A

Project Report

on

AGROGUIDE: CROP RECOMMENDATION SYSTEM USING MACHINE LEARNING

Submitted to

Sant Gadge Baba Amravati University, Amravati

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the requirements for the Degree of

Bachelor of Engineering in

Computer Science and Engineering

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SHRI SANT GAJANAN MAHARAJ COLLEGE OF ENGINEERING, SHEGAON – 444 203 (M.S.)

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

CERTIFICATE

This is to certify that **Mr. Soham Purushottam Ardhapurkar, Ms.Shruti Chatarkar, Mr.Suhas Sanjay Karanjkar , Mr.Ujwal Gajanan Deshmukh** students of final year Bachelor of Engineering in the academic year 2024-25 of Computer Science and Engineering Department of this institute have completed the project work entitled "**Agroguide: Crop Recommendation System Using Machine Learning**" and submitted a satisfactory work in this report. Hence recommended for the partial fulfillment of degree of Bachelor of Engineering in Computer Science and Engineering.

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Abstract

Agriculture is vital for the global economy, ensuring food security and supplying raw materials for various sectors. However, farmers face difficulties in selecting crops due to rapid climate changes, soil deterioration, and ineffective farming techniques. Conventional crop selection often hinges on intuition and previous experiences, which can result in reduced yields and financial setbacks. The Crop Recommendation System (CRS) introduced in this study utilizes Machine Learning (ML) algorithms along with the Django framework to help farmers make informed decisions regarding crop selection by considering environmental and soil factors.

The system is built to examine several elements, such as soil type, temperature, humidity, pH level, rainfall, and crucial soil nutrients like nitrogen (N), phosphorus (P), and potassium (K). It employs various machine learning algorithms, including Naïve Bayes Random Forest, Decision Tree, and Support Vector Machine (SVM), to train the model using an extensive dataset of historical agricultural information. The model forecasts the most appropriate crop for a specific location based on these environmental conditions.

Keywords: *Crop Recommendation System, Django-based Web Application, Gaussian Naive Bayes, Supervised Learning Algorithms, Random Forest Classifier, Decision Tree Algorithm*

List of Abbreviations

Abbreviation	Description
NPK	Nitrogen, Phosphorus, Potassium
SVM	Support Vector Machine
RF	Random Forest
DT	Decision Tree
KNN	K-nearest Neighbors
PCA	Principal Component Analysis
RFE	Recursive Feature Elimination
MAE	Mean Absolute Error
MSE	Mean Squared Error
RMSE	Root Mean Squared Error
GUI	Graphical User Interface

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CHAPTER 1

INTRODUCTION

INTRODUCTION

1.1 PREFACE

Agriculture has always been the backbone of many economies, providing sustenance, employment, and raw materials for diverse industries. As global demands rise and environmental uncertainties grow, the agricultural sector faces critical challenges, including unpredictable weather patterns, soil degradation, and inefficient crop selection practices. Traditional decision-making, often grounded in personal experience and local heuristics, is no longer sufficient to guarantee optimal yield or sustainability. In this context, integrating advanced technologies such as Machine Learning (ML) presents a transformative opportunity.

This project, titled **"Agroguide: Crop Recommendation System"**, emerges from the vision of leveraging data-driven intelligence to aid farmers in making scientifically-informed crop choices. By incorporating real-time environmental parameters and soil characteristics, and harnessing the power of supervised learning algorithms, our system aspires to enhance agricultural productivity and reduce resource wastage. This report documents our journey—from conceptualization to implementation—highlighting the methods, tools, and outcomes of our research and development efforts. It reflects our commitment to innovation in precision agriculture and the belief that technology can empower even the smallest of farming communities with the knowledge needed to thrive in a data-centric era.

In recent years, agriculture has witnessed a significant shift from traditional practices to technology-driven solutions. With the increasing challenges posed by climate change, soil nutrient imbalance, and inefficient farming techniques, there is an urgent need to adopt innovative approaches to enhance crop productivity and sustainability. This project, Agroguide: Crop Recommendation System Using Machine Learning, was undertaken as a response to these evolving needs.

1.2 MOTIVATION

Agriculture remains the primary source of livelihood for a large portion of the population in India and many other developing countries. However, despite its importance, farmers often face numerous challenges, especially when it comes to choosing the right crop to cultivate. With unpredictable weather patterns, fluctuating rainfall, and varying soil conditions, the traditional method of relying on past experiences or local advice is no longer sufficient.

As students of Computer Science, we were eager to apply our technical skills to a domain where our work could create real social impact. Agriculture presented a compelling field where modern technologies like Machine Learning and Artificial Intelligence could bring revolutionary changes. Our motivation stemmed from the belief that innovation should not only be theoretical but should reach those who need it most—like the farming communities who lack access to expert agricultural guidance.

With the growing focus on precision agriculture and sustainable resource use, we recognized the importance of developing tools that promote efficient farming methods. Our motivation was further fueled by the environmental aspect of the problem

1.3 PROBLEM STATEMENT

- Lack of Data-Driven Crop Selection Tools
- Difficulty in Real-Time Agricultural Decision Making
- Limited Integration of Nutrient Management with Crop Recommendation
- Inadequate Scalability and Personalization in Existing Systems

1.4 OBJECTIVES

1) To Enhance Agricultural Decision-Making.
2) To Compare Machine Learning Models for Accuracy.
3) To select machine learning algorithm for crop prediction.
4) To implement a web-based platform using Django.
5) To implement NPK recommendation module.
6) To Provide detailed information on the optimal conditions required for the recommended crop.

1.5 SCOPE OF PROJECT

- Predicts suitable crops based on soil and environmental factors (N, P, K, pH, temperature, humidity, rainfall).
- Uses machine learning algorithms like Random Forest, Decision Tree, Naive Bayes, and SVM.
- Implemented as a web application using Django for easy accessibility.
- Designed for use by farmers, agricultural experts, and institutions.
- Aims to improve crop selection, increase yield, and reduce resource wastage.
- Scalable for future integration with IoT, mobile apps, and cloud data.
- Promotes sustainable and data-driven agriculture.

1.6 ORGANIZATION OF PROJECT

Chapter 1 – Introduction:
Provides an overview of the problem, motivation, objectives, and the significance of the project.

Chapter 2 – Literature Review:
Reviews existing work and research related to crop recommendation systems and machine learning techniques in agriculture.

Chapter 3 – Methodology:
Describes the system architecture, algorithms used, and the overall design strategy of the project.

Chapter 4 – Implementation:
Details the development of the system including data set preprocessing, algorithm training, and integration using Django.

Chapter 5 – Results and Discussion:
Presents the output of various models, compares performance, and discusses the effectiveness of the system.

Chapter 6 – Conclusion and Future Scope:
Summarizes the project outcomes and suggests possible improvements and extensions for future development.

References :
Lists all the sources used in the project and includes additional supporting materials like screenshots, code snippets, or diagrams.

