SMART GREENHOUSES DECISION SUPPORT SYSTEMS FOR TOMATO CULTIVATION

GROUP ID: 24-25J-064

SLIIT
FACULTY OF COMPUTING

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 predicts **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 Schedules & IoT based Irrigation Control:

- Determine the best timing and frequency for watering to ensure healthy growth and efficient water use.

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

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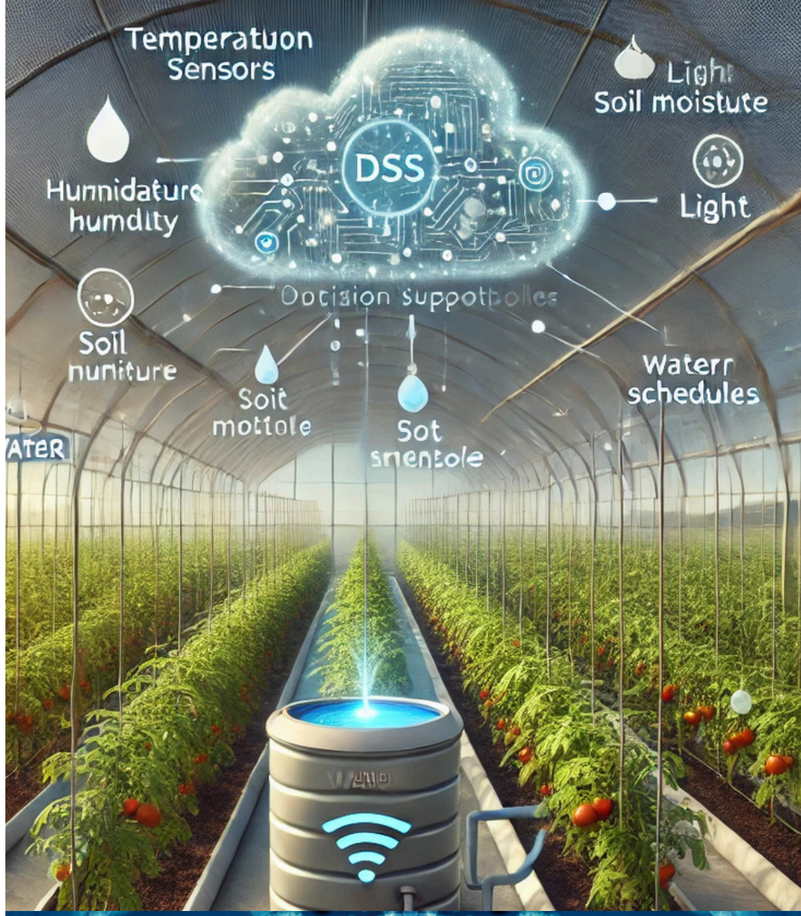
INTRODUCTION BACKGROUND

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 watering schedules and ensures the water availability, based on real-time environmental conditions?



RESEARCH GAP

Existing Products / Research	Features					
	Automated Water irrigation	Soil Moisture, Light & Temperature Monitoring	Temperature Control	Water level & Availability checking	Predict Watering Time, Schedule, Quantity	Real-Time Alerts (Dashboard)
IoT-Based Precision Irrigation System	✓	✓	✗	✓	✗	✗
Smart high-yield tomato cultivation System	✓	✗	✗	✓	✗	✓
Indoor Seedling Irrigation System	✗	✓	✗	✓	✗	✗
LoRaWAN based IoT system	✗	✓	✗	✓	✗	✓
Proposed System	✓	✓	✓	✓	✓	✓

