A

Major Project Report

On

# CROP RECOMMENDATION SYSTEM USING MACHINE LEARNING FOR ENHANCED YIELD PRODUCTION

*Submitted to CMREC, HYDERABAD*

*In Partial Fulfillment of the requirements for the Award of Degree of*

**BACHELOR OF TECHNOLOGY**
**IN**
**COMPUTER SCIENCE AND ENGINEERING (DATA SCIENCE)**

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**2024 - 2025**

# CMR ENGINEERING COLLEGE
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## CERTIFICATE

This is to certify that the major project entitled "**CROP RECOMMENDATION SYSTEM USING MACHINE LEARNING FOR ENHANCED YIELD PRODUCTION**" is a bonafide work carried out by

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in partial fulfillment of the requirement for the award of the degree of **BACHELOR OF TECHNOLOGY** in **COMPUTER SCIENCE AND ENGINEERING (DATA SCIENCE)** from CMR Engineering College, affiliated to JNTU, Hyderabad, under our guidance and supervision. The results presented in this major project have been verified and are found to be satisfactory. The results embodied in this major project have not been submitted to any other university for the award of any other degree or diploma.

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# DECLARATION

This is to certify that the work reported in the major project entitled "**CROP RECOMMENDATION SYSTEM USING MACHINE LEARNING FOR ENHANCED YIELD PRODUCTION"** is a record of bonafide work done by us in the Department of Computer Science and Engineering – Data Science, CMR Engineering College, JNTU Hyderabad. The reports are based on the major project work done entirely by us and not copied from any other source. We submit our major project for further development by any interested students who share similar interests to improve the major project in the future. The results embodied in this major project report have not been submitted to any other University or Institute for the award of any degree or diploma to the best of our knowledge and belief.


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# ABSTRACT

Agriculture plays a critical role in ensuring that there is enough food to feed our ever-growing global population. With the challenges posed by climate change and its uncertainties, it has become increasingly important to adopt sustainable practices in agriculture. One crucial aspect of this is optimizing how we use our land, water resources, and fertilizers while also increasing crop yields. Traditionally, farmers relied on their own experience, local knowledge, and trial- and-error methods to decide which crops to grow in their specific regions and soil types. Unfortunately, this subjective approach often led to uncertainties, reduced productivity, and economic losses. Inappropriate crop choices were also common, resulting in suboptimal yields and wasted resources. To address these issues, we are working on developing a Machine Learning-based Crop Recommendation System. This system holds immense promise in transforming agriculture by offering farmers data-driven insights to make informed decisions about their crop selection and management practices. The system uses a wealth of data, including historical crop performance, soil characteristics, and climate patterns, to empower farmers with intelligent recommendations. By analysing this vast array of information, the system guides farmers in making data-driven choices, reducing the risk of crop failure, and increasing profitability. Furthermore, it promotes the adoption of sustainable farming methods, thereby minimizing environmental impacts and preserving precious natural resources for future generations. Implementing this recommendation system can have far-reaching benefits. It can lead to economic advantages for farmers, ensuring food security, and encouraging the adoption of sustainable agricultural practices to protect our environment. By providing valuable insights, the system empowers farmers to make informed decisions that ultimately lead to improved crop yields, reduced resource wastage, and increased profitability. With the potential to revolutionize crop selection, this novel approach paves the way toward a more sustainable and food-secure future for all of us.

## LISTOF FIGURES


| S.NO | FIG.NO | DESCRIPTION | PAGE NO. |
|---|---|---|---|
| 1 | 4.1 | ProposedSystem Model | 15 |
| 2 | 4.2 | Random Forest Algorithm | 17 |
| 3 | 4.3 | RF Classifier Analysis | 19 |
| 4 | 4.4 | Boosting RF Classifier | 19 |
| 5 | 5.1 | Class Diagram | 21 |
| 6 | 5.2 | Sequence Diagram | 22 |
| 7 | 5.3 | Activity Diagram | 23 |
| 8 | 5.4 | Deployment Diagram | 24 |
| 9 | 5.5 | Use case Diagram | 25 |
| 10 | 5.6 | Component Diagram | 26 |
| 11 | 10.1 | SampleDataset Used | 50 |
| 12 | 10.2 | Correlation Between Numerical Columnof Data Frame | 50 |
| 13 | 10.3 | Distributionof Categoriesin label Columnof Data Frame | 51 |
| 14 | 10.4 | Features Column | 51 |
| 15 | 10.5 | Target Column | 52 |
| 16 | 10.6 | ClassificationReport of LR | 52 |
| 17 | 10.7 | ClassificationReport of RFC | 53 |
| 18 | 10.8 | Confusion Matrix of RFC | 54 |
| 19 | 10.9 | Accuracy Comparison Graph for ML Models | 54 |
| 20 | 10.10 | Prediction Results for RFC | 55 |

# LISTOF TABLES


| S.NO | TABLENO. | DESCRIPTION | PAGENO. |
|---|---|---|---|
| 1 | 1 | Overall Performance Comparisonof ML models | 55 |

# CONTENTS


| TOPIC | PAGE NO. |
|---|---|
| **ABSTRACT** | **I** |
| **LISTOF FIGURES** | **II** |
| **LISTOF TABLES** | **III** |
| **1.INTRODUCTION** | **1** |
| 1.1 Overview | 1 |
| 1.2 Motivation | 2 |
| 1.3 Problem Statement | 3 |
| 1.4 Applications | 4 |
| **2.LITERATURE SURVEY** | **6** |
| **3. EXISTING TECHNOLOGY** | **9** |
| 3.1 Logistic Regression | 9 |
| 3.2 Likelihood Ratio Test | 12 |
| **4.PROPOSED METHODOLOGY** | **13** |
| 4.1 Overview | 13 |
| 4.2 Data Preprocessing | 16 |
| 4.3 Data Splitting | 16 |
| 4.4 Random Forest Algorithm | 17 |
| 4.5 Advantages of Proposed Methodology | 20 |
| **5. UML DIAGRAMS** | **21** |
| 5.1 Class Diagram | 21 |
| 5.2 Sequence Diagram | 22 |
| 5.3 Activity Diagram | 23 |
| 5.4 Deployment Diagram | 24 |
| 5.5 Use Case Diagram | 25 |
| 5.6 Component Diagram | 26 |
| **6. SOFTWARE ENVIRONMENT** | **27** |
| 6.1 What is Python? | 27 |
| 6.2 Modules used in Project | 31 |
| 6.3 Installation of Python | 35 |

**7. SYSTEMREQUIREMENTS** **39**
7.1 Software Requirements 39
7.2 Hardware Requirements 39

**8. FUNCTION REQUIREMENTS** **40**

**9.SOURCE CODE** **45**

**10. RESULTS ANDDISCUSSION** **49**

**11. CONCLUSION ANDFUTURESCOPE** **56**

**12.REFERENCES** **59**

# CHAPTER– 1

# INTRODUCTION

## 1.1 Overview

Agriculture is the cornerstone of global food security and sustenance, making it an industry of paramount importance. However, the efficiency and productivity of agricultural practices are often constrained by factors such as soil quality, climate conditions, and crop choice. In this context, the development of a "Machine Learning-Based Crop Recommendation System for Enhanced Yield Production" emerges as a pivotal endeavour that holds the potential to revolutionize the way crops are cultivated and harvested. At its core, this research aims to bridge the gap between traditional agricultural practices and cutting-edge technology [1]. It leverages the power of machine learning, a subset of artificial intelligence, to optimize crop selection decisions made by farmers. This innovation is of immense significance given the growing challenges faced by the agriculture sector, including the need to feed an expanding global population, mitigate climate change impacts, and reduce resource wastage.

The primary motivation behind this research lies in addressing several pressing issues. Firstly, the unpredictable effects of climate change have significantly altered weather patterns and precipitation levels, making it increasingly difficult for farmers to make informed crop choices based on historical data alone [2]. Additionally, soil quality can vary dramatically even within a single farm, necessitating a more nuanced approach to crop selection. Traditional methods, which often rely on anecdotal knowledge and experience, are no longer sufficient to ensure optimal yield and resource efficiency. Machine learning offers a novel and data-driven solution to this dilemma. By analyzing a myriad of factors, including historical weather data, soil composition, and past crop performance, machine learning algorithms can provide personalized and accurate crop recommendations. This not only optimizes yield but also promotes sustainable farming practices by reducing the unnecessary use of water, pesticides, and fertilizers [3].

Furthermore, the research recognizes the global imperative of sustainable agriculture. In a world grappling with issues of food security and environmental conservation, the ability to recommend crops that are not only high-yielding but also environmentally responsible is crucial. Machine learning models can factor in environmental impact considerations, helping farmers make choices that align with conservation and resource preservation goals [4].

In this introductory overview, we will delve into the key components and objectives of this research. Firstly, we will explore the challenges faced by farmers and the limitations of conventional crop selection methods. Next, we will introduce the concept of machine learning-based crop recommendation systems, highlighting their potential to revolutionize agriculture. We will also discuss the role of data sources, including historical data, satellite imagery, and soil assessments, in training these models. Additionally, ethical considerations, such as data privacy and equitable access to technology, will be addressed [5]. The research on a "Machine Learning-Based Crop Recommendation System for Enhanced Yield Production" seeks to empower farmers with data-driven decision-making tools that can optimize crop selection, enhance yield, and promote sustainable agricultural practices. By harnessing the capabilities of machine learning, this research endeavours to usher in a new era of precision agriculture that is not only more productive but also environmentally responsible and equitable [6].

## 1.2 Motivation

The research motivation for a "Machine Learning-Based Crop Recommendation System for Enhanced Yield Production" is deeply rooted in the critical challenges facing agriculture today. As the global population continues to grow, the pressure on the agricultural sector to produce more food intensifies. This demand necessitates not only increased agricultural productivity but also a more efficient approach to crop selection [7]. Traditional farming methods often rely on historical practices and lack the adaptability required to optimize crop choices in the face of evolving climate conditions and soil quality. This research is motivated by the urgent need to bridge this gap between traditional farming practices and cutting-edge technology, as it holds the potential to significantlyenhance global food security.

Climate change further compounds the challenges in agriculture, introducing unpredictability into weather patterns and exacerbating the uncertainty surrounding crop selection. Farmers require adaptive strategies to cope with these changing conditions, and machine learning-based crop recommendation systems provide a promising solution by analyzing historical weather data and climate projections to offer data-driven guidance. Additionally, resource inefficiency in agriculture, including the excessive use of water, fertilizers, and pesticides, poses significant environmental and economic concerns [8]. By recommending crops that align with local conditions and resource availability, this research aims to optimize resource utilization, reduce waste, and promote sustainable farming practices, thereby mitigating environmental degradation [9].

Sustainability is a global imperative, and agriculture plays a pivotal role in this pursuit. The research is motivated by the goal of fostering sustainable farming practices that address environmental impact issues such as soil erosion, water pollution, and habitat destruction. Machine learning-based recommendations not only prioritize high-yield crops but also consider their environmental footprint, contributing to responsible land management and conservation efforts. Moreover, this research is driven by the desire to empower smallholder farmers, who often lack access to advanced agricultural technology and expertise. By providing accessible and user-friendly crop recommendation systems, it seeks to empower these farmers, improve their livelihoods, and reduce poverty [10].

In an era of big data, agriculture stands to benefit significantly from data-driven decision-making. The research motivation lies in harnessing vast datasets, including historical agricultural data, satellite imagery, and soil information, to enhance crop recommendations. This approach promises to usher in a more efficient and informed era of precision agriculture, where every decision is underpinned by comprehensive data analysis. Finally, ethical considerations underpin the research, as ensuring that machine learning-based crop recommendations are developed and deployed ethically is paramount. This involves addressing issues related to data privacy, fairness, and ensuring equitable access to technology to ensure that the benefits of these systems are accessible to all, irrespective of their resources or geographical location. In summary, the research on a "Machine Learning-Based Crop Recommendation System for Enhanced Yield Production" is motivated by the urgent need to address food security, adapt to climate change, promote resource efficiency, and foster sustainability in agriculture, while also empowering farmers and adhering to ethical principles in technology deployment.

## 1.3 Problem Statement

Modern agriculture faces multifaceted challenges that impede its ability to meet the growing global demand for food, ensure sustainability, and adapt to changing environmental conditions. One of the pivotal challenges is the suboptimal selection of crops for cultivation. Traditional crop selection methods often rely on historical practices, anecdotal knowledge, and limited consideration of factors such as soil quality, climate variability, and resource availability. These methods are becoming increasingly inadequate in the face of climate change-induced weather unpredictability, variations in soil health even within small geographic areas, and the imperative of resource efficiency. The consequence of suboptimal crop selection is diminished yield potential, resource wastage, increased vulnerability to climate-related risks, and an unsustainable environmental footprint.

The core problem, therefore, centers on the need for an innovative and data-driven approach to crop selection that leverages the capabilities of machine learning. This approach should harness diverse datasets, including historical agricultural data, weather records, soil composition information, and crop performance metrics, to provide farmers with precise, real-time, and personalized crop recommendations. However, this challenge extends beyond the technical domain; it also encompasses ethical considerations such as data privacy, fairness, and equitable access to technology. It is imperative to ensure that the benefits of machine learning-based crop recommendation systems are accessible to a wide range of farmers, irrespective of their geographical location, economic resources, or technological proficiency. Furthermore, the ethical framework must safeguard data privacy rights and prevent the unintentional reinforcement of biases within the technology. In essence, the problem is twofold: to develop a robust machine learning-based crop recommendation system that optimizes yield production while addressing sustainability and resource efficiency, and to ensure that its deployment adheres to ethical principles, promoting inclusivity and responsible technology adoption within the agricultural sector.

## 1.4Applications

Precision Agriculture: The primary application is in precision agriculture, where machine learning algorithms can provide farmers with tailored crop recommendations based on real-time data, including soil conditions, weather forecasts, and historical performance. This promotes resource-efficient and sustainable farming practices.

