A Smart IoT Framework for Enhanced Crop Management using Machine Learning

Report submitted to the SASTRA Deemed to be University in partial fulfillment of the requirements for the award of the degree of

MASTER OF COMPUTER APPLICATION

Submitted by

RAMPRASATH S

(Reg. No:124176077, MCA)

SARAN V

(Reg. No: 124176087, MCA)

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This is to certify that the project report titled "**A Smart IoT Framework for Enhanced Crop Management using Machine Learning "** submitted in partial fulfillment of the requirements for the award of the degree of Master of Computer Application to the SASTRA Deemed to be University, is a bona-fide record of the work done by **Mr. RAMPRASATH S** (Reg. No. 124176077) and **Mr. SARAN V** (Reg. No. 124176087) during the final semester of the academic year 2023-24, in the **School of Computing**, under my supervision. This report has not formed the basis for the award of any degree, diploma, associateship, fellowship or other similar title to any candidate of any University.

Signature of Project Supervisor :

Name of Affiliation : Dr. Venkastesh V, Assistant Professor - III

Date :19.05.2024

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Examiner 1 **Examiner 2**

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Declaration

We declare that the project report titled "**A Smart IoT Framework for Enhanced Crop Management using Machine Learning**" submitted by us is an original work done by us under the guidance of **Dr. Venkatesh V, Assistant Professor - III, School of Computing, SASTRA Deemed to be University** during the final semester of the academic year 2023-24, in the **School of Computing**. The work is original and wherever we have used materials from other sources, we have given due credit and cited them in the text of the report. This report has not formed the basis for the award of any degree, diploma, associate-ship, fellowship or other similar title to any candidate of any University.

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Abbreviations

IOT	Internet of Things
ML	Machine Learning
TN	True Negative
TP	True Positive
FP	False Positive
FN	False Negative

ABSTRACT

A smart agriculture system is proposed to recommend crops based on real-time sensor data and machine learning. Internet of Things (IoT) sensors monitor crucial environmental factors like temperature, soil pH, and nutrient levels nitrogen, phosphorus, potassium alongside moisture content. This data is fed into a Random Forest machine learning model to recommend the most suitable crop for a specific location. The sensor readings are continuously monitored live through a web dashboard and mobile application facilitated by a LoRaWAN gateway. The crop recommendation functionality, powered by the trained Random Forest model, is seamlessly integrated into a user-friendly website built using Flask web framework. This system empowers farmers with data-driven insights to optimize crop selection and potentially improve agricultural yields.

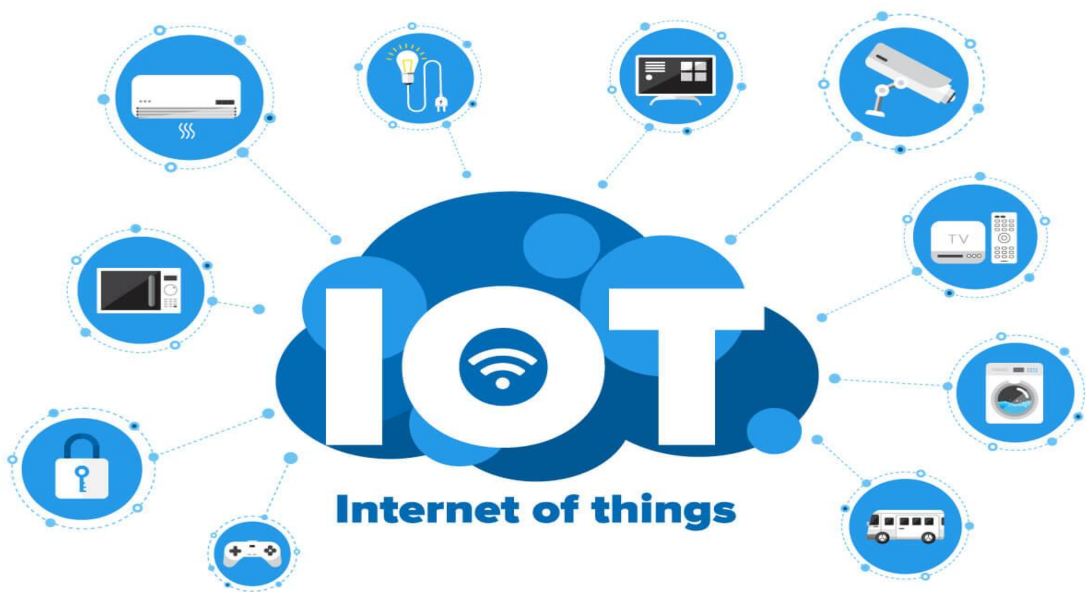
Keywords: LoRaWAN, Soil sensors, Random forest, Agriculture

CHAPTER 1

INTRODUCTION

1.1 Internet of Things

- IoT is a network of physical objects featuring sensors, software, and communication built-in that allow them to gather and share data online. It is known as the Internet of Things (IoT). IoT is used in several industries, including retail, transportation, smart cities, industrial operations, smart homes, and agriculture. Its benefits include task automation, increased productivity, improved safety, and the ability to make data-based decisions. Smart home appliances and thermostats, wearable fitness trackers in the medical field, sensors in industrial equipment for preventive maintenance, city traffic management systems, retail inventory management, precision agriculture methods, and Internet of Things-enabled cars for transportation are a few examples. IoT makes it easier to create networked ecosystems in which gadgets interact and communicate to streamline workflows, boost output, and increase quality of life.



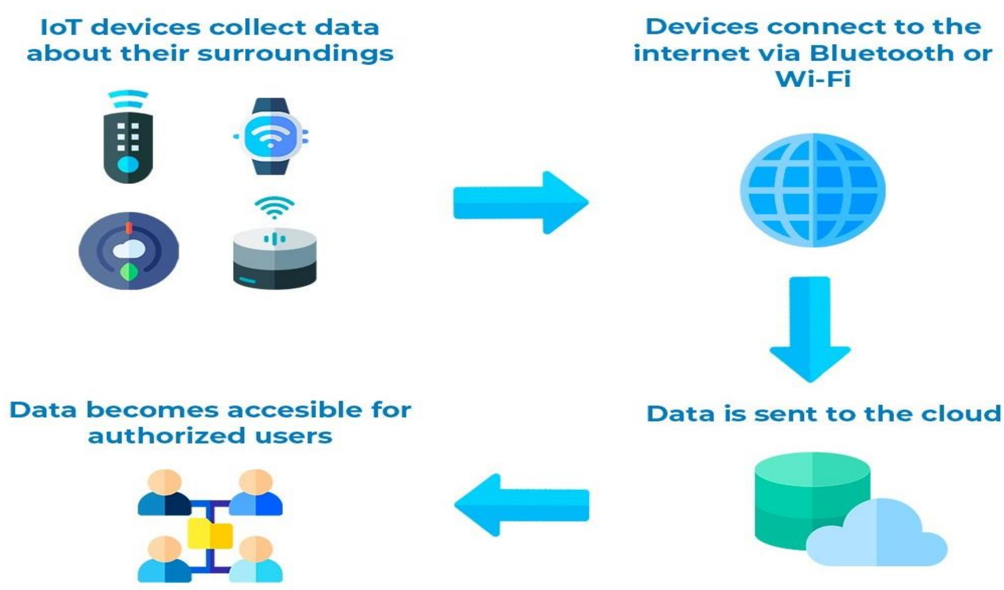
1.1. Internet of Things

- Diverse opportunities for enhancing agricultural methods have been made possible by the emergence of the Internet of Things (IoT) and the quick development of machine learning (ML) technologies, which have applications in everything from healthcare to transportation. An increasing amount of focus has been placed in recent years on using these kinds of innovations to address the obstacles farmers must overcome to maximize agricultural yield and minimize resource waste.
- Among these difficulties, precise crop recommendations and efficient management of soil nutrients are crucial for maintaining efficient and sustainable agricultural operations. Conventional techniques for crop recommendation and soil nutrient analysis have frequently involved lengthy, labour-intensive processes that depend on subjective evaluations. Consequently, farmers are frequently forced to make less-than-ideal choices, which increase their impact on the environment, diminish their yields, and waste resources.

1.2 How IoT Works

- To enable data transmission and interaction over the Internet, the Internet of Things (IoT) connects physical items integrated with sensors, software, and connections. It operates as a large network. Fundamentally, the Internet of Things functions by utilizing a blend of hardware elements, communication standards, and data processing techniques.
- To gather information about their internal or external conditions, such as moisture, temperature, motion, or location, IoT devices usually include sensors. These sensors transform analogue impulses into digital information, which is subsequently handled by the device's microcontrollers or specialty chips. For additional analysis and action, the information that has been processed is frequently wirelessly transferred to a centrally located system.
- Effective and secure data flow between IoT devices is made possible by communication protocols. Wireless LAN, Bluetooth, Zigbee, and mobile networks are examples of common protocols.