CHAPTER 2

LITERATURE REVIEW

LITERATURE REVIEW

The study referenced in this paper investigates the use of multiple machine learning models for crop recommendation, focusing on their ability to predict suitable crops based on various agricultural conditions. The authors compare three distinct algorithms, ultimately identifying the Random Forest (RF) model as the most effective in delivering accurate recommendations. The research demonstrates that RF outperforms other models in terms of prediction accuracy, making it a reliable tool for supporting farmers in selecting the most appropriate crops under specific environmental and soil conditions. [1]

The finest crop for an agricultural land by considering the input requirements like Rainfall, NPK nutrients, Soil PH, Humidity and Temperature. The proposed method predicts the future yield of the agricultural land using various supervised machine learning techniques, it also uses algorithms like KNN, Decision Tree, Support Vector Machine to recommend the appropriate crop for the agricultural land. This method helps farmers to get maximum yield and profit [2].

The Naive Bayes method outperformed the other three of the four machine learning algorithms used. The second set of information consists of information on yield projection. The Random Forest algorithm outperformed the other two machine learning algorithms. These algorithms can be utilized to build a web application where we can employ these models for in-depth analysis of real-world data [3].

This paper presents a crop recommendation system that incorporates five essential factors namely NPK values, temperature, humidity, pH, and rainfall. The purpose of this research is to predict the appropriate crop based on these conditions. In order to achieve this goal, machine learning algorithms, Gradient Boosting Regressor and XG-Boost have been used for rainfall prediction and crop recommendation respectively [4].

Comprehensive analysis of crop recommendation methodologies using soil property data. We explore various approaches, including machine learning algorithms and expert systems, to develop accurate and efficient crop recommendation systems. The integration of soil properties and their impact on crop growth and yield is examined to ensure the compatibility between recommended crops and soil conditions [5].

The paper by Gokila Brindha P. et al. (2023), titled "Crop Recommendation Systems using Machine Learning Algorithms," presents a comprehensive study on the application of various machine learning algorithms to enhance crop recommendation accuracy. The authors explore techniques such as Decision Trees, Random Forest, and Support Vector Machines (SVM), analyzing their performance in predicting the most suitable crops based on environmental and soil parameters like pH, temperature, humidity, and rainfall. The study emphasizes the importance of data preprocessing and feature selection to improve model efficiency. The paper concludes that machine learning, when integrated with reliable agricultural datasets, can significantly assist farmers in making informed crop choices, thereby boosting productivity and promoting sustainable farming. The authors also highlight potential areas for improvement, including the integration of real-time data and IoT technologies to further refine the recommendation process [6].

The paper by ManendraSai et al. (2023), titled "Machine Learning Techniques Based Prediction for Crops in Agriculture," investigates the use of machine learning models to predict suitable crops based on various agricultural parameters. The authors evaluate algorithms like Decision Tree, K-Nearest Neighbors (KNN), and Naive Bayes for their effectiveness in crop prediction. Their study demonstrates that machine learning can enhance agricultural decision-making by accurately recommending crops suited to specific soil and climatic conditions. The paper concludes that integrating these techniques can lead to improved crop yields and support farmers in adopting data-driven agricultural practices [7].

CHAPTER 3

METHODOLOGY

METHODOLOGY

3.1 Data Collection and Preprocessing

Data Collection and Preprocessing form the foundation of any machine learning-based crop recommendation system. The data used typically includes essential agricultural parameters such as Nitrogen (N), Phosphorus (P), Potassium (K), PH level, Temperature, Humidity, and Rainfall. These values are collected from various sources including public datasets (like Kaggle or government databases), real-time sensor data from IoT devices, and historical agricultural records. High-quality, diverse data ensures the model can make accurate predictions across a range of soil and environmental conditions.

Once the data is collected, it undergoes preprocessing to make it suitable for machine learning algorithms. This involves cleaning the data by handling missing values, removing duplicates, and standardizing units across all records. Outliers that could skew model results are identified and either corrected or removed. Numerical features are scaled using techniques like Min-Max Scaling or Standardization to ensure consistent input ranges, especially for models like SVM or KNN. Categorical variables, such as crop names, are encoded into numerical values using label encoding. Finally, the dataset is split into training and testing sets to train the model effectively and evaluate its performance. This meticulous preprocessing step enhances the system's accuracy, reliability, and applicability in real farming scenarios.

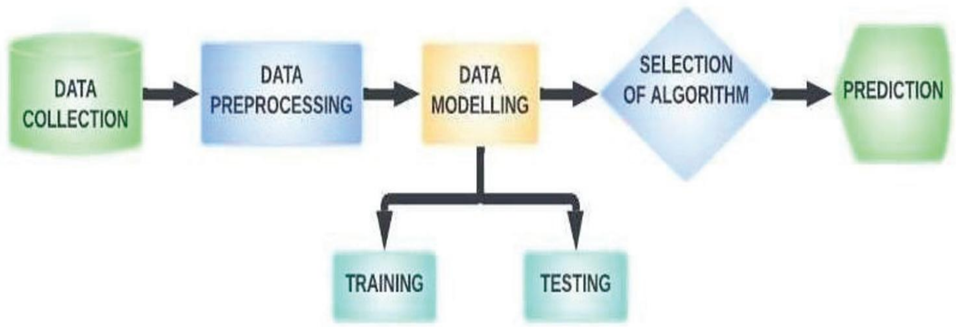


Figure 3.1.Proposed System

3.2 Data Cleaning

Handling Missing Values:

Missing values in a dataset can occur due to various reasons such as data entry errors, equipment malfunctions, or skipped survey questions. These missing values can negatively impact the performance of machine learning models. Common techniques to handle missing values include deletion, imputation, and using algorithms that support missing data. Deletion involves removing rows or columns with missing values, but it may lead to data loss. Imputation is more effective and includes replacing missing values with the mean, median, or mode of the column, or using more advanced methods like K-Nearest Neighbors or regression models to predict missing values. The choice of method depends on the nature and amount of missing data and the importance of the feature.

Label Encoding:

Label encoding is a technique used to convert categorical variables into numerical format so that machine learning algorithms can process them. In label encoding, each unique category in a feature is assigned an integer value. For example, the categories "red", "green", and "blue" can be encoded as 0, 1, and 2, respectively. This method is simple and memory-efficient but can introduce unintended ordinal relationships between the categories.

3.3 Exploratory Data Analysis

Exploratory Data Analysis (EDA) is the process of examining a dataset to summarize its main characteristics, often using visual methods. The goal is to gain insights, detect patterns, spot anomalies, and test assumptions before applying machine learning models. One of the first steps in EDA is understanding the data structure through summary statistics such as mean, median, mode, standard deviation, and data types. Data visualization plays a key role in EDA. Histograms and box plots help understand the distribution of numerical variables and detect outliers. Scatter plots are useful for identifying relationships or correlations between two variables, while bar plots and pie charts are ideal for analysing categorical data.

Correlation matrices and heatmaps are also widely used in EDA to study the relationships between multiple features at once, helping to detect multicollinearity or influential variables. For categorical data, cross-tabulations and group-by operations allow deeper insights into how different categories interact. Dimensionality reduction techniques like PCA (Principal Component Analysis) can be used to visualize high-dimensional data. EDA also includes checking for missing values and duplicates, understanding feature distributions, and identifying skewed data. Overall, EDA is an essential step that helps in refining features, selecting appropriate models, and ensuring data quality for accurate predictions.