Increased Crop Yields: Farmers can use the recommendations to optimize their crop selection, leading to increased yields and improved agricultural productivity. This application is particularlycrucial for feeding the growing global population.

Resource Efficiency: Machine learning-based recommendations can help reduce resource wastage, such as water, fertilizers, and pesticides. This contributes to environmental sustainabilityby minimizing the ecological footprint of agriculture.

Climate Resilience: Farmers can adapt to changing climate conditions by receiving timely advice on crop selection that is better suited to evolving weather patterns and climate variability.

Diversification of Crops: The system can encourage crop diversification, promoting biodiversity and reducing the risk of crop failures due to pests, diseases, or adverse weather events.

Farm Management: Farm managers and agricultural consultants can use these recommendations to make informed decisions about crop rotations, land-use planning, and farm management strategies.

Agricultural Extension Services: Agricultural extension officers can incorporate machine learning-based recommendations into their services to provide local farmers with valuable insights and guidance.

Educational Tools: Educational institutions and agricultural training programs can use these systems as teaching tools to educate future generations of farmers about data-driven agricultural practices.

Research and Development: Researchers in agriculture can use the data generated by these systems to study crop performance, evaluate the impact of different agricultural practices, and develop new insights into crop management.

Environmental Conservation: By recommending crops that are well-suited to local conditions, including soil types and precipitation levels, these systems can contribute to sustainable land use and conservation efforts.

Policy Development: Governments and policymakers can use the data collected from these systems to inform agricultural policies, subsidies, and incentives aimed at promoting sustainable farming practices.

Global Food Security: Machine learning-based crop recommendations can play a crucial role in improving food security by enhancing agricultural efficiency and productivity, especially in regions facing food shortages and agricultural challenges.

Smallholder Agriculture: These systems can empower smallholder farmers by providing them with access to advanced agricultural technology and knowledge, helping them increase their income and improve their livelihoods.

Community and Cooperative Farming: Agricultural cooperatives and community farming initiatives can use these recommendations to make collective decisions about crop selection, leading to improved overall outcomes for the community.

# CHAPTER– 2

# LITERATURE SURVEY

Prakash, et al. [11] proposed a Machine learning-based crop suggestion system. an intelligent model in crop suggestion predicts the right kind of crop that suits the soil and other environmental factors by using a machine learning algorithm. Temperature, wetness of the soil, environment dampness and pH are the essential information for crop suggestion in the agriculture field. Many existing works of IoT in the field of agriculture are related to yield predictionand few related to crop suggestion use fewer parametersand learning algorithms.

Indira, et al. [12] proposed A Machine Learning based New Recommendation System to the Farmer. An algorithm called MobileNet uses an image of a leaf to identify the disease present in a plant. The XGBoost model predicts a suitable crop based on the local soil nutrients and rainfall. Random Forest [RF] model was used to propose fertilizer and develop ideas for improving soil fertility depending on nutrients present in the soil. When compared to other approaches, the proposed model delivers a high level of accuracy.

Jeevaganesh, et al. [13] proposed a machine learning algorithm: AdaBoost to predict the yield of crops based on the parameters like state, district, area, seasons, rainfall, temperature, and area. To enhance the yield, this research study also suggests a fertilizer based on soil conditions like NPK values, soil type, soil PH, humidity, and moisture. Fertilizer recommendation is primarily done by using the Random Forest [RF] algorithm.

Wen, et al. [14] proposed Optimizing machine learning-based site-specific nitrogen application recommendations for canola production. This work employed four machine learning models, namely, support vector machine (SVM), gradient boosting (GB), random forest (RF), and ridge regression (RR) to predict the site-specific EONR values of canola crops, based on a 22-site-year field study across eastern Canada.

SSL, et al. [15] proposed An Intelligent Crop Recommendation System using Deep Learning. The purpose of this work is to examine the approaches employed in extracting the water bodies utilizing the mode of satellite remote sensing. The goal of the proposed work is to collect the data of temperature and humidity and utilize the algorithm of clustering with the method of k-Nearest Neighbor to find out the patterns which are all hidden in them with a help of huge amount of dataset.

Chowdhary, et al. [16] proposed An Ensemble Model to Predict Crops using Machine Learning Algorithms. The authors tried to form an ensemble model using various machine-learning algorithms for better rice production. Crop production prediction utilizing AI Strategies aims to deliver improved outcomes, but the ensemble model provides better predictive results compared to the individual algorithm. we tried to use a combination of symmetric machine-learning algorithms to form an ensemble model for better prediction.

Suresh, et al. [17] proposed a solution based on IoT and deep learning for improving paddy output. The system collects data through sensors and transfers it to the cloud in order to diagnose plant stress caused by soil fertility, environmental imbalance, and crop diseases (AWS EC2 Server). The proposed system is implemented in three stages. The stages of production are divided into three categories: the start stage (planting to panicle initiation), the middle stage (panicle initiation to flowering), and the end stage (flowering to maturity).

Raviraja, et al. [18] proposed machine learning-based mobile applications for autonomous fertilizer suggestion. In this work, the smartphone app will be used to construct an autonomous fertilizer suggestion system for farmers. The dataset was gathered from the website Kaggle. The encoding technique is used to make the data entries numeric. Three Machine Learning (ML) models K-Nearest Neighbour (KNN), Random Forest (RF), and Decision Tree (DT) are employed to predict fertilizer based on environmental and soil characteristics.

Mamatha, et al. [19] proposed Machine learning-based crop growth management in a greenhouse environment using hydroponics farming techniques. In this proposed system, in hydroponics for germination organic coconut coir medium is used rather than rock wool, because rock wool is not bio-degradable and is composed of volcanic materials. In the proposed research of hydroponics, the system is automated on a wide scale covering the entire green house with different crops produced in different climatic conditions.

Oikonomidis, et al. [20] proposed Hybrid deep learning-based models for crop yield prediction. The authors had developed deep learning-based models to evaluate how the underlying algorithms perform with respect to different performance criteria. The algorithms evaluated in our study are the XGBoost machine learning (ML) algorithm, Convolutional Neural Networks (CNN)-Deep Neural Networks (DNN), CNN-XGBoost, CNN-Recurrent Neural Networks (RNN), and CNN-Long Short-Term Memory (LSTM).

Apat, et al. [21] proposed proposed an IoT-HELE-based smart farming prediction and intelligent agriculture analytics model and a decision support system that effectively predicts crop production by utilizing cutting-edge machine learning and deep learning techniques. In this model, ensemble voting results in a more efficient, sustainable, and profitable agriculture enterprise. The multi-source dataset from the National Research Council (CNR), an ISTAT, and an IoT sensor will be analyzed.

Kumar, et al. [22] proposed Crop recommendations using machine learning algorithms. The proposed system in which ML is used for crop recommendation is based on previously recorded measurements of soil parameters. This technique lessens the possibility of soil degradation and aids in crop health maintenance. Temperature, pH, and N, P, K, humidity are analyzed using machine learning algorithms such as random forest, Naive Bayes, KNN, decision tree, Logistic regression on which suggestions are made for growing a suitable crop.

Sandhya, et al. [23] proposed Crop Recommendation System Using Ensembling Technique. This work focuses on figuring out the best crop to cultivate in order to get optimum yield based on the site-specific parameters. Our proposed model takes the data of soil characteristics, environmental characteristics of a farm and the appropriate crop recommendations are given to the farmer based on the parameter values. Crop Recommendation is done through an Ensemble model using KNN, Random Forest, Gaussian Naïve Bayes, Logistic regression, SVM as base learners.

Muhammed, et al. [24] proposed a user-friendly crop recommendation system called UACR. The users only need to insert their farm location and the system can automatically obtain other necessary information (e.g., rain level, soil type) based on the requested location and recommends the best crop(s) for growing in the location. To support and implement the proposed system, an architecture based on Artificial Intelligence of Things (AIoT) technology, as one of the main enablers for smart agriculture, is also proposed.

Venkatesan, et al. [25] proposed a machine learning-based prediction model for peak energy use by analyzing energy-related data collected from various environmental and growth devices in a smart paprika farm of the Jeonnam Agricultural Research and Extension Service in South Korea between 2019 and 2021. The proposed model may contribute to the development of various applications for environmental energy usage in a smart farm, such as a notification service for energy usage peak time or an energy usage control for each device.

# CHAPTER - 3

# EXISITING TECHNOLOGY

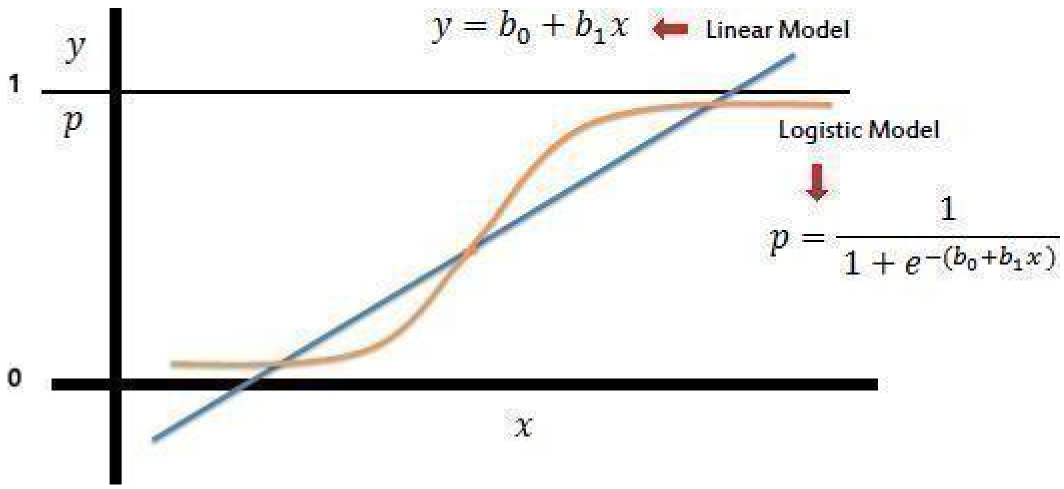
## 3.1 Logistic Regression

Logistic regression predicts the probability of an outcome that can only have two values (i.e. a dichotomy). The prediction is based on the use of one or several predictors (numerical and categorical). A linear regression is not appropriate for predicting the value of a binary variable for two reasons:

- A linear regression will predict values outside the acceptable range (e.g. predicting probabilities

- outsidetherange 0 to 1)
- Since the dichotomous experiments can only have one of two possible values for each experiment,the residuals will not be normally distributed about the predicted line.

On the other hand, a logistic regression produces a logistic curve, which is limited to values between 0 and 1. Logistic regression is similar to a linear regression, but the curve is constructed using the natural logarithm of the "odds" of the target variable, rather than the probability. Moreover, the predictors do not have to be normally distributed or have equal variance in each group.



In the logistic regression the constant (b0) moves the curve left and right and the slope (b1) defines the steepness of the curve. By simple transformation, the logistic regression equation can be written in terms of an odds ratio.

$$\frac{p}{1-p} = \exp\left(b_0 + b_1 x\right)$$

Finally, taking the natural log of both sides, we can write the equation in terms of log-odds (logit) which is a linear function of the predictors. The coefficient ($b_1$) is the amount the logit (log-odds) changes with a one unit change in $x$.

$$ln\left(\frac{p}{1-p}\right) = b_0 + b_1 x$$

As mentioned before, logistic regression can handle any number of numerical and/or categorical variables.

$$p = \frac{1}{1 + e^{-(b_0 + b_1 x_1 + b_2 x_2 + \cdots + b_p x_p)}}$$

There are several analogies between linear regression and logistic regression. Just as ordinary least square regression is the method used to estimate coefficients for the best fit line in linear regression, logistic regression uses maximum likelihood estimation (MLE) to obtain the model coefficients that relate predictors to the target. After this initial function is estimated, the process is repeated until LL (Log Likelihood) does not change significantly.

$$\boldsymbol{\beta}^1 = \boldsymbol{\beta}^0 + [\boldsymbol{X}^T \boldsymbol{W} \boldsymbol{X}]^{-1}.\boldsymbol{X}^T(\boldsymbol{y} - \boldsymbol{\mu})$$

*$\boldsymbol{\beta}$ is a vector of the logistic regression coefficients.*

*$\boldsymbol{W}$ is a square matrix of order N with elements $n_i \pi_i (1 - \pi_i)$ on the diagonal and zeros everywhere else.*

*$\boldsymbol{\mu}$ is a vector of length N with elements $\mu_i = n_i \pi_i$.*

A pseudo R2 value is also available to indicate the adequacy of the regression model.Likelihoodr atio testis a test of the significance of the difference betweent he likelihood ratio for the baseline model minus the likelihood ratio for a reduced model. This difference is called "model chi-square“. Wald test is used to test the statistical significance of each coefficient($b$) in the model (i.e., predictors contribution).

Pseudo R2

There are several measures intended to mimic the R2 analysis to evaluate the goodness-of-fit of logistic models, but they cannot be interpreted as one would interpret an R2 and different pseudo R2 can arrive at very different values. Here we discuss three pseudo R2measures.

| **PseudoR2** | **Equation** | **Description** |
|---|---|---|
| **Efron's** | $R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - p_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$ | ***'p'*** **is the logistic model predicted probability. The model residualsare squared, summed, and divided by the total variability in the dependent variable.** |
| **McFadden's** | $R^2 = 1 - \frac{LL_{full\ model}}{LL_{intercept}}$ | **The ratio of the log-likelihoodssuggests the level of improvement over the intercept model offered by the full model.** |
| **Count** | $R^2 = \frac{\#\ Corrects}{Total\ Count}$ | **The number of records correctly predicted, given a cutoff point of .5 divided by the total count of cases.** |

### 3.2 Likelihood Ratio Test

The likelihood ratio test provides the means for comparing the likelihood of the data under one model (e.g., full model) against the likelihood of the data under another, more restricted model (e.g., intercept model).

$$LL = \sum_{i=1}^{n} y_i ln(p_i) + (1 - y_i) ln(1 - p_i)$$

where'$p$'is the logisticmodelpredicted probability.The nextstep is to calculate the difference between these two log-likelihoods.

$$2(LL_1 - LL_2)$$

The differencebetween two likelihoodsis multipliedby a factor of 2 in order to be assessed for statisticalsignificanceusing standard significance levels (Chi2 test). The degreesof freedomfor the test will equal the difference in the numberof parametersbeing estimatedunder the models (e.g., full and intercept).