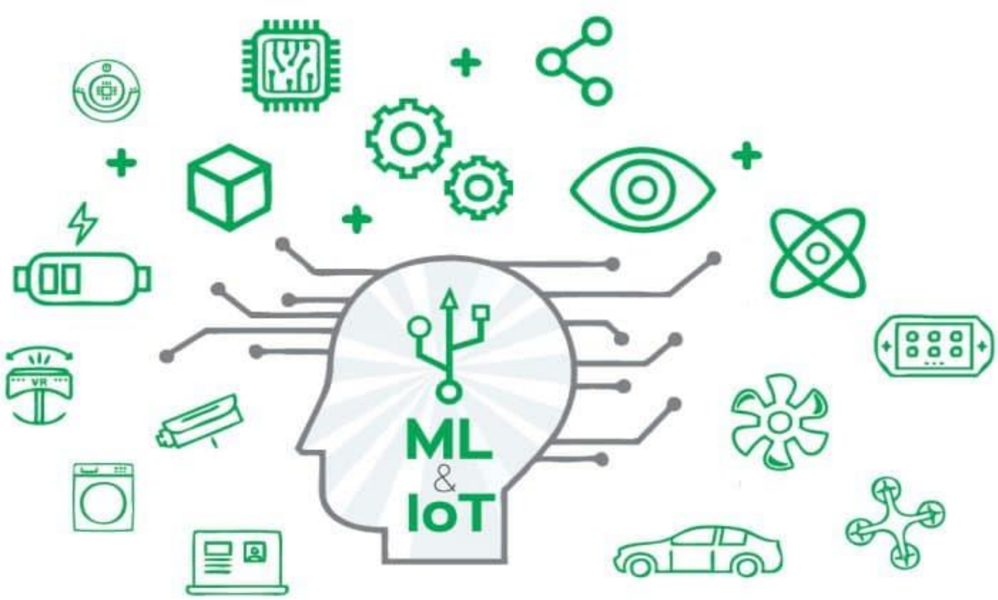
- Depending on parameters like data transfer rates, power consumption, and range, each protocol is appropriate for a particular use case. These protocols are used by Internet of Things devices to communicate with local gateways, cloud servers, edge computing platforms, and other devices. After being gathered and sent, data is processed and analyzed to produce valuable insights. The data streams are received by platforms based on the cloud or edge computing systems, where they can be processed using a variety of analytics methods, including statistical analysis, machine learning algorithms, and rules-based decision-making.
- Through online user interfaces, applications for smartphones, or other control mechanisms, users engage with Internet of Things technologies. Through these interfaces, customers may remotely change settings, keep an eye on the status of their devices, and gain insights from IoT data.
- All things considered, the Internet of Things functions through a complicated interaction of software, hardware, and communication methods, allowing for the development of intelligent, networked ecosystems that boost productivity, increase security and open up new application possibilities in variety of fields.



1.2. How IoT Works

1.3. IoT with Machine Learning

- Intelligent, data-based choices and automation are made possible by the synergy that results from the integration of machine learning (ML) and the Internet of Things. IoT devices work in symbiosis with their environment, gathering large volumes of data through sensors and sending it to edge computing platforms or centralized servers. Information regarding user behaviour, equipment status, ambient factors, and other topics is frequently included in this data.
- After that, this data is analysed using machine learning algorithms, which reveal trends, patterns, and anomalies that would not be visible using more conventional techniques. Algorithms like this can be trained to find possible improvement possibilities, anticipate future events, and detect intricate linkages within the data.
- To anticipate equipment breakdowns or quality concerns before they arise, for example, in a manufacturing context, IoT sensors may constantly monitor production processes, and machine learning algorithms would analyse the data. Reduced downtime, better product quality, and enhanced operational efficiency are all possible outcomes of this proactive strategy.



1.3. IoT & ML

- Furthermore, real-time decision-making is made possible without requiring constant communication to a centralized server by deploying machine learning models directly on Internet of Things devices or at the network's edge. IoT systems become more responsive and adaptable as a result of this edge intelligence, which enables them to respond quickly to changing circumstances.
- Intelligent, data-based choices and automation are made possible by the synergy that results from the integration of machine learning (ML) and the Internet of Things. IoT devices work in symbiosis with their environment, gathering large volumes of data through sensors and sending it to edge computing platforms or centralized servers. Information regarding user behaviour, equipment status, ambient factors, and other topics is frequently included in this data.
- After that, this data is analysed using machine learning algorithms, which reveal trends, patterns, and anomalies that would not be visible using more conventional techniques. Algorithms like this can be trained to find possible improvement possibilities, anticipate future events, and detect intricate linkages within the data.

1.4. IoT in Agriculture

- IoT transforms conventional agricultural methods by leveraging smart technologies to improve sustainability, production, and efficiency. Important environmental indicators like moisture in the soil, temperature, and crop health may be monitored in real-time thanks to the Internet of Things (IoT) and its network of sensors, drones, and various other linked devices. With the use of this information, farmers are better equipped to manage pests, fertilize their fields, and use water and fertilizer efficiently while reducing waste.
- Furthermore, IoT enables precision farming methods by offering useful information about crop growth patterns, which enables prompt interventions to reduce risks and increase yields. IoT-enabled devices also improve livestock monitoring, guaranteeing the health and welfare of animals while enhancing production results. IoT also helps in tracking and managing equipment, which makes predictive maintenance possible and cuts down on downtime.

- IoT weather stations weather forecasting skills help farmers prepare for and reduce risks associated with climate change, while optimizing the supply chain guarantees the quality and safety of products from farm to customer. In general, IoT is essential to contemporary agriculture since it uses data-driven strategies to solve problems and promote sustained, long-term development in the sector.

1.4. IoT In Agriculture

- IoT is typically used to optimize agricultural operations and increase crop yields through the use of sensors that are analytics of data, and machine learning in crop suggestion and prediction. IoT sensors collect data in real-time on temperature, humidity, crop health, and weather. This data is processed and individualized recommendations are sent to farmers. The best dates to plant, the best crop kinds, irrigation schedules, fertilization schedules, and pest control techniques adapted to particular environmental circumstances are a few examples of these suggestions. IoT systems can anticipate the yields of crops and identify potential threats by utilizing historical data and predictive analytics. This empowers farmers to make well-informed decisions and modify their farming operations accordingly. All things considered, IoT makes precision agriculture possible by providing farmers with useful information to improve crop production's sustainability, efficiency, and productivity.

1.5. Motivation

- The dire need to improve agricultural methods by incorporating modern technology and data-driven decision-making is what inspired this proposal. Using web-based platforms, algorithms for machine learning, and IoT sensors, you hope to solve several important issues that farmers and other agricultural stakeholders confront.
- First and foremost, this initiative seeks to maximize cultivation techniques and crop choices by offering tailored suggestions derived from real-time environmental data. Conventional crop selection techniques frequently depend on broad recommendations or anecdotal information, which might not take into consideration the constantly changing weather and soil conditions.
- This project can provide data-driven insights on the most appropriate crops for particular agricultural contexts by utilizing machine learning algorithms like Random Forest in conjunction with Internet of Things (IoT) sensors to continuously monitor critical parameters like humidity, temperature, pH, and nutrient levels.
- Additionally, the deployment of a web-based app and dashboard makes it easier for farming and stakeholders to easily access vital information. This can make sure that sensor data is easily accessible and useful by using technologies like Flask for web development and LoRaWAN for data transfer over wireless networks. Farmers can make more educated decisions in real-time thanks to this accessibility, which enhances crop yields, resource efficiency, and overall farm productivity.
- Furthermore, by encouraging precision agriculture methods, this proposal is in line with more general sustainability objectives. This can reduce resource waste, lessen the impact on the environment, and encourage more environmentally friendly farming methods by recommending crops according to ideal environmental circumstances. This project's main goal is to equip farmers with the knowledge and resources they need to improve agricultural operations' resilience, sustainability, and productivity. This will increase food security and boost the local economy of farming communities.