3.4 Feature Selection

Feature selection is the process of identifying and selecting the most relevant features from a dataset to improve model performance, reduce overfitting, and decrease computation time. It helps in building simpler and more interpretable models. Feature selection methods are broadly classified into three categories: filter, wrapper, and embedded methods. Filter methods evaluate the relevance of features using statistical tests like chi-square, correlation coefficient, or mutual information, independent of any machine learning model. Wrapper methods, on the other hand, use a predictive model to evaluate feature combinations and select the best-performing subset. Techniques like recursive feature elimination (RFE) fall under this category but are more computationally expensive. Embedded methods perform feature selection as part of the model training process. Examples include Lasso (L1 regularization) and decision tree-based algorithms like Random Forest, which provide feature importance scores. The choice of method depends on the dataset size, model type, and computational resources. Good feature selection can lead to more accurate models, easier debugging, and faster predictions.

3.5 Model Selection

Several supervised learning algorithms are evaluated, including:

3.5.1. Naive Bayes:

Naive Bayes is a simple yet powerful classification algorithm based on Bayes' Theorem, which calculates the probability of a class given a set of features. It assumes that all features are independent of each other, which is a "naive" assumption, hence the name. Despite this simplification, Naive Bayes performs well in many real-world applications, especially in text classification problems like spam detection, sentiment analysis, and document categorization. The algorithm works by calculating the prior probability of each class and the likelihood of the input features given each class, then uses Bayes' Theorem to compute the posterior probability for classification.

There are several types of Naive Bayes classifiers: Gaussian Naive Bayes is used when features follow a normal distribution, Multinomial Naive Bayes is suitable for discrete features like word counts, and Bernoulli Naive Bayes is ideal for binary/boolean features. Naive Bayes is highly efficient and works well with large datasets. However, its main limitation is the strong independence assumption, which may not hold true in many cases, potentially affecting accuracy. Still, it remains a popular choice due to its speed, simplicity, and surprisingly good performance.

3.5.2. Support Vector Machine (SVM):

A Support Vector Machine (SVM) is a supervised machine learning algorithm primarily used for classification tasks, though it can also be applied to regression. The main goal of SVM is to find the optimal hyperplane that best separates data points of different classes in a high-dimensional space. The hyperplane is the decision boundary that divides the data into distinct classes, and the algorithm aims to maximize the margin, which is the distance between the hyperplane and the nearest data points, known as support vectors. These support vectors are crucial because they directly influence the position of the hyperplane.In cases where the data is not linearly separable, SVM uses a technique called the kernel trick to map the data into a higher-dimensional space, allowing for a non-linear separation. SVM is highly effective in high-dimensional spaces and is known for its robustness against overfitting, especially in complex datasets. However, it can be computationally expensive, especially with large datasets, and requires careful tuning of parameters like the kernel and regularization factor. Despite its power, SVM models can be difficult to interpret, particularly when using non-linear kernels.

3.5.3. Decision Tree:

Decision Tree is a supervised machine learning algorithm used for both classification and regression tasks. It models data by splitting it into subsets based on the most significant feature, creating a tree-like structure. Each internal node represents a decision based on a feature, and each leaf node represents a predicted outcome. The tree is constructed by recursively choosing the feature that best splits the data at each step, typically using metrics such as Gini impurity or entropy (for classification) and variance (for regression). Decision trees are easy to understand and interpret, making them popular for tasks where model transparency is important. However, they can be prone to overfitting, especially with complex data, as they tend to create very deep trees that capture noise in the data. To mitigate this, techniques like pruning (removing parts of the tree that don't improve accuracy) or using ensemble methods like Random Forests can be applied. Despite their simplicity, decision trees provide a solid foundation for many machine learning algorithms.

3.5.4. Logistic Regression:

Logistic Regression is a statistical method used for binary classification tasks, where the goal is to predict one of two possible outcomes. Despite its name, logistic regression is a classification algorithm, not a regression algorithm. It works by modeling the probability that a given input belongs to a particular class using the logistic function (also known as the sigmoid function), which maps any input to a value between 0 and 1. The model is trained by finding the best-fitting parameters that minimize the difference between the predicted probabilities and the actual class labels. Logistic regression is a simple yet powerful algorithm that is easy to implement and interpret, making it a popular choice for tasks like spam detection or medical diagnoses.

Table I : Algorithm Accuracy

ALGORITHM	ACCURACY (%)
NB	97
KNN	90
SVM	92
LR	90
DT	90.6

3.6 Model Training and Evaluation

After selecting the model, the next step is to train it on the historical data. Training involves:

- **Splitting Data:** The dataset is divided into training and testing sets (commonly a 70/30 or 80/20 split).
- **Model Training:** The model learns from the training set by adjusting its internal parameters to minimize prediction errors. For supervised models, this is typically done by optimizing a loss function (e.g., cross-entropy for classification or mean squared error for regression).
- **Cross-Validation:** To ensure that the model generalizes well, cross-validation (e.g., k-fold cross-validation) is often used. This helps avoid overfitting by training and testing the model multiple times on different data splits

After training the model, it is essential to evaluate its performance using the testing set or through cross-validation. We use Evaluation Metrics.

3.7 Evaluation Metrics:

- **Accuracy**: Measures the proportion of correctly classified crops to total predictions.
- **Precision**: Measures how many of the recommended crops are actually correct (useful when false positives are costly).
- **Recall**: Measures how many of the correct crops were recommended (important if missing a good crop recommendation is critical).
- **F1-Score**: A balance between precision and recall, especially useful when class distribution is imbalanced.
- **Confusion Matrix**: A matrix that shows the true positives, false positives, true negatives, and false negatives, helping to understand the model's performance across different classes.
- **Mean Absolute Error (MAE)**: Measures the average of the absolute errors between predicted and actual values.
- **Mean Squared Error (MSE)**: Measures the average of the squared errors. It gives more weight to larger errors, which is useful when large errors are particularly undesirable.

- **Root Mean Squared Error (RMSE)**: The square root of the MSE, providing error magnitude in the same units as the target variable.
- **R-squared**: Measures how well the model explains the variance in the data. An R-squared value closer to 1 indicates a better fit.

3.8 Prediction and Recommendation

What is Prediction?

In the context of crop recommendation systems, **prediction** refers to forecasting the most suitable crop(s) based on the given features (inputs) such as soil properties, climate conditions, and geographical factors. Machine learning algorithms are trained on historical data to predict the likely success of different crops in a given area.

Key Steps in Prediction

Input Features: The system takes several input features to predict the best crop for a particular area. These features might include:

- **Soil Properties**: PH, texture, fertility (levels of nitrogen, phosphorus, potassium), organic content, and moisture.
- **Climate Factors**: Temperature, rainfall, humidity, and seasonal changes.
- **Geographical Information**: Elevation, proximity to water bodies, latitude, and longitude.
- **Historical Crop Yield Data**: Data on previous crops grown in the area and their yields.
- **Farming Practices**: Use of irrigation, fertilizers, pest management, and crop rotation practices.