**Disadvantages of Logistic Regression:**

- Limited to binary classification problems.
- Assumes a linear relationship between predictors and the log-odds of the outcome.
- Sensitive outliers in the data.
- Not suitablefor capturing complex, non-linear relationships.
- Requires complete data without missingvalues.
- Assumes observations are independent of each other.
- Proneto overfitting,especiallywith many predictors.

# CHAPTER - 4

# PROPOSED METHODOLOGY

## 4.1 Overview

The system leverages data analysis, visualization, machine learning models, and evaluation techniques to provide farmers with informed crop recommendations. It ensures that data is appropriately prepared and understood, models are trained and evaluated, and predictions are madeusingthe learned patternsfrom historicaldata. The goal is to optimizecrop yield based on environmental conditions and nutrient levels. Figure 4.1 shows the proposed system model. The detailed operation illustratedas follows:

**step1:Data Import and Preparation**:

- Data is a critical component in machine learning-based systems. In this context, data includes information about different crops, such as their nutrient requirements (N, P, K), temperature preferences, humidity tolerance, pH levels, and rainfall needs.
- Data is typically stored in structured formats like CSV files. The system uses libraries like Pandas and NumPy for data manipulation. Pandas allows for efficient data storage, retrieval, and manipulation, while NumPy provides numerical operations for data analysis.

**step2: Exploratory Data Analysis (EDA)**:

- EDA is the process of summarizing and visualizing key characteristics of a dataset. It helps understand the data's distribution, potential outliers, and relationships among variables.
- The **df.tail()** function displays the last few rows of the dataset, providing a glimpse of the data.
- **df.size** and **df.shape** reveal the overall size and dimensions of the dataset, respectively.
- **df.columns** lists the column names, which are essential for identifying features and the target variable.

**step3: Data Visualization**:

- Data visualization techniques, like count plots and heatmaps, are employed to gain insights from data.
- Count plots help visualize the distribution of different crops in the dataset, which is vital for understanding class imbalances and model biases.
- A heatmap is used to visualize the correlation between features. High positive or negative correlations between features can impact the model's performance. For instance, if temperature and humidity are highly correlated, the model may struggle to distinguish their individual effects on crop growth.

**step4: Feature Selection and Target**:

- Features are the variables used as input to the machine learning model. In this case, features include factors like nutrient levels (N, P, K), environmental conditions (temperature,humidity, pH), and rainfall.
- The target variable ('label') represents the outcome or prediction the model is designed to make, which is the type of crop to recommend.

**step5: Model Training and Evaluation**:

- Model training involves using historical data (features) and their corresponding outcomes(target)to teach the machine learning model how to make predictions.

- Twomodelsareused here:LogisticRegressionand RandomForest.
- Evaluation metrics like accuracy scores, precision, recall, F1-score, and classification reports are used to assess model performance. Accuracy measures how often the model makes correct predictions, while precision and recall provide insightsinto the model's abilityto avoid false positivesand negatives.

**step6: Confusion Matrix**:

- A confusion matrix is a table used to describe the performance of a classification model. It shows the number of true positives, true negatives, false positives, and false negatives.
- True positives are instances where the model correctly predicts a positive class, while true negatives are instances where the model correctly predicts a negative class. False positives and false negatives represent prediction errors.

**step7:Accuracy Comparison Plot**:

- The bar plot comparing the accuracies of different models helps users understand which model is more effective in making crop recommendations. Accuracy is a widely used metric for comparing models, but it may not tell the whole story, especially if class imbalances exist.

**step8: Making Predictions**:

- Once the model is trained and evaluated, it can be used to make predictions for new, unseen data points. Users can input environmental conditions, and the model will predict the most suitable crop based on the patterns it learned during training.

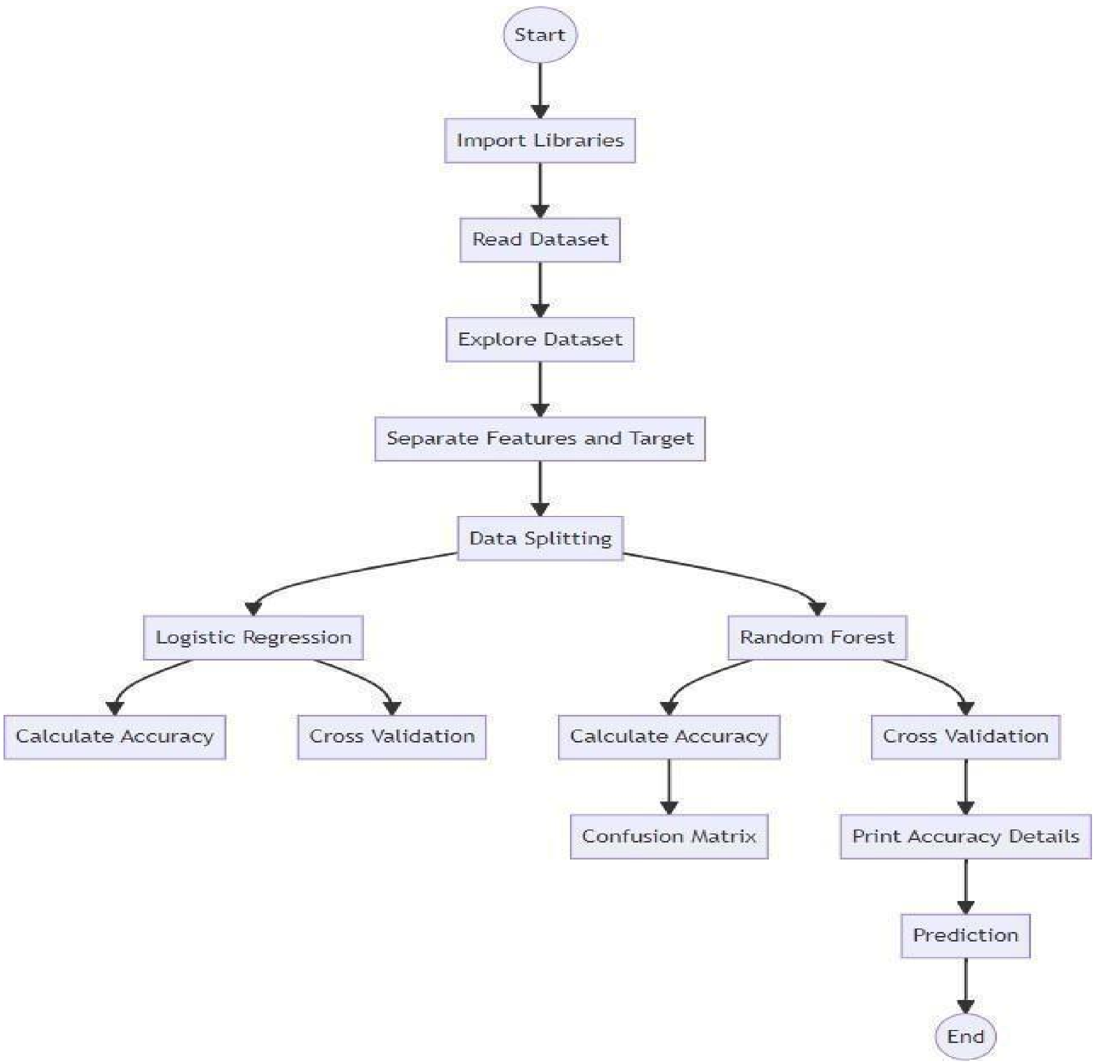



Figure4.1.ProposedSystem model.

## 4.2 Data Preprocessing

Data pre-processing is a process of preparing the raw data and making it suitable for a machine learning model. It is the first and crucial step while creating a machine learning model. When creating a machine learning project, it is not always a case that we come across the clean and formatted data. And while doing any operation with data, it is mandatory to clean it and put in a formatted way. So, for this, we use data pre-processing task. A real-world data generally contains noises, missing values, and maybe in an unusable format which cannot be directly used for machine learning models. Data pre-processing is required tasks for cleaning the data and making it suitable for a machine learning model which also increases the accuracy and efficiency of a machine learning model.

- Getting the dataset
- Importing libraries
- Importing datasets
- Finding Missing Data
- Encoding Categorical Data
- Splitting dataset into training and testset

## 4.3 Data set Splitting

In machine learning data pre-processing, we divide our dataset into a training set and test set. This is one of the crucial steps of data pre-processing as by doing this, we can enhance the performance of our machine learning model. Suppose if we have given training to our machine learning model by a dataset and we test it by a completely different dataset. Then, it will create difficulties for our model to understand the correlations between the models. If we train our model very well and its training accuracy is also very high, but we provide a new dataset to it, then it will decrease the performance. So we always try to make a machine learning model which performs well with the training set and also with the test dataset. Here, we can define these datasets as:

**Training Set**: A subset of dataset to train the machine learning model, and we already know the output.

**Test set**: A subset of dataset to test the machine learning model, and by using the test set, model predicts the output.

## 4.4 Random Forest Algorithm

Random Forest is a popular machine learning algorithm that belongs to the supervised learning technique. It can be used for both Classification and Regression problems in ML. It is based on the concept of ensemble learning, which is a process of combining multiple classifiers to solve a complex problem and to improve the performance of the model. As the name suggests, "Random Forest is a classifier that contains a number of decision trees on various subsets of the given dataset and takes the average to improve the predictive accuracy of that dataset." Instead of relying on one decision tree, the random forest takes the prediction from each tree and based on the majority votes of predictions, and it predicts the final output. The greater number of trees in the forest leadsto higher accuracy and preventsthe problem of overfitting.

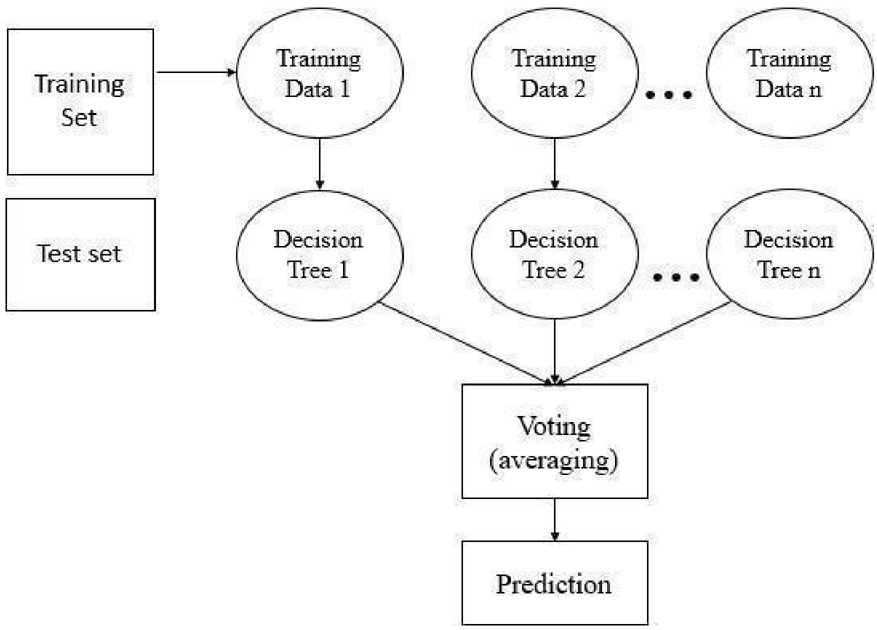



Fig.4.2: RandomForest algorithm.

### 4.4.1 Random Forest algorithm

Step1: In Random Forestn numberof random records are taken from the datasethaving k number of records.

Step2: Individual decision trees are constructed for each

sample. Step3: Each decision tree will generatean output.

Step4: Final output is consideredbasedon Majority Voting or Averagingfor Classification and regression respectively.

## 2. Important Features of Random Forest

- **Diversity** -Not all attributes/variables/features are considered while making an individualtree, each tree is different.

.

## 3. Assumptions for Random Forest

Since the random forest combines multiple trees to predict the class of the dataset, it is possible that some decision trees may predict the correct output, while others may not. But together, all the trees predict the correct output. Therefore, below are two assumptions for a better Random Forest classifier:

\There should be some actual values in the feature variable of the dataset so that the classifiercan predict accurate resultsrather than a guessed result.

The predictions from each tree must have very low correlations.

## 4.Types of Ensembles

Before understanding the working of the random forest, we must look into the ensemble technique. Ensemble simply means combining multiple models. Thus, a collection of models is used to make predictions rather than an individual model. Ensemble uses two types of methods:

**Bagging**– It creates a different training subset from sample training data with replacement & the final output is based on majority voting. For example, Random Forest. Bagging, also known as Bootstrap Aggregation is the ensemble technique used by random forest. Bagging chooses a random sample from the data set. Hence each model is generated from the samples (Bootstrap Samples) provided by the Original Data with replacement known as row sampling. This step of row sampling with replacement is called bootstrap. Now each model is trained independently which generates results. The final output is based on majority voting after combining the results of all models. This step which involves combining all the results and generating output based on majority voting is known as aggregation.

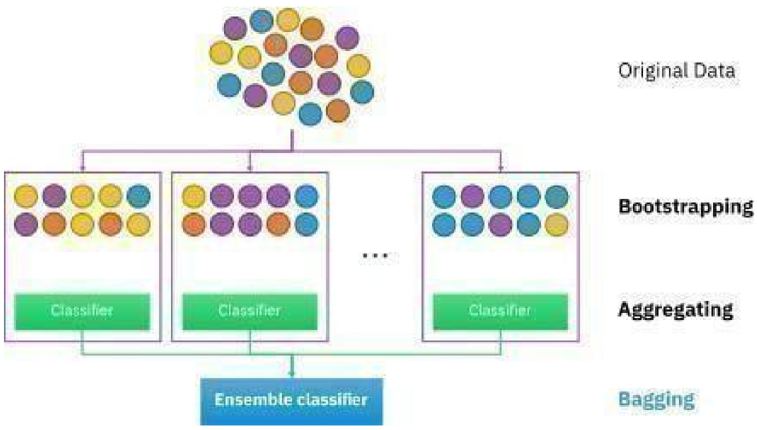



Fig.4.3: RF Classifier analysis.