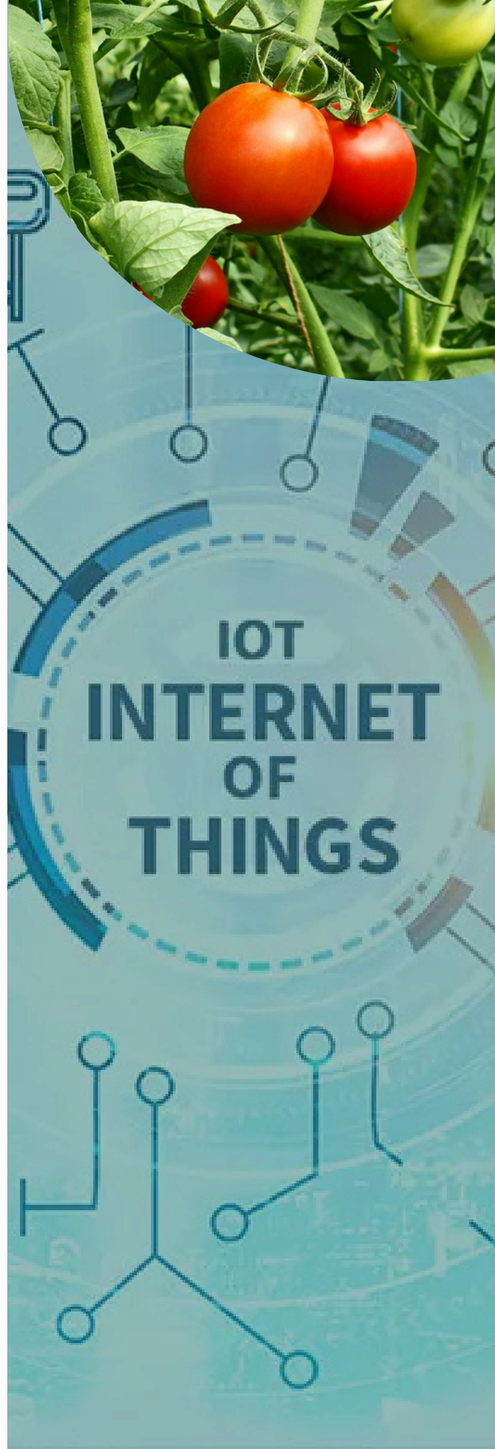
MAIN & SPECIFIC OBJECTS

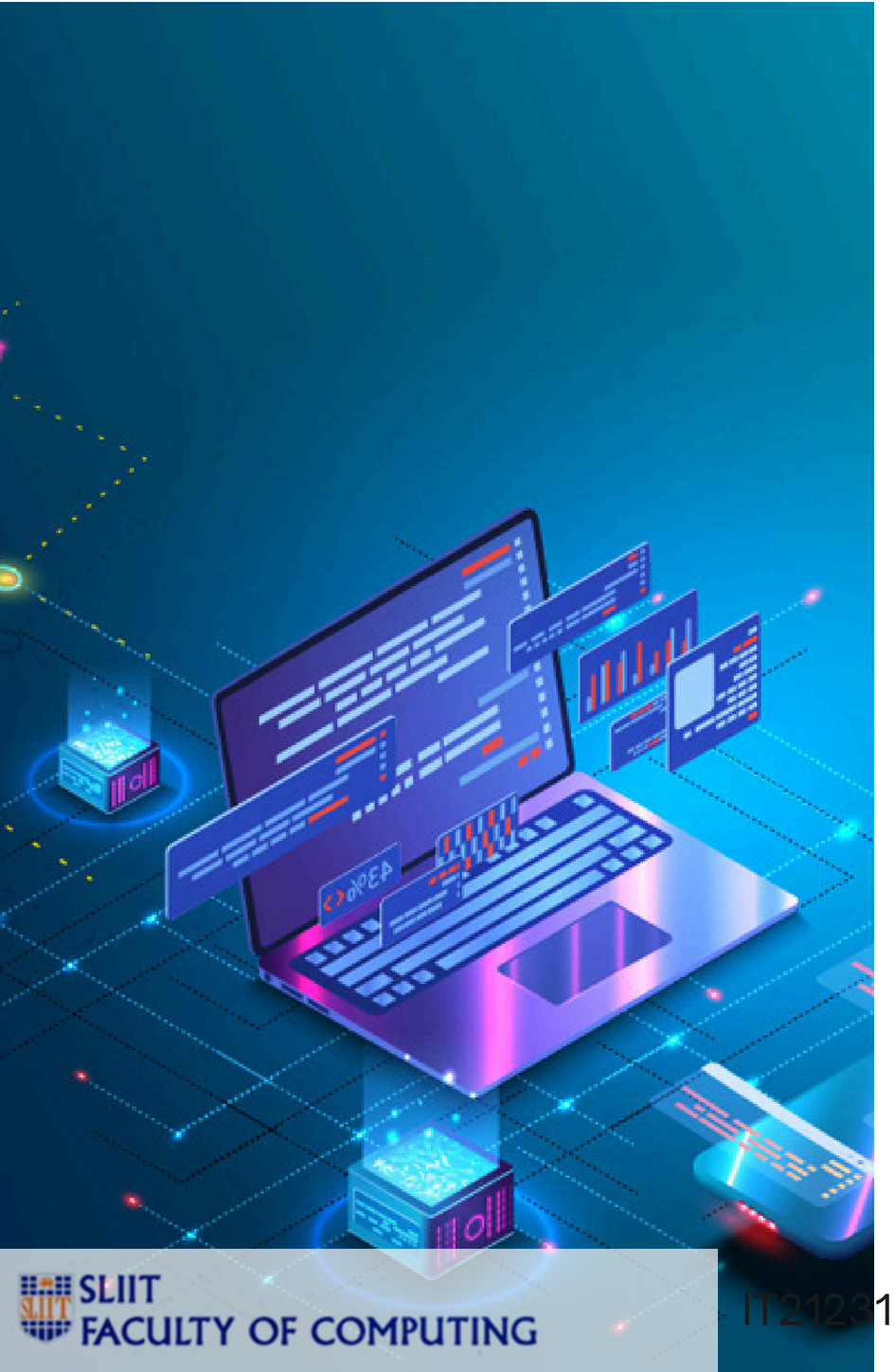
Main objectives

Develop a IoT Device and ML model decision support system to **predict optimal watering schedules** and **ensure water availability** in tomato greenhouse.

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 watering need(Liters) based on environmental data.
- **Ensure water availability** by monitoring **water levels in the Tank**.
- **Train the machine learning model** using real preprocessed datasets.
- **Automate temperature and water supply control** in the greenhouse.
- **Develop a web application** for control and monitoring of greenhouse conditions.