Model Selection: A suitable machine learning model is chosen to make predictions based on the input features. Common models for prediction include:

- **Regression Models** (if predicting continuous outcomes like crop yield): Linear regression, decision tree regression, and support vector regressor (SVR).
- **Classification Models** (if predicting discrete outcomes like the type of crop): Decision trees, random forests, logistic regression, k-nearest neighbors (KNN), and neural networks.

Model Training: The model is trained using historical data (features and their corresponding crop outcomes). The model learns the relationships between the input features and the crop outcomes (e.g., which crops thrive under specific conditions).

For example, if the temperature is between 25-30°C and the soil is rich in nitrogen, the model might predict that crops like tomatoes or maize are optimal.

- **Prediction Process**: After training, the model makes predictions based on new input data. For instance, if a farmer inputs data for their Soil Properties, Temperature the model predicts which crop would most likely grow successfully in those conditions.
- **Evaluating Prediction Accuracy**: The model's prediction accuracy is assessed using evaluation metrics like Mean Squared Error, Root Mean Squared Error, Mean Absolute Error, Accuracy**,** Precision**,** Recall**,** and F1-Score**.**

Example:

Imagine a farmer has data about their land: soil pH of 6.5, average temperature of 28°C, and annual rainfall of 900 mm. The trained prediction model would assess this data against historical data and predict which crops are most suitable, such as maize, tomatoes, or peppers, based on factors like temperature tolerance, soil pH, and water requirements.

What is Recommendation?

Recommendation is the process of suggesting the best crops for a given environment based on the predictions made by the system. The recommendation system outputs a list of crops that are most likely to thrive in the specific conditions input by the user.

Key Steps in Recommendation

Recommendation System Design: The recommendation system can use either a **classification** or **ranking** approach:

- **Classification-Based Recommendation**: The system classifies crops into categories based on environmental suitability and recommends the top classes.
- **Ranking-Based Recommendation**: After generating predictions, the system ranks the crops by their suitability for the given conditions and recommends the top-ranked crops.

Personalized Recommendations: Some systems use **collaborative filtering** or **content-based filtering** to personalize recommendations:

- **Collaborative Filtering**: This method relies on the preferences and behaviors of similar farmers. For example, if farmers with similar soil conditions and climates have had success with certain crops, the system recommends those crops

- **Content-Based Filtering**: In this approach, recommendations are made based on the characteristics of the crops themselves (e.g., soil type, temperature range) and how they match the input conditions.

Incorporating Expert Knowledge: In addition to data-driven predictions, expert agricultural knowledge can be integrated into the recommendation system. For example, the system might incorporate local knowledge about specific crops that grow well in particular regions or provide guidance on pest management and disease control.

1. **Ranking the Crops**: Once predictions are made, the system ranks crops based on their likelihood of success. For example:
   The system might provide a list of crops ranked by their expected yield, water usage, or resistance to local pests. The crops are ranked in terms of factors like climate tolerance, soil compatibility, and water requirements.

2. **User Interaction**: Recommendations are often presented to the user (e.g., a farmer) through an interactive interface. The farmer can filter or adjust recommendations based on their specific needs or preferences, such as high yield, low water usage, or resistance to certain diseases.

3. **Continuous Learning**: As more data becomes available (e.g., new farming seasons, crop yields), the recommendation system can continuously learn and refine its suggestions to stay up-to-date with the latest farming trends and results.

Example:

A farmer inputs data about their farm: soil is loamy with a pH of 6.8, temperatures are between 25-30°C, and the region has moderate rainfall. Based on this, the recommendation system might suggest:

Top Recommendations: Maize, tomatoes, beans, and peppers.

Additional Recommendations: The system could rank these crops based on factors like expected yield, market demand, and resistance to common pests in the region.

3.9 Web-Based Interface Development

Web-Based Interface Development plays a vital role in making the crop recommendation system accessible and easy to use for farmers and agricultural stakeholders. For this purpose, the Django framework is utilized due to its robustness, scalability, and built-in administrative features. The web application provides a clean and interactive interface where users can manually input key agricultural parameters such as soil nutrients (N, P, K), pH, temperature, humidity, and rainfall. In more advanced implementations, data can also be automatically fetched from sensors or IoT devices integrated into the system, enabling real-time input without manual entry.

The frontend of the web application is designed with simplicity in mind, often using HTML, CSS, and JavaScript to ensure usability even for non-technical users. Once the user submits the input data, it is sent to the Django backend, where the trained machine learning model processes the information. The backend then returns an instant prediction of the most suitable crop based on the input conditions. Additionally, the platform can provide detailed insights such as the ideal growing conditions for the recommended crop and suggested fertilizer usage. This real-time, user-friendly system bridges the gap between complex machine learning models and practical, on-field farming decisions, empowering farmers to make data-driven agricultural choices.

3.10 NPK Recommendation Module

The **NPK Recommendation Module** is an essential extension of the crop recommendation system, aimed at guiding farmers in maintaining soil fertility and ensuring optimal crop growth. This module functions by analyzing the nutrient requirements of the crop recommended by the system and comparing it with the existing NPK (Nitrogen, Phosphorus, Potassium) levels provided by the user. Based on this comparison, the module calculates and suggests the precise amount of each nutrient needed to meet the ideal conditions for that specific crop. This helps in determining the right type and quantity of fertilizers to be applied.

The module leverages a database of agronomic standards and crop-specific nutrient demands to generate accurate recommendations. For example, if a crop requires a high nitrogen content but the soil test shows a deficiency, the system will suggest nitrogen-rich fertilizers like urea or ammonium nitrate in the right dosage. This targeted approach minimizes overuse or misuse of fertilizers, which not only saves costs for the farmer but also prevents soil degradation and environmental harm. By incorporating this module, the crop recommendation system not only advises what to grow but also how to grow it more effectively, promoting sustainable and resource-efficient farming practices.

3.11 System Output and Feedback

The **System Output and Feedback** component is the final and crucial stage of the crop recommendation system, where users receive actionable insights based on the input data. Once the machine learning model processes environmental and soil parameters, the system outputs a list of the most suitable crop(s) for cultivation under the given conditions. Along with the crop recommendation, the system provides detailed information on ideal environmental requirements such as temperature, humidity, rainfall, and soil pH, enabling farmers to better understand the growing conditions needed for optimal yield. Additionally, the system integrates fertilizer guidance, specifically through the NPK recommendation module, which informs users about the required nutrient levels and appropriate fertilizers for the suggested crop.

To enhance user engagement and system adaptability, a feedback mechanism is incorporated. Farmers and agricultural professionals can share their experiences or suggest improvements based on the recommendations they receive. This feedback is valuable for continuously refining the system by identifying patterns of success or failure in specific regions or conditions. Over time, as more feedback is collected and analyzed, the system becomes smarter and more accurate, contributing to a cycle of learning and improvement. Ultimately, this feature ensures the system remains relevant, reliable, and user-centric in real-world agricultural practices.

CHAPTER 4

IMPLEMENTATION

IMPLEMENTATION

The Implementation involves key components such as

4.1 Data Collection:

Gather historical agricultural data from reliable sources. This typically includes features like temperature, humidity, nitrogen (N), phosphorus (P), potassium (K) levels, and previous yield data, so we apply data collection here.

