = db.reference('/sensors')
26        data = ref.get()
27        return data
28
29
30    # Prediction function
```
- Run Tab:** Run → App
- Output Tab:** Shows log entries:

```
127.0.0.1 - - [18/Mar/2025 11:19:50] "GET /static/css/tooplate.css HTTP/1.1" 304 -
127.0.0.1 - - [18/Mar/2025 11:19:50] "GET /static/js/jquery-3.3.1.min.js HTTP/1.1" 304 -
127.0.0.1 - - [18/Mar/2025 11:19:51] "GET /static/js/bootstrap.min.js HTTP/1.1" 304 -
```
- Status Bar:** 31:16 CRLF UTF-8 4 spaces Python 3.8

PREDICTION FUNCTION

The screenshot shows the PyCharm IDE interface with two code editors open:

- App.py:** This file contains the main application logic. It imports pandas and numpy, and uses them to load sensor data from a database and perform predictions. It includes routes for both GET and POST requests to handle sensor data and predict outcomes.

```
30 # Prediction function
31 def predict(input_data):
32     input_df = pd.DataFrame(input_data)
33     input_df = pd.get_dummies(input_df, columns=['Fertilizer Type'], drop_first=True)
34     input_df = input_df.reindex(columns=scaler.feature_names_in_, fill_value=0)
35     X_scaled = scaler.transform(input_df)
36     predicted_quantity = rf_model.predict(X_scaled)
37     predicted_timing = gb_model.predict(X_scaled)
38     return predicted_quantity[0], predicted_timing[0]
39
40 @app.route('/', methods=['GET', 'POST'])
41 def index():
42     prediction_result = None
43     sensor_data = get_sensor_data()
44
45     temperature = humidity = soil_moisture = light_level = None
46
47     if sensor_data:
48         temperature = sensor_data.get('temperature', '')
49         humidity = sensor_data.get('humidity', '')
50         soil_moisture = sensor_data.get('soilMoisture', '')
51         light_level = sensor_data.get('lightLevel', '')
52
53     if request.method == 'POST':
54         humidity = float(request.form['humidity'])
55         temperature = float(request.form['temperature'])
56         fertilizer_type = request.form['fertilizer_type']
57
58     input_data = {
59         'Humidity (%)': [humidity],
60         'Temperature (°C)': [temperature],
61         'Fertilizer Type': [fertilizer_type]
62     }
63
64     quantity, timing = predict(input_data)
65     prediction_result = {
66         'quantity': quantity,
67         'timing': timing
68     }
69
70     return render_template(template_name_or_list='index.html', prediction=prediction_result, temperature=temperature, hu
71
72
73 if __name__ == '__main__':
74     app.run(debug=True)
```

- API.py:** This file contains a single function, `index()`, which returns sensor data and a light level.

```
41 def index():
42     light_level = sensor_data.get('lightLevel', '')
43
44     if request.method == 'POST':
45         humidity = float(request.form['humidity'])
46         temperature = float(request.form['temperature'])
47         fertilizer_type = request.form['fertilizer_type']
48
49     input_data = {
50         'Humidity (%)': [humidity],
51         'Temperature (°C)': [temperature],
52         'Fertilizer Type': [fertilizer_type]
53     }
54
55     quantity, timing = predict(input_data)
56     prediction_result = {
57         'quantity': quantity,
58         'timing': timing
59     }
60
61     return render_template(template_name_or_list='index.html', prediction=prediction_result, temperature=temperature, hu
62
63
64 if __name__ == '__main__':
65     app.run(debug=True)
```

API S

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

- Project:** MylastFyp (C:\Users\user\Desktop\MylastFyp)
- File Structure:** MylastFyp folder contains static, css, img, js, uploads, webfonts, templates (index.html, main.html), API.py, App.py, fertilization_data.csv, gb_model.pkl, Predict_Fertilization.py, rf_model.pkl, scaler.pkl, Train_Fertilization.py, and watering-7b4c7-firebase-adminsdk-ntnzb-ee048fb927.json.
- Current File:** API.py
- Code Content:** Python code for a machine learning API. It includes a `predict` function for local predictions and a `predict_api` function for handling POST requests via Flask. It uses pandas, scikit-learn, and jsonify.
- Toolbars and Status:** Top bar shows App, Version control, and various icons. Bottom status bar shows file path (MylastFyp > API.py), line count (10:1), encoding (CRLF), and Python version (Python 3.8).