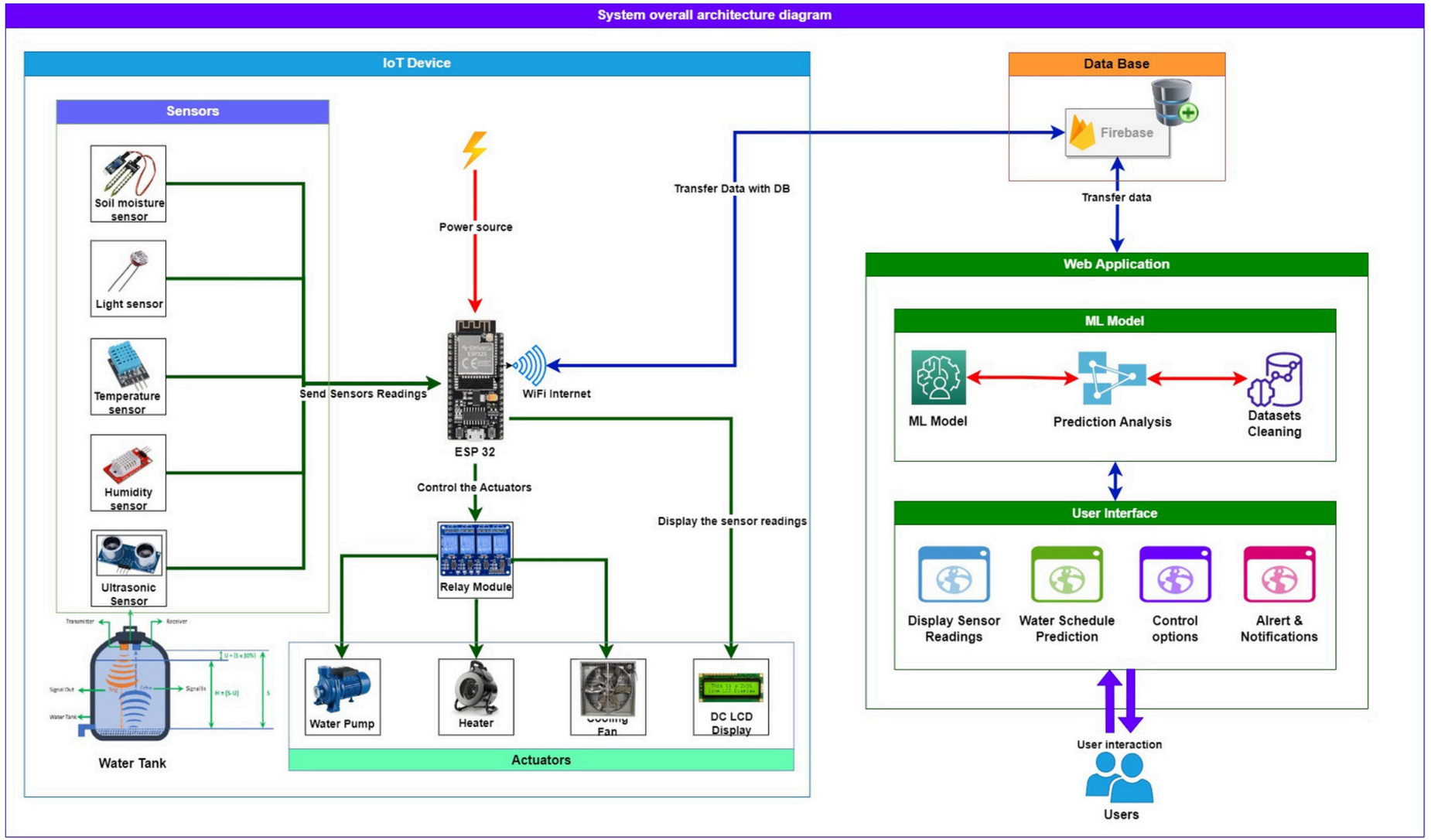




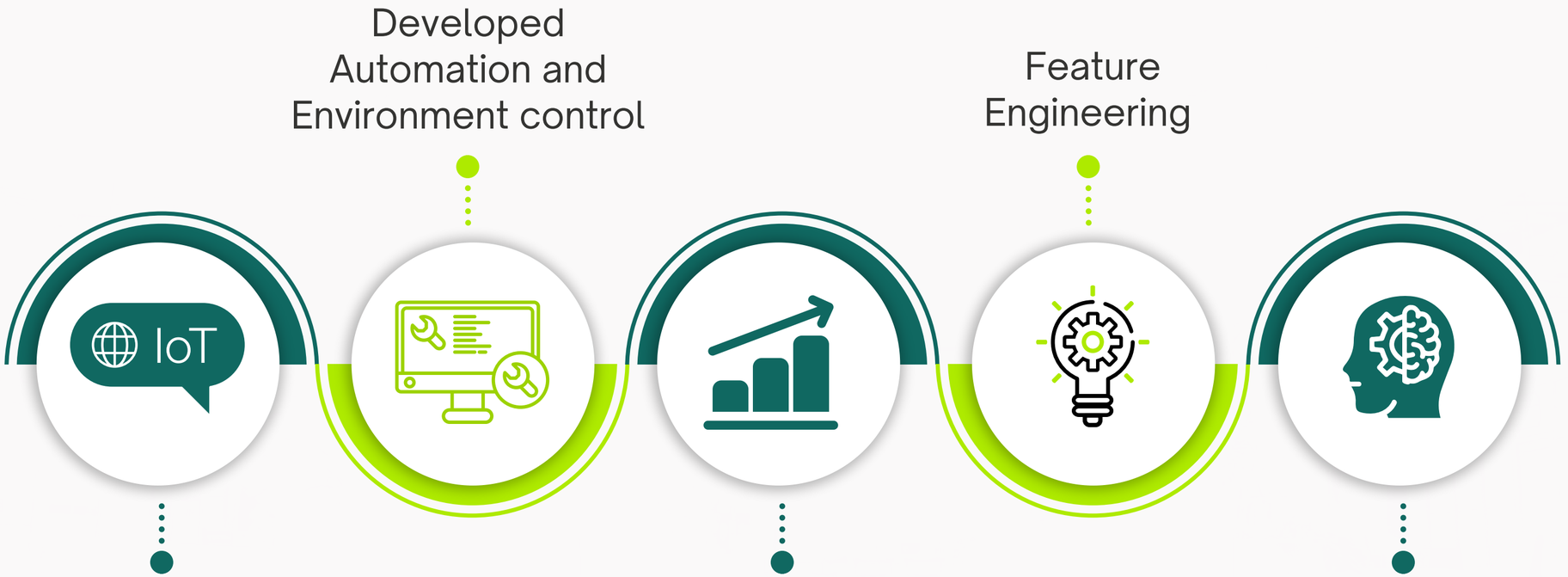
METHODOLOGY

1. Develop the IoT device & Collect and analyze sensors data.
2. Develop and train ML models
3. Build a web Application for monitoring and control.

METHODOLOGY - DIAGRAM



COMPLETION OF THE PROJECT



ABOUT THE IOT DEVELOPMENT

IoT Code

```
#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, SC
  // 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.println(soilMoisture);
Serial.print("Light Level: ");
Serial.println(lightLevel);
```

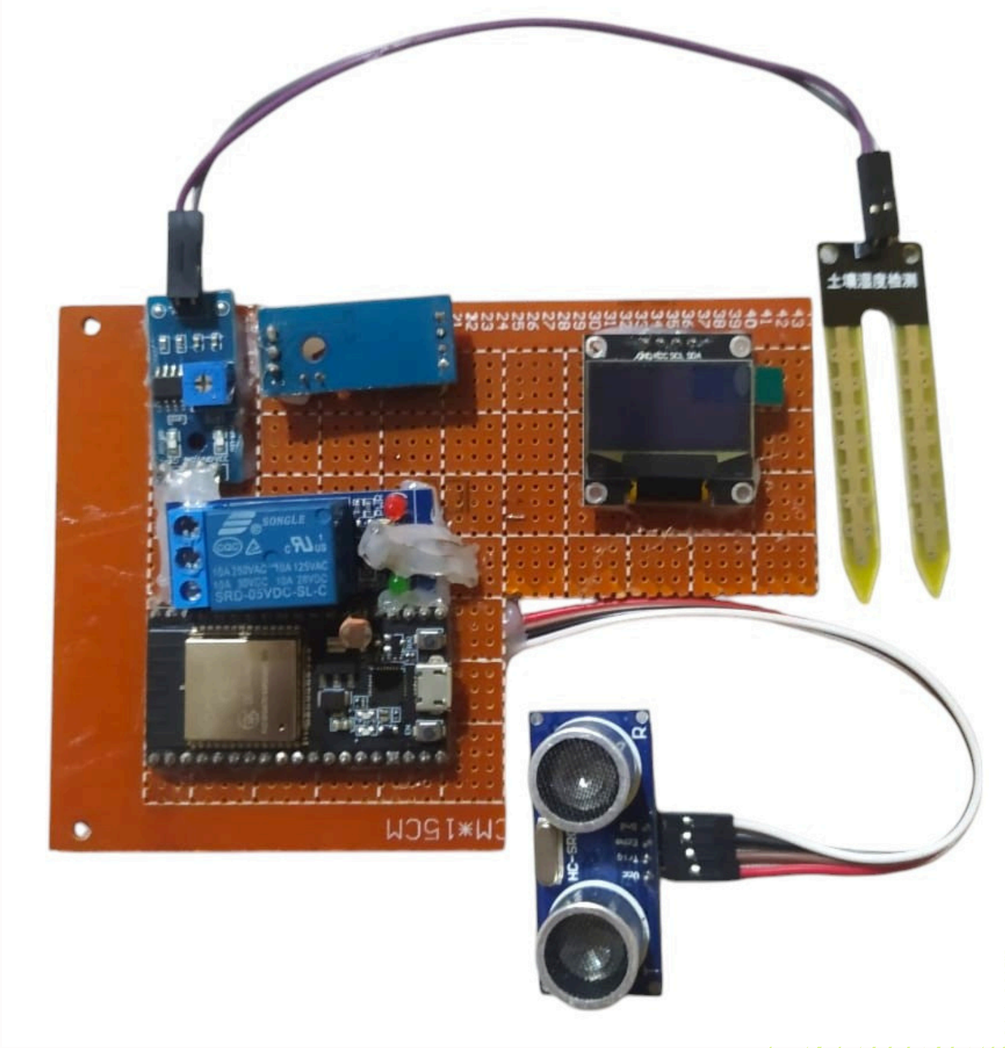
IoT Firebase Configurations

```
// 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

The IoT device successfully developed



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 (Â°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
11/2/2024 2:00	28.6	65.3	32.6	714	9.4
11/2/2024 3:00	25.8	34.1	12.6	1248	5.1

DATA PREPROCESSING

```
# Load dataset
file_path = "irrigation_dataset.csv"
data = pd.read_csv(file_path)

# Preprocess the data
data['Timestamp'] = pd.to_datetime(data['Timestamp'])

# Feature Engineering
data['Hour'] = data['Timestamp'].dt.hour
data['DayOfWeek'] = data['Timestamp'].dt.dayofweek
data['Month'] = data['Timestamp'].dt.month
data['Year'] = data['Timestamp'].dt.year

# Handle missing values
imputer = SimpleImputer(strategy='median')
data[['Temperature (°C)', 'Humidity (%)', 'Soil Moisture (%)', 'Light Level (lux)']] = imputer.fit_transform(
    data[['Temperature (°C)', 'Humidity (%)', 'Soil Moisture (%)', 'Light Level (lux)']]
)
```

FEATURE ENGINEERING

