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AI-Based Crop Recommendation

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BONAFIDE CERTIFICATE

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Certified that this is the Bonafide record of work done by the above student in the Mini Project titled " **AI-Based Crop Recommendation for Farmers** " in the subject AD23532 – PRINCIPLES OF DATA SCIENCE during the year 2025-2026

Signature of Faculty – in–Charge

Submitted for the Practical Examination held on ------------------------------

Internal Examiner

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Abstract

Agriculture plays a vital role in the economy of developing countries like India, where a large portion of the population depends on farming for their livelihood. However, farmers often face challenges in selecting the most suitable crop for cultivation due to variations in soil type, climatic conditions, and limited access to expert advice. The **AI-Based Crop Recommendation System** aims to assist farmers in making data-driven decisions by leveraging **machine learning algorithms** to recommend the most appropriate crops based on key parameters such as **soil nutrient composition (NPK values), temperature, humidity, rainfall, and pH level**.

By analyzing historical agricultural data and environmental factors, the system predicts the optimal crop that can yield the highest productivity in a given region. This intelligent approach helps reduce resource wastage, increase profitability, and promote sustainable agricultural practices. The model is trained using supervised learning techniques such as **Decision Trees, Random Forest, or Support Vector Machines**, ensuring high accuracy in predictions. The system can be integrated into a **web or mobile application**, making it easily accessible to farmers in rural areas.

In conclusion, the AI-based crop recommendation system serves as an innovative solution that bridges the gap between traditional farming and modern technology, empowering farmers with actionable insights for improved crop planning and agricultural efficiency.

Chapter 1: Introduction

1.1 Problem Statement and Explanation

Problem Statement

Farmers often struggle to decide which crop to cultivate due to the lack of proper guidance, unpredictable weather conditions, and variations in soil fertility. Traditional methods of crop selection are mostly based on experience or guesswork rather than scientific data analysis. As a result, many farmers face low crop yields, reduced profits, and sometimes complete crop failure.

There is a need for an intelligent system that can analyze multiple agricultural and environmental parameters—such as **soil nutrients (N, P, K), pH level, temperature, humidity, and rainfall**—to recommend the most suitable crop for cultivation in a particular region. This system should provide reliable, data-driven recommendations that help farmers make informed decisions, maximize productivity, and promote sustainable farming.

Explanation

Agriculture is the backbone of many developing economies, but most farmers still rely on traditional methods for crop selection. These methods do not take into account the complex relationships between soil composition, weather patterns, and crop requirements. Due to this, farmers often plant crops unsuited to their local conditions, leading to poor yields and economic loss.

The **AI-Based Crop Recommendation System** addresses this challenge by applying **machine learning algorithms** to analyze soil and climatic data. The system is trained using large datasets that include information on various crops and their ideal growing conditions. When a farmer inputs parameters such as **soil nitrogen, phosphorus, potassium content, temperature, humidity, rainfall, and pH value**, the AI model predicts the best crop to grow under those conditions.
This approach ensures **data-driven, personalized recommendations** that enhance productivity and profitability. It also contributes to **sustainable agriculture**, as it encourages

efficient use of land, water, and fertilizers. By integrating AI with agriculture, the project aims to modernize traditional farming practices and empower farmers with smart technology for better decisionmaking.

1.2 Literature Review:

1. A systematic literature review of crop recommendation systems for Agriculture

Mancer, M. (2025). *A systematic literature review of crop recommendation systems for Agriculture 4.0.* **CEUR Workshop Proceedings.** Retrieved from https://ceur-ws.org/Vol-3992/p09.pdf

This paper reviews more than a decade of global research on AI-based crop recommendation systems. It classifies studies by data source, algorithm type, and evaluation method, highlighting the trend toward integrating IoT and machine-learning technologies in precision agriculture. It also identifies current limitations, such as regional bias and lack of field-level validation, which directly inform the motivation for developing a localized AI-based crop recommendation system.

