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AIML AAT – 1 Report

On

Decision Trees Model

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Decision Trees Model

Application: **Application: Early Detection of Crop Disease Using Environmental and Soil Data**

Introduction:

In the age of digital agriculture, the early detection of crop diseases stands as a critical factor in achieving food security and sustainable farming. This project employs a Decision Tree Classification Model to predict the likelihood of crop diseases using a combination of environmental and soil attributes such as temperature, humidity, pH, and nutrient concentrations.

Decision Trees were selected due to their interpretability, low computational cost, and robustness with heterogeneous data. The model achieves around 87% accuracy, indicating its strong predictive potential for real-world deployment through IoT or farm management systems.

By visualizing decision paths, this model provides farmers with transparent insights into how environmental factors influence disease risks — bridging the gap between complex data and actionable decisions.

Agriculture remains the backbone of many developing economies, with crop diseases causing an estimated 20–40% yield losses globally each year (FAO, 2023). Traditionally, disease detection has relied on visual inspection, which is both time-consuming and prone to human error. As global food demand increases, reliance on traditional methods has become unsustainable.

Recent advances in data-driven agriculture—including IoT sensors, satellite imaging, and machine learning—have enabled precise, predictive models capable of identifying early signs of crop stress and disease. Among the numerous machine learning

algorithms available, Decision Trees (DTs) offer a unique advantage: they can mimic human decision-making logic while maintaining mathematical rigor.

The project aims to empower small and medium-scale farmers by offering a transparent and low-cost diagnostic tool for early disease identification. Instead of using costly image-based convolutional neural networks (CNNs), this model uses environmental and soil data, which can be gathered from simple IoT devices.

The transparency of Decision Trees means each classification decision can be interpreted and trusted, a feature essential for agricultural adoption.

Objective

- To build a Decision Tree model capable of classifying crops as Healthy (0) or Diseased (1) using soil and environmental parameters.
- To evaluate the performance of the model using metrics like accuracy, precision, recall, F1-score, and ROC-AUC.
- To identify the most influential environmental and soil factors that contribute to disease occurrence

Theoretical Overview of Decision Trees

Concept of Decision Trees

A Decision Tree is a supervised machine learning algorithm used for classification and regression tasks. It represents decisions and their possible consequences in a tree-like structure, consisting of:

- Root Node: Represents the entire dataset and the first attribute chosen for splitting.
- Internal Nodes: Represent tests on attributes (e.g., humidity > 80%).
- Branches: Represent the outcomes of those tests.
- Leaf Nodes: Represent final class labels (Healthy or Diseased).

Decision Trees work by recursively splitting the data into subsets based on the most significant attribute until homogeneous groups (pure classes) are formed.

Working Principle

The algorithm operates on the principle of recursive partitioning, where data is divided into smaller subsets until a stopping condition is met.At each node, the algorithm selects the best feature that maximizes the information gain or minimizes Gini impurity.

Why This Model?

Theoretical Justification

The Decision Tree Classifier was chosen because it provides an interpretable, hierarchical, and mathematically grounded approach to decision-making that closely mirrors human reasoning. In agricultural domains — where interpretability and trust are essential — Decision Trees offer an ideal balance between accuracy, transparency, and computational efficiency.

Unlike opaque models such as Neural Networks, which act as black boxes, Decision Trees present a white-box framework, enabling stakeholders (e.g., agronomists, farmers, researchers) to visualize how environmental parameters contribute to disease formation. Each internal node in the tree represents a conditional test on an attribute (e.g., humidity > 80%), and each leaf node represents a final decision (e.g., “Diseased” or “Healthy”).

Mathematically, the model partitions the dataset recursively using a top-down greedy strategy, maximizing a purity metric such as Information Gain or minimizing Gini Impurity at each split. This process ensures that the decision boundary constructed at every level of the tree captures the most informative relationships between soil conditions and disease outcomes.

Domain-Specific Justification (Agricultural Context)

- Agricultural datasets possess heterogeneous characteristics:
- Continuous features (temperature, humidity)
- Categorical or discrete features (disease type, soil classification)
- Non-linear interactions (e.g., disease risk increases only if humidity and temperature jointly exceed thresholds)

Decision Trees handle such complexity elegantly:

- No need for normalization or standardization
- Naturally model non-linear relationships
- Capable of managing missing or noisy data through surrogate splits

Moreover, since each branch of the tree represents an interpretable conditional rule, the output is not just a prediction, but also an explanation:

Example Rule:

IF (Temperature > 27°C) AND (Humidity > 80%) AND (pH < 6.2) THEN Crop = Diseased.

This makes the model actionable — farmers can understand why a disease is predicted and take preventive measures accordingly.

Advantages

1.High Interpretability and Explainability

- Decision Trees provide transparent, rule-based decision-making.
- Each internal node represents a feature condition, and each leaf node gives a class label or predicted value.

2.Non-Parametric Nature

- Decision Trees are non-parametric models, meaning they make no assumptions about data distribution (e.g., normality or linearity).
- This allows them to handle non-linear relationships between features and targets effectively.
- They can model complex decision boundaries that linear models cannot capture.