```
# Preprocess the data
data['Timestamp'] = pd.to_datetime(data['Timestamp'])

# Feature Engineering
data['Hour'] = data['Timestamp'].dt.hour
data['DayOfWeek'] = data['Timestamp'].dt.dayofweek
data['Month'] = data['Timestamp'].dt.month
data['Year'] = data['Timestamp'].dt.year
```

```
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
```

```
# Feature Scaling and Polynomial Expansion
# Feature Scaling
scaler = StandardScaler()
features = ['Temperature (°C)', 'Humidity (%)', 'Soil Moisture (%)', 'Light Level (lux)', 'Hour', 'DayOfWeek', 'Month', 'Year']
data[features] = scaler.fit_transform(data[features])

# Polynomial Feature Expansion
poly = PolynomialFeatures(degree=2, include_bias=False)
X_poly = poly.fit_transform(data[features])
```

MODEL TRAINING

```python
# Split data into training
X = X_poly
y = data['Water Level Needed (Liters)']
X_train, X_temp, y_train, y_temp = train_test_split( *arrays: X, y, test_size=0.3, random_state=42)
X_val, X_test, y_val, y_test = train_test_split( *arrays: X_temp, y_temp, test_size=0.5, random_state=42)

# Hyperparameter Tuning
param_grid = {
    'n_estimators': [100, 200, 300],
    'max_depth': [10, 20, 30, None],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'bootstrap': [True, False]
}

grid_search = GridSearchCV(estimator=RandomForestRegressor(random_state=42),
                           param_grid=param_grid,
                           cv=5,
                           n_jobs=-1,
                           verbose=2,
                           scoring='neg_mean_squared_error')
grid_search.fit(X_train, y_train)
```

```python
# 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}")
```

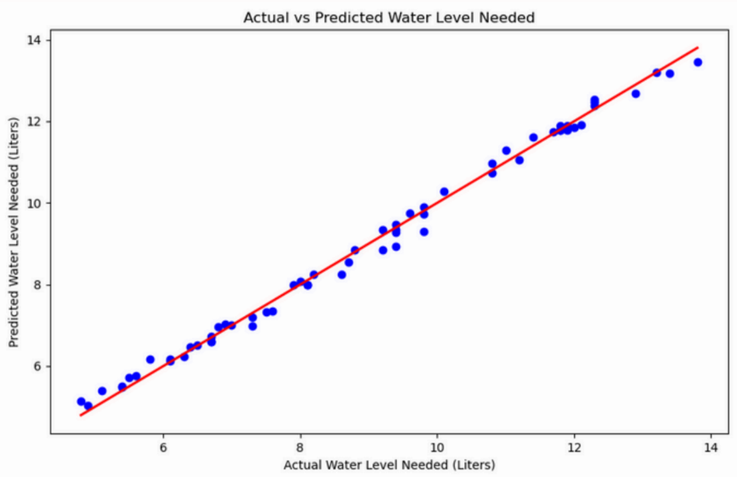
```python
# Save Models
joblib.dump(best_model, filename: "irrigation_model.pkl")
joblib.dump(scaler, filename: "scaler.pkl")
joblib.dump(poly, filename: "poly.pkl")
print("Best model, scaler, and poly transformer saved successfully.")
```

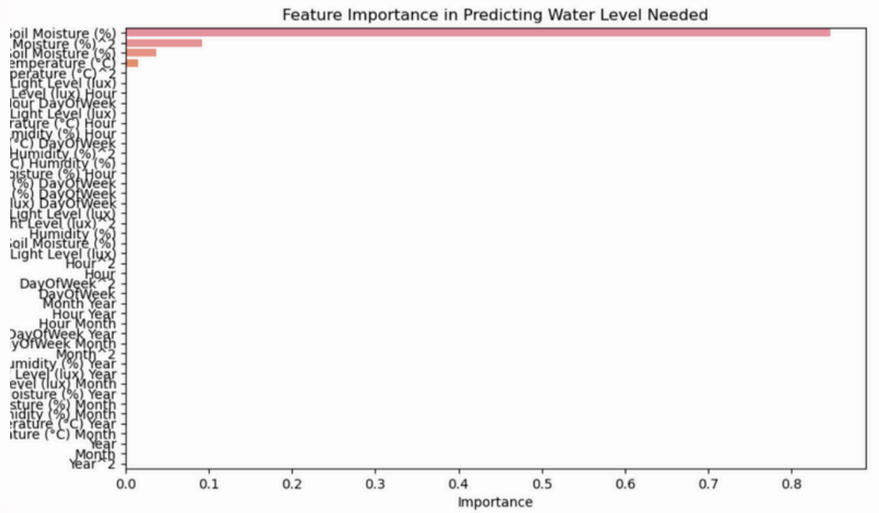
PERFORMANSE MATRIC ACCURECY :

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

MODEL PERFORMANCE EVALUATION

```python
#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)], co
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=F

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()
```



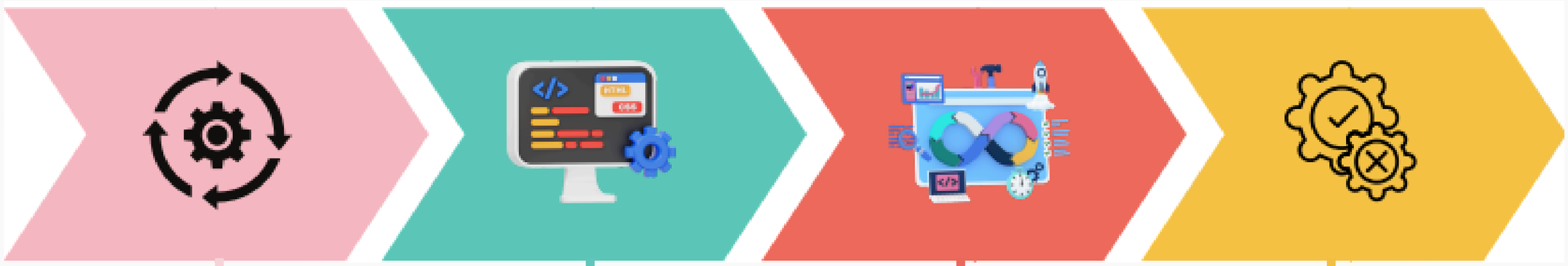



```python
#  predict watering needs
def predict_watering(temperature, humidity, soil_moisture, light_level, timestamp):  1 usage
    timestamp = pd.to_datetime(timestamp)
    hour = timestamp.hour
    day_of_week = timestamp.dayofweek
    month = timestamp.month
    year = timestamp.year

    # DataFrame input
    input_data = pd.DataFrame( data: [[temperature, humidity, soil_moisture, light_level, hour, day_of_week,
                               columns=['Temperature (°C)', 'Humidity (%)', 'Soil Moisture (%)', 'Light Leve

