A Report On

Crop Production Prediction Using Decision Tree

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1.Abstract

Agriculture plays a vital role in India's economy, and accurately predicting crop production is essential for improving planning, resource distribution, and food security. This project aims to predict crop yield for selected districts of Andhra Pradesh using machine learning techniques. The dataset used is the "Crop Production in India" dataset from Kaggle, which contains detailed information such as state, district, crop type, season, crop year, cultivated area, and production. For this study, the data was filtered to include four major districts—Krishna, Guntur, Kadapa, and Kurnool—and four important crops: Rice, Onion, Maize, and Groundnut.

After preprocessing steps such as cleaning, normalization, and label encoding, a Decision Tree Regressor model was trained to learn the relationships between area, season, crop type, and production. The model was tuned with constraints like maximum depth and minimum samples to reduce overfitting. The final trained model achieved a **training accuracy of 96.76%** and a **testing accuracy of 90.03%**, showing strong generalization. Performance metrics including MAE, RMSE, MAPE, and SMAPE further validated the model's reliability.

The results demonstrate that machine learning can effectively support agricultural prediction systems and assist farmers and policymakers in better estimating crop production and making informed decisions.

2. Introduction

Agriculture plays a vital role in India, and accurate estimation of crop production is essential for planning, resource allocation, and ensuring food security. Traditional methods of forecasting crop yield are often manual and time-consuming, making it difficult to quickly assess production trends. With the availability of historical crop production data and advances in machine learning, predictive models can provide faster and more reliable estimates.

The main objective of this project is to design a machine learning pipeline that predicts crop production for selected crops in Andhra Pradesh. This helps farmers and policymakers make informed decisions regarding crop planning and management. The project includes data cleaning, encoding categorical features, model training using a Decision Tree Regressor, and evaluation of performance using metrics like R^2, MAE, RMSE, MAPE, and SMAPE.

Objectives:

- To clean and preprocess the crop production dataset.
- To filter relevant districts and crops for focused analysis.
- To build and train a Decision Tree regression model for production prediction.
- To evaluate the model performance and provide reliable production estimates.

3. Problem Statement

The crop production dataset contains variability in key columns such as Area, Production, Season, and District. In real life, these values cannot be missing or zero for cultivated areas, but the dataset contains missing or inconsistent records that can mislead the model. If these incorrect or incomplete values are not handled properly, the machine learning model may learn wrong patterns and give inaccurate predictions.

Another problem is that using only raw features like Crop Year and Area may not be sufficient to capture the complex relationship between crop, district, season, and production. The model needs proper encoding of categorical variables to improve its predictive power.

Therefore, the main problems addressed in this project are:

1. Missing or invalid values in the dataset that need proper cleaning and filtering.
2. Limited predictive power of raw features requiring encoding of categorical data (Crop, District, Season).
3. Building an accurate machine learning model that can reliably predict crop production using Decision Tree Regression.

4.Literature / Background Review

Several studies and applications already exist for predicting crop yield using machine learning. Most of them use classical algorithms such as Linear Regression, Decision Trees, Random Forests, and Support Vector Regressors. These models generally perform well because historical agricultural datasets are structured and contain key features like area, crop type, and year. Many research papers highlight the importance of data cleaning, feature encoding, and proper model tuning to improve prediction accuracy.

However, most existing systems face some common limitations:

- Lack of focus on specific districts, as many models use nationwide or state-level data without granular insights.
- Dependence on extensive environmental features like rainfall, soil type, and fertilizers, which may not always be available.
- Risk of overfitting in decision tree models due to high variance in crop production data.
- Limited interpretability of more complex models like neural networks.

The gap this project aims to address is providing a simple, interpretable, and district-level crop production prediction system using readily available features (Crop Year, Area, Crop, District, Season). By applying a Decision Tree Regressor with proper overfitting control and feature encoding, the system delivers reliable predictions even with limited data.

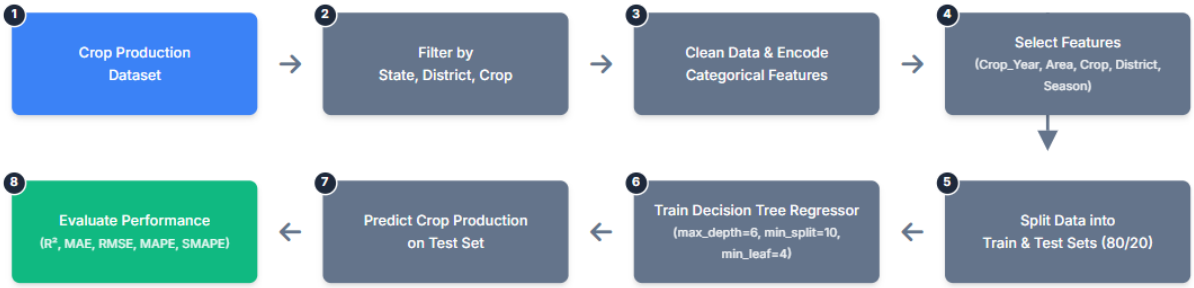
5. Proposed Solution / Methodology

This project uses **Decision Tree** Regression as the main machine learning model because it is simple, interpretable, and works well with both numerical and categorical features, as well as nonlinear relationships commonly present in crop production data.