**Boosting**–It combines weak learners into strong learners by creating sequential models such that the final model has the highest accuracy. For example, ADABOOST, XG BOOST.

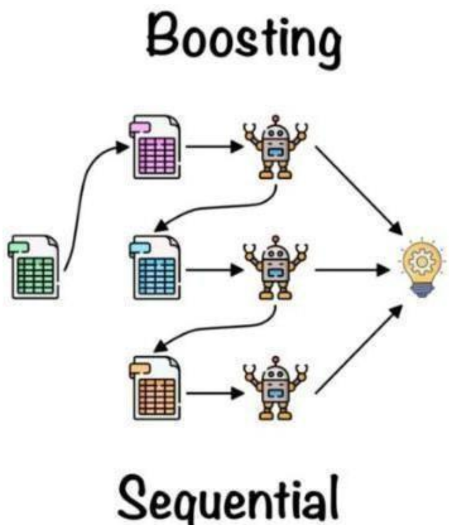



Fig.4.4: Boosting RF Classifier.

### 4.5 Advantages of proposed system

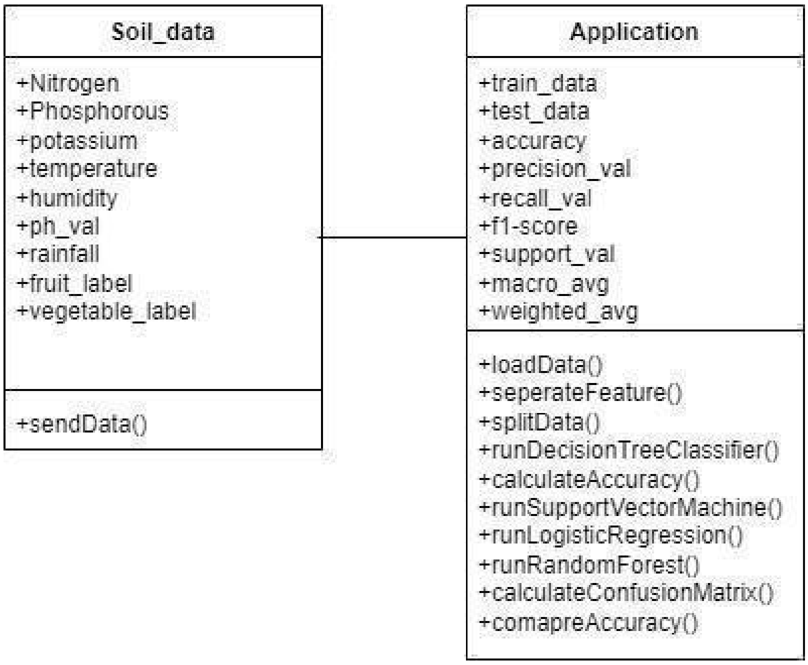
It can be usedin classificationand regression problems.

- It solves the problem of overfitting as output is based on majority voting o averaging.
- Each decision tree created is independent of the other thusit shows the property of parallelization.
- It is highly stable as the average answers given by a large numberof trees are taken.
- It maintains diversity as all the attributes are not considered while making each decision tree though it is not true in all cases.
- It is immune tot he curseof dimensionality.Since each tree does not consider the attributes,feature space is reduced.

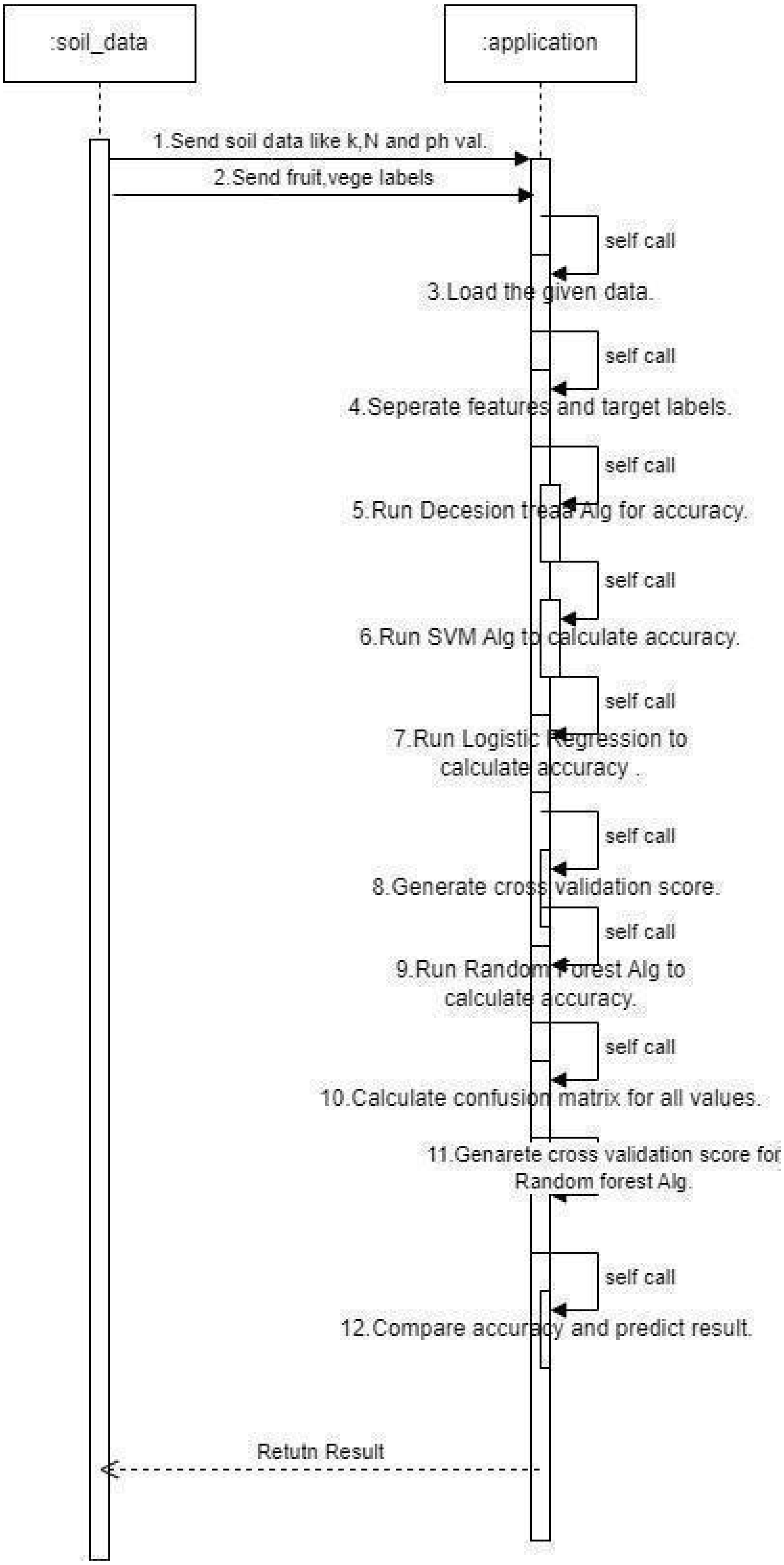
# CHAPTER- 5

# UML DIAGRAMS

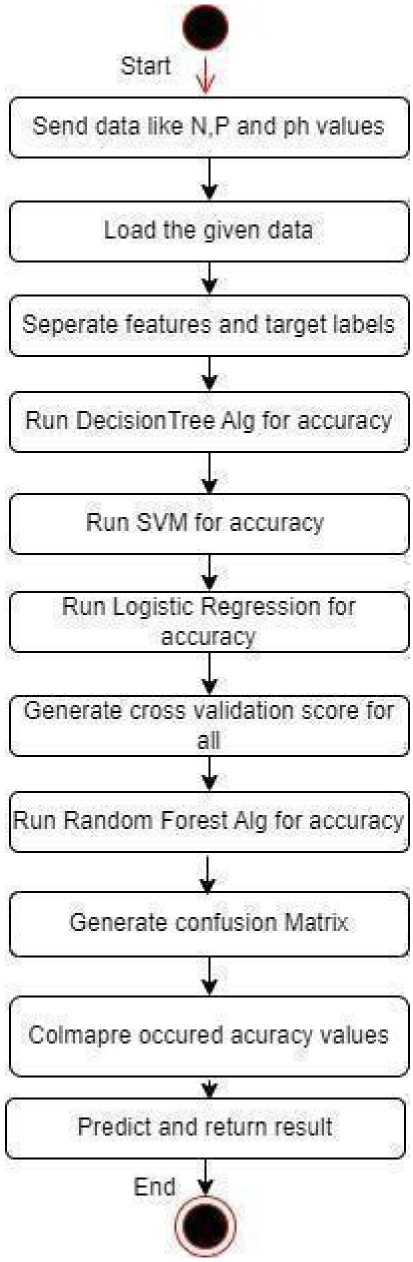
**5.1 Class Diagram**: Class diagram isa static diagram. It representsthe static view of an application.



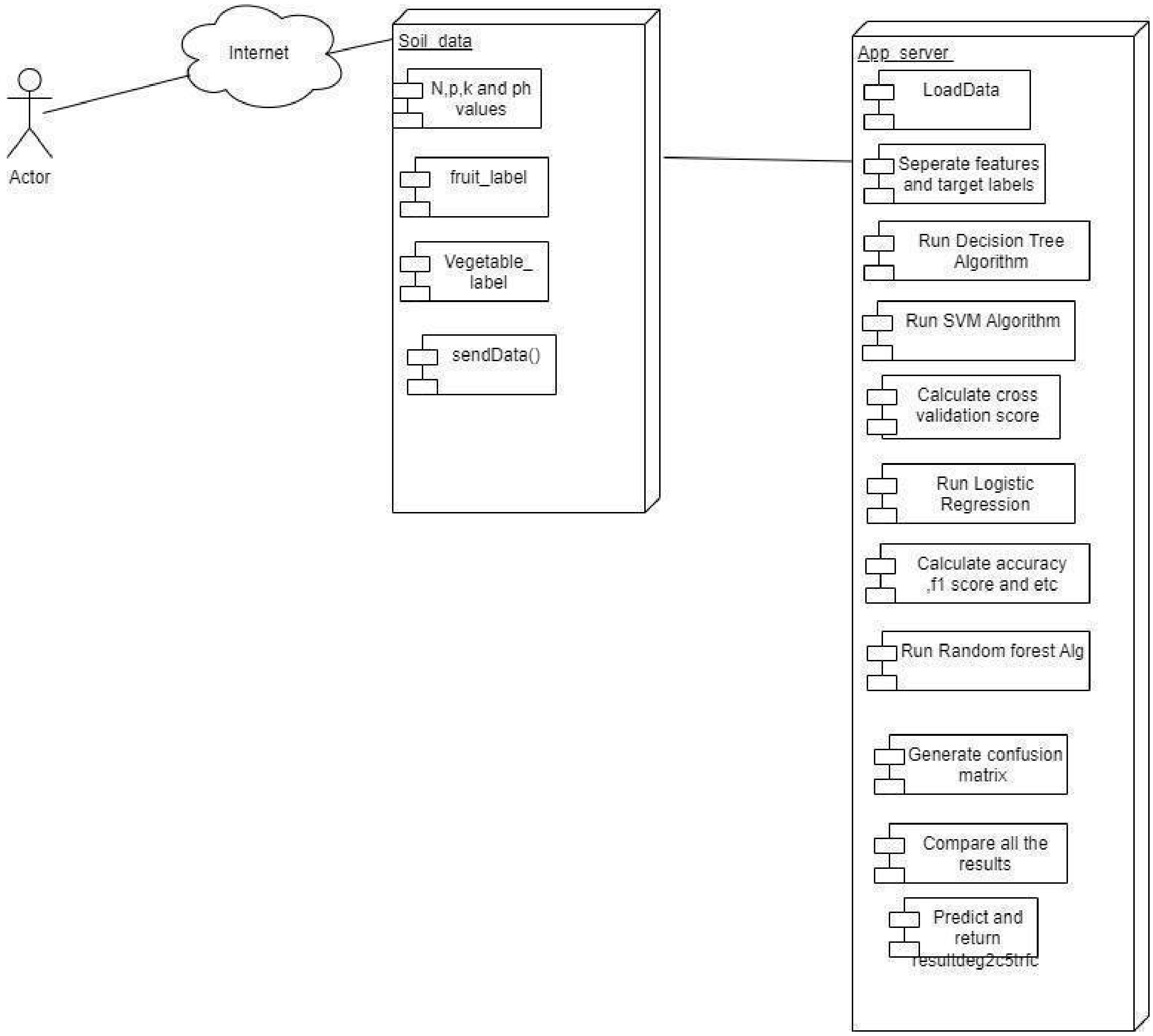
**5.2 Sequence Diagram**: Sequence diagram is an interaction diagram that detail show operations are carried out.