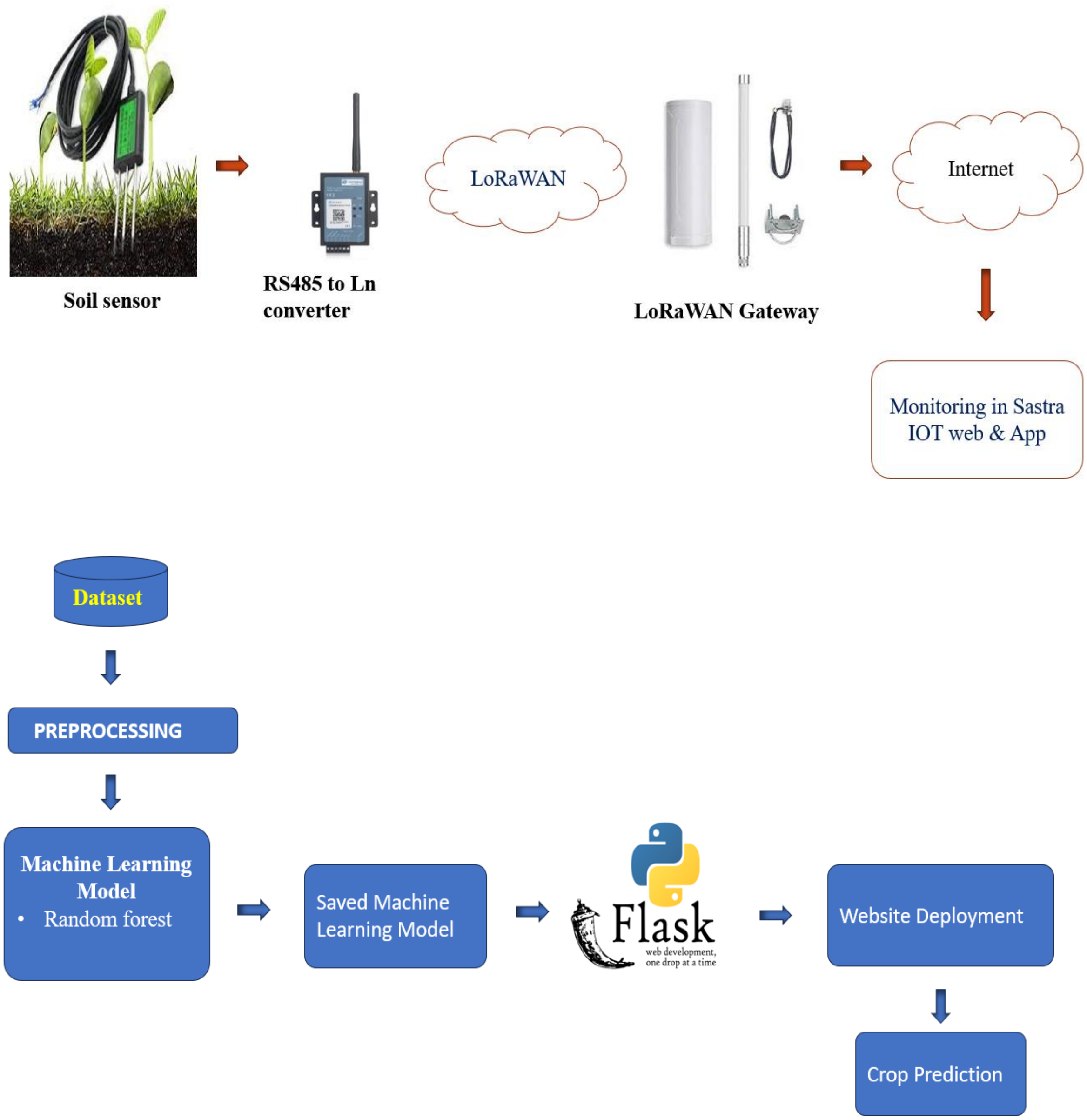
CHAPTER 2
OBJECTIVES

- **Data Collection and Sensor Integration:** Integrate Internet of Things (IoT) sensors to get data in real-time on soil moisture, pH levels, temperature, humidity, nitrogen, phosphorus, and potassium. To ensure seamless data flow, integrate these sensors with your system.
- **Data Pre-processing:** To address values that are missing, outliers, and inconsistencies, clean up and pre-process the gathered sensor data. Make sure the data is appropriately prepared so that machine learning algorithms can use it.
- **Selecting a Machine Learning Model:** Examine different machine learning algorithms, like Random Forest, that are fit for task and choose the best one based on performance metrics like recall, accuracy, and precision.
- **Model Training:** Utilizing previously collected information on crop attributes and accompanying sensor readings, train the chosen machine learning model. Adjust the model's parameters to maximize efficiency.
- **Integrating with LoRaWAN Gateway:** To enable communication between application and IoT sensors, interface the device with a LoRaWAN gateway. Assure dependable and safe data transfer across extended distances.
- **Website Development:** Create a website that offers recommendations for crops based on predictions made by a machine learning model using the Flask framework. Create a user interface that is simple to navigate and engage with.
- **Live Monitoring:** Incorporate live monitoring features to show the most recent readings from sensors from the field continuously on the web application. Give consumers the ability to monitor changes in the surrounding environment in real-time.
- **Crop Recommendation System:** Put into practice the crop system of recommendations using the machine learning model that has been trained. Permit users to enter current sensor data and get suggestions for appropriate crop selection based on those findings.

CHAPTER 3

EXPERIMENTAL WORK

3.1 Proposed system



3.1. Proposed work

3.1.1 Soil Sensor

- A sensor that combines several characteristics, including temperature, humidity, conductivity, NPK, and PH, is called the 7-in-1 Soil Sensor. With the usage of such sensors, users can quickly access a variety of important soil data, improving their understanding of the soil's state and enabling them to make modifications and judgments appropriately.

3.2. 7 in 1 Integrated Soil Sensor

- The true moisture content of different soils can be reliably and easily determined by monitoring the dielectric value of the soil. It can be used for a variety of purposes, including soil moisture monitoring, scientific research, water-saving irrigation, greenhouses, vegetable and flower production, grass pastures, soil fast tests, plant cultivation, sewage treatment, and fine agriculture.
- The three components of the sensor—the power supply, the sensing probe, and the signal output—are totally isolated, safe, dependable, and aesthetically pleasing. The stainless-steel probe further provides steady performance and resistance to corrosion.

3.1.2 RS485 to LN Convertor

- A converter from RS485 to LoRaWAN is the Dragino RS485-LN. It transforms RS485 devices into LoRaWAN wireless networks, which lowers installation and maintenance costs and simplifies IoT setup.
- The user can monitor and control RS485 devices at very long distances with RS485-LN. It minimizes current consumption while offering exceptional interference immunity and

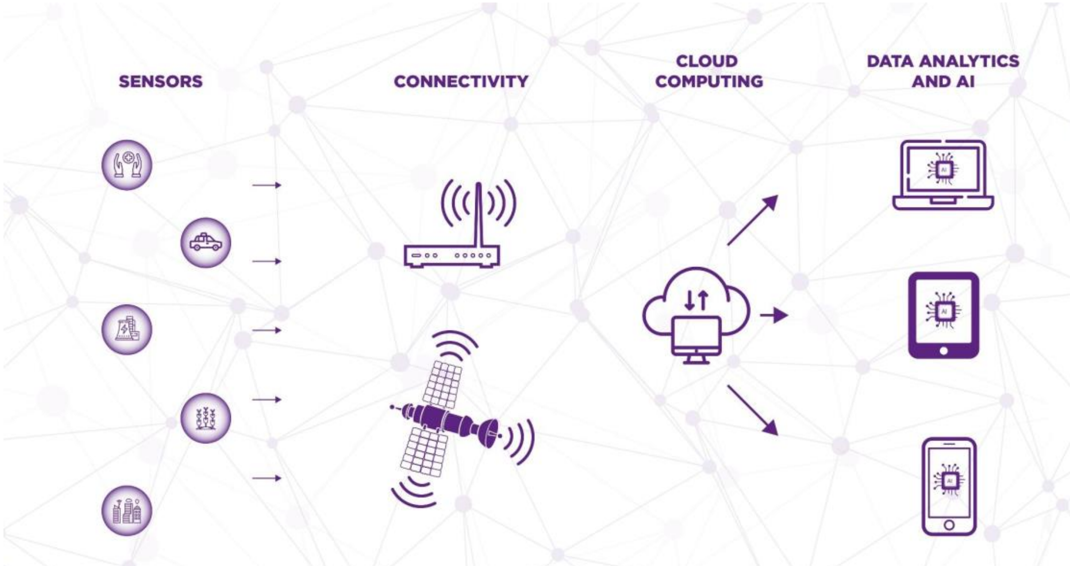
ultra-long distance spread spectrum communication. It is intended for use with professional wireless sensor networks, including building automation, smart metering, smart cities, irrigation systems, and smartphone detection.