    # 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]
```

```python
    # 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, ligl
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
```

FUTURE CHECKLIST



Model Fine-Tuning and Optimization

Web application development

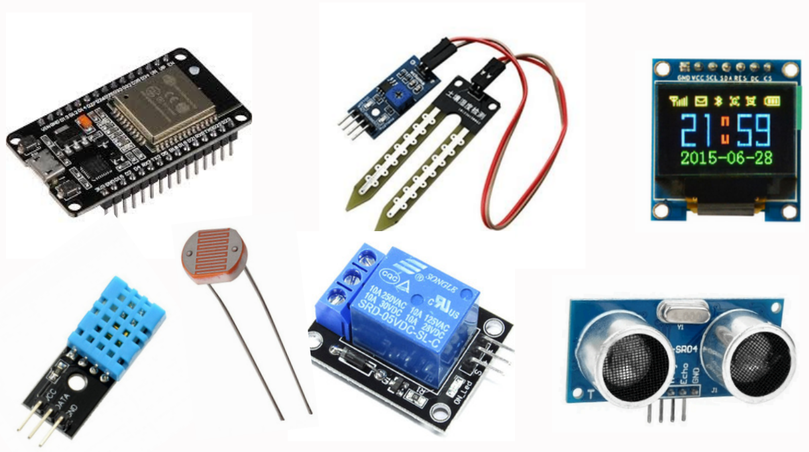
Integration and deployment

Testing and validation

TECHNOLOGY STACK

Softwares :

- Python
- Pycharm IDE
- Matplotlib and Seaborn - **data visualization**
- Scikit-learn library - **machine learning**
- Pandas and NumPy - data manipulation
- C++
- Arduino IDE
- Firebase as Database



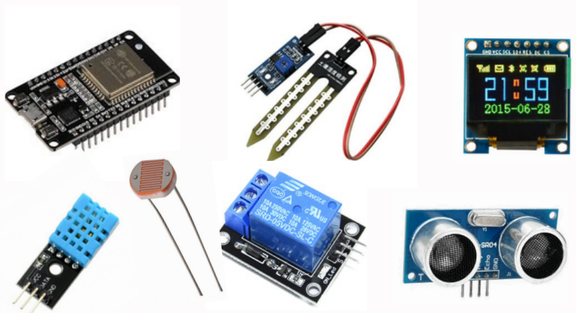
Machine learning Algorithms :

- Random Forest Regressor (RFR)

REQUIREMENTS

Hardware :

- ESP32(Microcontroller)
- Sensors :
  - Soil Moisture
  - Temperature
  - Humidity(DH11)
  - Light(LDR)
  - Ultrasonic
- OLED Display
- Relay Modules