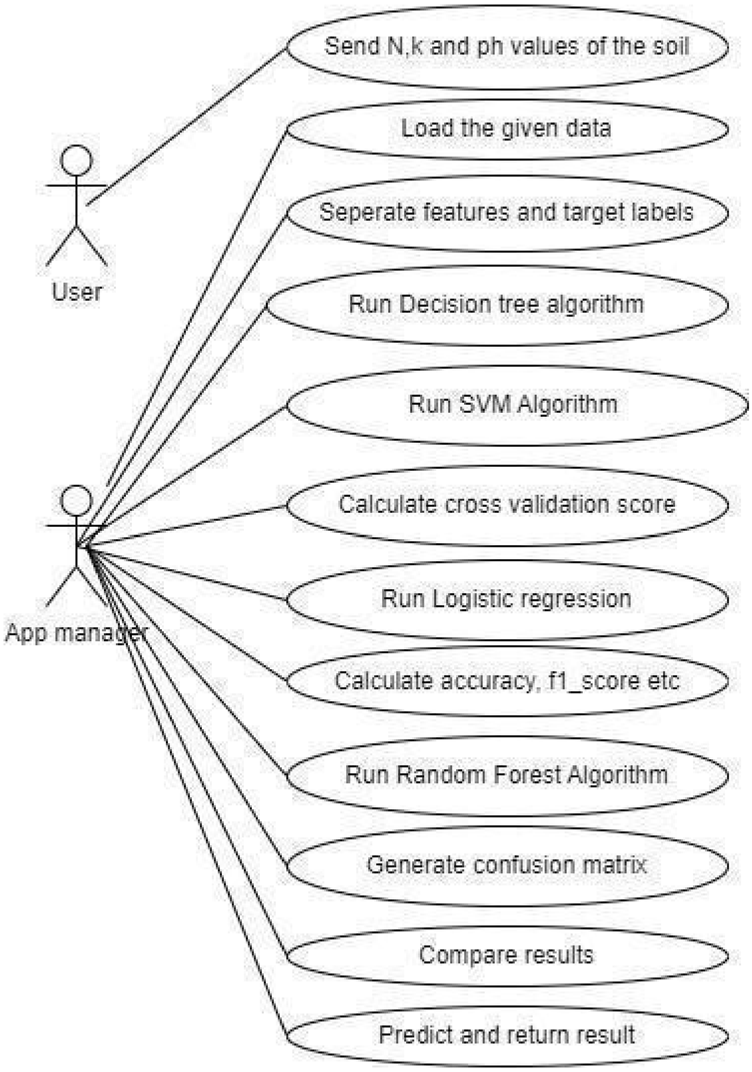
**5.3 Activity diagram:** Activity diagram is another important diagram in UML to describe the dynamic aspects of the system.



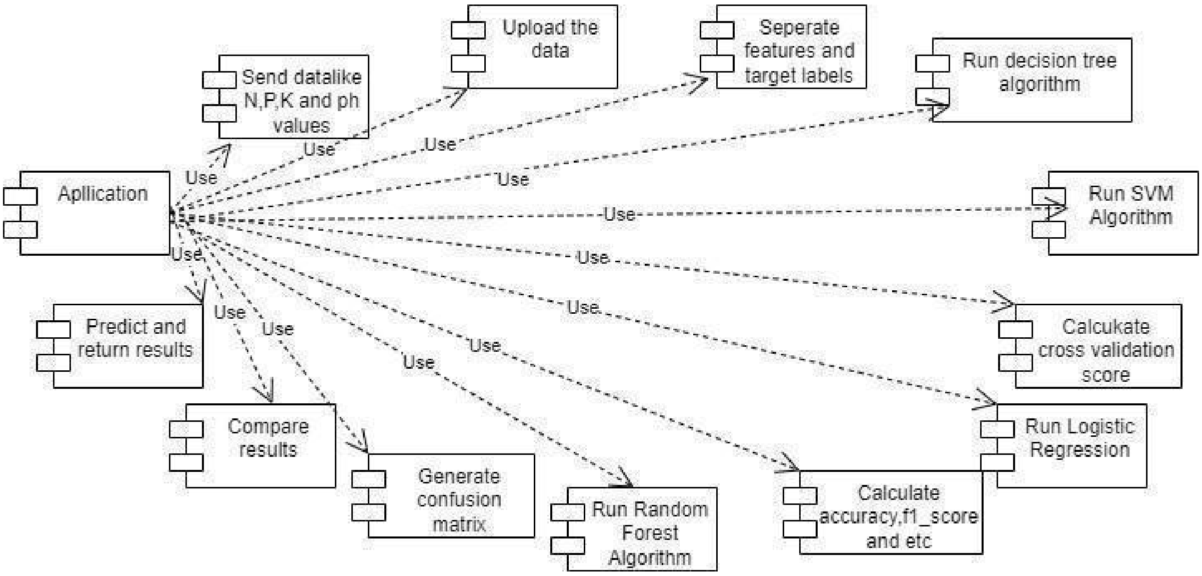
**5.4 Deployment diagram**:The deploymen tdiagram visualizes the physical hardware on which the software will be deployed.



**5.5 Use case diagram:** The purpose of use case diagram is to capture the dynamic aspect of a system.



**5.6 Component diagram**:Component diagram describes the organization and wiringof the physical components in a system.



# CHAPTER - 6

# SOFTWARE ENVIRONMENT

## 6.1 What is Python?

Beloware some facts about Python.
1. Python is currently the most widely used multi-purpose, high-level programming language.

2. Python allows programming in Object-Oriented and Procedural paradigms. Python programs generally are smallerthan other programming languages like Java.

3. Programmers haveto typerelatively less and indentation requirementof the language, makes them readable all the time.

4. Python language is being used by almost all tech-giant companies like – Google, Amazon, Facebook, Instagram, Dropbox, Uber… etc.

The biggest strength of Python is huge collection of standard libraries which can be used for the following –

- Machine Learning
- GUIApplications (like Kivy, Tkinter, PyQt etc.)
- Web frame works like Django (used by YouTube, Instagram, Dropbox)
- Image processing (like Opencv, Pillow)
- Web scraping (like Scrapy, BeautifulSoup, Selenium)
- Test frame works
- Multimedia

## Advantages of Python

Let'see how Python dominate over other languages.

1. **Extensive Libraries**

Python downloads with an extensive library and it contain code for various purposes like regular expressions, documentation-generation, unit-testing, web browsers, threading, databases, CGI, email, image manipulation, and more. So, we don't have to write the complete code for that manually.

**2. Extensible**

As we have seen earlier, Python can be extended to other languages. You can write some of your code in languages like C++ or C. This comes in handy, especially in projects.

**3. Embeddable**

Complimentary to extensibility, Python is embeddable as well. You can put your Python code in your source code of a different language, like C++. This lets us add scripting capabilities to our code in the other language.

**4. Improved Productivity**

The language's simplicity and extensive libraries render programmers more productive than languages like Java and C++ do. Also, the fact that you need to write less and get more things done.

**5. IOTO pportunities**

Since Python forms the basis of new platforms like Raspberry Pi, it finds the future bright for the Internet Of Things. This is a way to connect the language with the real world.

**6. Simple and Easy**

When working with Java, you may have to create a class to print 'Hello World'. But in Python, just a print statement will do. It is also quite easy to learn, understand, and code. This is why when people pick up Python, they have a hard time adjusting to other more verbose languages like Java.

**7. Readable**

Because it is not such a verbose language, reading Python is much like reading English. This is the reason why it is so easy to learn, understand, and code. It also does not need curly braces to define blocks, and indentation is mandatory. This further aids the readability of the code.

**8. Object Oriented**

This language supports both the procedural and object-oriented programming paradigms. While functions help us with code reusability, classes and objects let us model the real world. A class allows the encapsulation of data and functions into one.

**9. Free and Open-Source**

Like we said earlier, Python is freely available. But not only can you download Python for free, but you can also download its source code, make changes to it, and even distribute it. It downloads with an extensive collection of libraries to help you with your tasks.

**10. Portable**

When you code your project in a language like C++, you may need to make some changes to it if you want to run it on another platform. But it isn't the same with Python. Here, you need to code only once, and you can run it anywhere. This is called Write Once Run Anywhere (WORA). However, you need to be careful enough not to include any system-dependent features.

**11. Interpreted**

Lastly, we will say that it is an interpreted language. Since statements are executed one by one, debugging is easier than in compiled languages.

**Advantages of Python Over Other Languages**

**1. Less Coding**

Almost all of the tasks done in Python requires less coding when the same task is done in other languages. Python also has an awesome standard library support, so you don't have to search for any third-party libraries to get your job done. This is the reason that many people suggest learning Python to beginners.

**2. Affordable**

Python is free therefore individuals, small companies or big organizations can leverage the free available resources to build applications. Python is popular and widely used so it gives you better community support.

The 2019 Github annual survey showed us that Python has overtaken Java in the most popular programming language category.

**3. Python is for Everyone**

Python code can run on any machine whether it is Linux, Mac or Windows. Programmersneed to learn different languages for different jobs but with Python, you can professionally build web apps, perform data analysis and machine learning, automate things, do web scraping and also build games and powerful visualizations.It is an all-rounder programming language.

## Disadvantagesof Python

So far, we've seen why Python is a great choice for your project. But if you choose it, you should be aware of its consequences as well. Let's now see the downsides of choosing Python over another language.

**1.Speed Limitations**

We have seen that Python code is executed line by line. But since Python is interpreted, it often results in slow execution. This, however, isn't a problem unless speed is a focal point for the project. In other words, unless high speed is a requirement, the benefits offered by Python are enough to distract us from its speed limitations.

**2. Weak in MobileComputingand Browsers**

While it serves as an excellent server-side language, Python is much rarely seen on the client-side. Besides that, it is rarely ever used to implement smartphone-based applications. One such applicationis called Carbonnelle.

**3. DesignRestrictions**

As you know, Python is dynamically typed. This means that you don't need to declare the type of variable while writing the code. It uses duck-typing. But wait, what's that? Well, it just means that if it looks like a duck, it must be a duck. While this is easy on the programmers during coding, it can raise run-time errors.

**4. UnderdevelopedDatabaseAccess Layers**

Compared to more widely used technologies like JDBC (Java DataBase Connectivity) and ODBC (Open DataBase Connectivity), Python's database access layers are a bit underdeveloped. Consequently, it is less offers applied in huge enterprises.

**5. Simple**

No, we're not kidding. Python's simplicity can indeed be a problem. Take my example. I don't do Java, I'm more of a Python person. To me, its syntax is so simple that the verbosity of Java code seems unnecessary.

This was all about the Advantages and Disadvantages of Python Programming Language.

## 6.2 Modules Used in Project

**NumPy**

NumPy is a general-purpose array-processing package. It provides a high-performance multidimensional array object, and tools for working with these arrays.
It is the fundamental package for scientific computing with Python. It contains various features including these important ones:

- A powerful N-dimensional array object
- Sophisticated (broadcasting) functions
- Tools for integrating C/C++ and Fortran code
- Useful linear algebra, Fourier transform, and random number capabilities

Besides its obvious scientific uses, NumPy can also be used as an efficient multi-dimensional container of generic data. Arbitrary datatypes can be defined using NumPy which allows NumPy to seamlessly and speedily integrate with a wide variety of databases.

**Pandas**

Pandas is an open-source Python Library providing high-performance data manipulation and analysis tool using its powerful data structures. Python was majorly used for data munging and preparation. It had very little contribution towards data analysis. Pandas solved this problem. Using Pandas, we can accomplish five typical steps in the processing and analysis of data, regardless of the origin of data load, prepare, manipulate, model, and analyze. Python with Pandas is used in a wide range of fields including academic and commercial domains including finance, economics, Statistics, analytics, etc.

**Matplotlib**

Matplotlib is a Python 2D plotting library which produces publication quality figures in a variety of hardcopy formats and interactive environments across platforms. Matplotlib can used in Python scripts, the Python and Ipython shells, the Jupyter Notebook, web application servers, and four graphical user interface toolkits. Matplotlib tries to make easy things easy and hard things possible. You can generate plots, histograms, power spectra, bar charts, error charts, scatter plots, etc., with just a few lines of code. For examples, see the sample plots and thumbnail gallery.

For simple plotting the pyplot module provides a MATLAB-like interface, particularly when combined with Ipython. For the power user, you have full control of line styles, font properties, axes properties, etc, via an object oriented interface or via a set of functions familiar to MATLAB users.

**Scikit– learn**

Scikit-learn provides a range of supervised and unsupervised learning algorithms via a consistent interface in Python. It is licensed under a permissive simplified BSD license and is distributedunder many Linux distributions,encouraging academic and commercial use. Python

**Install Python Step-by-Stepin Windows and Mac**

Python a versatile programming language doesn't come pre-installed on your computer devices. Python was first released in the year 1991 and until today it is a very popular high-level programming language. Its style philosophy emphasizescode readabilitywith its notable use of great whitespace.

The object-oriented approach and language construct provided by Python enables programmers to write both clear and logical code for projects. This software does not come pre-packaged with Windows.

**Howto Install Pythonon WindowsandMac**

There have been several updates in the Python version over the years. The question is how to install Python? It might be confusing for the beginner who is willing to start learning Python but thistutorialwill solve your query. The latest or the newest version of Python is version

3.7.4 or in otherwords, itis Python 3.

Note:Thepython version3.7.4 cannotbe used on WindowsXPor earlierdevices.

Before you start with the installation process of Python. First, you need to know about your System Requirements. Based on your system type i.e. operating system and based processor, you mustdownloadthe python version.My system type is a Windows64-bit operating system.

So the steps below are to install python version 3.7.4 on Windows 7 deviceor to install Python 3. Downloadt he Python Cheat sheet here.Thestepson how to install Python on Windows10, 8 and 7 are divided into 4 parts to help understand better.

**Download the Correct version into the system**

Step1: Go to the official site to download and install python usingGoogle Chrome or any other web browser. OR Click on the following link: https://www.python.org


Now, check for the latest and the correct version for your operatingsystem.

Step2: Click on the Download Tab.

Step 3: You can either select the Download Python for windows 3.7.4 button in Yellow Color or you can scroll further down and click on download with respective to their version. Here, we are downloading the most recent python version for windows 3.7.4

Looking for a specific release?

Python releases by version number:

| Release version | Release date | | Click for more |
|---|---|---|---|
| Python 3.7.4 | July 8, 2019 | Download | Release Notes |
| Python 3.6.9 | July 2, 2019 | Download | Release Notes |
| Python 3.7.3 | March 25, 2019 | Download | Release Notes |
| Python 3.4.10 | March 18, 2019 | Download | Release Notes |
| Python 3.5.7 | March 18, 2019 | Download | Release Notes |
| Python 2.7.16 | March 4, 2019 | Download | Release Notes |
| Python 3.7.2 | Dec. 24, 2018 | Download | Release Notes |

Step4: Scroll down the page until you find the Files option.