3.3. RS485 to LN convertor

- In data uplink, RS485-LN communicates with RS485 devices by sending user-defined commands and receiving their responses. To obtain the final payload for uploading to the LoRaWAN server, RS485-LN is going to process these returns by the user-define rule.
- In LoRaWAN Class C, RS485-LN operates for data downlink. When RS485-LN receives downlink commands from the LoRaWAN server, it forwards those commands to the RS485 devices.

3.1.3 LoRaWAN Gateway

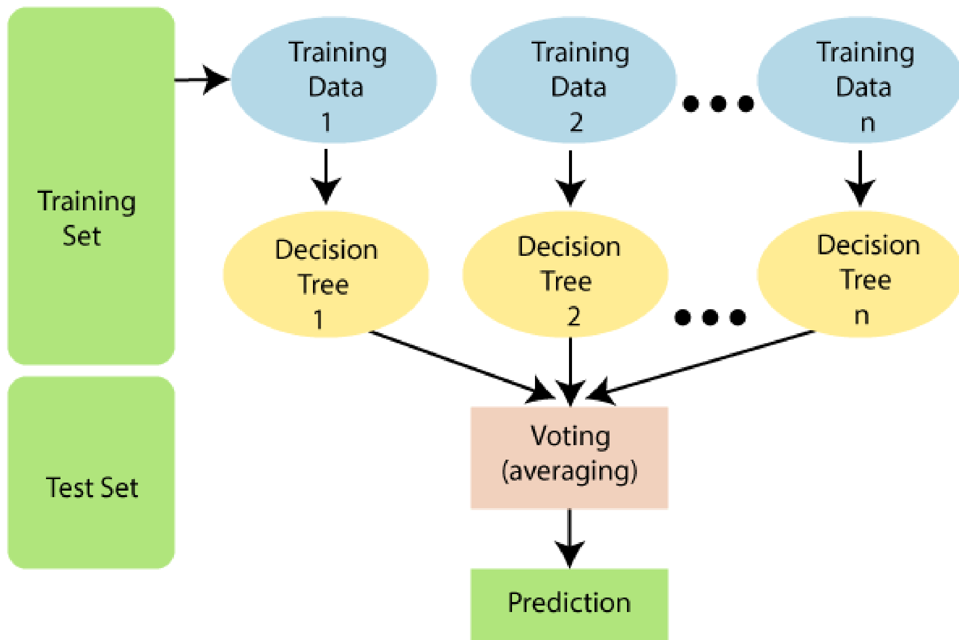
A physical box or enclosure that houses both the software and the hardware needed to connect Internet of Things devices to the Internet through the cloud is commonly referred to as a gateway. IoT devices connect sensed data to other systems by using an interface as a hub from which to drop the data. A gateway and a Wi-Fi router are similar. Because it features a LoRa concentrator, it can accept RF signals from LoRaWAN devices and transform them into a signal that can be used to transport data to the cloud via a server, like Wi-Fi. A gateway serves as a starting point for network connectivity since every device must be able to send data back to it.



3.4. LoRaWAN Gateway

3.2. Random forest Machine learning model:

- In machine learning, Random Forest is a potent ensemble learning method frequently applied to regression and classification problems. It is well known for being reliable, adaptable, and simple. It is a member of a family of tree-based algorithms.
- Fundamentally, Random Forest works by building many decision trees during training. Through a technique called bootstrap aggregating or bagging, each tree is constructed using a random portion of the training data and a random subset of the features. The individual trees' decorrelation is aided by this randomization, which lowers overfitting and enhances generalization performance.



3.5. Random Forest Model

- Every tree in the forest grows to its full depth throughout the training phase, or until a stopping requirement is satisfied. To further increase the diversity among trees, the algorithm, at each node of the tree, chooses the optimum division among a random subset of characteristics instead of considering all features.
- The capacity of Random Forest to provide feature importance estimates is one of its main advantages. Random Forest determines which characteristics are most useful for prediction by evaluating the relative contribution of each feature to the overall reduction in impurity among all trees in the forest.
- Random Forest combines all of the different trees' outputs to create predictions. It uses a majority voting approach for classification tasks, in which every tree "vote" for a class; the class with the highest number of votes is projected to be the class that will occur.
- Large data sets with high complexity can be handled by Random Forest, which is extremely scalable. Furthermore, contrasted to individual decision trees, it is less susceptible to chaotic data and outliers, which makes it a popular option in a variety of industries, including banking, healthcare, agriculture, and more.

3.2.1 Random forest in Crop Recommendations:

Managing Big Dimensionality: Random Forest is a good choice for datasets containing a lot of features, which are common in IoT sensor data since several parameters are being watched over at once. These multidimensional datasets can be analysed it to find trends and connections between crop suitability and sensor parameters.

Robustness to Noise: Environmental influences and inaccurate sensors can occasionally cause IoT sensor data to be noisy. Working with poor sensor data is appropriate for Random Forest since it is resistant to outliers and noise, which won't materially affect the model's performance.

Feature Importance: Knowing which sensor settings have the biggest effects on crop suitability can be accomplished by using Random Forest's insights into feature importance. Farmers and other agricultural specialists can use this information to prioritize particular factors and make well-informed decisions for improved crop management.

Performance in Classification: Random Forest is renowned for its excellent classification accuracy. The goal is to use sensor data to determine which crops will be most suitable. Random Forest is a good fit for this purpose since it may produce precise forecasts by combining the results of several decision trees.

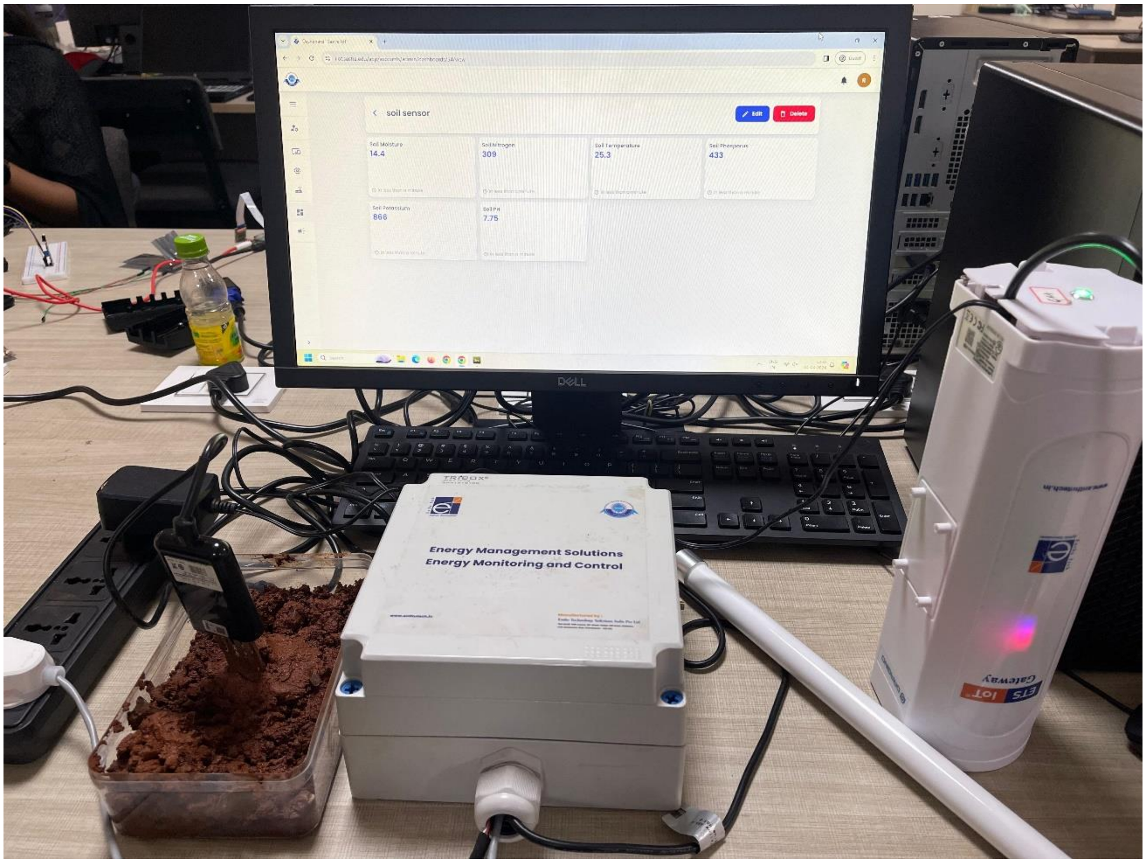
Ensemble Learning: Random Forest lowers the chance of overfitting and boosts generalization performance by combining predictions from several decision trees. This is especially helpful if you want to be sure that all of the crop suggestions are supported by solid and trustworthy forecasts.