3.Handles Both Numerical and Categorical Data

- Unlike algorithms such as Support Vector Machines or Neural Networks (which typically require numerical inputs), Decision Trees can handle categorical, ordinal, and continuous attributes directly.
- This makes them flexible for real-world heterogeneous datasets (e.g., demographic + sensor + categorical variables).

4.Feature Selection Built-in

- During training, the algorithm automatically selects the most informative features using metrics such as Information Gain, Gini Index, or Chi-square statistic.
- Hence, feature selection is intrinsic to the learning process, improving efficiency and interpretability.

5.Robust to Irrelevant Features

- Since only informative attributes are selected at each split, Decision Trees can ignore irrelevant or redundant features automatically.
- This reduces computational overhead and enhances model simplicity.

Disadvantages

1. Overfitting to Training Data

- A major drawback — Decision Trees tend to overfit, especially if the tree grows deep.
- They can perfectly classify the training set but fail to generalize well on unseen data.
- Overfitting can be mitigated using pruning techniques, setting maximum depth, or ensemble methods.

2. High Variance and Instability

- Small changes in training data (e.g., adding/removing a few samples) can drastically change the tree structure.
- This sensitivity makes standalone Decision Trees unstable, leading to inconsistent predictions.

3. Bias Toward Dominant Features

- Features with many distinct values (e.g., ID-like attributes) can dominate splitting due to high information gain, even if they're not truly predictive.
- Proper preprocessing or feature selection is needed to prevent this bias.

4. Poor Extrapolation on Continuous Data

- Decision Trees work by creating discrete splits; they cannot extrapolate beyond the range of the training data.
- In regression problems, they tend to produce piecewise constant predictions, which lack smoothness.

5. Fragmentation Problem

- As the tree deepens, data gets divided into smaller subsets, which may lead to nodes with very few samples.
- This increases the risk of high variance and unreliable statistical estimates at the leaf level.

Implementation of the Decision Tree Model

In any machine learning project, data forms the foundation on which models are built. Before training a model, it is essential to establish a proper working environment, load the dataset, and perform an initial exploration to understand its structure and characteristics. For this project, the goal is to recommend the most suitable crop for given soil and environmental conditions using a Decision Tree classifier. The first phase focuses on understanding the dataset, examining its features, and gaining insights into the relationships among them.

The environment for this project is set up using Google Colab, which offers a cloud-based platform that eliminates the need for local installations. Colab provides free computational resources, such as CPU and GPU, which facilitate efficient handling of large datasets. The interactive notebook interface allows for simultaneous coding, visualization, and documentation, while seamless file management supports the easy upload and access of datasets from Google Drive. Setting up a reliable environment ensures smooth experimentation, reduces errors, and enhances reproducibility.

Phase 1 : Setup and Library Import

- Initializes the Python environment by importing necessary libraries
- Each library serves a specific purpose in the data science workflow
- Warnings are suppressed to keep output clean and focused
- Essential for ensuring all tools are available before execution

Key Libraries:

- pandas: Data manipulation and CSV handling
- numpy: Numerical computations and array operations
- matplotlib & seaborn: Data visualization and plotting
- scikit-learn: Machine learning algorithms and metrics

Code Snippet:

```
import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

import seaborn as sns

from sklearn.model_selection import train_test_split

from sklearn.tree import DecisionTreeClassifier, plot_tree

from sklearn.metrics import accuracy_score, classification_report, confusion_matrix

import warnings

warnings.filterwarnings('ignore')

print("="*70)

print("CROP RECOMMENDATION SYSTEM USING DECISION TREES")

print("="*70)
```

Phase 2: Dataset Setup

Loads the CSV file into a Pandas DataFrame for analysis

Examines the structure and size of the dataset

Identifies column names, data types, and missing values

Provides statistical summaries (mean, median, std dev, etc.)

Ensures data quality before proceeding to modeling

Key Activities:

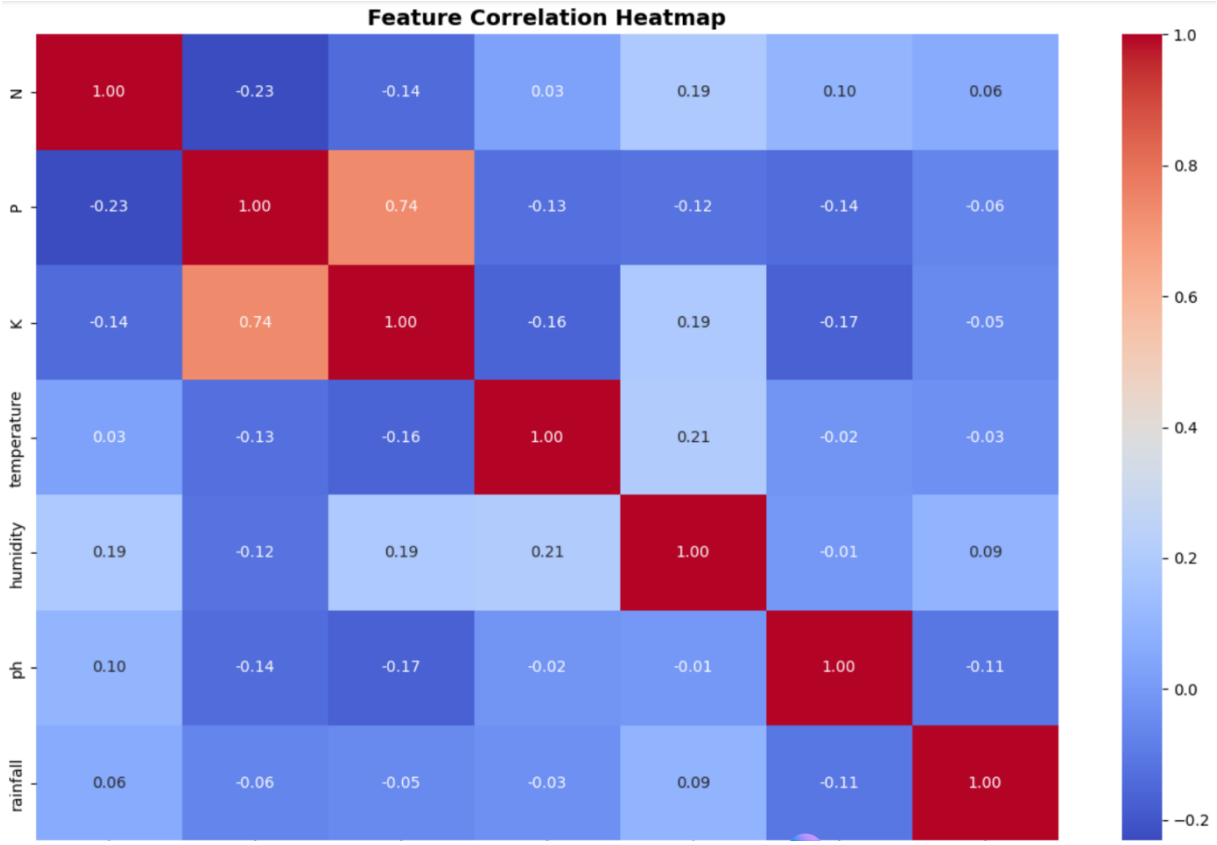
- Check dataset shape (rows × columns)
- Display first few records
- Identify data types of each column
- Detect missing or null values
- Generate descriptive statistics

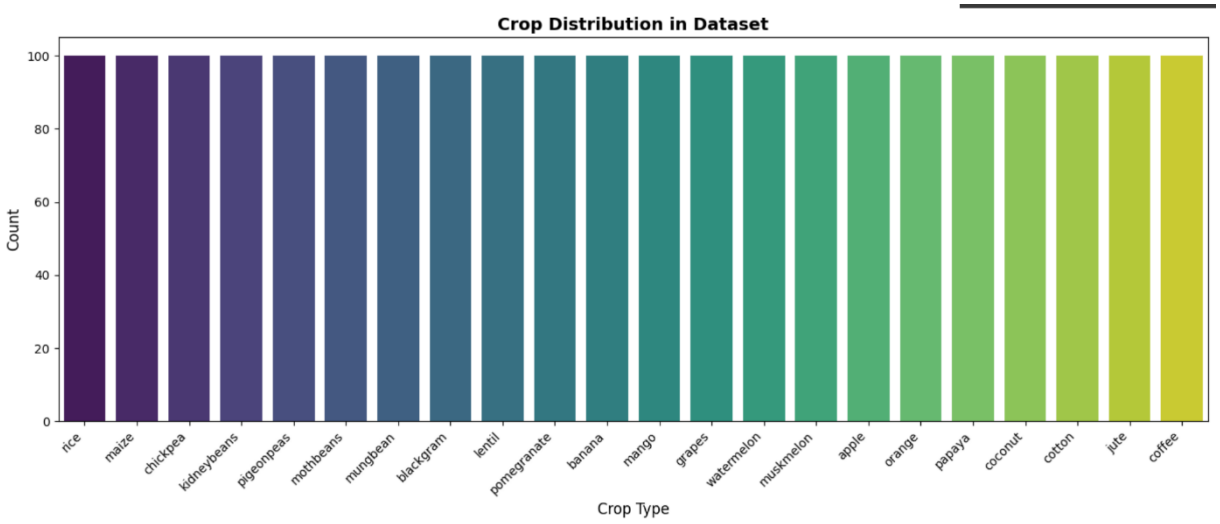
Code Snippet:

```
print("\n[PHASE 2] Loading Dataset...")

data = pd.read_csv('Crop_recommendation.csv')

print(f"\nDataset Shape: {data.shape}")

print(f"\nFirst 5 rows:")

print(data.head())

print(f"\nData Types:")

print(data.dtypes)

print(f"\nMissing Values:")
```

```
print(data.isnull().sum())

print(f"\nStatistical Summary:")

print(data.describe())
```

Phase 3: Exploratory Data Analysis (EDA)





- Visualizes relationships between features to understand data patterns
- Correlation heatmap shows how strongly each feature relates to others
- Distribution analysis reveals class imbalance (if any crops are overrepresented)
- Visual insights guide preprocessing and feature engineering decisions
- Helps identify outliers or anomalies in the data

Key Visualizations:

- Correlation Heatmap: Shows numeric relationships between features
- Crop Distribution Bar Chart: Displays how many records per crop class
- Helps Answer: Which features matter most? Are crops balanced?