Step5: Here you see a different version of python along with the operating system.

## Files

| Version | Operating System | Description | MD5 Sum | File Size | GPG |
|---|---|---|---|---|---|
| Gzipped source tarball | Source release | | [illegible] | 23017663 | SIG |
| XZ compressed source tarball | Source release | | [illegible] | 17131432 | SIG |
| macOS 64-bit/32-bit installer | Mac OS X | for Mac OS X 10.6 and later | [illegible] | 34898416 | SIG |
| macOS 64-bit installer | Mac OS X | for OS X 10.9 and later | [illegible] | 28082845 | SIG |
| Windows help file | Windows | | [illegible] | 8131761 | SIG |
| Windows x86-64 embeddable zip file | Windows | for AMD64/EM64T/x64 | [illegible] | 7504391 | SIG |
| Windows x86-64 executable installer | Windows | for AMD64/EM64T/x64 | [illegible] | 26680368 | SIG |
| Windows x86-64 web-based installer | Windows | for AMD64/EM64T/x64 | [illegible] | 1362904 | SIG |
| Windows x86 embeddable zip file | Windows | | [illegible] | 6741626 | SIG |
| Windows x86 executable installer | Windows | | [illegible] | 25663848 | SIG |
| Windows x86 web-based installer | Windows | | [illegible] | 1324608 | SIG |

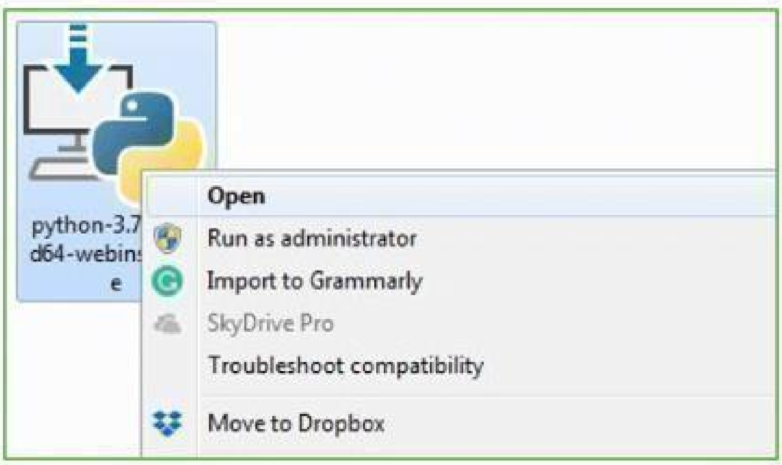
- To download Windows 32-bit python, you can select any one from the three options: Windows x86 embeddable zip file, Windows x86 executable installer or Windows x86 web-based installer.
- To download Windows 64-bit python, you can select any one from the three options: Windows x86-64 embeddable zip file, Windows x86-64 executable installer or Windows x86-64 web-based installer.

Here we will install Windows x86-64 web-based installer. Here your first part regarding which version of python is to be downloaded is completed. Now we move ahead with the second part in installing python i.e. Installation

Note: To know the changes or updates that are made in the version you can click on the Release Note Option.

### 6.3 Installation of Python

Step 1: Go to Download and Open the downloaded python version to carry out the installation process.




Step2:Before you click on Install Now, Makesure to put a tickon Add Python 3.7 to PATH.


Step3:Click on Install NOW Aftert he installation is successful.Click on Close.

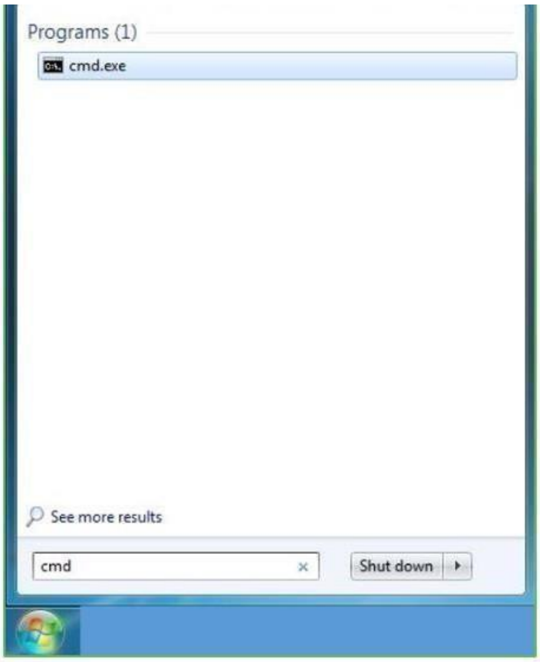

Withthese abovethree stepson python installation,you havesuccessfullyand correctly installedPython. Now is the time to verify the installation.

Note:Theinstallationprocessmighttakea couple of minutes.

**Verify the Python Installation**

Step1:Clickon Start

Step2: In the Windows RunCommand,type “cmd”.




Step3: Open the Commandpromptoption.

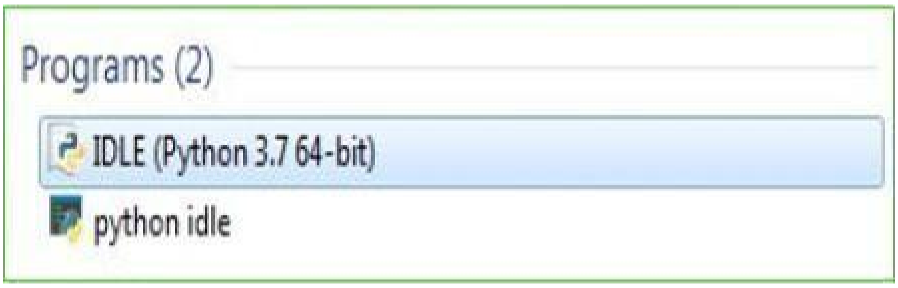
Step4:Let us testwhetherthe pythonis correctlyinstalled.Type python –V and press Enter.


Step5:You will get theanswer as 3.7.4

**Check how the Python IDLE works**

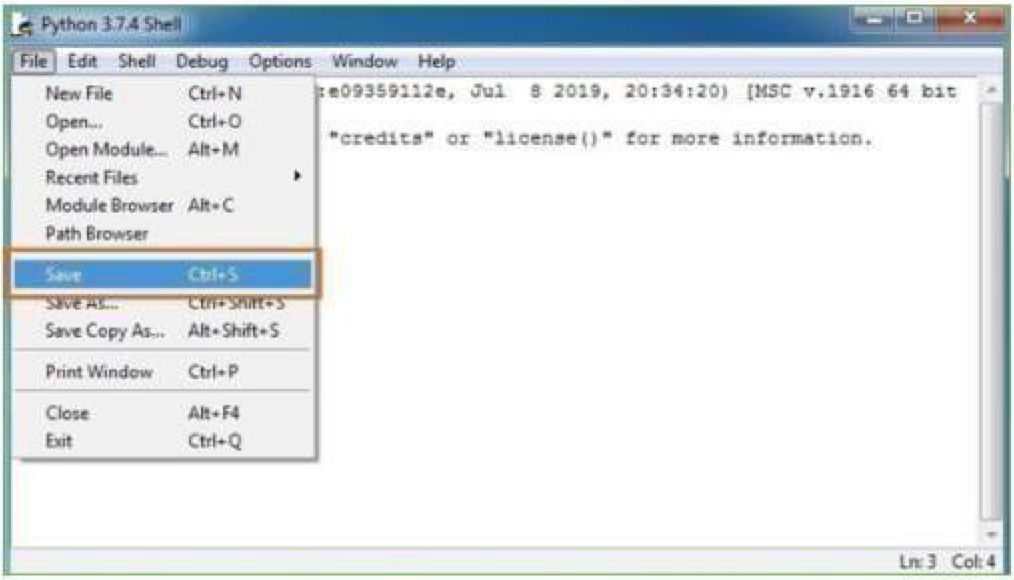
Step1:Clickon Start

Step2:In the Windows Run command,type "pythonidle".



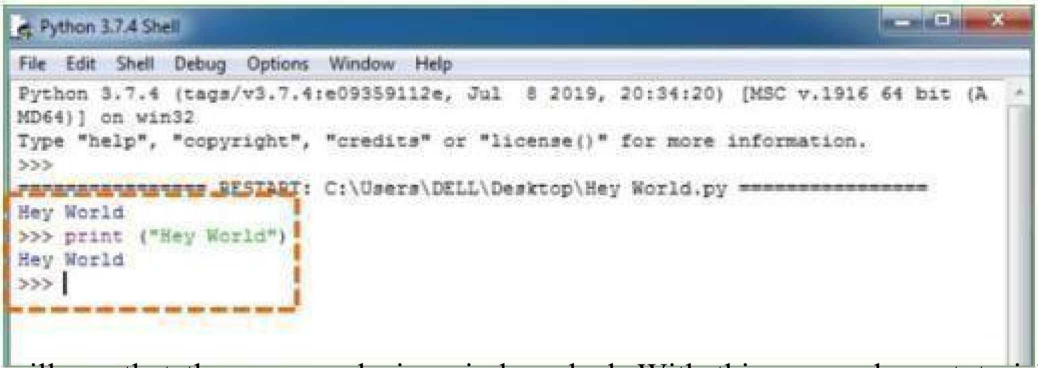

Step3:ClickonIDLE(Python 3.7 64-bit)and launch theprogram

Step4:To go ahead with working in IDLE you must first save the file.Clickon File> Click on Save




Step5: Name the fileand saveas typeshouldbe Pythonfiles.Clickon SAVE.HereI have named the filesas Hey World.

Step6:Nowfore.g. enterprint("Hey World")andPressEnter.




You will see that the command given is launched. With this, we end our tutorial on how to install Python. You have learned how to download python for windows into your respective operating system.

Note: Unlike Java, Python does not need semicolons at the end of the statements otherwise it won't work.

# CHAPTER - 7

# SYSTEM REQUIREMENTS

## 7.1 Software Requirements

The functional requirements or the overall description documents include the product perspective and features, operating system and operating environment, graphics requirements, design constraints and user documentation.

The appropriation of requirements and implementation constraints gives the general overview of the project in regard to what the areas of strength and deficit are and how to tackle them.

- PythonIDLE 3.7 version(or)
- Anaconda3.7 (or)
- Jupiter (or)
- Google colab

## 7.2 Hardware Requirements

Minimum hardware requirements are very dependent on the particular software being developed by a given Enthought Python / Canopy / VS Code user. Applications that need to store large arrays/objects in memory will require more RAM, whereas applications that need to perform numerous calculations or tasks more quickly will require a faster processoor.

- Operating system : windows,,linux
- Processor : minimumintel i3
- Ram : minimum4 GB
- Harddisk : minimum250GB

# CHAPTER - 8

# FUNCTIONAL REQUIREMENTS

**Output Design**

Outputs from computer systems are required primarily to communicate the results of processing to users. They are also used to provides a permanent copy of the results for later consultation.The various types of outputsin general are:

- ExternalOutputs,whosedestinationis outside the organization
- Interna lOutputs whose destination is within organization and they are the
- User's main interface with thec omputer.
- Operationaloutputswhoseuse is purely withinthe computer department.
- Interfaceoutputs,which involvethe user in communicatingdirectly.

**Output Definition**

The output should be defined in terms of following patterns:

- Type of the output
- Content of the output
- Format of the output
- Locationof theoutput
- Frequency of the output
- Volume of the output
- Sequence of the output

Itis not alwaysdesirableto printor display data as it is heldon a computer.Itshould be decided as which form of the output is the most suitable.

**Input Design**

Inputdesign is a part of overall system design. The mainobjective during the inputdesign is as given below:

To producea cost-effective method of input.

- To ensure that the input is acceptable and understood by theuser.

**InputStages**

The main input stages can be listedasbelow:

- Data recording
- Data transcription
- Data conversion
- Data verification
- Data control
- Data transmission
- Data validation
- Data correction

**Input Types**

It is necessary to determinethevarious types of inputs. Inputs canbe categorized as follows:

- External inputs,which areprimeinputsforthe system.
- Internal inputs,whichare usercommunicationswiththe system.
- Operational,whichare computerdepartment'scommunications to the system?
- Interactive,whichare inputs entered duringa dialogue.

**Inpu tMedia**

To concludeabouttheinput media considerationhas to be given to;

- Type of input
- Flexibility of format
- Speed
- Accuracy
- Verification methods
- Rejection rates
- Easeof correction
- Storageand handling requirements
- Security

- Easyto use
- Portability

Keeping in view the above descriptiono f the input ypes and input media,it can be said that mostof the inputsare of the form of internaland interactive. As
Input data is to be the directly keyed in by the user, the keyboard can be considered to be the most suitable input device.

**Error Avoidance**

At this stage care is to be taken to ensure that input data remains accurate form the stage at which it is recorded up to the stage in which the data is accepted by the system. This can be achieved only by means of careful control each time the data is handled.

**Error Detection**

Even though every effort is make to avoid the occurrence of errors, still a small proportion of errors is always likely to occur, these types of errors can be discovered by using validations to check the input data.

**Data Validation**

Procedures are designed to detect errors in data at a lower level of detail. Data validations have been included in the system in almost every area where there is a possibility for the user to commit errors. The system will not accept invalid data. Whenever an invalid data is keyed in, the system immediately prompts the user and the user has to again key in the data and the system will accept the data only if the data is correct. Validations have been included where necessary.

The system is designed to be a user friendly one. In other words the system has been designed to communicateeffectivelywith the user. The system has been designed withpopup menus.

**UserInterface Design**

It is essential to consult the system users and discuss their needs while designing the user interface:

Computer initiated interfaces

In the computer-initiated interfaces the computer guides the progress of the user/computer dialogue. Information is displayed and the user response of the computer takes action or displays further information.

**User Initiated Interfaces**

Userinitiated interface fall into two approximateclasses:

Commanddriven interfaces:In thistype of interfacethe user inputscommandsor queries which are interpreted by the computer.