Scalability: Random Forest can effectively handle big datasets and is scalable. Given that it entails real-time crop advice and real-time sensor data monitoring, Random Forest's scalability guarantees that its predictions can accommodate growing data sets without sacrificing efficiency.

3.3. Hardware Setup:

IoT Sensors:

- Deploy IoT sensors capable of measuring temperature, pH, nitrogen, phosphorus, potassium, and soil moisture in the agricultural field.
- Ensure the sensors are compatible with RS485 communication protocol.



3.6. Hardware Setup

RS485-LN convertor:

- Use RS485 to LoRaWAN converters to transmit sensor data wirelessly to the LoRaWAN gateway.
- Install converters at each sensor node to facilitate communication with the central gateway.

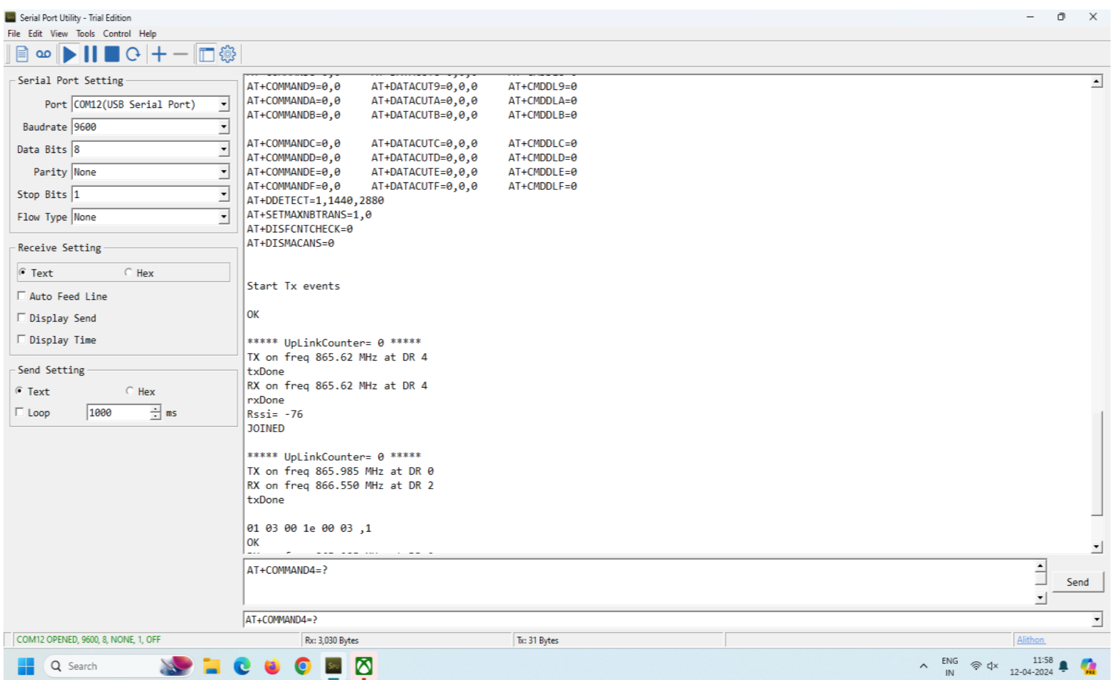
LoRaWAN Gateway:

- Set up a LoRaWAN gateway to receive sensor data transmitted by the RS485 to LoRaWAN converters.
- Position the gateway strategically for optimal coverage and communication range within the agricultural area.

3.4. Software Setup:

IoT platform integration:

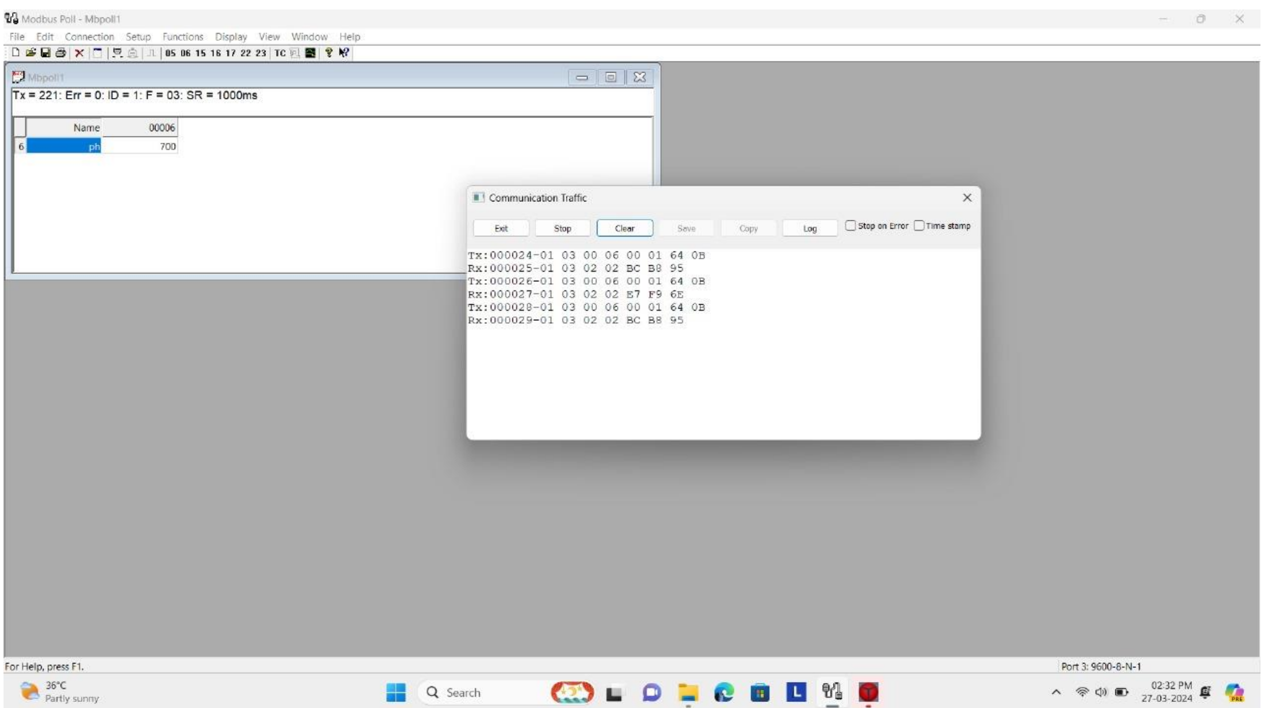
- Configure the IoT sensors, RS485 to LoRaWAN converters, and LoRaWAN gateway to transmit data to the IoT platform.
- Implement device provisioning, data ingestion, and management functionalities within the IoT platform.



3.7. Serial port utility configuration

Modbus poll Configuration:

For RS485 to LoRaWAN converters, Modbus configuration entails setting up communication parameters like baud rate, information bits, stop bits, and parity settings to create dependable serial connections between devices. Every converter is given a distinct Modbus address so that Modbus master devices can address and communicate with them separately. Data exchange function codes are defined for each converter, like Read Holding Registers to retrieve sensor data or Write Single Registers to configure device settings. Modbus registers, like input and holding registers, are used to read data from sensors, device operational information, setup parameters, and control commands. Extensive testing and validation of the Modbus settings guarantee smooth communication and appropriate data exchange.



3.8. Modbus poll configuration

ML model development:

- Collect historical sensor data for various crops and environmental conditions.
- Train a Random Forest classifier using libraries to predict crop suitability based on sensor parameters.
- Validate and fine-tune the model using cross-validation techniques to ensure robust performance.