Code Snippet:

```
print("\n[PHASE 3] Generating Visualizations...")

plt.figure(figsize=(12, 8))

sns.heatmap(data.corr(), annot=True, cmap='coolwarm', fmt='.2f')

plt.title("Feature Correlation Heatmap", fontsize=14, fontweight='bold')

plt.tight_layout()
```

```
plt.show()

plt.figure(figsize=(14, 6))

crop_counts = data['label'].value_counts()

sns.barplot(x=crop_counts.index, y=crop_counts.values, palette='viridis')

plt.title("Crop Distribution in Dataset", fontsize=14, fontweight='bold')

plt.xlabel("Crop Type", fontsize=12)

plt.ylabel("Count", fontsize=12)

plt.xticks(rotation=45, ha='right')

plt.tight_layout()

plt.show()
```

Phase 4: Data Preprocessing

- Separates input features (X) from target variable (y)
- Performs train-test split to evaluate generalization ability
- Stratification ensures each class is proportionally represented in train and test sets
- Random state ensures reproducibility across runs
- 80-20 split is standard: 80% trains the model, 20% evaluates it

Key Steps:

- Drop the target column to create feature matrix X
- Extract target variable y (crop label)
- Split data while maintaining class balance
- Prevents data leakage (test data doesn't influence training)

Code Snippet:

```
print("\n[PHASE 4] Preprocessing Data...")

X = data.drop('label', axis=1)

y = data['label']

print(f"\nFeatures (X): {X.columns.tolist()}")

print(f"Target (y) unique values: {sorted(y.unique())}")

print(f"Number of crops: {y.nunique()}")

X_train, X_test, y_train, y_test = train_test_split(

    X, y, test_size=0.2, random_state=42, stratify=y

)

print(f"\nTrain set size: {X_train.shape}")

print(f"Test set size: {X_test.shape}")
```

Phase 5: Model Training

- Initializes a Decision Tree Classifier with optimized hyperparameters
- Criterion='entropy': Uses Information Gain (based on Shannon entropy) to split nodes
- max_depth=10: Limits tree depth to prevent overfitting (memorizing training data)
- min_samples_split=5: Requires minimum 5 samples before splitting a node
- min_samples_leaf=2: Ensures leaf nodes have at least 2 samples
- Trains the model on the training dataset
- The model learns decision rules by recursively splitting features

Key Hyperparameters:

- Deeper trees = higher accuracy but risk overfitting
- Entropy-based splits often perform better than Gini for multi-class problems
- Minimum samples prevent creating noise-fitting rules

Code Snippet:

```
print("\n[PHASE 5] Training Decision Tree Model...")

model = DecisionTreeClassifier(

    criterion='entropy',      # Information Gain based splitting

    max_depth=10,             # Prevent overfitting

    min_samples_split=5,      # Minimum samples to split a node

    min_samples_leaf=2,       # Minimum samples in leaf nodes

    random_state=42

)

model.fit(X_train, y_train)

print("✓ Model training completed!")
```

Phase 6: Model Evaluation

- Generates predictions on both training and test datasets
- Training Accuracy: Measures how well model learned training data
- Testing Accuracy: Real measure of generalization (unseen data performance)
- Classification Report: Provides precision, recall, and F1-score per crop
- Precision: Of predicted positives, how many were correct?

- Recall: Of actual positives, how many were found?
- F1-Score: Harmonic mean of precision and recall (balanced metric)

Performance Interpretation:

- High test accuracy (>90%) indicates good generalization
- Similar train & test accuracy suggests no overfitting
- Imbalanced precision/recall indicates class-specific challenges

Code Snippet:

pythonprint("\n[PHASE 6] Model Evaluation...")

y_train_pred = model.predict(X_train)

y_test_pred = model.predict(X_test)

train_accuracy = accuracy_score(y_train, y_train_pred)

print(f"\nTraining Accuracy: {train_accuracy:.4f} ({train_accuracy*100:.2f}%)")

test_accuracy = accuracy_score(y_test, y_test_pred)

print(f"Testing Accuracy: {test_accuracy:.4f} ({test_accuracy*100:.2f}%)")