Python Code

```
import pandas as pd
d = pd.read_csv("Crop_recommendation.csv")
```

4.2 Data Preprocessing:

- **Handling missing values:**

  Fill in missing values using techniques such as mean, median, or interpolation, depending on the nature of the data. For example, numerical values like temperature or humidity can be imputed with the mean, while categorical values like soil type can use the mode.

- **Label Encoding:**

  Convert categorical features (such as *soil type*, *crop type*, or *season*) into numeric form using label encoding. Label encoding assigns each unique category a numeric value.

  Implementing Label Encoding on the Target Variable:

  In a crop recommendation system, the target variable is the crop (e.g., rice, wheat, maize, etc.), which is categorical. Machine learning models require the target variable to be in numeric form, so we apply label encoding here.

  ```
  from sklearn.preprocessing import LabelEncoder
  le=LabelEncoder()
  c['crop_num']=le.fit_transform(c['label'])
  c['crop_num'].value_counts()
  ```

  This process allows the model to interpret the crop labels numerically while maintaining a mapping that can later be converted back to actual crop names for recommendations.

4.3 Feature Selection:

Feature selection is a crucial step in developing a crop recommendation system, as it helps identify the most relevant features (input variables) that influence the model's prediction accuracy. In this project, the goal is to recommend the most suitable crop based on environmental and soil conditions.

Feature Selection Techniques:

- Correlation Matrix:

  A correlation matrix is a table used to measure the strength and direction of linear relationships between multiple numerical features in a dataset. Each cell in the matrix displays a correlation coefficient ranging from **-1 to +1**. A value of **+1** indicates a perfect positive correlation, **-1** indicates a perfect negative correlation, and **0** means no correlation. It helps identify which features are strongly related, potentially redundant, or independent. In machine learning, analysing a correlation matrix is useful for feature selection, as it helps remove multicollinearity and ensures that only the most informative variables are used for model training.

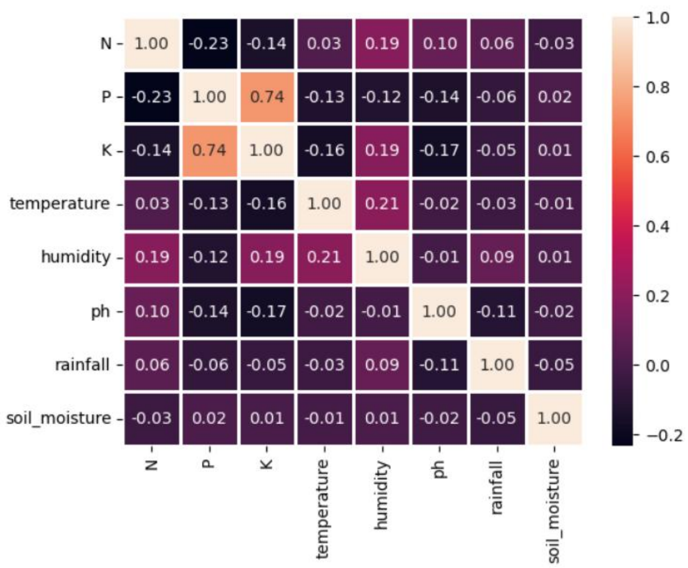


Figure 4.3.1: Correlation Matrix

4.4 Splitting the Dataset:

Splitting the dataset is a crucial step in building a machine learning model. It involves dividing the available data into two or more subsets—typically a training set and a testing set. The training set (usually 70–80% of the data) is used to teach the model to learn patterns and relationships. The testing set (remaining 20–30%) is used to evaluate the model's performance on unseen data. This process ensures that the model generalizes well and doesn't just memorize the training data. Sometimes, a **validation set** is also used to fine-tune hyperparameters and prevent overfitting before final testing.

Here's an example using train_test_split from Scikit-learn in Python:

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

This code splits the dataset into training and testing sets, ensuring the model is evaluated on data it hasn't seen before.

4.5 Model Selection and Training

In a Crop Recommendation System, Gaussian Naive Bayes (GNB) is chosen for its simplicity, speed, and effectiveness with small datasets and continuous features like temperature, humidity, and soil nutrients. GNB assumes feature independence and a normal distribution, making it suitable for agricultural data. During model selection, GNB outperforms others by achieving higher accuracy and lower training time. The model is trained on features such as soil type, crop type, and nutrient levels, then predicts the most suitable crop. Cross-validation is used to evaluate performance, ensuring robustness before deploying the model for real-time recommendations.

Python Code

```
from sklearn.naive_bayes import GaussianNB
# Initialize and train model
gnb = GaussianNB()
gnb.fit(X_train, y_train)
# Predictions
y_pred = gnb.predict(X_test)
```

4.6 Model Evaluation

Model evaluation in a Crop Recommendation System assesses the model's accuracy, precision, recall, and F1-score using test data. Tools like confusion matrix and cross-validation help verify performance. This ensures the model reliably predicts the best crop based on soil, climate, and nutrient features before real-world deployment.

- **Accuracy Score:**

  Accuracy measures the proportion of correct predictions out of all predictions made. It gives an overall idea of the model's performance.

  Accuracy = (Total Number of Predictions/Number of Correct Predictions) ×100

  Python Code

  from sklearn.metrics import accuracy_score

  accuracy = accuracy_score(y_test, y_pred)

- **Precision Score:**

  Precision Score measures the accuracy of positive predictions — it tells us what proportion of predicted positive results are actually correct. It's especially important in cases where false positives are costly. Precision is calculated as:

  Precision = True Positives / (True Positives + False Positives)

  Python Code:

  from sklearn.metrics import precision_score

  precision = precision_score(y_true, y_pred)

- **F1-Score:**

  F1 Score is a metric that combines precision and recall into a single value, especially useful for imbalanced datasets. It is the harmonic mean of precision and recall, giving a better measure of a model’s accuracy in classification tasks.

  F1_Score=2×(Precision+Recall)/Precision×Recall

  from sklearn.metrics import f1_score

  f1_score(y_true, y_pred)

- **Recall Score:**

  Recall Score measures the ability of a model to correctly identify all relevant instances (true positives) out of actual positives. It is especially useful in imbalanced datasets where missing positive cases is critical. A higher recall means fewer false negatives.

Recall = (True Positives (TP)+False Negatives (FN))/True Positives (TP)

Here's an example using recall_score from scikit-learn:

from sklearn.metrics import recall_score

recall_score(y_true, y_pred)

- **Classification Report:**

  A classification report provides a detailed summary of a model's performance using metrics like precision, recall, F1-score, and support for each class (e.g., crop). It helps evaluate how well the model predicts each category, highlighting strengths and weaknesses, especially in multi-class classification like crop recommendation systems.