USER INTERFACE

The screenshot shows a web browser window with the URL `127.0.0.1:5000` in the address bar. The page title is "OPTIMIZING FERTILIZATION". A sidebar on the right contains the text "Optimizing fertilization". The main content area features a header "Fertilizer Prediction" and a sub-instruction "Enter the details below to predict the required fertilizer quantity and timing." It includes three input fields: "Humidity (%)" with value "10.0", "Temperature (°C)" with value "32.3", and a dropdown menu for "Fertilizer Type" currently set to "Ammonium Nitrate". A large green button labeled "Predict Fertilizer" is prominent. Below the prediction form, a section titled "Prediction Result" displays the output "Fertilizer Quantity: 148.40121079380006 kg/ha". The background of the page features a photograph of agricultural irrigation equipment.

OPTIMIZING FERTILIZATION

Optimizing fertilization

Fertilizer Prediction

Enter the details below to predict the required fertilizer quantity and timing.

Humidity (%)

10.0

Temperature (°C)

32.3

Fertilizer Type

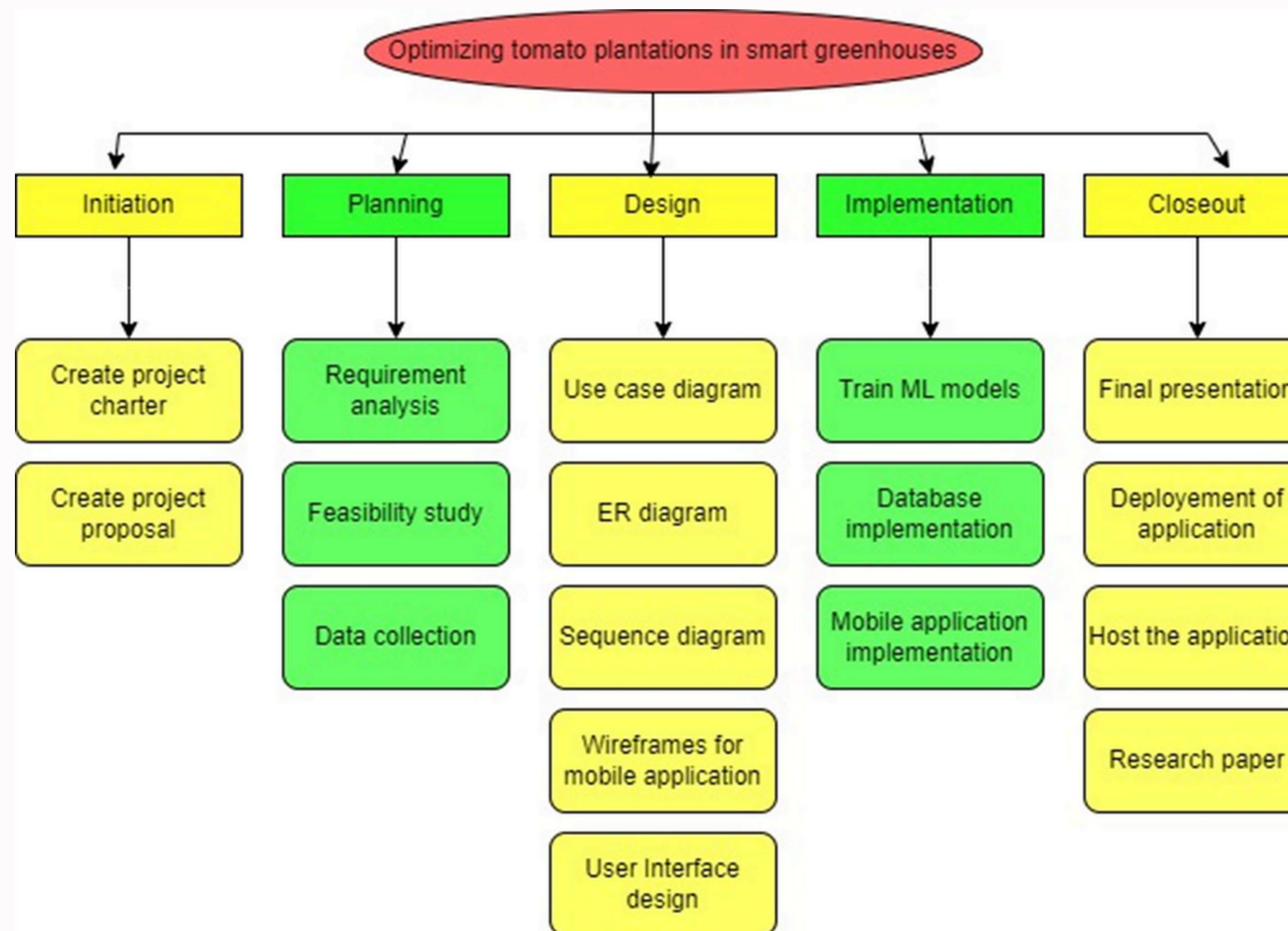
Ammonium Nitrate

Predict Fertilizer

Prediction Result

Fertilizer Quantity: 148.40121079380006 kg/ha

WORK BREAKDOWN STRUCTURE



REFERENCES

- [1] "Big Data Analytics for Smart Agriculture" by Rajasekaran, et al. Explores the role of big data analytics in agriculture, including data processing and visualization.