Forms oriented interface:The user callsup an imageof theformto his/herscreenand fills in the form. The forms-orientedinterface is chosenbecauseit is the best choice.

- **Computer-Initiated Interfaces**

The following computer– initiated interfaces were used:

The menu system for the user is presented with a list of alternatives and the user chooses one; of alternatives.

Questions – answer type dialog system where the computer asks question and takes action based on the basis of the users reply.

Right from the start the system is going to be menu driven, the opening menu displays the available options. Choosing one option gives another popup menu with more options. In this way every option leads the users to data entry form where the user can key in the data.

**Error Message Design**

The design of error messages is an important part of the user interface design. As user is bound to commit some errors or other while designing a system the system should be designed to be helpful by providing the user with informationregarding the error he/she has committed.

**Performance Requirements**

Performance is measured in terms of the output provided by the application. Requirement specification plays an important part in the analysis of a system. Only when the requirement specificationsare properly given, it is possibleto design a system, which will fit into required environment. It rests largely in the part of the users of the existing system to give the requirement specifications because they are the people who finally use the system. This is becausethe requirementshave to be known during the initialstages so that the system can be designed according to those requirements. It is very difficult to change the systemonce it has been designed and on the other hand designing a system, which does not cater to the requirementsof the user, is of no use.

# CHAPTER- 9

## SOURCE CODE

```
# # Import necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn import metrics
import warnings

# Ignore warnings
warnings.filterwarnings('ignore')


# Load dataset
df = pd.read_csv("Crop_recommendation.csv")

# Display dataset summary
print("Dataset Summary:")
print(df.tail())
print(f"Dataset Size: {df.size}")
print(f"Dataset Shape: {df.shape}")
print(f"Columns: {df.columns.tolist()}")
print(f"Unique Labels: {df['label'].unique()}")
print(f"Label Distribution:\n{df['label'].value_counts()}")
```

```
# Correlation heatmap for numeric features
numeric_df = df.select_dtypes(include=[np.number])
plt.figure(figsize=(10, 8))
sns.heatmap(numeric_df.corr(), annot=True, cmap='coolwarm')
plt.title("Correlation Heatmap")
plt.show()

# Count plot for crop labels
plt.figure(figsize=(12, 6))
sns.countplot(x='label', data=df, palette="Set2",
order=df['label'].value_counts().index)
plt.title("Crop Distribution")
plt.xticks(rotation=90)
plt.show()

# Features and target
features = df[['N', 'P', 'K', 'temperature', 'humidity', 'ph', 'rainfall']]
target = df['label']

# Train-test split
Xtrain, Xtest, Ytrain, Ytest = train_test_split(features, target, test_size=0.2,
random_state=2)

# Model performance tracking
acc = []
model = []
```

```
# Logistic Regression
LogReg = LogisticRegression(C=0.01, penalty='l1', solver='liblinear')
LogReg.fit(Xtrain, Ytrain)
predicted_values = LogReg.predict(Xtest)
logreg_accuracy = metrics.accuracy_score(Ytest, predicted_values)
acc.append(logreg_accuracy)
model.append('Logistic Regression')
print(f"Logistic Regression Accuracy: {logreg_accuracy}")
print(classification_report(Ytest, predicted_values))

# Random Forest Classifier
RF = RandomForestClassifier(n_estimators=20, random_state=0)
RF.fit(Xtrain, Ytrain)
predicted_values = RF.predict(Xtest)
rf_accuracy = metrics.accuracy_score(Ytest, predicted_values)
acc.append(rf_accuracy)
model.append('Random Forest')
print(f"Random Forest Accuracy: {rf_accuracy}")
print(classification_report(Ytest, predicted_values))

# Confusion Matrix for Random Forest
cm = confusion_matrix(Ytest, predicted_values, labels=target.unique())
plt.figure(figsize=(10, 8))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=target.unique(),
yticklabels=target.unique())
plt.title("Confusion Matrix for Random Forest")
plt.xlabel("Predicted Labels")
plt.ylabel("True Labels")
plt.show()
```

```
# Accuracy Comparison
plt.figure(figsize=(10, 5))
sns.barplot(x=acc, y=model, palette="viridis")
plt.title("Model Accuracy Comparison")
plt.xlabel("Accuracy")
plt.ylabel("Algorithm")
plt.show()

# Interactive user input for predictions
print("\nEnter the values to predict the recommended crop:")

N = int(input("Enter the value of N: "))
P = int(input("Enter the value of P: "))
K = int(input("Enter the value of K: "))
temperature = float(input("Enter the value of Temperature: "))
humidity = float(input("Enter the value of Humidity: "))
ph = float(input("Enter the value of pH: "))
rainfall = float(input("Enter the value of Rainfall: "))

# Creating a new input array
new_input = np.array([[N, P, K, temperature, humidity, ph, rainfall]])

# Making a prediction
predicted_crop = RF.predict(new_input)
print(f"\nThe Recommended crop is: {predicted_crop[0]}")
```

# CHAPTER - 10

# RESULTS AND DISCUSSION

The dataset contains agricultural-related information with various features related to the cultivation of different crops. Here are columns in the dataset:

- N: This column appears to represent the nitrogen content in the soil, which is an essential nutrient for plant growth.
- P: This column likely represents the phosphorus content in the soil, another crucial nutrient for plant development.
- K: This column could represent the potassium content in the soil, which is important for various plant processes.
- Temperature: This column represents the temperature of the environment in which the crops are grown. Temperature significantly affects plant growth and development.
- Humidity: This column likely represents the humidity level of the environment. Humidity can influence plant transpiration and overall moisture conditions.
- pH: This column represents the pH level of the soil. Soil pH affects nutrient availability to plants.
- Rainfall: This column could represent the amount of rainfall in the region where the crops are cultivated. Rainfall is a critical factor in determining irrigation needs and water availability.
- Label: This column appears to be the target variable or the label that indicates the type of crop being grown. It seems to be a categorical variable representing different types of crops, such as "rice" and "coffee."

The dataset is organized with rows corresponding to different instances or observations, each with values for the different features (N, P, K, Temperature, Humidity, pH, Rainfall) and a label indicating the type of crop. This kind of dataset is used for various machine learning tasks, such as classification (predicting the crop type) or regression (predicting some numerical outcome based on the features).

| | N | P | K | temperature | humidity | ph | rainfall | label |
|---|---|---|---|---|---|---|---|---|
| **0** | 90 | 42 | 43 | 20.879744 | 82.002744 | 6.502985 | 202.935536 | rice |
| **1** | 85 | 58 | 41 | 21.770462 | 80.319644 | 7.038096 | 226.655537 | rice |
| **2** | 60 | 55 | 44 | 23.004459 | 82.320763 | 7.840207 | 263.964248 | rice |
| **3** | 74 | 35 | 40 | 26.491096 | 80.158363 | 6.980401 | 242.864034 | rice |
| **4** | 78 | 42 | 42 | 20.130175 | 81.604873 | 7.628473 | 262.717340 | rice |
| ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **2195** | 107 | 34 | 32 | 26.774637 | 66.413269 | 6.780064 | 177.774507 | coffee |
| **2196** | 99 | 15 | 27 | 27.417112 | 56.636362 | 6.086922 | 127.924610 | coffee |
| **2197** | 118 | 33 | 30 | 24.131797 | 67.225123 | 6.362608 | 173.322839 | coffee |
| **2198** | 117 | 32 | 34 | 26.272418 | 52.127394 | 6.758793 | 127.175293 | coffee |
| **2199** | 104 | 18 | 30 | 23.603016 | 60.396475 | 6.779833 | 140.937041 | coffee |

2200 rows × 8 columns

Figure10.1:Sample datasetused for Crop RecommendationSystem.

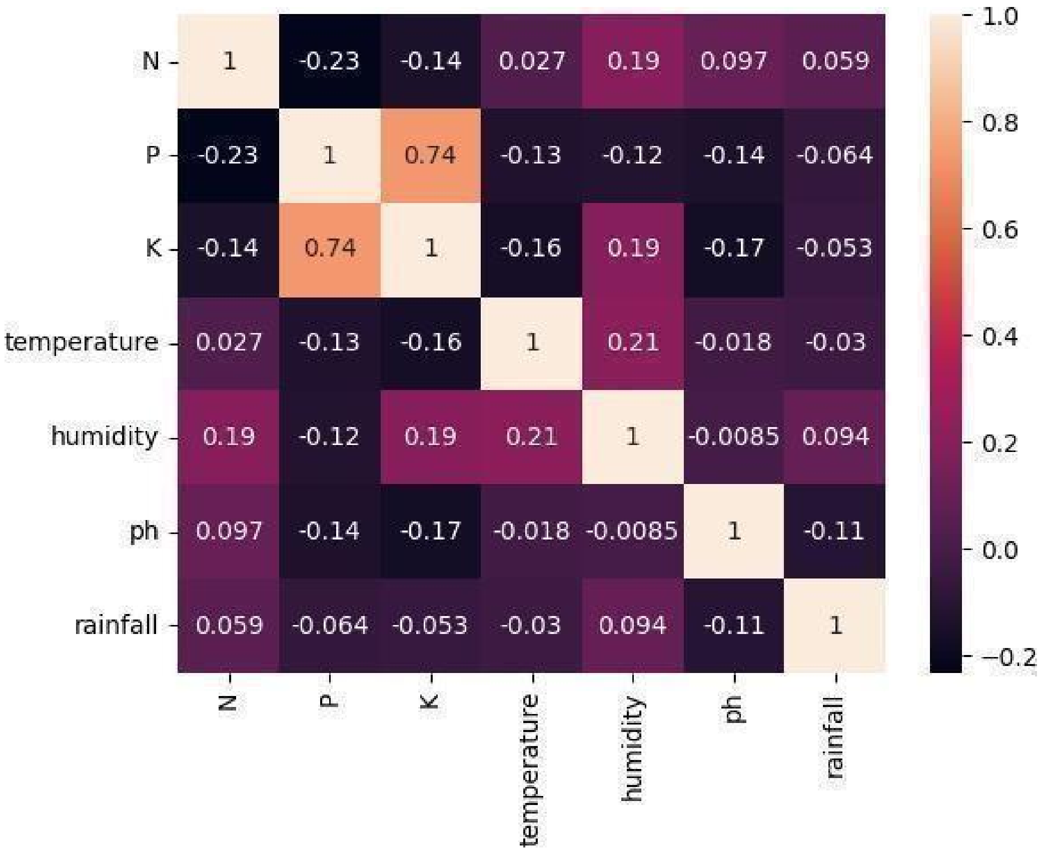



Figure10.2: correlation betweennumericalcolumns inthe Data Frame

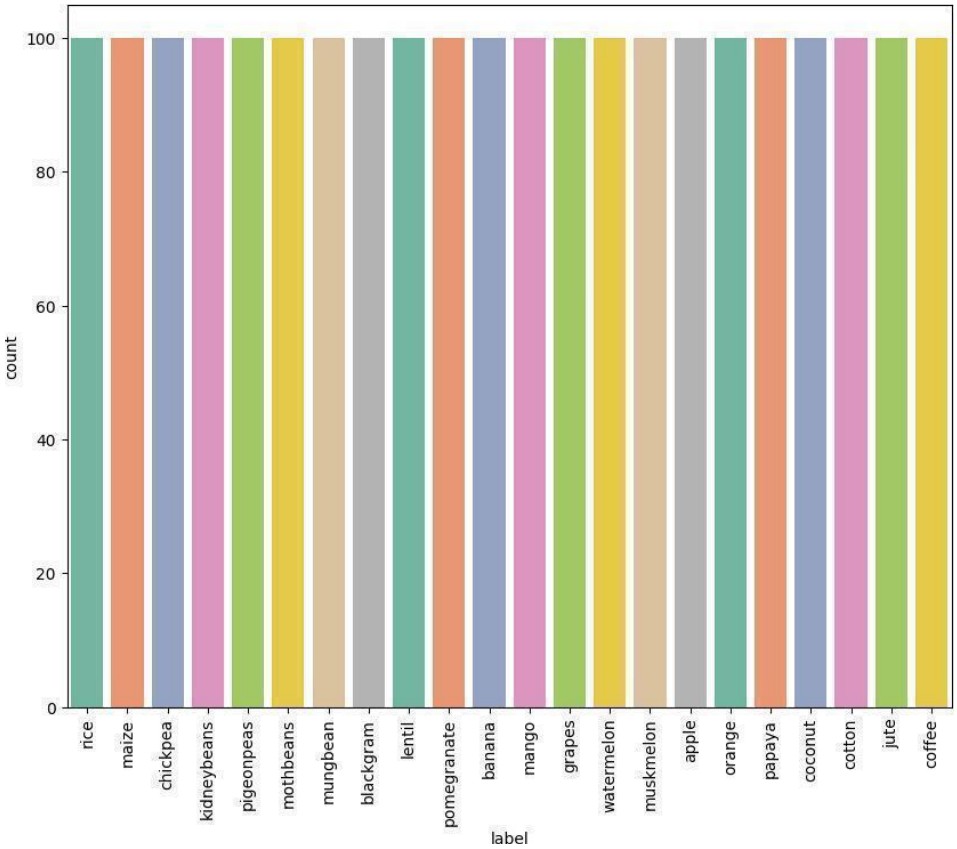



Figure10.3:show case the distribution of categories in the "label" column of the Data Frame

| | N | P | K | temperature | humidity | ph | rainfall |
|---|---|---|---|---|---|---|---|
| **0** | 90 | 42 | 43 | 20.879744 | 82.002744 | 6.502985 | 202.935536 |
| **1** | 85 | 58 | 41 | 21.770462 | 80.319644 | 7.038096 | 226.655537 |
| **2** | 60 | 55 | 44 | 23.004459 | 82.320763 | 7.840207 | 263.964248 |
| **3** | 74 | 35 | 40 | 26.491096 | 80.158363 | 6.980401 | 242.864034 |
| **4** | 78 | 42 | 42 | 20.130175 | 81.604873 | 7.628473 | 262.717340 |
| **...** | ... | ... | ... | ... | ... | ... | ... |
| **2195** | 107 | 34 | 32 | 26.774637 | 66.413269 | 6.780064 | 177.774507 |
| **2196** | 99 | 15 | 27 | 27.417112 | 56.636362 | 6.086922 | 127.924610 |
| **2197** | 118 | 33 | 30 | 24.131797 | 67.225123 | 6.362608 | 173.322839 |
| **2198** | 117 | 32 | 34 | 26.272418 | 52.127394 | 6.758793 | 127.175293 |
| **2199** | 104 | 18 | 30 | 23.603016 | 60.396475 | 6.779833 | 140.937041 |