  Python Code**:**

  from sklearn.metrics import classification_report

  report = classification_report(y_test, y_pred)

	precision	recall	f1-score	support
0	1.00	1.00	1.00	23
1	1.00	1.00	1.00	21
2	1.00	1.00	1.00	20
3	1.00	1.00	1.00	26
4	1.00	1.00	1.00	27
5	1.00	1.00	1.00	17
6	1.00	1.00	1.00	17
7	1.00	1.00	1.00	14
8	0.92	1.00	0.96	23
9	1.00	1.00	1.00	20
10	1.00	1.00	1.00	11
11	1.00	1.00	1.00	21
12	1.00	1.00	1.00	19
13	1.00	1.00	1.00	24
14	1.00	1.00	1.00	19
15	1.00	1.00	1.00	17
16	1.00	1.00	1.00	14
17	1.00	1.00	1.00	23
18	1.00	1.00	1.00	23
19	1.00	1.00	1.00	23
20	1.00	0.89	0.94	19
21	1.00	1.00	1.00	19
accuracy			1.00	440
macro avg	1.00	1.00	1.00	440
weighted avg	1.00	1.00	1.00	440

Figure 4.6.1: Classification Report

- **Confusion Matrix:**

  A confusion matrix is a table used to visualize the performance of a classification model. It shows the actual vs. predicted classifications, highlighting true positives, false positives, false negatives, and true negatives. In crop recommendation, it helps identify where the model is confusing one crop prediction with another.

Python Code:

```
from sklearn.metrics import confusion_matrix
import seaborn as sns
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(10, 8))
sns.heatmap(cm, annot=True, fmt="d", cmap="YlGnBu")
plt.title("Confusion Matrix")
plt.show()
```

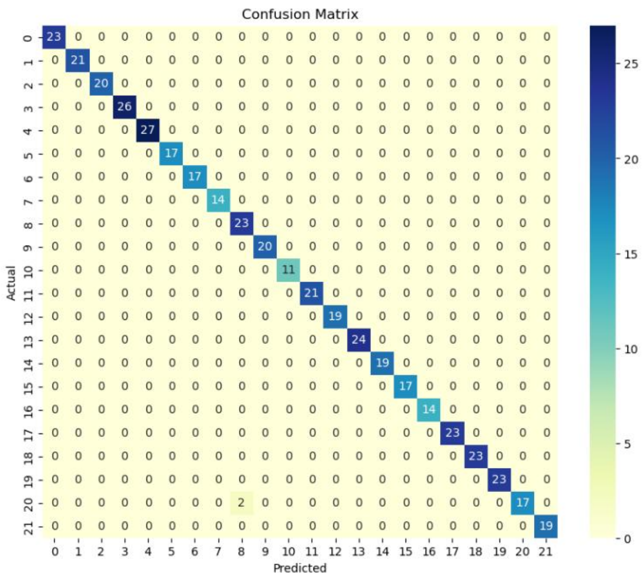


Figure 4.6.2: Confusion Matrix

4.7 NPK Recommendation Module:

The NPK (Nitrogen, Phosphorus, Potassium) Recommendation Module predicts the optimal nutrient levels required for soil based on environmental and crop-related parameters. Using the Random Forest Regressor, which is an ensemble learning method, we can build robust regression models that consider multiple decision trees to make accurate predictions. This model is trained on features like temperature, humidity, moisture, soil type, and crop type. Once trained, it can predict the required N, P, and K values for a given input, aiding farmers in balanced fertilization and boosting yield.

Python Code:

```
from sklearn.ensemble import RandomForestRegressor
rfr=RandomForestRegressor()
rfr.fit(x_train,y_train)
rfr.score(x_test,y_test)
```

4.8 Prediction and Recommendation:

In a crop recommendation system, prediction involves using a trained machine learning model to forecast the most suitable crop based on input features like temperature, humidity, nitrogen, phosphorus, and potassium levels. The system analyses patterns in historical data to make accurate predictions. Recommendation refers to suggesting the best crop to cultivate under given conditions. Once a user inputs the current environmental and soil parameters, the system predicts the ideal crop and recommends it to the farmer. This helps in increasing yield, efficient resource use, and sustainability by aligning agricultural practices with data-driven insights.

4.9 Deployment using Django:

Deploying a crop recommendation system using Django involves building a web application that allows users to input their environmental data (e.g., temperature, humidity) and receive crop recommendations. First, create a Django project and app. Use the trained machine learning model (e.g., Gaussian Naive Bayes) in the app’s views to make predictions. Then, set up URLs and forms to capture user input. The model's prediction is displayed to the user. For deployment, host the Django project on a server (like Heroku or AWS) and connect the backend with the frontend for real-time interaction.

CHAPTER 5

RESULT

AND

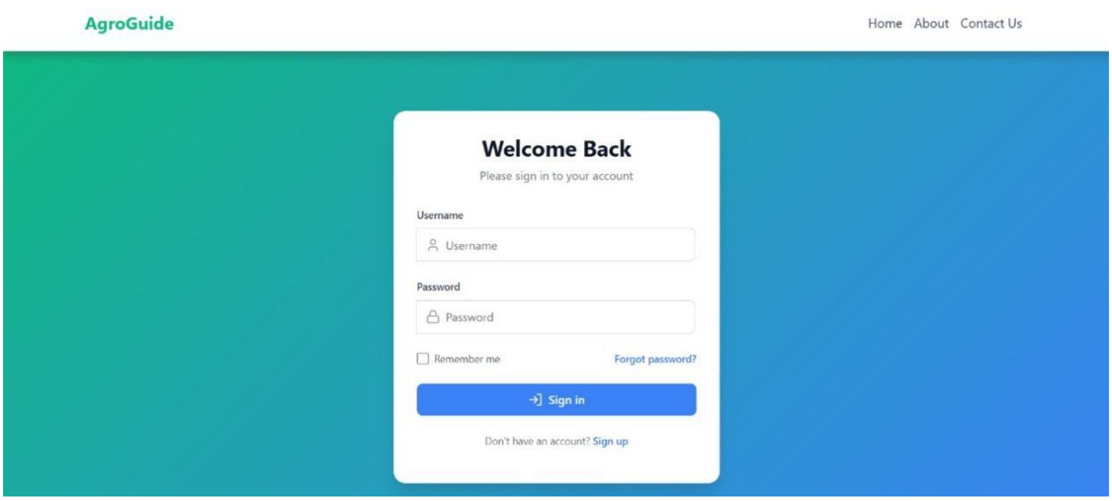
DISCUSSION

RESULT AND DISCUSSION

5.1 AUTHENTICATION:

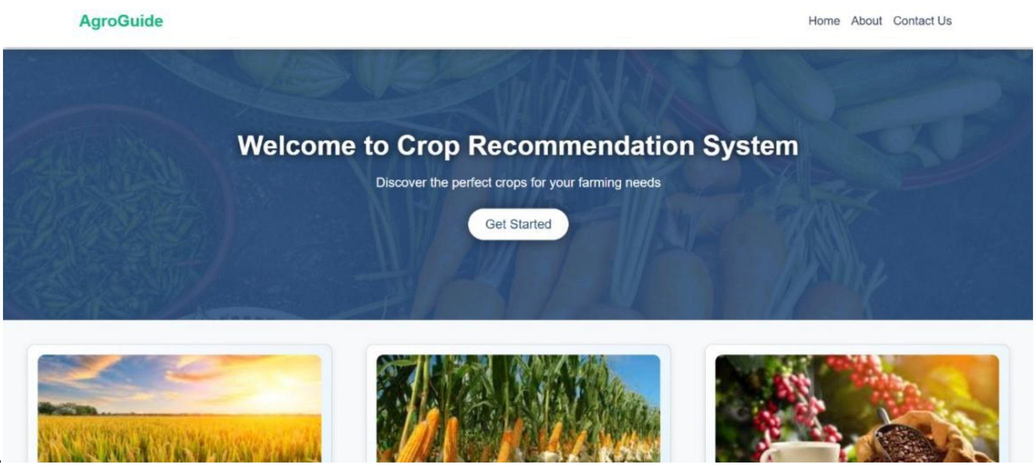
Login page

The login of the crop recommendation system provides secure user authentication, granting personalized access to crop suggestions based on user-specific data and preferences.