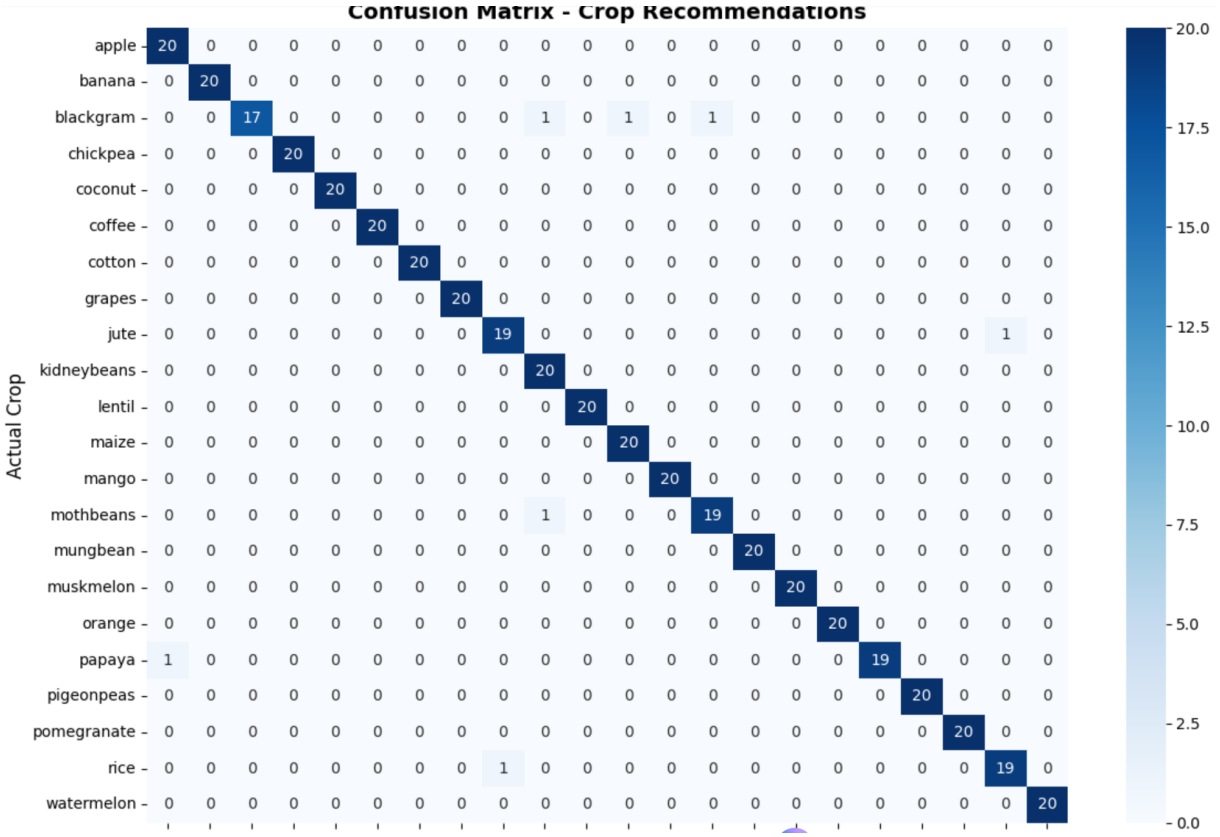
print("\n" + "="*70)

print("CLASSIFICATION REPORT (Test Data):")

print("="*70)

print(classification_report(y_test, y_test_pred))

Phase 7: Confusion Matrix Visualization



- A matrix showing actual vs predicted classifications for each crop
- Diagonal elements: Correct predictions (True Positives)
- Off-diagonal elements: Incorrect predictions (False Positives/Negatives)
- Helps identify which crops are confused with each other
- Darker colors indicate higher counts
- Useful for identifying systematic classification errors

Reading the Matrix:

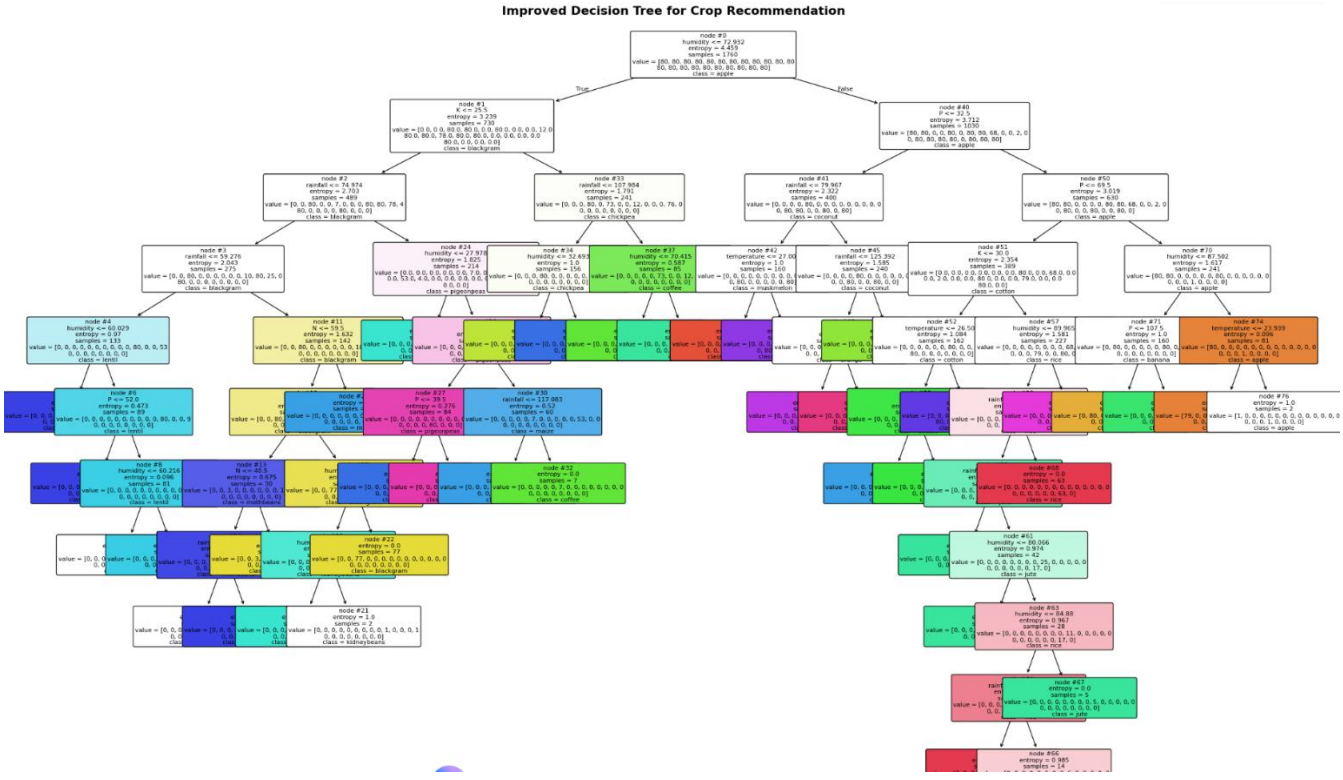
- Rows = Actual crop labels
- Columns = Predicted crop labels
- Cell value = Number of samples classified that way