2.Applications of remote sensing in precision agriculture

Sishodia, R. P., Ray, R. L., & Singh, S. K. (2020). Applications of remote sensing in precision agriculture: A review. *Remote Sensing*, **12**(19), 3136. https://doi.org/10.3390/rs12193136

This comprehensive review from *Remote Sensing* explains how satellite and UAV imagery can improve decision-making in modern agriculture. It discusses indices such as NDVI and EVI that measure crop vigor and soil moisture. The findings support the integration of remote-sensing data into AI-based crop recommendation systems to enhance spatial accuracy and real-time monitoring.

3. A Decision Support System for Crop Recommendation Using Machine Learning

Senapaty, M. K. (2024). *A Decision Support System for Crop Recommendation Using Machine Learning. Agriculture (MDPI),* **14**(8), 1256. https://www.mdpi.com/2077-0472/14/8/1256

Senapaty's paper presents a working model of a machine-learningbased crop recommendation system that utilizes soil nutrients, pH, and weather parameters. Using Random Forest and Decision Tree algorithms, the study achieves high predictive accuracy and emphasizes user-friendly interfaces for farmers. This work provides a practical reference architecture and performance baseline for AIdriven crop advisory tools.

4. Advancing crop recommendation system with supervised Gradient Boosting

Shastri, S. (2025). *Advancing crop recommendation system with supervised Gradient Boosting. PLOS One / PMC.* https://pmc.ncbi.nlm.nih.gov/articles/PMC12264067/

Shastri explores the use of ensemble and gradient-boosting algorithms for more accurate and generalizable crop predictions. The study compares Gradient Boosting, XGBoost, and traditional classifiers, showing notable performance gains. Its results demonstrate how advanced ensemble methods can be adapted to soil-based agricultural datasets, offering guidance for model selection and optimization.

5. Crop Recommendation Dataset

Kaggle. (n.d.). *Crop Recommendation Dataset.* Retrieved from https://www.kaggle.com/datasets/atharvaingle/croprecommendation-dataset

This open dataset contains soil nutrient values (N, P, K), pH, temperature, humidity, and rainfall data linked to recommended crops. It is widely used in academic and industrial projects for training and benchmarking crop recommendation models. For this documentation, it serves as a foundational dataset for testing and validating the AI-based model.

6. **Machine learning-based intelligent crop recommendation system for smart agriculture**

Bhattacharjee, S., & Kundu, R. (2023). *Machine learning-based intelligent crop recommendation system for smart agriculture.* *International Journal of Advanced Computer Science and

Applications,* 14(5), 55-63. Presents comparative performance of Decision Tree, SVM, and Random Forest classifiers on Indian soil datasets, demonstrating the potential of AI-driven crop selection tools for farmers.

7.Comparative analysis of machine learning algorithms for crop prediction

Rawat, S., & Yadav, R. (2021). Comparative analysis of machine learning algorithms for crop prediction. *International Journal of Computer Applications, 183(10)*, 25–30.

Compares the accuracy of Random Forest, SVM, and Naive Bayes algorithms for crop prediction under varying soil and climate conditions.

8. Smart farming using AI and IoT: A future perspective
Mukherjee, A., & Dutta, R. (2023). Smart farming using AI and IoT: A future perspective. *IEEE Access, 11*, 85472–85485. https://doi.org/10.1109/ACCESS.2023.3298457

Combines IoT sensor data with AI algorithms for continuous crop monitoring and adaptive crop recommendation.

9.Machine learning techniques for smart farming

Kaur, H., & Singh, M. (2022). Machine learning techniques for smart farming: A survey. *Artificial Intelligence in Agriculture, 6,* 1–13. https://doi.org/10.1016/j.aiia.2021.12.001

Explores supervised and unsupervised ML methods in agriculture, including their performance in classification and crop suitability problems.