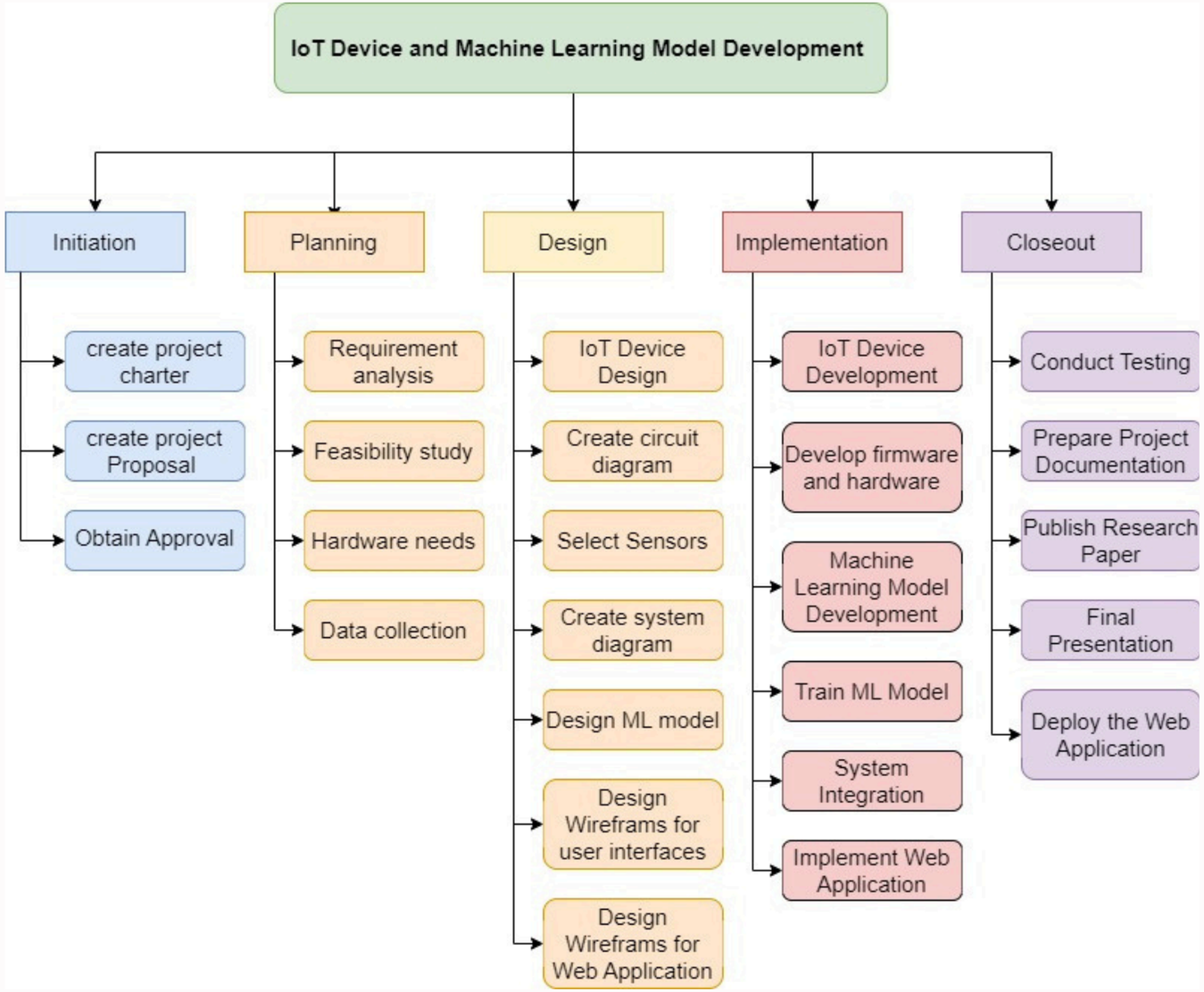
Functional requirements :

- Real-time Data Collection
- Model Training & Evaluation
- Automated Temperature Control
- Real-Time Alerts & Notifications
- Water Level Monitoring
- Allow Manual Control
- Responsive UI

Non functional :

- Reliability
- Security
- Maintainability
- Accuracy

WORK BREAKDOWN CHART



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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	Environmentally 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

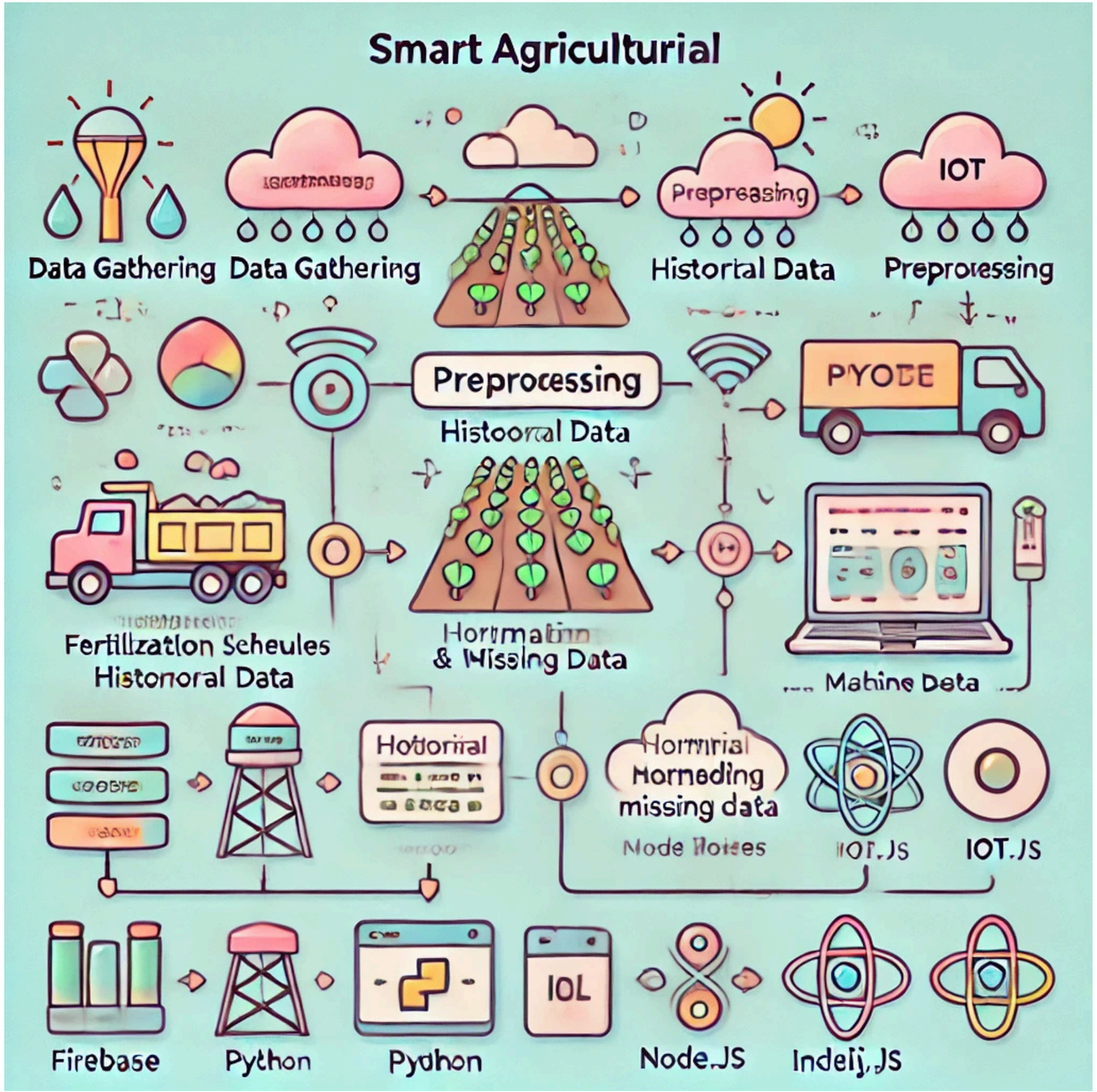
1.Gather soil, nutrient data and environmental conditions.

2.Collect historical fertilization schedules and crop yield data.

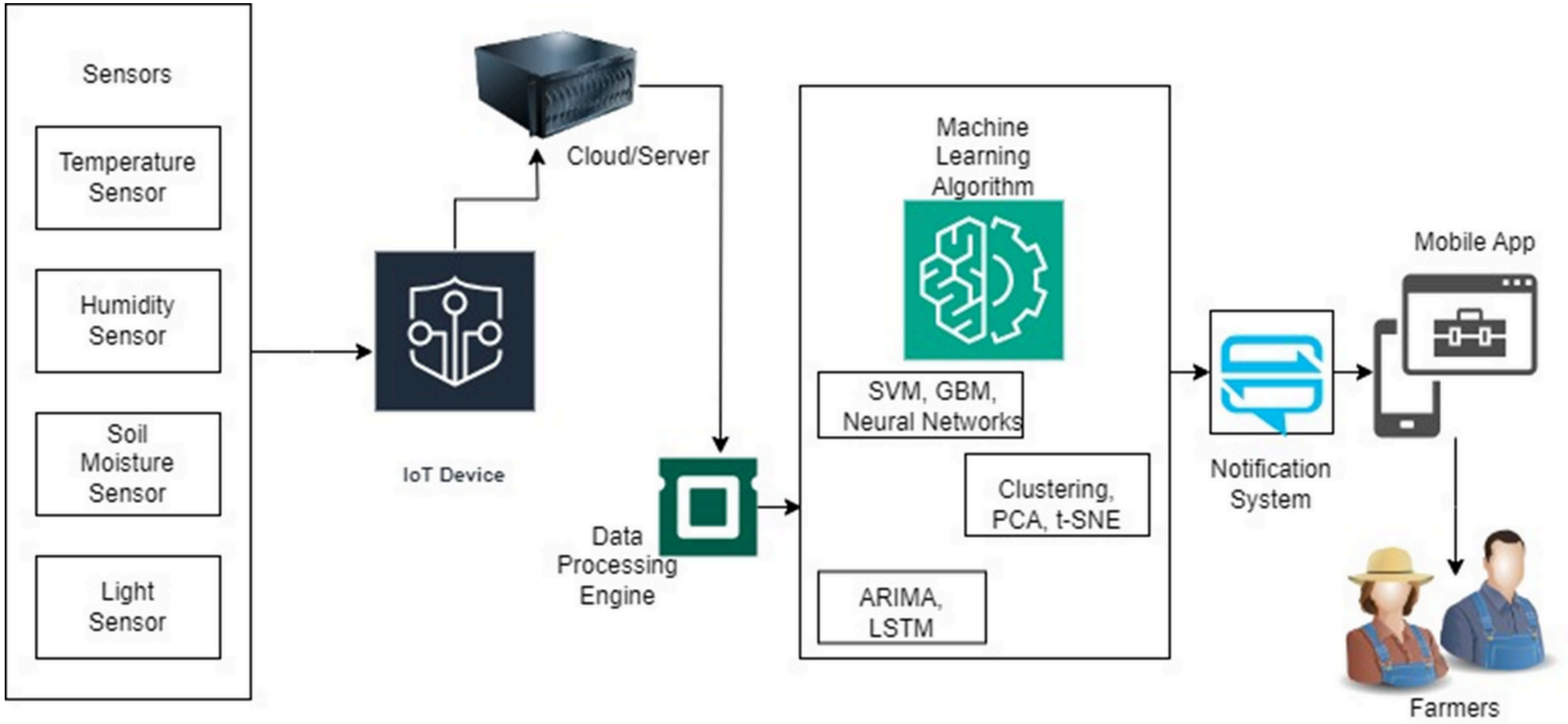
3.Preprocess the data to handle missing values and normalize it.

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 (ツ-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