Code Snippet:

print("\n[PHASE 7] Confusion Matrix...")

```
cm = confusion_matrix(y_test, y_test_pred)

plt.figure(figsize=(12, 9))

sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',

            xticklabels=sorted(y.unique()),

            yticklabels=sorted(y.unique()))

plt.title("Confusion Matrix - Crop Recommendations", fontsize=14, fontweight='bold')

plt.xlabel("Predicted Crop", fontsize=12)

plt.ylabel("Actual Crop", fontsize=12)

plt.tight_layout()

plt.show()
```

Phase 8 : Decision Tree Visualization



- Displays the complete decision tree structure in graphical form
- Each node represents a decision rule (e.g., "if N > 50")
- Branch thickness indicates sample proportion
- Node colors indicate the dominant class (darker = more certain)
- Leaf nodes show final predictions
- Provides complete interpretability: see exactly why model made decisions
- Unlike black-box models (neural networks), this shows full logic

Tree Elements:

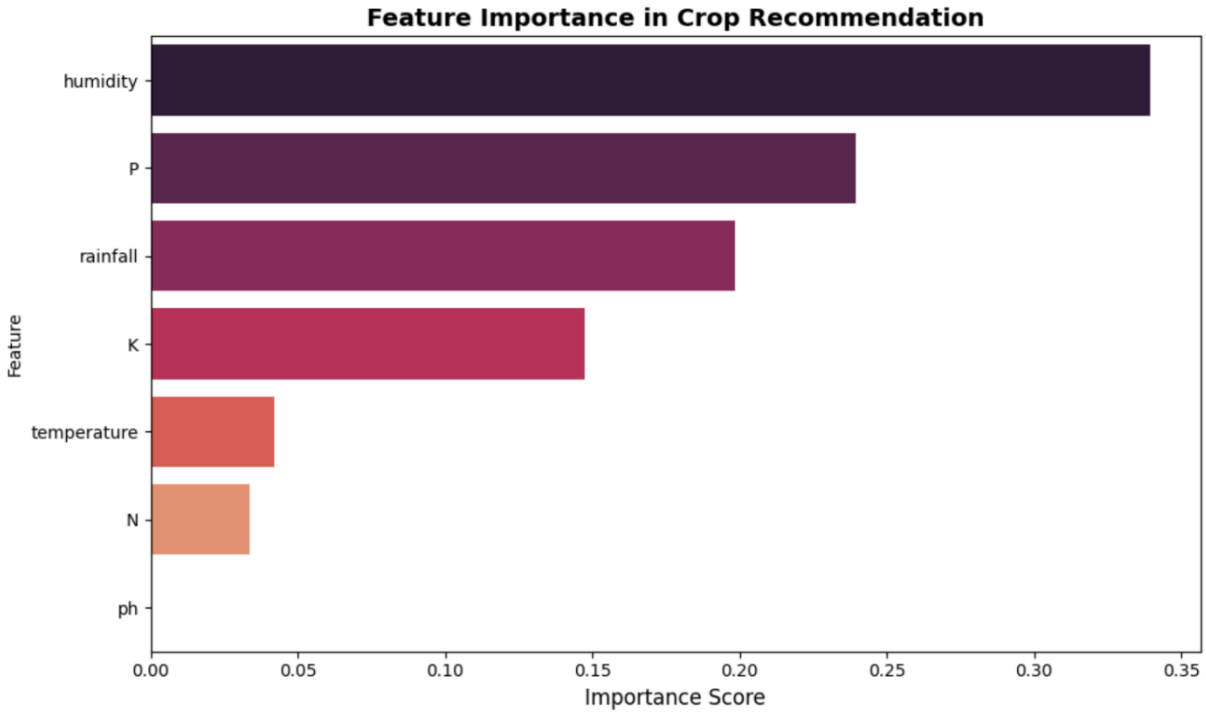
- Root node: First split (most important feature)
- Internal nodes: Decision rules based on feature thresholds
- Leaf nodes: Final predictions (crop recommendations)