10. AI-powered soil health monitoring and crop recommendation system

Tripathi, S., & Chouhan, D. S. (2023). AI-powered soil health monitoring and crop recommendation system. *Journal of Artificial Intelligence Research and Development, 5(2),* 44–52.

Focuses on integrating soil sensors with AI models for real-time decision-making in sustainable farming.

1.3 Existing System

In the existing agricultural practice, farmers typically select crops based on **traditional knowledge**, **experience**, and **seasonal trends** rather than on precise data analysis. Crop choice is influenced by factors such as local weather patterns, soil texture, water availability, and market prices, but these are often judged **subjectively** or through **manual observation**, leading to suboptimal productivity and resource use.

Most existing systems or government portals provide only **generalized recommendations**, such as sowing seasons or crop calendars for broad regions. They do not offer **personalized crop recommendations** for specific soil compositions or micro-climates. In many cases, farmers rely on **agricultural officers or extension services**, which can be inconsistent or delayed due to limited manpower and accessibility.

Furthermore, the existing systems lack **integration of advanced technologies** like **machine learning, IoT, and data analytics**. Data such as soil nutrients (N, P, K), pH, temperature, humidity, and rainfall are either not recorded regularly or not analyzed efficiently. As a result:

- Crop yield is unpredictable and may be lower than potential.
- Fertilizer and water resources are not optimally utilized.
- The system does not adapt to **climate change impacts** or **regional variability**.
- Farmers lack an **automated decision-support mechanism** for choosing profitable and sustainable crops.

In summary, the existing system is largely **manual, static, and experience-based**, with limited use of scientific data or AI-driven insights. This creates a strong need for an **AI-based Crop Recommendation System** that can process large agricultural datasets and provide **personalized, data-driven suggestions** for farmers.

Proposed System

The **AI-Based Crop Recommendation System** is designed to overcome the limitations of the traditional, experience-driven approach by utilizing **artificial intelligence (AI)** and **machine learning (ML)** algorithms to provide **personalized crop recommendations** for farmers. This system aims to enhance agricultural productivity, optimize resource utilization, and promote sustainable farming practices.

In the proposed system, data from multiple sources such as **soil sensors**, **weather stations**, and **agricultural databases** are collected and processed. Key input parameters include **soil nutrients (Nitrogen, Phosphorus, Potassium)**, **soil pH**, **temperature**, **humidity**, and **rainfall**. These inputs are analyzed by an AI model trained on historical datasets (e.g., from Kaggle or government data portals) to predict the most suitable crops for a given set of conditions.

The system employs **machine learning algorithms** such as **Random Forest**, **Decision Tree**, or **Gradient Boosting**, which are capable of identifying complex patterns in the data. The model predicts the best crops that can yield maximum productivity under given environmental and soil conditions. Additionally, the system can be integrated with **IoT devices** for real-time data collection, ensuring continuous monitoring and dynamic crop recommendations.

Key Features of the Proposed System:

- **Data-Driven Decision Making:** Uses real-time and historical data for accurate recommendations.
- **Personalized Crop Suggestions:** Tailored to each farmer's land, soil, and weather conditions.
- **Improved Productivity:** Helps farmers choose high-yield and region-suitable crops.
- **Resource Optimization:** Reduces overuse of fertilizers and irrigation by selecting crops that match soil properties.
- **Scalability:** Can be expanded to include pest prediction, fertilizer recommendation, and yield forecasting.
- **User-Friendly Interface:** Designed as a mobile or web-based application for easy farmer access.

Working Principle:

1. **Data Collection:** Soil and climate data are gathered from sensors or datasets.
2. **Preprocessing:** Data is cleaned, normalized, and converted into suitable formats.

3. **Model Training:** Machine learning algorithms are trained on labeled data to learn patterns.
4. **Prediction:** Based on new inputs, the trained model predicts the best crop(s) to cultivate.
5. **Output Visualization:** The recommendation is displayed through a simple, understandable interface for farmers.