Website development and Model integration:

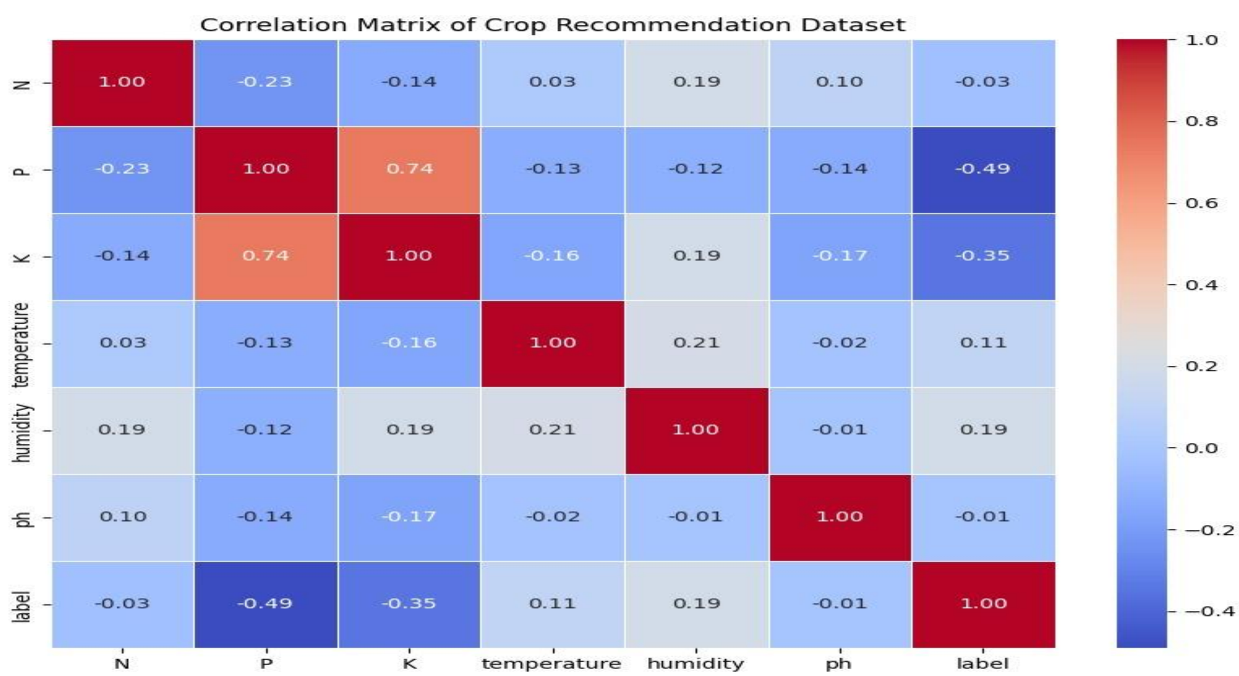
- Incorporate the trained Random Forest model into the Flask-based web application for crop recommendation.
- Deploy the complete system in the target agricultural environment, ensuring proper setup and configuration of hardware and software components.

CHAPTER 4

RESULTS AND DISCUSSIONS

4.1. Data collections and preprocessing:

The crop recommendation system was developed using a wide range of data from 22 different crop types, including apple, banana, black gram, grapes, kidney beans, chickpea, coconut, coffee, cotton, jute, lentil, maize, moth beans, mung beans, pomegranate, pigeon peas, muskmelon, orange, papaya, rice, and watermelon. This extensive dataset ensures that the system is applicable in a variety of farming scenarios by representing a broad range of crops that are often grown in different agricultural locations. Based on the six properties of the agriculture field, nitrogen (N), potassium (K), phosphorus (P), temperature, pH, and soil moisture, We may suggest a crop that would be good for it. Furthermore, we used a unique dataset to understand.



4.1. Correlation matrix of crop recommendation

4.1.1 Accuracy

The percentage of correctly categorized samples relative to all samples in the dataset is referred to as accuracy.

Accuracy = (TP + TN) / (TP + TN + FP + FN)

4.1.2 Precision

By dividing the total amount of positive samples, the model predicts by the number of genuine positive samples, one can estimate precision.

Precision = (TP) / (TP + FP)

4.1.3 Recall

Recall, sometimes referred to as the true positive rate (TPR), is computed by dividing the total amount of crops by the number of correctly advised or projected crops or fertilizers.

Recall = (TP) / (TP + FN)

4.1.4. F1 score

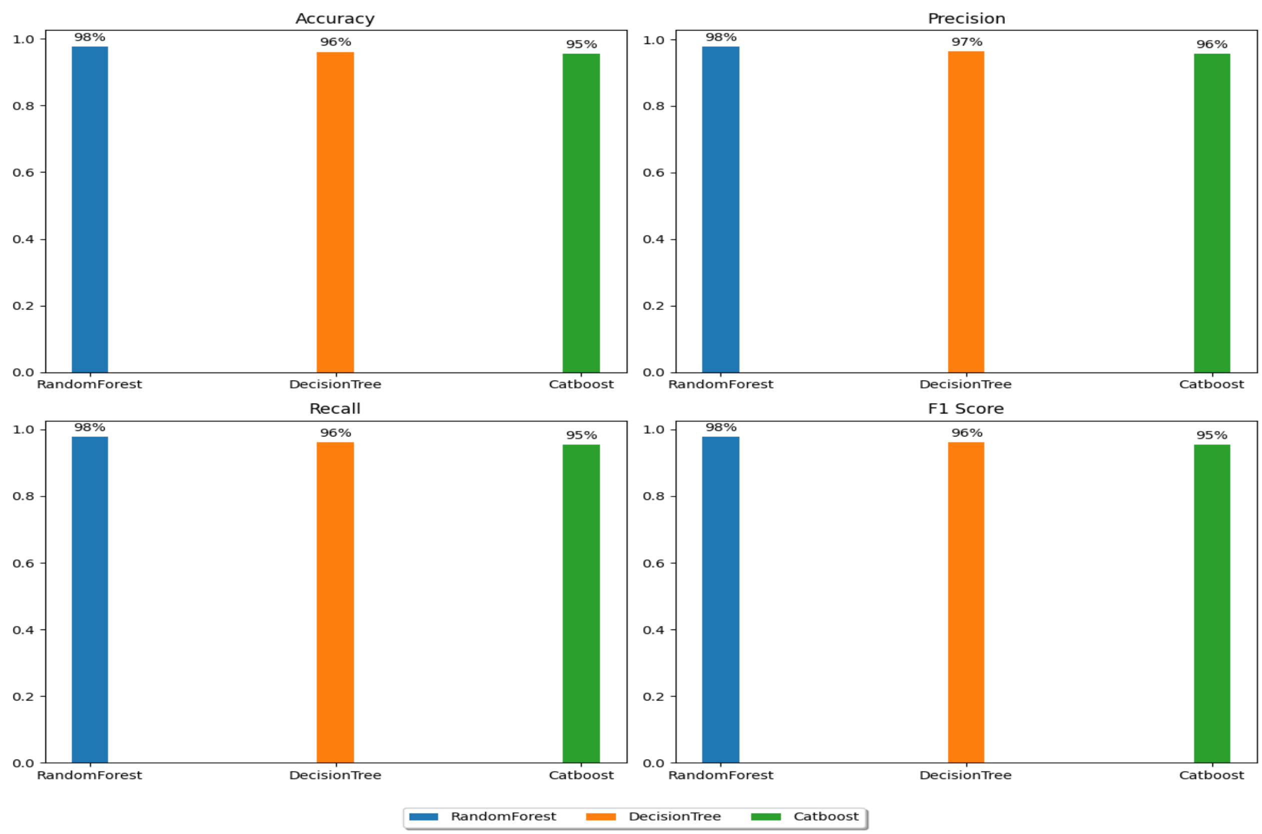
The equation defines it as the harmonic mean (average) of precision and recall.

$F1 - \text{Score} = (2 * \text{Precision} * \text{Recall}) / (\text{Precision} + \text{Recall})$