[https://www.researchgate.net/publication/379404505_Role_of_Data_Visualization_and_Big_Data_Analytics_in_Smart_Agriculture]
- [2] Lee, E. Y., & Parker, R. S. (2019). Mobile App Development with React Native. Packt Publishing.
[<https://www.packtpub.com/en-us/product/react-cross-platform-application-development-with-react-native-9781789136081>]
- [3] Lee, G. J., & Lee, M. Y. (2018). Cloud Computing for Smart Agriculture: A Survey. Future Generation Computer Systems, 78, 287-299.
[https://www.researchgate.net/publication/321896167_A_Survey_Smart_agriculture_IoT_with_cloud_computing]
- [4] Kim, Y. H., et al. (2020). Optimizing Cloud Resources for Machine Learning Applications. IEEE Transactions on Cloud Computing, 8(1), 123-135.



IT21186592 | Najas MNM

Information technology



IT21186592 | NAJAS MNM | 24-25J-064

COMPONENT

Detecting Tomato Diseases and Recommending Appropriate Treatment



INTRODUCTION BACKGROUND

- This project aims to develop a comprehensive system that leverages image analysis and machine learning to detect tomato diseases and recommend appropriate treatments.
- The Impact of Diseases on Tomato Crops.
- Challenges in Disease Management.



RESEARCH QUESTIONS

How can we develop a decision support system for tomato greenhouses ?



RESEARCH GAP

Existing Products / Research	Predictive Analytics				
	Image Analysis Tools	Manual Inspection	Disease Specific Detection	Automated Treatment Recommendation	Predictive Analytics
Current Methods	✗	✓	✓	✗	✗
Basic Automated Tools	✓	✓	✗	✗	✗
Proposed System	✓	✗	✓	✓	✓

MAIN & SPECIFIC OBJECTS

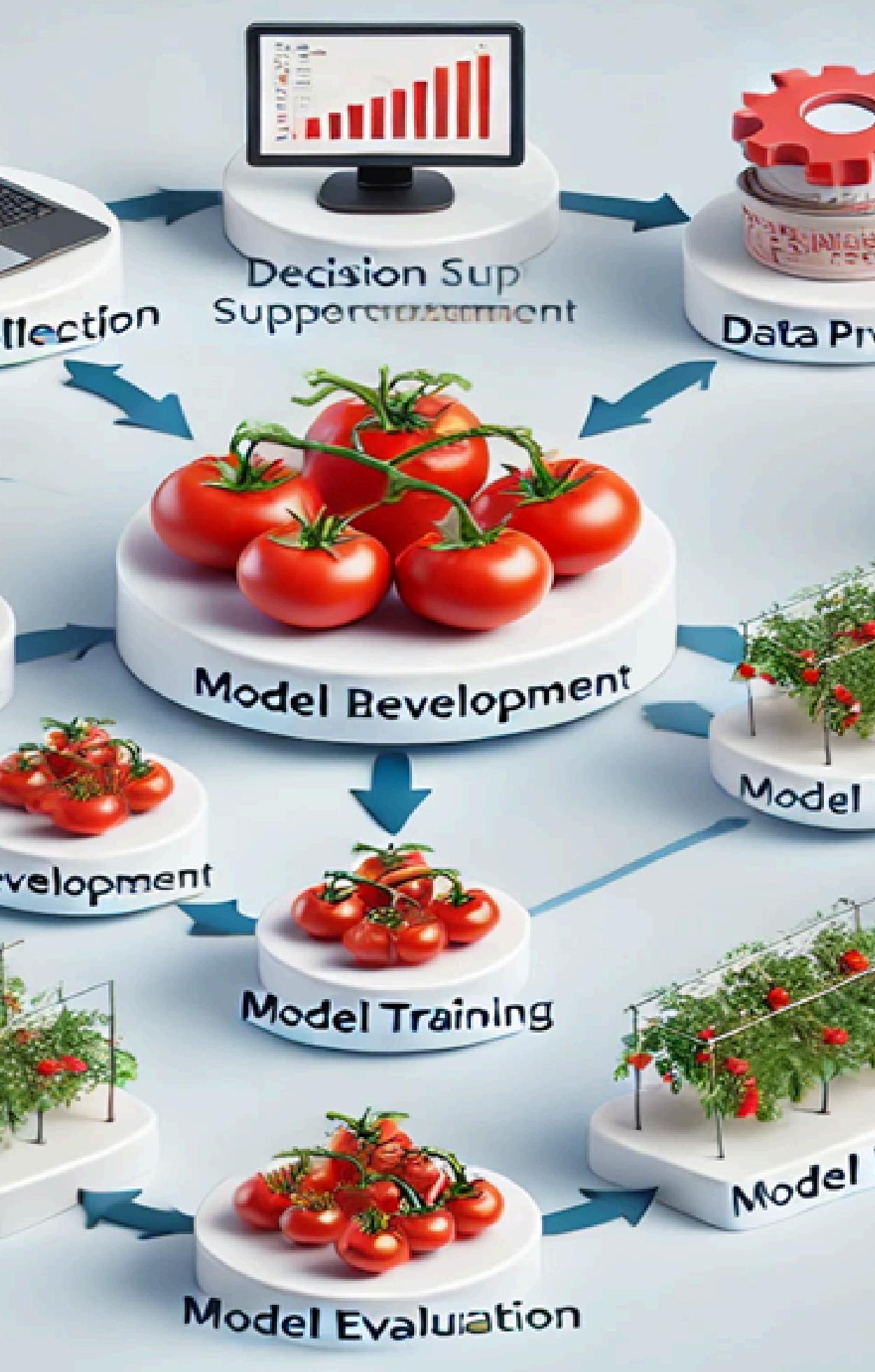
Main objectives

Develop a comprehensive system to detect tomato diseases and recommend appropriate treatments using image analysis and machine learning.

Sub objectives

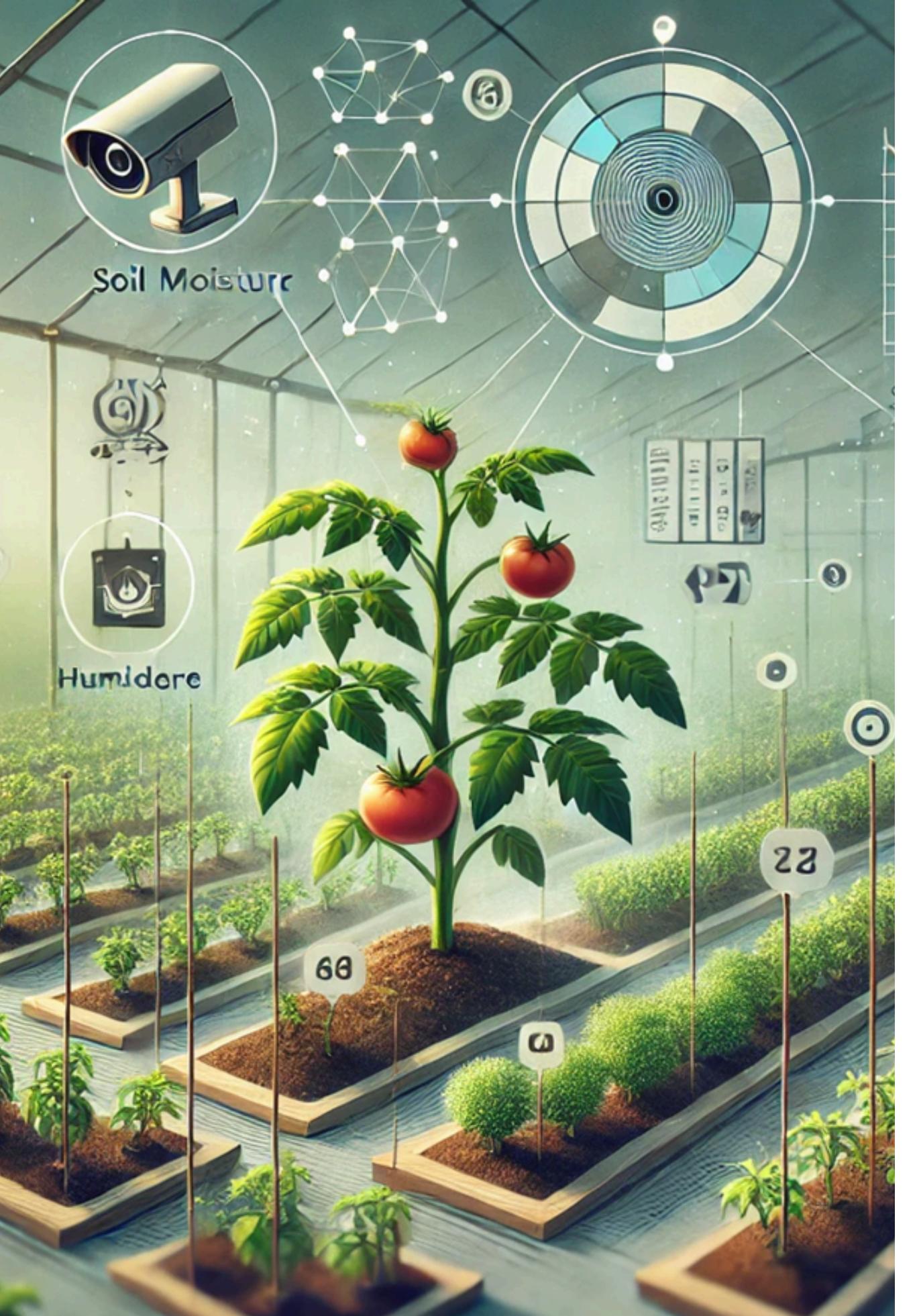
- Select data from Kaggle.
- Label the images with corresponding disease types.
- Preprocess the images (resize, normalize, augment) for model training.
- Develop a model architecture suitable for image classification.
- Train the CNN model on the labeled dataset and evaluate its performance.





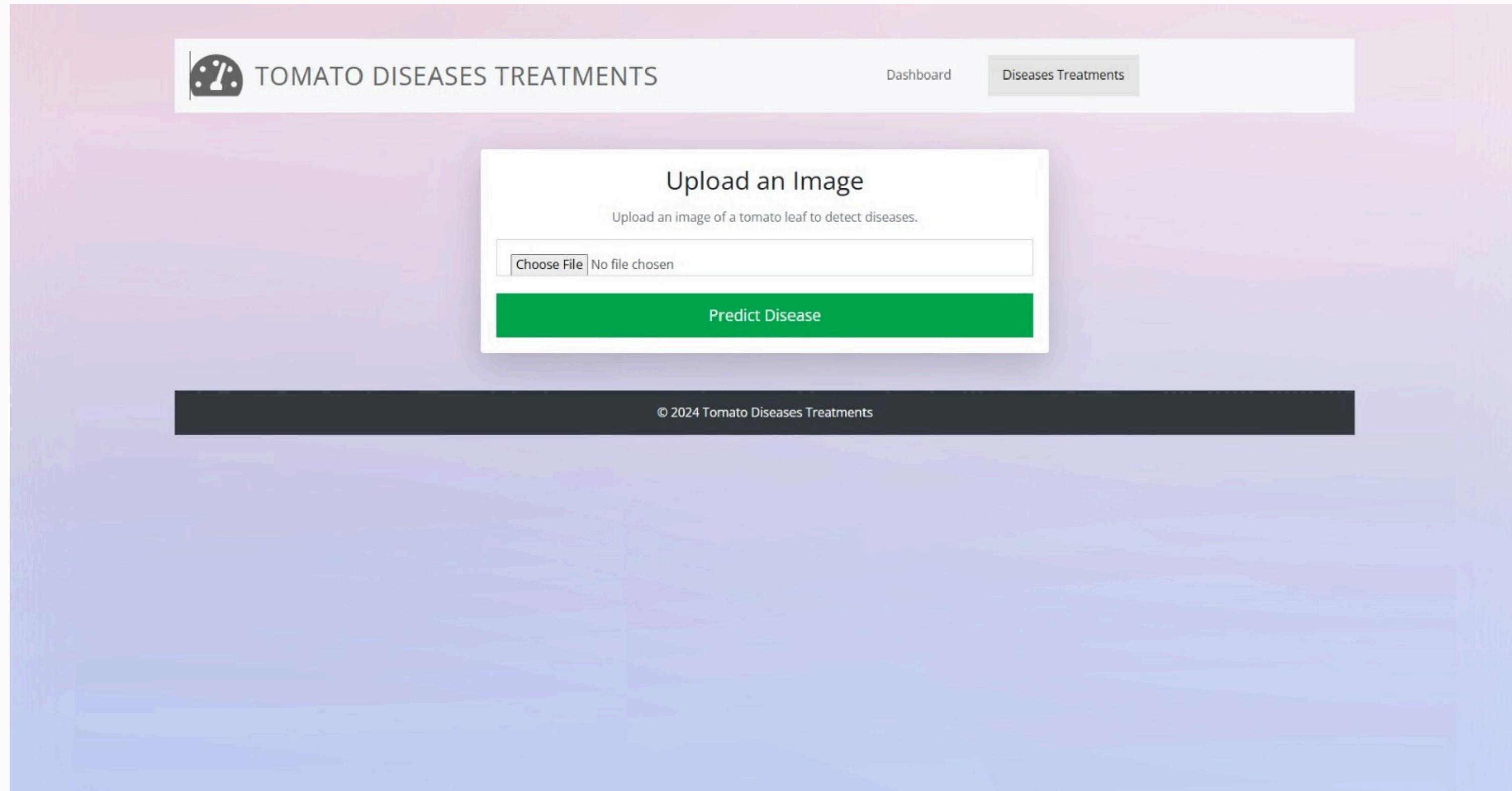
METHODOLOGY

- Python, TensorFlow(Open-Source ML framework), Keras.