```
# Load the dataset
file_path = "fertilization_data.csv"
df = pd.read_csv(file_path)

# Preprocess
df = pd.get_dummies(df, columns=['Fertilizer Type'], drop_first=True)

# Split data
X = df.drop(['Fertilizer Quantity (kg/ha)', 'Fertilizer Timing (Week)'], axis=1)  # Features
y = df[['Fertilizer Quantity (kg/ha)', 'Fertilizer Timing (Week)']]  # Targets

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

# Normalize
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

MODEL TRAINING

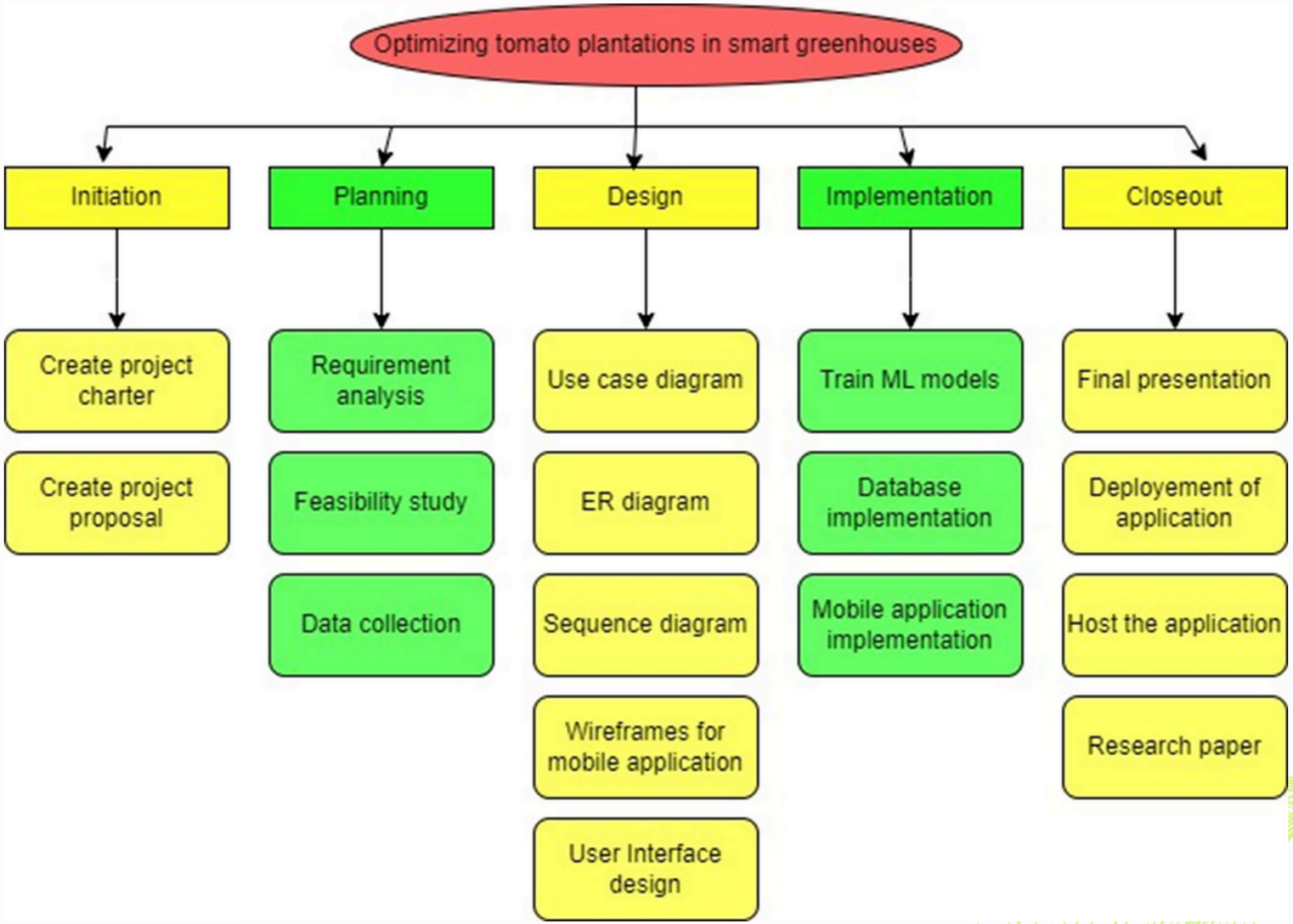
```
# Train the models
rf_model = RandomForestRegressor(n_estimators=100, random_state=42)
gb_model = GradientBoostingRegressor(n_estimators=100, random_state=42)
rf_model.fit(X_train_scaled, y_train['Fertilizer Quantity (kg/ha)'])
gb_model.fit(X_train_scaled, y_train['Fertilizer Timing (Week)'])
rf_predictions = rf_model.predict(X_test_scaled)
gb_predictions = gb_model.predict(X_test_scaled)

# Evaluate
rf_mae = mean_absolute_error(y_test['Fertilizer Quantity (kg/ha)'], rf_predictions)
rf_mse = mean_squared_error(y_test['Fertilizer Quantity (kg/ha)'], rf_predictions)
rf_r2 = r2_score(y_test['Fertilizer Quantity (kg/ha)'], rf_predictions)

gb_mae = mean_absolute_error(y_test['Fertilizer Timing (Week)'], gb_predictions)
gb_mse = mean_squared_error(y_test['Fertilizer Timing (Week)'], gb_predictions)
gb_r2 = r2_score(y_test['Fertilizer Timing (Week)'], gb_predictions)
rf_cv_scores = cross_val_score(rf_model, X_train_scaled, y_train['Fertilizer Quantity (kg/ha)'], cv=5, scoring='neg_mean_absolute_
gb_cv_scores = cross_val_score(gb_model, X_train_scaled, y_train['Fertilizer Timing (Week)'], cv=5, scoring='neg_mean_absolute_err