4.2. Crop Recommendation

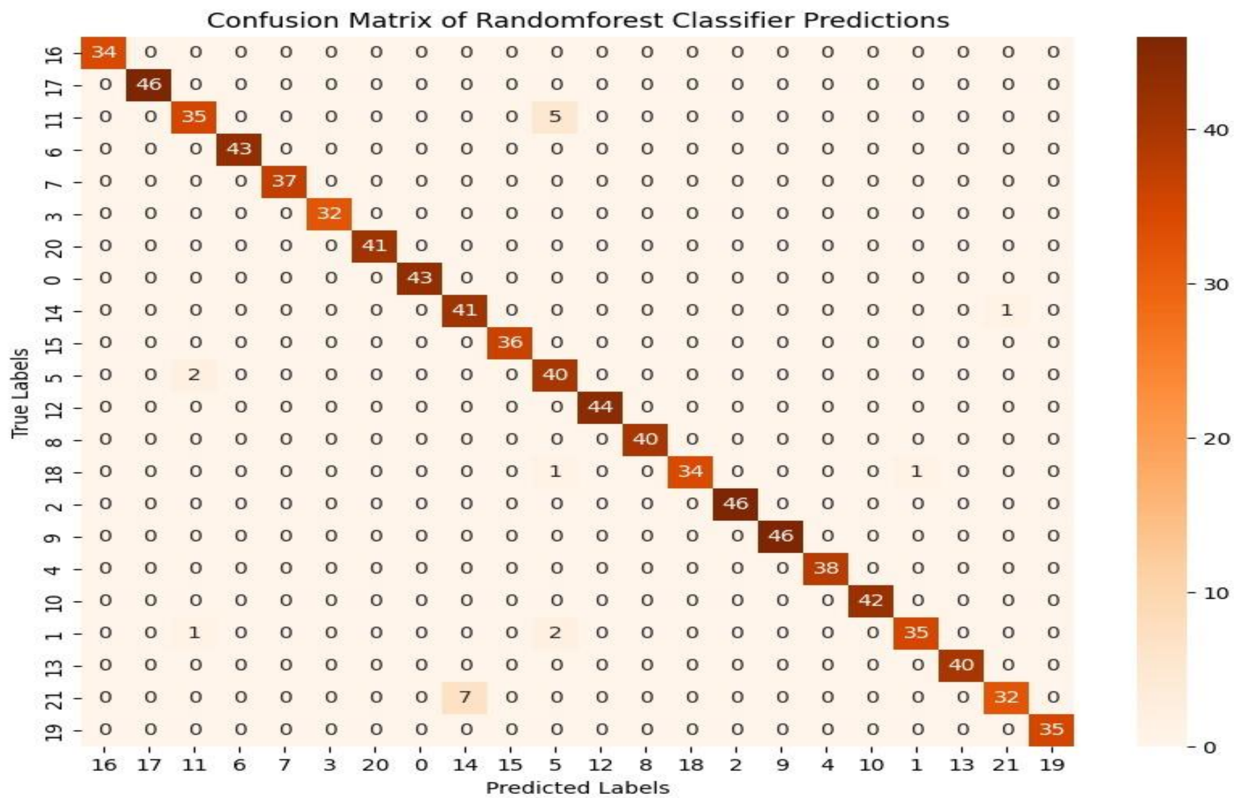
The accuracy metric shows how accurate the system's crop suggestions are generally. Precision is the percentage of crops that the system correctly suggests among all the crops it suggests, whereas recall gauges how well the system can recognize and suggest the appropriate crops. Precision and recall are combined in the F1 score to give a fair evaluation of the classifier's performance.

Fig.4.2 represents the comparison of three distinct model evaluation measures that show how well the applied Random forest performs in terms of F1-measure, accuracy, precision, and recall. With accuracy of 98%, precision of 98%, recall of 98%, and F1-score of 98%, the Random Forest model performed the best. Other models function admirably as well. The Decision Tree achieved 96% accuracy, 97% precision, 96% recall, and 96% F1-score, whereas the Cat boost achieved 95% accuracy, 96% precision, 95% recall, and 95% F1-score.



4.2. Comparison of 3 different model's

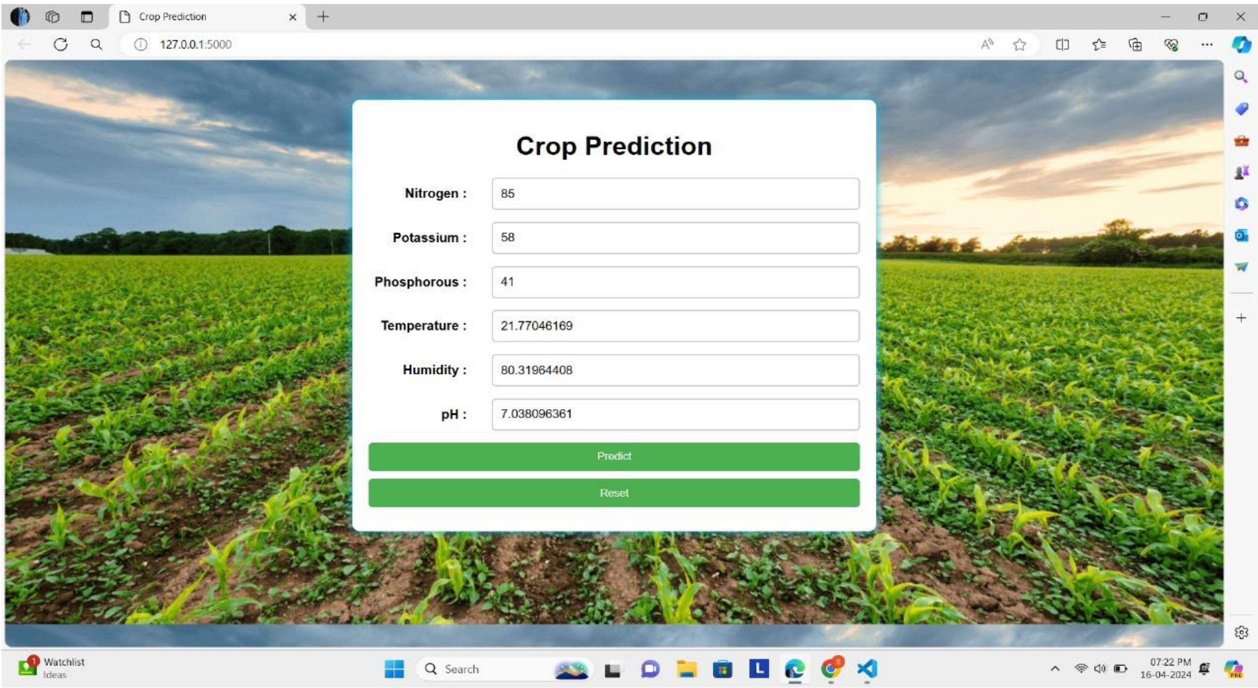
Furthermore, an analysis of the confusion matrix was conducted to obtain an understanding of the particular categories of classification errors that the system displayed in Fig 4.3 made. It is clear from examining the data that the model makes a sizable number of correct both positive and negative predictions in a variety of classes. However, there are times when the model produces inaccurate results. These errors may have the potential to impact crop selection decisions within the agricultural domain.



4.3. Confusion matrix of Random forest

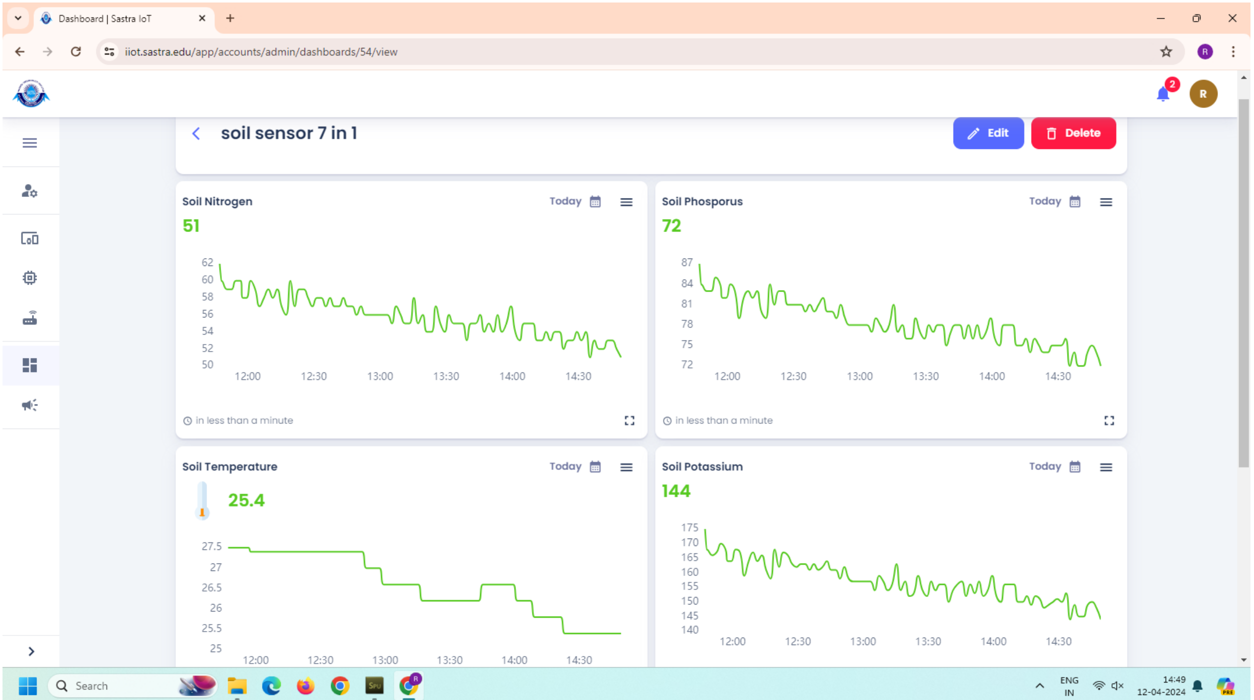
The effectiveness of several machine learning algorithms that have been employed recently in the literature to suggest the best crop to grow on agricultural land. With 98% accuracy and 98% F1 score, it shows that the Random Forest performs admirably when it comes to correctly selecting crops based on the input parameters provided. These results demonstrate the potential of the Random forest in agricultural decision-making procedures and prove the efficacy of the deployed crop recommendation system.