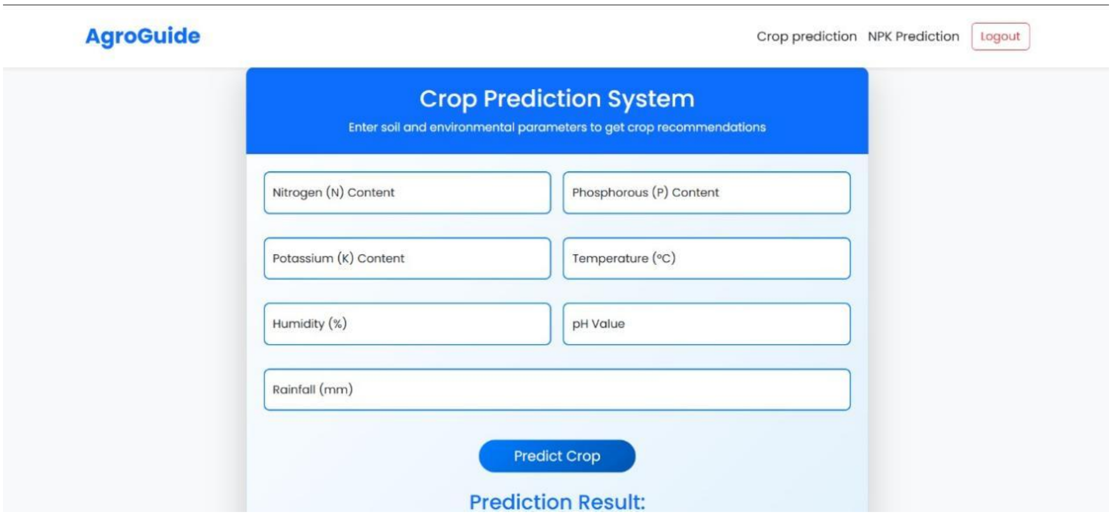
Screenshot 5.1 Authentication page

5.2 Interface: The interface of the crop recommendation system is user-friendly and visually intuitive, designed to ensure easy navigation, seamless interaction, and efficient access to all essential features for both novice and experienced users.



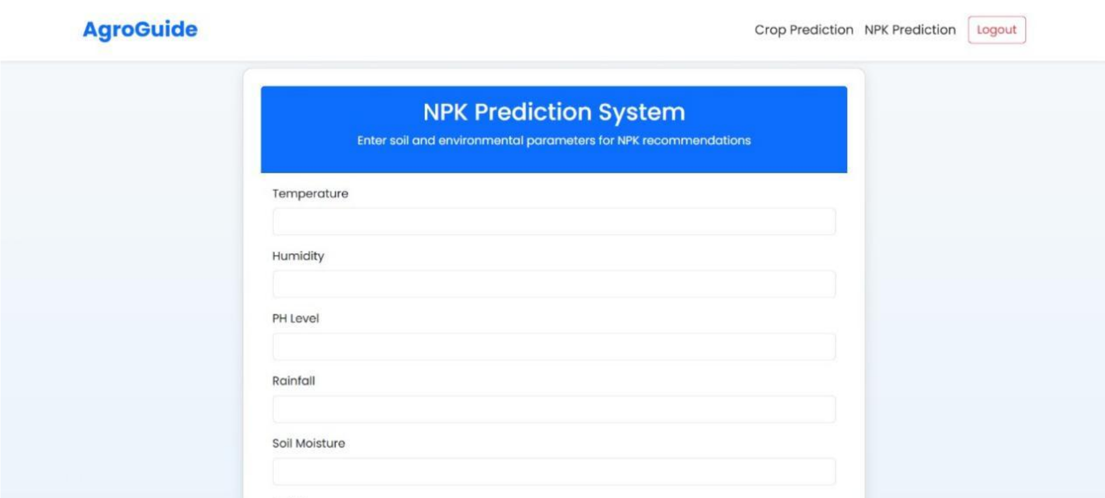
Screenshot 5.2 Interface

5.3 Crop Prediction System: The crop prediction page of the system is a dynamic and interactive web interface where users input key agricultural factors such as soil type, temperature, humidity, and nutrient levels; upon submission, the system processes this data using advanced algorithms to generate accurate crop recommendations tailored to the given conditions.

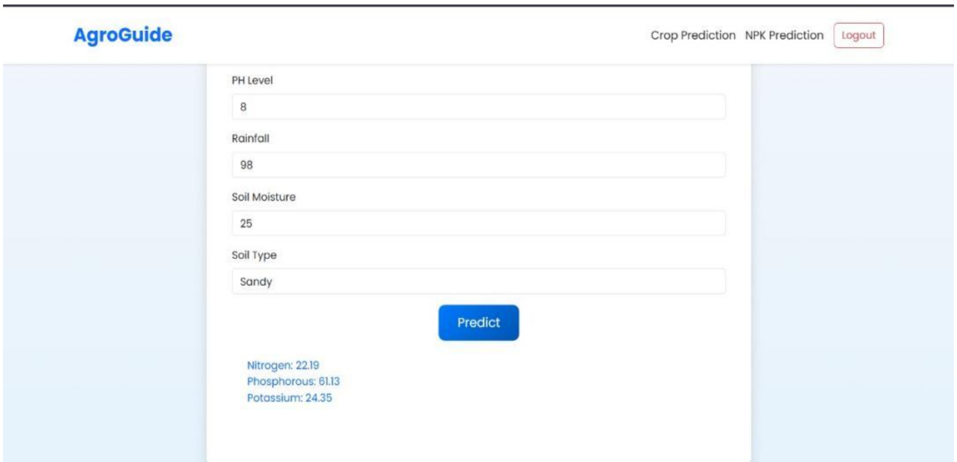


Screenshot 5.3 Crop Recommendation System

5.4 NPK Recommendation module: The NPK recommendation module analyzes soil nutrient levels—specifically nitrogen (N), phosphorus (P), and potassium (K)—provided by the user and delivers precise fertilizer suggestions to optimize soil health and enhance crop productivity based on current agricultural standards and crop requirements.