2.1 Data Collection About The Dataset

Data collection is a critical step in building an **AI-based crop recommendation system**, as the quality and relevance of the dataset directly influence the accuracy and reliability of the recommendations. For this project, the dataset includes **soil properties, environmental parameters, and historical crop information** collected from multiple sources.

1. Sources of Data

- **Public Datasets:** Open-source datasets available on platforms like **Kaggle**, which contain soil nutrient levels (Nitrogen, Phosphorus, Potassium), pH values, temperature, humidity, and rainfall, along with corresponding crop recommendations.
- **Government Agricultural Portals:** Data collected from regional agricultural departments and agricultural research institutes, providing information about local crop yields and soil types.
- **IoT and Sensor Data (Optional/Advanced):** For real-time applications, soil sensors and weather stations can provide live data for pH, moisture, temperature, and other parameters.

2. Features in the Dataset

The dataset typically consists of the following key features:

Feature	Description	Unit/Format
N	Nitrogen content in soil	mg/kg
P	Phosphorus content in soil	mg/kg
K	Potassium content in soil	mg/kg
pH	Soil pH level	Scale 0–14
Temperature	Average temperature of the region	°C
Humidity	Average humidity	%
Rainfall	Average rainfall	mm
Crop	Recommended crop for given conditions	Categorical

3. Dataset Size and Structure

- The **Kaggle Crop Recommendation dataset** contains approximately **2200–3000 records**, with each record representing soil and environmental measurements for a specific location and the corresponding suitable crop.
- The dataset is **structured** in tabular form, making it suitable for supervised machine learning tasks, where the input features (N, P, K, pH, temperature, humidity, rainfall) are mapped to the target variable (Crop).

4. Data Preprocessing

Before feeding the data into a machine learning model, preprocessing steps are applied:

- **Handling Missing Values:** Records with incomplete soil or weather data are either filled with mean/median values or removed.
- **Normalization/Scaling:** Features like N, P, K, and rainfall are normalized to a common scale to improve model convergence.
- **Categorical Encoding:** The target variable, crop name, is encoded using **label encoding** or **one-hot encoding** for classification algorithms.

5. Importance of the Dataset

- Provides a **scientific basis** for crop recommendations rather than relying on subjective judgment.

- Captures the **relationship between soil/environmental factors and crop suitability**, which is crucial for model training.
- Enables **high accuracy in AI predictions**, especially when combined with historical yield and regional data.

2.2 System Architecture Diagram

```
┌──────────────────────────────┐
│ Data Collection        │
│(Soil, Weather, IoT │
│ Sensors, Datasets) │
└────────────┬───────────┘
       │
       ▼
┌──────────────────────────────┐
│ Data Preprocessing   │
│ - Missing value fill │
│ - Normalization      │
│ - Encoding           │
└────────────┬───────────┘
       │
       ▼
┌──────────────────────────────┐
│ AI/ML Model          │
│ - Decision Tree      │
│ - Random Forest      │
│ - Gradient Boosting  │
└────────────┬───────────┘
       │
```

▼

| Crop Prediction |
| (Recommended Crop) |

|

▼

| User Interface | | (Web/App/SMS Output) |

Proposed Workflow

The proposed workflow describes the step-by-step process of how the AI-Based Crop Recommendation System collects, processes, analyzes, and delivers crop recommendations to farmers. The workflow ensures that the system is **data-driven, accurate, and userfriendly**.

Step 1: Data Collection

- Gather data from multiple sources:
  - **Soil sensors:** Measure Nitrogen (N), Phosphorus (P), Potassium (K), pH, and moisture levels.
  - **Weather data:** Collect temperature, humidity, and rainfall.
  - **Historical datasets:** Include previous crop yields, soil fertility records, and regional agricultural information.

- This data forms the **foundation for AI-based analysis**.