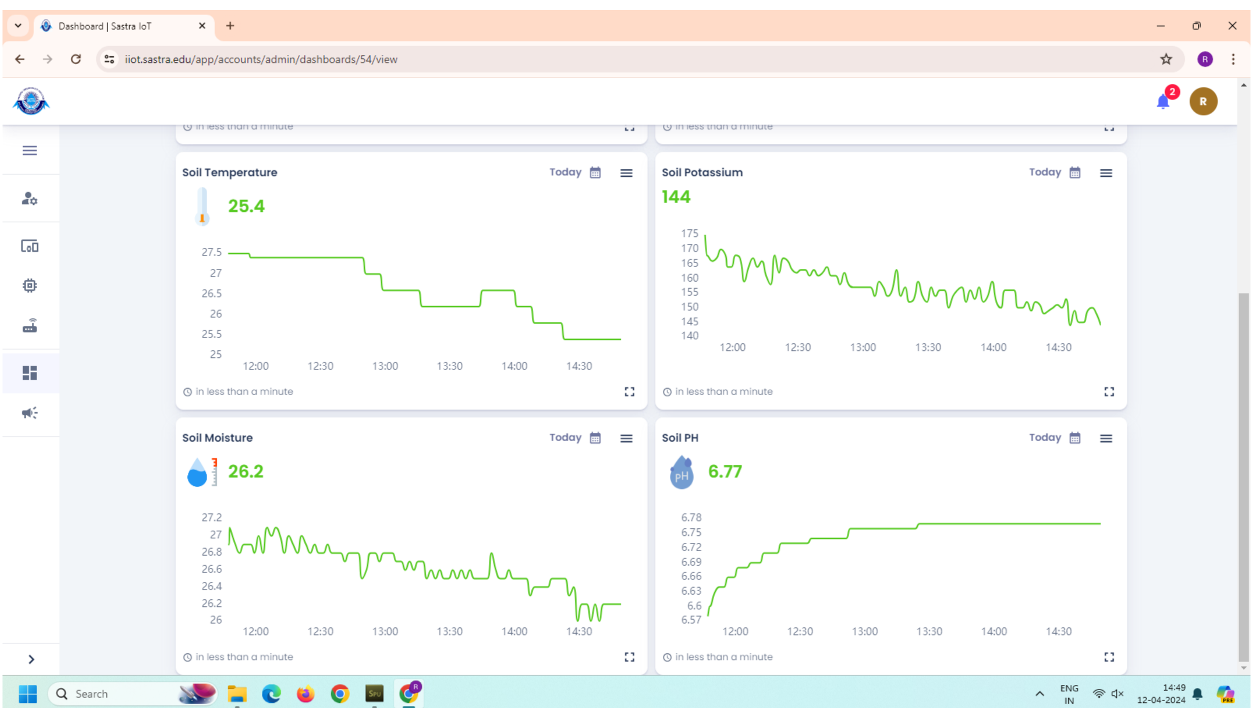
4.3. Snapshots



4.4. Crop prediction website interface

4.5. Predicted result page





4.6. Web dashboard

CHAPTER 5

CONCLUSION

In conclusion, the integration of LoRaWAN technology for real-time sensor monitoring and Flask architecture for predictive crop analysis using random forest marks a significant step forward in precision agriculture. By harnessing the power of IoT sensors and advanced machine learning algorithms, this system offers farmers a holistic solution for optimizing crop selection and resource management.Through the live monitoring capabilities facilitated by LoRaWAN, farmers gain immediate access to crucial environmental data, enabling proactive decision-making in response to changing conditions. The predictive capabilities of the random forest model, embedded within the Flask-based web application, provide farmers with actionable insights into which crops are most suitable for their specific environmental parameters.

Future works:

- **Integration of satellite imaging and weather data:** Future research should concentrate on integrating satellite imagery and weather data into the system to deliver more thorough and accurate recommendations. The device can provide more precise insights regarding crop health, growth trends, and environmental variables by utilizing these new sources of information.
- **Improving scalability and usability:** To meet the demands of farmers in various locations with diverse technology infrastructures, the device's scalability and usability should be enhanced. This includes designing user-friendly interfaces that are understandable to farmers with differing degrees of technology literacy and making sure the gadget can adapt to various communication networks and power sources.
- **Enhanced Crop Recommendations:** Add more variables to the crop recommendation system, such as soil type, elevation, sunlight exposure, and past crop performance information, to further improve it. This could enhance the recommendations' precision and focus, benefiting farmers in the process.

CHAPTER 6

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CHAPTER 7

SOURCE CODE

RANDOM FOREST MACHINE LEARNING MODEL:

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report
from sklearn.preprocessing import LabelEncoder
data=pd.read_csv('C:\\Users\\saran\\Desktop\\new\\croprecommendation\\Crop_recommendation
.csv')
data
label_encoder = LabelEncoder()
data['label'] = label_encoder.fit_transform(data['label'])
X = data.drop('label', axis=1)
y = data['label']
import joblib
joblib.dump(label_encoder, "C:\\Users\\saran\\Desktop\\labelcrop.pkl")
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.4, random_state=44)
rf_classifier = RandomForestClassifier(n_estimators=100, random_state=44)
rf_classifier.fit(X_train, y_train)
y_pred = rf_classifier.predict(X_test)
corr = data.corr()
import seaborn as sns
import matplotlib.pyplot as plt
plt.figure(figsize=(10, 8))
plt.figure(figsize=(10, 8))
sns.heatmap(corr, annot=True, cmap='coolwarm', fmt=".2f", linewidths=0.5)
plt.title('Correlation Matrix of Crop Recommendation Dataset')
plt.show()
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score,
roc_auc_score, classification_report
accuracy_random = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy_random:.2f}')
precision_random= precision_score(y_test, y_pred, average='weighted')
print(f'Precision: {precision_random:.2f}')
recall_random = recall_score(y_test, y_pred, average='weighted')
print(f'Recall: {recall_random:.2f}')
f1_random = f1_score(y_test, y_pred, average='weighted')
print(f'F1 Score: {f1_random:.2f}')
```

```
report = classification_report(y_test, y_pred)
print('Classification Report:\n', report)
from sklearn.metrics import confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt
import pandas as np
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(10, 8))0
sns.heatmap(cm, annot=True, fmt="d", cmap='Oranges', square=True,
            xticklabels=np.unique(y_test), yticklabels=np.unique(y_test))
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.title('Confusion Matrix of Randomforest Classifier Predictions')
plt.show()
```

UPLINK FORMATTER CODE:

```
function Decoder(bytes, port) {
  var decode = {};
  decode.soilmoisture = ((bytes[1] << 8 | bytes[2]) / 10);
  decode.soiltemp = ((bytes[3] << 8 | bytes[4]) / 10);
  decode.ph = ((bytes[5] << 8 | bytes[6]) / 100);
  decode.ec = ((bytes[7] << 8 | bytes[8]));
  decode.soilnitrogen = ((bytes[9] << 8 | bytes[10]));
  decode.soilphosporus = ((bytes[11] << 8 | bytes[12]));
  decode.soilpotassium = ((bytes[13] << 8 | bytes[14]));
  return decode;
}
```

FLASK CODE:

```
from flask import Flask, render_template, request, send_from_directory
import joblib
import os
app=Flask(_name_,template_folder=r"C:\Users\saran\Desktop\new\second\template")
model_filename = r"C:\Users\saran\Desktop\new\second\random_forest_model1.pkl"
label_encoder_crop_filename = r"C:\Users\saran\Desktop\new\second\labelcrop.pkl"
loaded_model = joblib.load(model_filename)
label_encoder_crop = joblib.load(label_encoder_crop_filename)
csv_directory = os.path.join(os.getcwd(), 'second', 'static')
@app.route('/static/<path:filename>')
def download_file(filename):
   return send_from_directory(csv_directory, filename)
@app.route('/')
```

```
def home():
    return render_template('index.html')
@app.route('/predict', methods=['POST'])
def predict_crop():
    N = int(request.form['N'])
    P = int(request.form['P'])
    K = int(request.form['K'])
    temperature = float(request.form['temperature'])
    humidity = float(request.form['humidity'])
    ph = float(request.form['ph'])
    predicted_class_index = loaded_model.predict([[N, P, K, temperature, humidity, ph]])
    predicted_crop = label_encoder_crop.inverse_transform(predicted_class_index)
    result_message = f"Predicted crop Name: {predicted_crop[0]}"
    return render_template('result.html', result=result_message)
if _name_ == '_main_':
    app.run(host='0.0.0.0')
```