 - Image preprocessing techniques.
 - CNN model design and training.
 - Data visualization tools.
- Data Collection and Labeling:** Select and annotate images from Kaggle.
- Image Preprocessing:** Resize, normalize, and augment images.
- CNN Model Development:** Design and train a CNN model for disease classification.
- Performance Evaluation:** Evaluate the model's performance using metrics such as accuracy, precision, and recall.
- Implementation of Recommendation System:** Provide treatment recommendations based on disease detection.



DATA COLLECTION

- Kaggle datasets.



A screenshot of a web application interface titled "TOMATO DISEASES TREATMENTS". The title bar includes a tomato icon and two navigation links: "Dashboard" and "Diseases Treatments". The main content area features a white box with a title "Upload an Image" and a subtitle "Upload an image of a tomato leaf to detect diseases." It contains a file input field labeled "Choose File" with the message "No file chosen" and a green button labeled "Predict Disease". At the bottom of the page is a dark footer bar with the copyright text "© 2024 Tomato Diseases Treatments".

TOMATO DISEASES TREATMENTS

Dashboard Diseases Treatments

Upload an Image

Upload an image of a tomato leaf to detect diseases.

Choose File No file chosen

Predict Disease

© 2024 Tomato Diseases Treatments

OUTPUT

 TOMATO DISEASES TREATMENTS

Dashboard Diseases Treatments

Upload an Image

Upload an image of a tomato leaf to detect diseases.

Choose File No file chosen

Predict Disease

Uploaded Image



Predicted Disease

Tomato Spider mites

Suggested Treatment

Recommended treatment: Use miticides or introduce natural predators like ladybugs.

REQUIREMENTS

System requirements

- High-quality annotated image datasets.
- Efficient CNN model for disease detection.
- Treatment recommendation algorithms.
- User-friendly dashboard for real-time alerts and recommendations.

Non-functional Requirements

- Performance
- Reliability
- Scalability
- Security
- Usability
- Maintainability
- Accuracy

REFERENCES

- Mohanty, S. P., Hughes, D. P., & Salathé, M. (2016). Using deep learning for image-based plant disease detection. *Frontiers in Plant Science*, 7, 1419.