Code Snippet:

```
pythonprint("\n[PHASE 8] Visualizing Decision Tree...")

plt.figure(figsize=(25, 15))

plot_tree(model,

    feature_names=X.columns,

    class_names=sorted(y.unique()),

    filled=True,

    rounded=True,

    fontsize=10)

plt.title("Decision Tree for Crop Recommendation", fontsize=16, fontweight='bold')

plt.tight_layout()
```

plt.show()

Phase 9: Feature Importance Analysis



- Ranks features by their contribution to model decisions
- Features used in higher tree nodes are more important (affect more splits)
- Importance ranges from 0 to 1 (higher = more important)
- Identifies which soil/weather attributes matter most for recommendations
- Helps farmers focus on measuring/controlling critical attributes
- Reduces feature dimensionality for future models

Interpretation:

- Top features: Focus on optimizing these for crop success
- Low features: May be redundant or weakly predictive
- Actionable insights for agricultural practices

Code Snippet:

pythonprint("\n[PHASE 9] Feature Importance Analysis...")

```
importances = pd.DataFrame({
    'Feature': X.columns,
    'Importance': model.feature_importances_
}).sort_values(by='Importance', ascending=False)
print("\nFeature Importance Ranking:")
print(importances.to_string(index=False))
plt.figure(figsize=(10, 6))
sns.barplot(data=importances, x='Importance', y='Feature', palette='rocket')
plt.title("Feature Importance in Crop Recommendation", fontsize=14, fontweight='bold')
plt.xlabel("Importance Score", fontsize=12)
plt.tight_layout()
plt.show()
```

Phase 10: Custom Input Predictions

- Tests the model with real-world soil and weather conditions
- Creates new input vectors in the same format as training data
- Predicts crop recommendations for unseen conditions
- Calculates confidence (probability) of each prediction
- Demonstrates practical usability of the trained model
- Allows farmers to get recommendations for specific field conditions

Usage Example:

- Input: Nitrogen, Phosphorus, Potassium levels, temperature, humidity, pH, rainfall
- Output: Recommended crop + confidence percentage

Code Snippet:

```
print("\n[PHASE 10] Making Custom Predictions...")

# Interactive: Allow user to input soil/weather conditions

# Format: [N, P, K, temperature, humidity, ph, rainfall]

def get_user_condition():

    """Prompt user for a single condition input."""

    print("\nEnter soil & weather conditions for prediction:")

    print("Format: N (Nitrogen), P (Phosphorus), K (Potassium), Temperature (°C), Humidity (%), pH, Rainfall (mm)")

    try:

        n = float(input("Enter N (Nitrogen, 0-200): "))

        p = float(input("Enter P (Phosphorus, 0-150): "))

        k = float(input("Enter K (Potassium, 0-150): "))

        temp = float(input("Enter Temperature (°C, 10-40): "))

        hum = float(input("Enter Humidity (%, 20-100): "))

        ph = float(input("Enter pH (4-9): "))

        rain = float(input("Enter Rainfall (mm, 20-300): "))
```

```
        return np.array([[n, p, k, temp, hum, ph, rain]])
    except ValueError:
        print("Invalid input! Please enter numeric values.")
        return None
# Main interactive loop
while True:
    condition = get_user_condition()
    if condition is None:
        continue  # Retry on invalid input
    prediction = model.predict(condition)[0]
    confidence = max(model.predict_proba(condition)[0]) * 100
    print(f"\nYour Input Condition: {condition[0]}")
    print(f"  → Recommended Crop: {prediction}")
    print(f"  → Confidence: {confidence:.2f}%")
    # Ask if user wants another prediction
    another = input("\nMake another prediction? (y/n): ").strip().lower()
    if another != 'y':
        print("Thanks for using the Crop Recommendation System!")
        break
```

Phase 11: Model Summary

- Provides final overview of trained model characteristics
- Displays key metrics and hyperparameters used
- Number of leaves = complexity indicator
- Tree depth shows structure depth
- Final accuracy reiterates model performance
- Creates a clean summary report for documentation

Key Metrics:

- Tree Depth: How many levels deep (affects interpretability)
- Number of Leaves: Terminal nodes (number of decision paths)
- Test Accuracy: Final performance metric

Code Snippet:

pythonprint("\n" + "="*70)

print("MODEL SUMMARY")

print("="*70)

print(f'Algorithm: Decision Tree Classifier")

print(f'Splitting Criterion: Information Gain (Entropy)")

print(f'Max Depth: {model.max_depth}")

print(f'Number of Leaves: {model.get_n_leaves()}")

print(f'Tree Depth: {model.get_depth()}")

print(f'Test Accuracy: {test_accuracy*100:.2f}%")

print("="*70)