```

WORK BREAKDOWN STRUCTURE



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SLIIT
FACULTY OF COMPUTING

COMPONENT

Detecting Tomato Diseases and Recommending Appropriate Treatment

IT21186592 | NAJAS MNM | 24-25J-064

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	✓	✗	✓	✓	✓

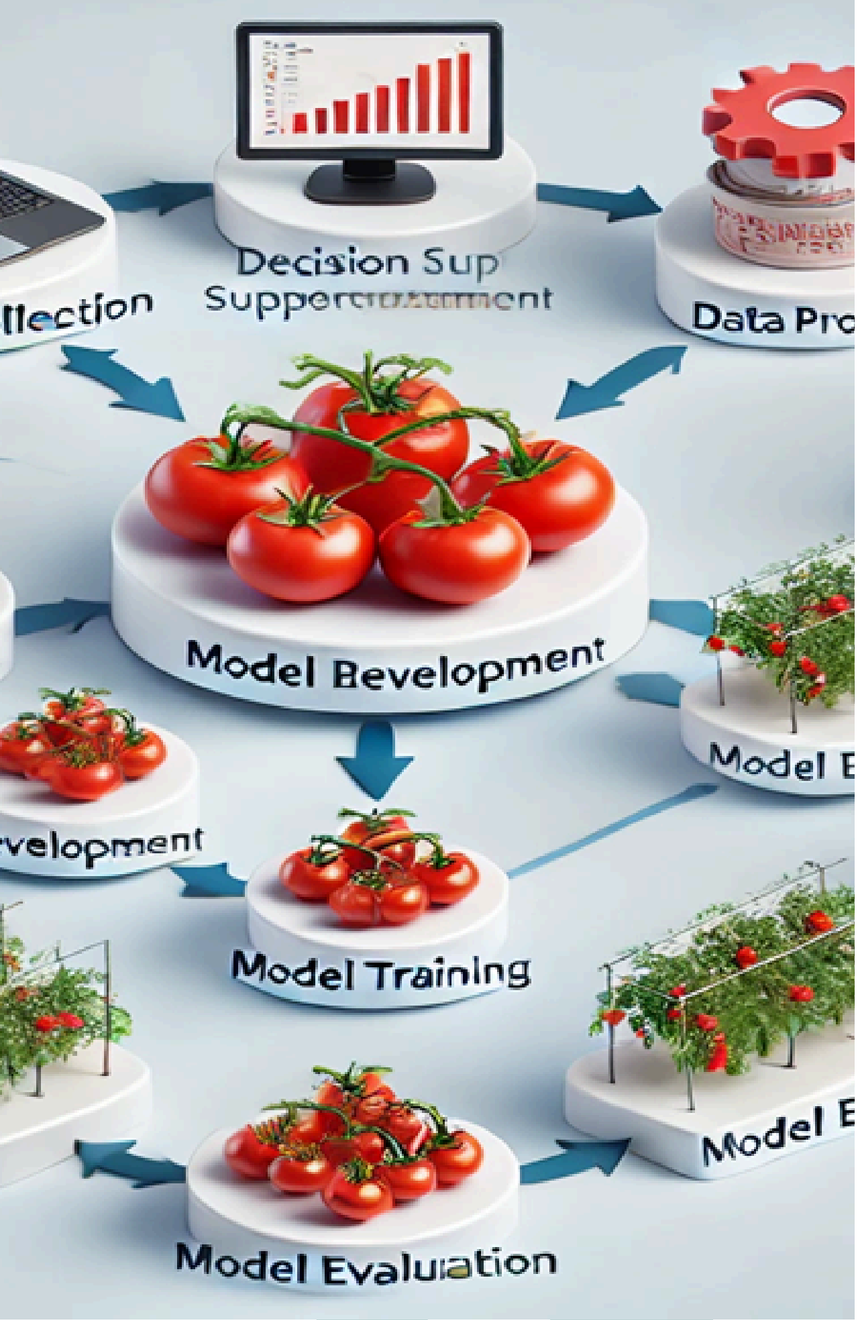
MAIN & SPECIFIC OBJECTS

Main objectives

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

Sub objectives

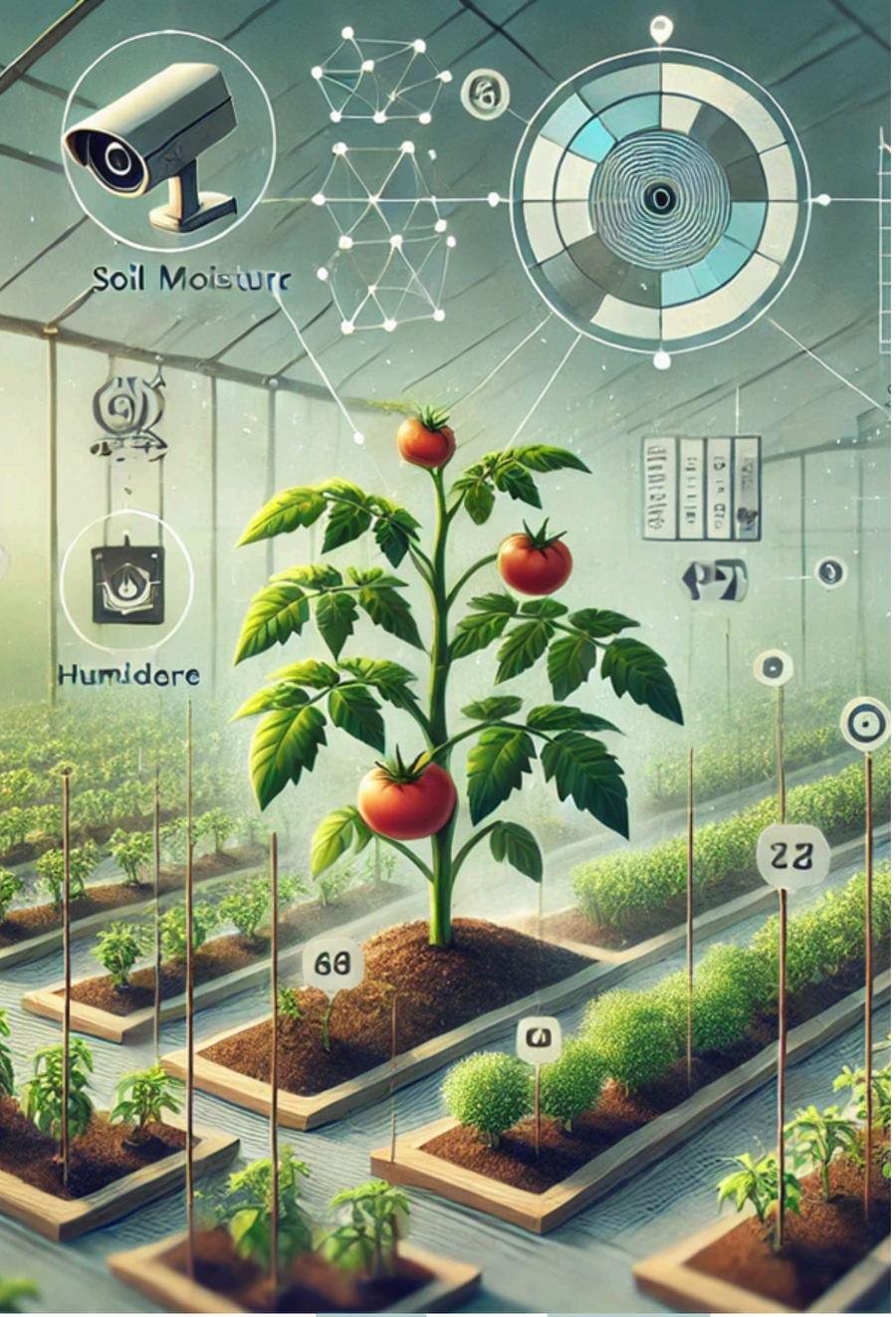
- Select data from Kaggle.
- Label the images with corresponding disease types.
- Preprocess the images (resize, normalize, augment) for model training.
- Develop a model architecture suitable for image classification.
- Train the CNN model on the labeled dataset and evaluate its performance.



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.**

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

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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.

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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 a like.

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**: 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

- Current Progress

model is trained and the model part is finished.
harvest date prediction

- Future Progress

add the sensor data and connect it to the UI.

EVIDENCE

```python
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_absolute_error, r2_score
import joblib

# dataset
file_path = "harvest_dataset.csv"
df = pd.read_csv(file_path)
df["Planting Date"] = pd.to_datetime(df["Planting Date"]).map(lambda x: x.toordinal())

# Separate features and target
X = df.drop( labels: "Harvest Days (Target)", axis=1)
y = df["Harvest Days (Target)"]

# Preprocess
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Split the data
X_train, X_test, y_train, y_test = train_test_split( *arrays: X_scaled, y, test_size=0.2, random_state=42)

# Train the model
model = RandomForestRegressor(n_estimators=100, random_state=42)
model.fit(X_train, y_train)

# Validate the model
y_pred = model.predict(X_test)
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
```

Import Necessary dataset

```python
port pandas as pd
port joblib

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

new data
w_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],



w_data_scaled = scaler.transform(new_data)

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

Model Building

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