- Zhang, S., Huang, W., Zhang, C., & Wang, X. (2018). Plant disease recognition based on plant leaf image. *Journal of Agricultural Mechanics Research*, 9, 94-99.
- Barbedo, J. G. A. (2016). A review on the main challenges in automatic plant disease identification based on visible range images. *Biosystems Engineering*, 144, 52-60.



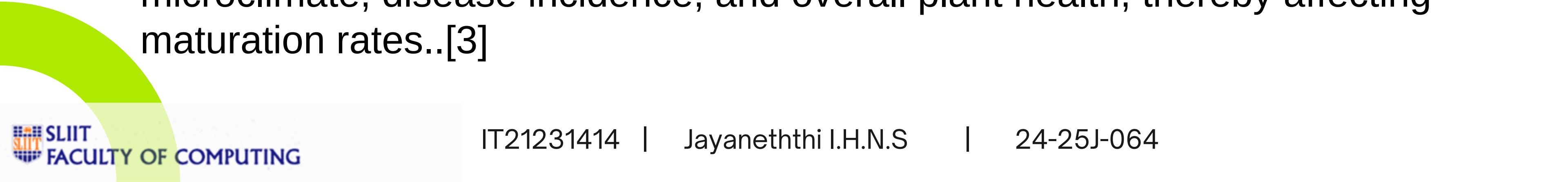
IT21231414 | Jayaneththi I.H.N.S

Information technology



BACKGROUND

- **The Forecasting tomato harvest dates :**
 - The growth and development of tomato plants are highly sensitive to temperature. Optimal temperatures range between 20°C to 25°C. Both high and low temperatures can slow growth, affect pollination, and delay fruit ripening. Heat stress, particularly during flowering and fruit set, can significantly impact yield and quality.[1]
- The timing of planting relative to the local climate and season affects the growing conditions experienced by the plants, thus influencing the harvest date. [2]
- Practices such as pruning, staking, and mulching can influence plant microclimate, disease incidence, and overall plant health, thereby affecting maturation rates..[3]



RESEARCH GAP

These research gaps contribute to the development of more advanced and effective devices for quality check of fresh tomatoes, ultimately benefit tomato producers, processors, and consumers alike.

According to that research,

Developing advanced algorithms for real-time data analysis to enable immediate feedback on the quality of fresh tomatoes

Understanding the impact of environmental factors on the performance of quality check devices

Research could focus on developing intuitive interfaces that provide clear and actionable insights into the quality of fresh tomatoes.

RESEARCH QUESTION

How can environmental and agronomic factors be integrated into a predictive model to accurately forecast the optimal harvest dates for different tomato varieties?



SPECIFIC AND SUBJECTIVE

Specific Objective

To develop and validate a machine learning-based model that accurately predicts the optimal harvest dates for tomatoes by analyzing key environmental factors (temperature, humidity, light) and agronomic practices (soil fertility, irrigation, and planting schedules).

Sub Objective

- Develop a predictive model using machine learning algorithms
 - Identify and engineer relevant features from the collected data
 - Design and implement a decision support tool that integrates the predictive model

TECHNOLOGIES & ALGORITHMS

1. Real-time data collection and analysis
2. Machine Learning for prediction models

Algorithms

- **Machine Learning Models:** random forest Regression algorithms for predicting schedule
- **Time Series Analysis:** ARIMA or LSTM for predicting environmental conditions

EVIDENCES FOR THE COMPLETION

Literature Review

Tomatoes (*Solanum lycopersicum*) are a globally important crop, both economically and nutritionally. The timing of tomato harvest significantly influences fruit quality, marketability, and post-harvest losses. Traditional methods for determining harvest readiness often rely on visual inspection and subjective judgment, leading to inconsistencies and potential quality issues (Hewett, 2006). This variability has prompted the development of more objective and reliable methods, including predictive models, to forecast optimal harvest dates.

Data Collection for the project is being carried out using the following ways:

- Public data sets
- Previous researches
- Surveys
- From Agriculture department

REQUIREMENTS

System requirements

- Data Processing and Storage
- Data Processing and Analytics
- Data Collection Devices
- Real-Time Alerts and Notifications
- Temperature Control

Non-functional requirements

- Performance
- Reliability
- Scalability
- Security
- Usability
- Maintainability
- Accuracy

PROGRESS

90% COMPLETION OF THE PROJECT

model is trained and the model part is finished.
harvest date prediction and add the sensor data and connect it to the UI.