2200 rows × 7 columns

Figure10.4:Features column of the Data Frame

```
0         rice
1         rice
2         rice
3         rice
4         rice
         ...
2195    coffee
2196    coffee
2197    coffee
2198    coffee
2199    coffee
Name: label, Length: 2200, dtype: object
```

Figure10.5:Target column of theData Frame

```
classification_report:
               precision    recall  f1-score   support

       apple       1.00      1.00      1.00        13
      banana       0.81      1.00      0.89        17
   blackgram       0.67      0.75      0.71        16
    chickpea       1.00      1.00      1.00        21
     coconut       1.00      0.95      0.98        21
      coffee       1.00      1.00      1.00        22
      cotton       0.74      1.00      0.85        20
      grapes       1.00      1.00      1.00        18
        jute       0.89      0.57      0.70        28
 kidneybeans       0.93      1.00      0.97        14
      lentil       0.81      0.91      0.86        23
       maize       1.00      0.43      0.60        21
       mango       1.00      1.00      1.00        26
   mothbeans       0.76      0.68      0.72        19
    mungbean       1.00      1.00      1.00        24
   muskmelon       1.00      1.00      1.00        23
      orange       1.00      1.00      1.00        29
      papaya       0.78      0.74      0.76        19
  pigeonpeas       1.00      0.83      0.91        18
 pomegranate       1.00      0.94      0.97        17
        rice       0.48      0.88      0.62        16
  watermelon       1.00      1.00      1.00        15

    accuracy                           0.89       440
   macro avg       0.90      0.89      0.89       440
weighted avg       0.91      0.89      0.89       440
```

Figure10.6: Classificationreport of Logistic Regression

Randomforest Classifier classification_report:

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| apple | 1.00 | 1.00 | 1.00 | 13 |
| banana | 1.00 | 1.00 | 1.00 | 17 |
| blackgram | 0.94 | 1.00 | 0.97 | 16 |
| chickpea | 1.00 | 1.00 | 1.00 | 21 |
| coconut | 1.00 | 1.00 | 1.00 | 21 |
| coffee | 1.00 | 1.00 | 1.00 | 22 |
| cotton | 1.00 | 1.00 | 1.00 | 20 |
| grapes | 1.00 | 1.00 | 1.00 | 18 |
| jute | 0.90 | 1.00 | 0.95 | 28 |
| kidneybeans | 1.00 | 1.00 | 1.00 | 14 |
| lentil | 1.00 | 1.00 | 1.00 | 23 |
| maize | 1.00 | 1.00 | 1.00 | 21 |
| mango | 1.00 | 1.00 | 1.00 | 26 |
| mothbeans | 1.00 | 0.95 | 0.97 | 19 |
| mungbean | 1.00 | 1.00 | 1.00 | 24 |
| muskmelon | 1.00 | 1.00 | 1.00 | 23 |
| orange | 1.00 | 1.00 | 1.00 | 29 |
| papaya | 1.00 | 1.00 | 1.00 | 19 |
| pigeonpeas | 1.00 | 1.00 | 1.00 | 18 |
| pomegranate | 1.00 | 1.00 | 1.00 | 17 |
| rice | 1.00 | 0.81 | 0.90 | 16 |
| watermelon | 1.00 | 1.00 | 1.00 | 15 |
| accuracy | | | 0.99 | 440 |
| macro avg | 0.99 | 0.99 | 0.99 | 440 |
| weighted avg | 0.99 | 0.99 | 0.99 | 440 |

Figure10.7:Classification report of Random Forest Classifier

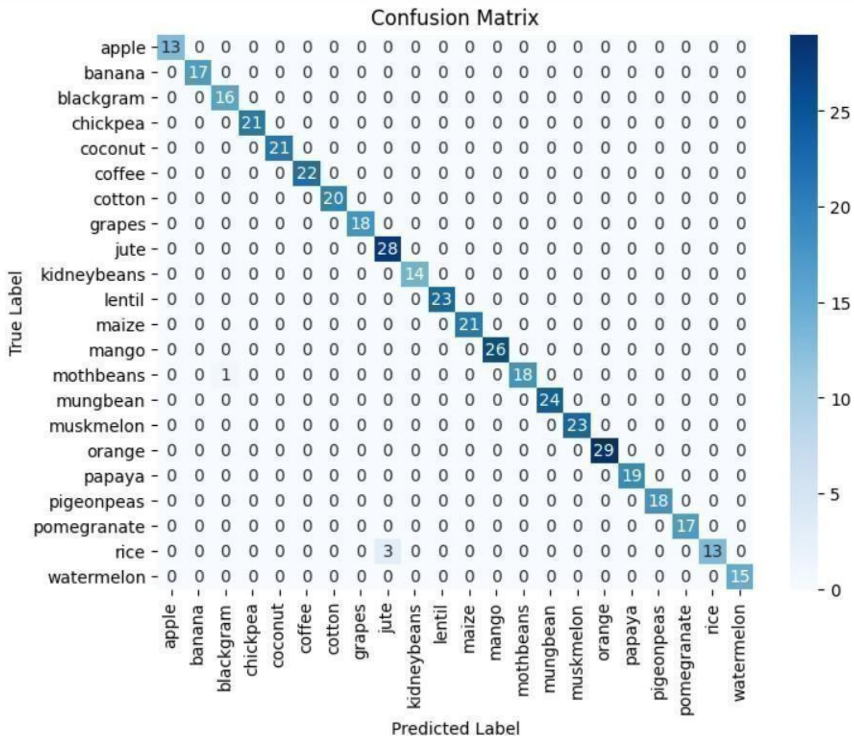



Figure10.8:Confusion matrix of Random Forest Classifier

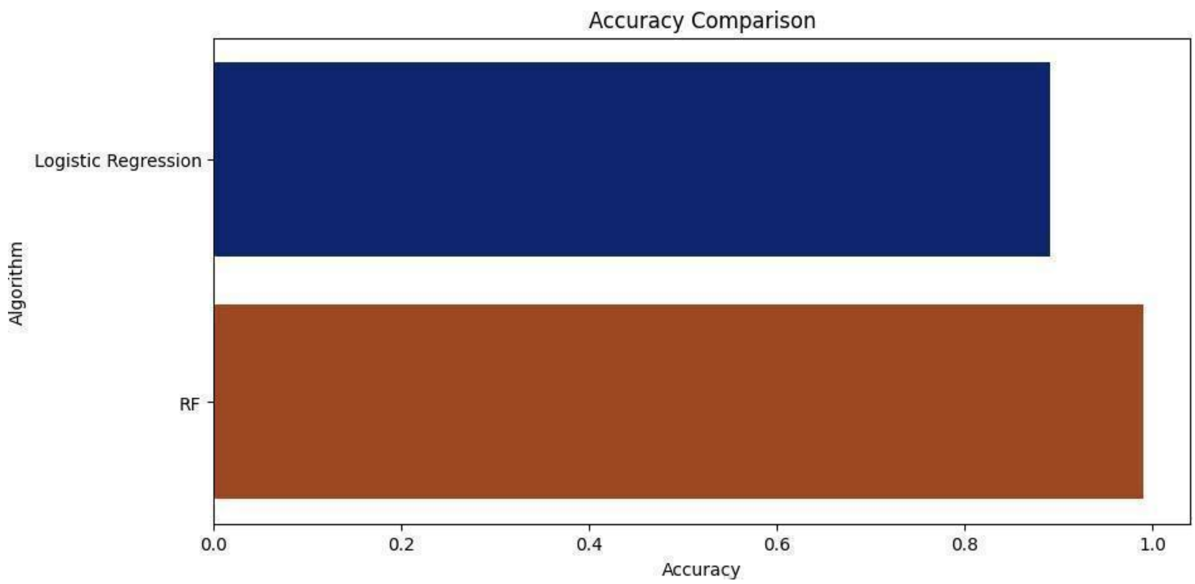



Figure10.9:Accuracy Comparison Graph for ml models

```
# Get input values from the user
N = int(input("Enter the value of N: "))
p = int(input("Enter the value of P: "))
K = int(input("Enter the value of K: "))
Temperature = int(input("Enter the value of Temperature: "))
humidity=int(input("Enter the value of Humidity:"))
ph = int(input("Enter the value of pH: "))
rainfall = int(input("Enter the value of Rainfall: "))

# Create a new input array with the user-provided values
new_input = [N, p, K, Temperature, humidity,ph, rainfall]

# Make a prediction using the RandomForest model
predict = RF.predict([new_input])

print("The Recomende crop is ",predict)
```

```
Enter the value of N: 83
Enter the value of P: 45
Enter the value of K: 60
Enter the value of Temperature: 28
Enter the value of Humidity:71
Enter the value of pH: 7
Enter the value of Rainfall: 151
The Recomende crop is  ['jute']
```

Figure10.10: Prediction results for Random Forest classifiers

Table1:Overall performance comparison of ML models.

| Modelname | Accuracy (%) | Precision (%) | Recall(%) | F1-score |
|---|---|---|---|---|
| Random Forest | 99 | 99 | 99 | 99 |
| Logistic Regression | 89 | 90 | 89 | 89 |

# CHAPTER - 11

# CONCLUSION AND FUTURESCOPE

## 11.1 Conclusion

In conclusion, the "Machine Learning-based Crop Recommendation System for Enhanced Yield Production" represents a comprehensive approach to empower farmers with data-driven insights for making informed decisions about crop selection. This system operates on fundamental principles of data science and machine learning. Beginning with data import and preparation, the system recognizes the critical role of data in its operations. It leverages libraries like Pandas and NumPy for efficient data handling, ensuring that historical information about various crops' growth requirements is readily accessible. Exploratory Data Analysis (EDA) forms the foundation for understanding the dataset's characteristics. By utilizing functions like **df.tail()**, **df.size**, and **df.shape**, it gains insights into the data's structure and size. Furthermore, examining the dataset's columns with **df.columns** sets the stage for feature selection and target variable identification.

Data visualization techniques, including count plots and heatmaps, enable a visual understanding of crop distribution and feature correlations. These visuals provide invaluable context, aiding in better-informed decisions during subsequent stages of model development. Feature selection involves extracting relevant factors such as nutrient levels (N, P, K), environmental conditions (temperature, humidity, pH), and rainfall. These features become the basis for training machine learning models, and the target variable ('label') defines the model's prediction goal. The training and evaluation of models, specifically Logistic Regression and Random Forest, embody the heart of this system. Model performance is rigorously assessed using metrics like accuracy, precision, recall, and F1-score. These evaluations ensure that the models can make accurate crop recommendations. A critical aspect is the confusion matrix, which provides a detailed breakdown of prediction results, highlighting true positives, true negatives, false positives, and false negatives. This aids in understanding model strengths and weaknesses. The system also facilitates model selection by comparing accuracies through a bar plot, enabling users to identify the most suitable model for their specific needs. Finally, the ability to make predictions for new data points based on environmental conditions allows farmers to apply the system's insights directly to their farming practices, potentially leading to optimized crop yield production.

## 11.2 Future Scope

The "Machine Learning-based Crop Recommendation System for Enhanced Yield Production" holds significant potential for future advancements and broader applications in agriculture and relatedfields. Here are somepotential future scopes and areasof development for thissystem:

**Integration of IoT and Sensor Data**: Future iterations of this system can incorporate data from IoT (Internet of Things) sensors placed in farms. These sensors can provide real-time data on soil moisture, temperature, humidity, and other environmental variables. Integrating this data can enhance the accuracy of crop recommendations by accounting for current conditions.

**Advanced Machine Learning Models**: While Logistic Regression and Random Forest are effective, future research can explore more advanced machine learning algorithms, including deep learning techniques like neural networks. These models may capture more intricate relationshipsin agricultural data

**Personalized Recommendations**: Develop personalized crop recommendations for individual farms. Consider historical data specific to each farm, allowing the system to adapt to unique conditions and farming practices.

**Crop Disease Detection**: Expand the system's capabilities to include the detection of crop diseases and pests. Machine learning can be used to identify disease symptoms from imagesof crops and suggest appropriate interventions.

**Climate Change Adaptation**: As climate change continues to impact agriculture, the system can be adapted to consider changing climate patterns. It can provide recommendationsthat are resilient to climatevariationsand extreme weather events.

**Mobile Applications**: Create user-friendly mobile applications for farmers to access recommendations and input data directly from the field. This would make the systemmore accessibleand practical for everyday use.

**Data Sharing and Collaboration**: Enable farmers to share their anonymized data with agricultural research institutions, creating a collaborative network that can lead to more comprehensiveand accurate recommendations.

**Crop Rotation Planning**: Extend the system to include recommendations for crop rotation,which can improvesoil health and reduce the risk of pestsand diseases.

**Market Integration**: Integrate market data and price predictions to help farmers make decisions not only about what to plant but also when and where to sell their crops for maximum profit.

**Global Scalability**: Adapt the system for use in different regions and countries by considering local variations in soil types, climate, and crop varieties. Translate the system into multiplelanguages to make it accessibleworldwide.

**Machine Learning Explainability**: Improve the interpretability of machine learning models used in the system, ensuring that farmers can understand why specific recommendationsaremade. This can build trust in the system's recommendations.

**Education and Training**: Offer training and educational resources to farmers on how to use the system effectively and understand the importance of data-driven agriculture.

**Environmental Sustainability**: Incorporate sustainability metrics into crop recommendations, encouraging environmentally friendly farming practices.

# CHAPTER - 12

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