Screenshot 5.4 NPK Prediction Module

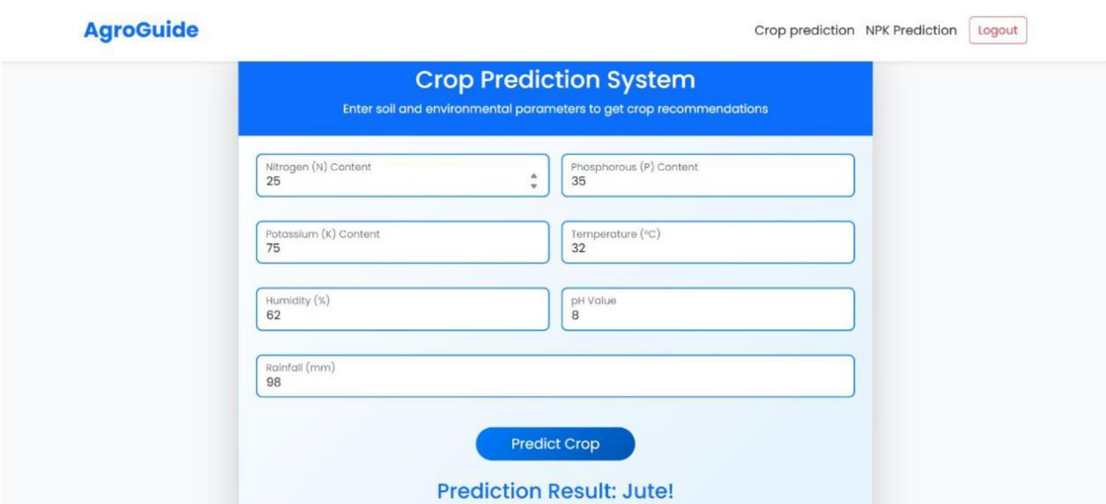


Screenshot 5.5 NPK Prediction

5.5 RESULT: The final result of the system presents users with a tailored crop recommendation along with optimal NPK values, empowering farmers to make informed decisions that enhance yield, improve soil management, and promote sustainable agricultural practices. We used Naive Bayes algorithm for prediction as we get the maximum(97%) accuracy for it.

Table II :Comparison

Metric	**Naive Bayes**	**SVM (Support Vector Machine)**
Accuracy (%)	97	91.6
Precision	0.84	0.92
Recall	0.83	0.91
F1-Score	0.83	0.91



Screenshot 5.6 Crop Prediction

CHAPTER 6

CONCLUSION

CONCLUSION

6.1 CONCLUSION

Crop recommendation systems powered by machine learning are transforming traditional agriculture by offering data-driven crop suggestions based on factors like soil type, pH, temperature, rainfall, and humidity. These systems help farmers, especially in developing regions, move beyond guesswork and make informed decisions that boost productivity and sustainability. By leveraging historical and real-time data, they ensure optimal use of resources and support food security. With the rise of mobile technology, internet access, and local language support, these systems are becoming more accessible. In the future, they are expected to evolve into intelligent platforms offering guidance on planting schedules, fertilizers, irrigation, and harvesting.

6.2 FUTURE SCOPE

The future scope of crop recommendation systems using machine learning is vast,with the potential to significantly enhance agricultural productivity, sustainability, and efficiency.

One of the most promising advancements lies in the integration of real-time data from various sources such as satellite imagery, weather forecasts, and IoT-enabled sensors. These technologies can provide critical, up-to-date insights into soil moisture levels, temperature, humidity, and rainfall, enabling machine learning models to make precise, region-specific crop recommendations

Future systems will be designed to take into account individual farmer profiles, including factors such as land size, financial constraints, local market conditions, and available resources.

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Agroguide: Crop Recommendation System Using Machine Learning

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Abstract— Agriculture is vital for the global economy, ensuring food security and supplying raw materials for various sectors. However, farmers face difficulties in selecting crops due to rapid climate changes, soil deterioration, and ineffective farming techniques. Conventional crop selection often hinges on intuition and previous experiences, which can result in reduced yie nd financial setbacks. The Crop Recommendation Syste S) introduced in this study utilizes Machine Learning (ML) algorithms along with the Django framework to help farmers make informed decisions regarding crop selection by considering environmental and soil factors.

The system is built to examine several elements, such as soil type, temperature, humidity, pH level, rainfall, and crucial soil nutrients like nitrogen (N), phosphorus (P), and potassium (K). It employs various machine learning algorithms, including Random Forest, Decision Tree, and Support Vector Machine (SVM), to train the model using an extensive dataset of historical agricultural information. The model forecasts the most appropriate crop for a specific location based on these environmental conditions.[5]

To enhance usability and implementation, the system is developed as a web application utilizing Django, a robust Python framework. This application allows users, such as farmers and agricultural specialists, to enter particular soil and climate data through an intuitive interface and receive immediate crop recommendations. Experimental findings reveal that the Random Forest algorithm surpasses other models, demonstrating greater accuracy and dependability in identifying the most suitable crop.

This research advances precision agriculture by merging machine learning methods with a flexible web-based system, which encourages sustainable farming approaches, maximizes crop yields, and minimizes resource waste. Future improvements could include real-time IoT-enabled soil monitoring, cloud storage solutions, and integration with mobile applications for broader accessibility. This system aims to equip farmers with intelligent decision-making tools, ultimately boosting agricultural productivity and economic resilience.

Keywords—Crop Recommendation System, Django based Web Application, Gaussian Naive Bayes, Supervised Learning Algorithms, Random Forest Classifier, Decision Tree Algorithm

INTRODUCTION

Agriculture plays a vital role in food production, economic security, and the livelihoods of millions around the world. Yet, the efficiency and sustainability of this sector often face challenges such as climate changes, soil deterioration, and inappropriate crop choices. Traditionally, farmers have depended on their experiences and local practices to decide which crops to grow. While this approach has proven effective to an extent, it frequently lacks accuracy, resulting in lower yields, inefficient resource use, and financial setbacks. However, with the rapid progress in technology, especially in Machine Learning (ML) and Artificial Intelligence (AI), there is an increasing opportunity to improve agricultural decision-making with data-informed strategies.

Machine learning brings robust predictive power that can sift through vast amounts of agricultural data, recognize trends, and offer suggestions based on current environmental factors. A Crop Recommendation System (CRS) harnesses these features to assist farmers in making informed decisions about which crops to sow by considering important variables like soil type, pH, nitrogen (N), phosphorus (P), potassium (K), temperature, humidity, and precipitation. By utilizing ML algorithms such as Random Forest, Decision Tree, and Support Vector Machine (SVM), this system can accurately forecast the most suitable crops for a specific area. This method not only enhances agricultural yields but also reduces resource wastage, curtailing excessive fertilizer and water usage while ensuring improved crop productivity.

To enhance accessibility and user experience, this research incorporates Django, a powerful web framework based on Python, to create an engaging web application. This platform enables farmers to enter soil and climate-related data to receive immediate crop suggestions. In contrast to traditional methods, which can be slow and may require agricultural expertise, this system offers fast, precise, and data-driven advice, giving farmers scientific insights that can improve their farming practices. Moreover, the web application is designed to be scalable, facilitating continual updates and enhancements in predictive accuracy as new data is integrated.

The introduction of a machine learning-driven Crop Recommendation System has the potential to transform precision agriculture, making farming more efficient, sustainable, and financially rewarding. By combining technology with conventional farming methods, growers can make informed crop selections, enhance soil health

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