EVIDENCE

```
1 import pandas as pd
2 from sklearn.model_selection import train_test_split
3 from sklearn.ensemble import RandomForestRegressor
4 from sklearn.preprocessing import StandardScaler
5 from sklearn.metrics import mean_absolute_error, r2_score
6 import joblib
7
8 # dataset
9 file_path = "harvest_dataset.csv"
10 df = pd.read_csv(file_path)
11 df["Planting Date"] = pd.to_datetime(df["Planting Date"]).map(lambda x: x.toordinal())
12
13 # Separate features and target
14 X = df.drop(labels="Harvest Days (Target)", axis=1)
15 y = df["Harvest Days (Target)"]
16
17 # Preprocess
18 scaler = StandardScaler()
19 X_scaled = scaler.fit_transform(X)
20
21 # Split the data
22 X_train, X_test, y_train, y_test = train_test_split(*arrays: X_scaled, y, test_size=0.2, random_state=42)
23
24 # Train the model
25 model = RandomForestRegressor(n_estimators=100, random_state=42)
26 model.fit(X_train, y_train)
27
28 # Validate the model
29 y_pred = model.predict(X_test)
30 mae = mean_absolute_error(y_test, y_pred)
31 r2 = r2_score(y_test, y_pred)
```

```
import pandas as pd
import joblib

# Load the trained model
model = joblib.load("harvest_model.pkl")
scaler = joblib.load("scaler.pkl")

# New data
new_data = pd.DataFrame({
    "Planting Date": [pd.to_datetime("2024-07-01").toordinal()],
    "Growth Stage (Days)": [20],
    "Temperature (°C)": [29],
    "Humidity (%)": [67],
    "Light Exposure (hrs/day)": [11],
    "Soil Moisture (%)": [30],
    "Pesticide Used (Yes=1, No=0)": [1],
})

# Scale the new data
new_data_scaled = scaler.transform(new_data)

# Predict
predicted_harvest_days = model.predict(new_data_scaled)
int(f"Predicted Harvest Days for new data: {predicted_harvest_days[0]:.0f} days")
```

Import Necessary dataset

Model Building

REFERENCES

- [1] Gutiérrez, S., Diacono, M., Castrignanò, A., & Sardone, R. (2016). Application of multivariate geostatistical methods for managing precision viticulture. *Computers and Electronics in Agriculture*, 121, 386–396. <https://doi.org/10.1016/j.compag.2016.02.018>
- [2] Hewett, E. W. (2006). An overview of pre-harvest factors influencing postharvest quality of horticultural products. *International Journal of Postharvest Technology and Innovation*, 1(1), 4–15. <https://doi.org/10.1504/IJPTI.2006.009629>
- [3] Saggi, M.K. & Jain, S. A. (2022). Survey Towards Decision Support System on Smart Irrigation Scheduling Using Machine Learning approaches. *Archives of Computational Methods in Engineering*, 29, 4455–4478. <https://doi.org/10.1007/s11831-022-09746-3>.
- [4] Salim, O., Fouad, K. & Hassan, B. (2022). Dual-Level Sensor Selection with Adaptive Sensor Recovery to Extend WSNs' Lifetime, *Human-centric Computing and Information Sciences*, Vol. 12, Article number: 18, <https://doi.org/10.22967/HCIS.2022.12.018>.
- [5] Goap, A., Sharma, D., Shukla, A.K. & Krishna, R. (2018). An IoT based smart irrigation management system using Machine learning and open source technologies, *Computers and Electronics in Agriculture*, Vol. 155, PP: 41–49, ISSN 0168-1699, <https://doi.org/10.1016/j.compag.2018.09.040>.
- [6] Fouad, K. & Elbably, D. (2020). Intelligent approach for large-scale data mining. *Int. J. Computer Applications in Technology*, Vol. 63, Nos. 1/2, PP: 93–112.
- [7] Fouad, K., Hassan, B. & Salim, O. (2022). Hybrid Sensor Selection Technique for Lifetime Extension of Wireless Sensor Networks. *Computers, Materials & Continua* 2022, 70(3), 4965–4985. <https://doi.org/10.32604/cmc.2022.020926>.