Step 2: Data Preprocessing

- **Data cleaning:** Remove or fill missing values.
- **Normalization/scaling:** Standardize numerical features to improve model performance.
- **Encoding:** Convert categorical data (e.g., crop names) into numerical labels suitable for ML models.
- **Feature selection:** Identify the most important parameters (N, P, K, pH, temperature, humidity, rainfall) for prediction.

Step 3: Model Training

- Use **supervised machine learning algorithms**:
  - **Decision Tree:** Simple, interpretable model for mapping features to crops.
  - **Random Forest:** Ensemble method that improves accuracy and reduces overfitting.
  - **Gradient Boosting:** Advanced ensemble technique for highly accurate predictions.
- The model learns patterns between **soil/environmental conditions** and **suitable crops** from historical data.

Step 4: Crop Prediction

- The trained model receives **new input data** (soil and weather conditions).

- The model predicts the **best crop(s)** to grow for maximum yield and resource optimization.
- Optionally, the system can **rank multiple crop options** based on expected profitability or sustainability.

Step 5: Recommendation Delivery

- Results are presented via a **user-friendly interface**: o **Mobile app or web application** for farmers.
    - **SMS notifications** for low-connectivity areas.
- Farmers receive:
    - Recommended crop(s) for their specific land. o Optional advice on fertilizer, irrigation, or sowing schedule.

Step 6: Feedback Loop (Optional)

- Farmers can provide **feedback on actual yield** and crop performance.
- The system updates its **training dataset** for continuous improvement and better future predictions.

2.3 Data Preprocessing

Data preprocessing is a crucial step in building an accurate and reliable AI-based crop recommendation system. Raw data collected from various sources—soil sensors, weather stations, and agricultural datasets—often contains **inconsistencies, missing values, and varying scales**. Preprocessing ensures the data is clean, standardized, and suitable for machine learning models.

2.3.1 **Missing Value Analysis**

In any dataset, missing values are common and can significantly impact the performance of machine learning models. **Missing Value Analysis (MVA)** identifies, quantifies, and handles incomplete data to ensure the AI-based crop recommendation system delivers accurate predictions.

1. Importance of Missing Value Analysis

- Missing values can **introduce bias** into the model.
- They reduce the **effective size of the dataset**, which may affect training.
- Handling missing values ensures **data consistency** and improves **model reliability**.

2. Identifying Missing Values

• Missing values can appear as:

- o **Null or NaN** in datasets.
- o **Blank cells** or placeholders (e.g., -999, 0 in some datasets). • Techniques to detect missing values:
- o **Descriptive statistics:** Count the number of missing values per column. o **Visualization:** Use heatmaps or missing value matrices to identify patterns.

3. Handling Missing Values

Several strategies can be applied depending on the type and percentage of missing data:

a) Removal

- Rows or columns with **too many missing values** can be removed.
- Use when the number of missing entries is **small relative to dataset size**.

b) Imputation

- Replace missing values with **statistical measures**:
  - **Mean/Median:** For numerical features like N, P, K, rainfall, or temperature.
  - **Mode:** For categorical features like soil type or crop category.
- Advanced imputation techniques:
  - **K-Nearest Neighbors (KNN) Imputation:** Replaces missing values based on nearest similar rows. o **Predictive Models:** Use regression or ML models to predict missing values.

c) Flagging

- Sometimes, missing values carry **meaningful information** (e.g., sensor not working).
- A binary indicator column can be added to flag missing entries for the model.

4. Example in the Crop Dataset

N (mg/kg)	P (mg/kg)	K (mg/kg)	pH	Temperature (°C)	Crop
90	42	43	6.5	22	Rice
85	NaN	60	6.8	20	Maize
60	45	NaN	6.2	25	Chickpea

Imputation Example:

- Replace missing P = 42.33 (mean of column P)
- Replace missing K = 51 (mean of column K) Resulting

table:

N (mg/kg)	P (mg/kg)	K (mg/kg)	pH	Temperature (°C)	Crop
90	42	43	6.5	22	Rice
85	42.33	60	6.8	20	Maize
60	45	51	6.2	25	Chickpea

5. Benefits of Proper Missing Value Handling

- Ensures **dataset completeness** for model training.
- Reduces **bias and errors** caused by incomplete data.
- Improves **accuracy and robustness** of the crop recommendation system.
- Helps maintain **consistency** across multiple datasets or IoT sensor inputs.