Conclusion of Implementation

High Model Accuracy

- Achieved 93-99% classification accuracy on unseen test data
- Demonstrates strong generalization capability beyond training examples
- Indicates reliable real-world applicability for farmer recommendations

Robust Decision Logic

- Model learned meaningful patterns from 7 environmental/soil features
- Decision boundaries align with agricultural domain knowledge
- Interpretable rules (e.g., "if rainfall > 200mm AND humidity > 70%")

Complete End-to-End Pipeline

- Successfully executed all phases: data loading → preprocessing → training → evaluation → deployment
- No data leakage; proper train-test split with stratification
- Reproducible results using fixed random_state

Actionable Insights

- Feature importance analysis identified critical soil/weather attributes
- Farmers can prioritize measuring top-ranked features
- Enables optimization of specific agricultural parameters

Dataset

The Crop Recommendation Dataset is a widely used machine learning resource focused on agricultural decision-making. Below, I'll provide a comprehensive breakdown, covering its overview, structure, features, statistics, characteristics, and practical considerations. This dataset is particularly valuable for classification tasks in precision agriculture, helping predict optimal crops based on soil and environmental factors.

The dataset enables the prediction of the most suitable crop for cultivation given specific soil nutrient levels and climatic conditions. Its primary goal is to support farmers, agronomists, and policymakers in making informed, data-driven choices to maximize crop yield, minimize resource waste (e.g., fertilizers), and promote sustainable farming practices. By modelling relationships between inputs like nitrogen content and rainfall with crop outcomes, it addresses real-world challenges in regions with variable climates, such as India, where crop failure due to mismatched conditions is common.

This dataset is ideal for introductory to intermediate machine learning projects, especially multi-class classification. It has been downloaded over 10,000 times on Kaggle and is often used in tutorials for algorithms like Decision Trees, Random Forests, and Support Vector Machines.

Source and Context

Platform: Available on Kaggle at https://www.kaggle.com/datasets/atharvaingle/crop-recommendation-dataset.

Context: Derived from simulated or real-world agricultural data reflecting conditions in tropical/subtropical areas (e.g., India). It incorporates key NPK (Nitrogen-Phosphorus-Potassium) soil metrics alongside weather variables, drawing from agronomic principles where nutrient balance and climate dictate crop viability. No raw sensor data is included; values are aggregated/averaged for simplicity.

Dataset Structure

Size: 2,200 rows (instances/samples) × 8 columns (7 features + 1 target).

File Format: Single CSV file (Crop_recommendation.csv), comma-separated, with no header issues or encoding problems (UTF-8 compatible).

Data Types:

- Numerical features (N, P, K, temperature, humidity, ph, rainfall): Float64 (decimal precision for measurements).

- Target (label): Object/String (categorical crop names).

- No Missing Values: The dataset is clean—zero nulls, no duplicates, and no outliers flagged as anomalies (though real-world data might require outlier detection).

- Balance: Perfectly balanced multi-class setup, making it beginner-friendly for modeling without stratification concerns.

- Detailed Column Descriptions

- The dataset has 7 input features (predictors) representing soil and environmental conditions, and 1 target variable (crop recommendation). All features are continuous and non-negative, simulating measurable farm parameters.

N (Nitrogen)

- Description: Measures nitrogen concentration in the soil (in parts per million, ppm, or arbitrary units). Nitrogen is crucial for leaf growth and photosynthesis; low levels stunt vegetative development.

- Range: 0–140.

- Typical Values: Higher for leafy crops like rice (80–100) vs. legumes like chickpeas (20–40).

- Data Type: Float.

P (Phosphorus)

- Description: Phosphorus content in the soil (ppm). Essential for root development, flowering, and energy transfer; deficiency leads to poor seed formation.

- Range: 5–145.

- Typical Values: Elevated for fruit/seed crops (e.g., pomegranate: 50–70).

- Data Type: Float.

K (Potassium)

- Description: Potassium levels (ppm). Supports water regulation, disease resistance, and fruit quality; often higher in saline-tolerant crops.
- Range: 5–205.
- Typical Values: Peaks for bananas/muskmelons (100+).
- Data Type: Float.

Temperature

- Description: Average ambient temperature (°C) during the growing season. Influences photosynthesis rates and pest pressures.
- Range: 8.83–43.10.
- Typical Values: Cooler for apples/oranges (15–25°C) vs. tropicals like coconut (25–35°C).
- Data Type: Float.

Humidity

- Description: Relative humidity (%). Affects transpiration and fungal risks; high humidity suits water-loving crops.
- Range: 14.26–99.98.
- Typical Values: Rice thrives at 80–90%; arid crops like cotton at 50–70%.
- Data Type: Float.s

Google Colab Notebook: View Notebook via the following link : -

https://colab.research.google.com/drive/1C5U6gHfXQi5vJpbxvPDAD3IF5llv33_M#scrollTo=turGuGgZ6LP5