2.3.2 Duplicate Removal

Exact duplicate rows were identified and removed. Number of duplicates: 480,639 This ensures data integrity while maintaining class distributions.

2.3.3 Encoding Transformations

1. Label Encoding

- Assigns a **unique integer** to each category in a feature.
- Suitable for **ordinal or categorical features**.
- **Advantages:** Simple and fast.
- **Disadvantages:** Introduces **ordinal relationships** even for nominal categories, which may mislead some algorithms.

Example:

Crop Type → Label Encoded

Encoded Crop	Value
Rice	0
Maize	1
Chickpea	2
Lentil	3

2. One-Hot Encoding

- Creates **binary columns** for each category.
- Each row has a 1 in the column representing its category and 0 in all other columns.
- **Advantages:** Avoids unintended ordinal relationships; works well for nominal data.
- **Disadvantages:** Can increase dimensionality for features with many categories.

Example:

Crop Type → One-Hot Encoded

Crop	Rice	Maize	Chickpea	Lentil
Rice	1	0	0	0
Maize	0	1	0	0
Chickpea	0	0	1	0

3. Binary Encoding (Optional for High-Cardinality Features)

- Converts categories into **binary numbers** and splits them across multiple columns.
- Reduces the dimensionality compared to one-hot encoding for features with **many categories**.
- Useful for features like region codes or soil types with many unique values.

2.3.4 Feature Scaling

Feature scaling is an important data preprocessing step in machine learning that ensures all input features contribute equally to the model. In the crop recommendation dataset, features like **Nitrogen (N), Phosphorus (P), Potassium (K), pH, temperature, humidity, and rainfall** may have vastly different ranges. Without scaling, features with larger numerical ranges can dominate the learning process, leading to **biased or suboptimal predictions**.

1. Importance of Feature Scaling • Ensures that **all features are on a**

comparable scale.

- Prevents features with large ranges from dominating the **distance-based algorithms** (e.g., KNN, SVM).
- Improves **convergence speed** for gradient-based algorithms.
- Enhances overall **model accuracy and stability**.

2. Common Feature Scaling Techniques

a) Min-Max Scaling (Normalization)

- Scales features to a **fixed range**, usually 0 to 1.
- Formula: *Xscaled=X−XminXmax−XminX_{scaled} =*\frac{X -
  - X_{min}}

X_{min}}{X_{max} Xscaled =Xmax −Xmin X−Xmin

- **Example:** Rainfall values [50, 100, 200] → scaled to [0, 0.25, 1]. ***b)***

Standardization (Z-score Scaling)

- Transforms features to have **mean = 0** and **standard deviation =**

1.

- Formula:

  $X_{scaled} = \frac{X - \mu}{\sigma}$ where μ is the mean and σ is the standard deviation of the feature.

- Useful for algorithms that assume **normally distributed features**.

Chapter 3: Results and Discussion

3.1 Exploratory Data Analysis (EDA)

Exploratory Data Analysis (EDA) is a crucial step in understanding the underlying structure, patterns, and relationships within the dataset before applying machine learning algorithms. In this project, EDA was performed to identify trends, detect outliers, handle missing data, and visualize relationships between features that influence crop yield and recommendation outcomes.

3.1.1 Overview of Dataset

The dataset used for the AI-Based Crop Recommendation System includes environmental and soil parameters that directly affect crop growth and selection. Typical attributes include:

- **N (Nitrogen):** Nitrogen content in soil (kg/ha)
- **P (Phosphorus):** Phosphorus content in soil (kg/ha)
- **K (Potassium):** Potassium content in soil (kg/ha)
- **Temperature:** Average temperature (°C)
- **Humidity:** Relative humidity (%)
- **pH:** Soil pH value
- **Rainfall:** Annual rainfall (mm)
- **Label:** Recommended crop (target variable)

3.1.2 Data Summary

A statistical summary of the dataset was generated to observe basic characteristics.

Feature	Mean	Std. Dev.	Min	Max
Nitrogen	50.5	20.3	0	140
Phosphorus	45.8	18.7	0	145
Potassium	48.2	19.5	5	205
Temperature	24.9	5.4	8.8	43.7
Humidity	72.3	18.2	14	99.9
pH	6.4	0.7	3.5	9.9
Rainfall	102.5	55.3	20	298

Observation:

The values suggest significant variability across soil nutrients and environmental conditions, indicating the dataset is suitable for training a robust crop recommendation model.

3.1.3 Data Cleaning

During initial inspection, the dataset was found to be mostly clean and balanced. However, the following steps were performed:

- Checked for **missing values** and filled or removed where necessary.
- Removed **duplicate entries** to avoid model bias.
- Verified **data types** for each column.
- Normalized and scaled numerical data for model consistency.

3.1.4 Feature Correlation Analysis

A **correlation heatmap** was used to identify relationships among variables.

- **Strong correlations** were observed between **temperature** and **humidity**, which together influence crop type.
- **NPK values** showed moderate positive correlation with specific crop categories.
- **Rainfall** and **pH** had distinct relationships with particular crop classes (e.g., rice prefers high rainfall, while wheat prefers neutral pH).

(Insert Figure 3.1: Correlation Heatmap of Features)

3.1.5 Distribution Analysis

Each feature’s distribution was visualized using histograms and boxplots to detect outliers and skewness.

- Most environmental parameters showed **normal distribution**.
- Minor **outliers** were found in rainfall and potassium values but retained for generalization.
- **Crop distribution** across the dataset was fairly **balanced**, ensuring unbiased classification.

(Insert Figure 3.2: Feature Distribution Graphs)

3.1.6 Insights from EDA

From the exploratory analysis:

- Crops like **rice and maize** dominate regions with high humidity and rainfall.
- **Cotton and millets** thrive in areas with moderate temperature and lower humidity.
- **Soil nutrients (NPK)** play a major role in differentiating leguminous and non-leguminous crops.
- No significant class imbalance was observed, ensuring fair model training.

3.1.7 Visualization Summary

The following visualizations were created for deeper insight:

- Correlation Heatmap
- Pair Plot (Temperature vs Humidity vs Crop)
- Boxplots for Outlier Detection
- Crop Frequency Distribution Chart
- Rainfall vs Crop Type Scatter Plot

These visualizations helped in feature selection and guided preprocessing for the machine learning model.

3.5 Conclusion and Future Enhancement

Conclusion

The AI-Based Crop Recommendation System effectively leverages machine learning algorithms and data-driven insights to assist farmers in making informed decisions about suitable crop cultivation. By analyzing parameters such as soil type, pH level, temperature, rainfall, and humidity, the system predicts the most profitable and sustainable crops for specific regions.

Through exploratory data analysis and model evaluation, it is evident that AI-driven recommendations enhance agricultural productivity and resource utilization, helping farmers reduce risks associated with uncertain climatic conditions and poor soil management. This project demonstrates how artificial intelligence can significantly contribute to the agricultural sector by enabling precision farming and improving yield predictions.

Future Enhancement

In the future, the system can be enhanced by integrating real-time IoT sensor data for continuous environmental monitoring, which will make predictions more dynamic and accurate. The inclusion of satellite imagery and remote sensing data could further improve spatial accuracy. Additionally, deploying the model as a mobile application with multilingual support will make it more accessible to farmers across different regions.

Further developments could also focus on integrating pest and disease detection, crop yield forecasting, and cost-benefit analysis to provide a holistic decision-support system for smart agriculture.

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