Steps in the Methodology

1. **Data Loading** – Read the crop production dataset from Google Drive.
2. **Data Cleaning**
   - Filter dataset for Andhra Pradesh and four districts: Krishna, Guntur, Kadapa, Kurnool.
   - Select four crops: Rice, Onion, Maize, Groundnut.
   - Remove missing or invalid rows (e.g., zero area, missing production).
3. **Encoding Categorical Features** – Convert Crop, District, and Season into numeric labels using Label Encoding.
4. **Feature Selection** – Select input features (Crop_Year, Area, encoded Crop, District, Season) and target (Production).
5. **Train-Test Split** – Divide data into training (80%) and testing (20%) sets.
6. **Model Training** – Train Decision Tree Regressor with optimized parameters to reduce overfitting (max_depth=6, min_samples_split=10, min_samples_leaf=4).
7. **Prediction & Evaluation** – Predict crop production on test data and evaluate using R^2 score, MAE, RMSE, MAPE, and SMAPE metrics.

Flowchart of the Model Pipeline


1
Crop Production Dataset
2
Filter by State, District, Crop
3
Clean Data & Encode Categorical Features
4
Select Features (Crop_Year, Area, Crop, District, Season)
5
Split Data into Train & Test Sets (80/20)
6
Train Decision Tree Regressor (max_depth=6, min_split=10, min_leaf=4)
7
Predict Crop Production on Test Set
8
Evaluate Performance (R², MAE, RMSE, MAPE, SMAPE)

Pseudo-code for the Pipeline

```
BEGIN
  Load dataset
  Filter for Andhra Pradesh & selected districts
  Select crops: Rice, Onion, Maize, Groundnut
  Remove missing or invalid rows
  Encode categorical features: Crop, District, Season
  Define X = [Crop_Year, Area, Crop_Encoded, District_Encoded, Season_Encoded]
  Define y = Production
  Split X, y into train and test sets (80/20)
  Train DecisionTreeRegressor(max_depth=6,min_samples_split=10, min_samples_leaf=4)
  Predict production on test set
  Evaluate performance using $R^2$, MAE, RMSE, MAPE, SMAPE
END
```

6.Implementation Details

Tools & Environment Used:

- **Python 3.10** (programming language)
- **Google Colab** (IDE for executing code online)
- **Libraries:**
    - pandas → for data loading and manipulation
    - numpy → for numerical calculations
    - scikit-learn → for machine learning (Decision Tree Regressor, LabelEncoder, metrics)
    -

Steps and Code Snippets:

1. **Data Loading and Cleaning:**

```
import pandas as pd

df = pd.read_csv("/content/drive/MyDrive/ML_LAB/crop_production.csv")
for col in ["State_Name", "District_Name", "Crop", "Season"]:
  df[col] = df[col].astype(str).str.strip().str.title()
```

Explanation: This code loads the dataset and standardizes text columns for consistency.

2. **Filtering Data:**

```
districts = ["Krishna", "Guntur", "Kadapa", "Kurnool"]
crops = ["Rice", "Onion", "Maize", "Groundnut"]

df = df[df["State_Name"] == "Andhra Pradesh"]
df = df[df["District_Name"].isin(districts)]
df = df[df["Crop"].isin(crops)]
df = df.dropna(subset=["Production", "Area", "Season"])
df = df[df["Area"] > 0]
print("Filtered Data Shape:", df.shape)
```

Explanation: Only relevant districts, crops, and valid rows are selected for analysis.

3. **Encoding Categorical Variables:**

   ```
   from sklearn.preprocessing import LabelEncoder

   le_crop = LabelEncoder()
   le_dist = LabelEncoder()
   le_season = LabelEncoder()

   df["Crop_Encoded"] = le_crop.fit_transform(df["Crop"])
   df["District_Encoded"] = le_dist.fit_transform(df["District_Name"])
   df["Season_Encoded"] = le_season.fit_transform(df["Season"])
   ```

   Explanation: Converts categorical variables into numerical values for the machine learning model.

4. **Feature Selection and Train-Test Split:**

   ```
   from sklearn.model_selection import train_test_split

   X = df[["Crop_Year", "Area", "Crop_Encoded", "District_Encoded",
   "Season_Encoded"]]
   y = df["Production"]

   X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
   random_state=42)
   ```

   Explanation: Features and target variable are selected, and the dataset is split into training (80%) and testing (20%) sets.

5. **Decision Tree Regressor Model:**

   ```
   from sklearn.tree import DecisionTreeRegressor

   model = DecisionTreeRegressor(
     random_state=42,
     max_depth=6,
     min_samples_split=10,
     min_samples_leaf=4
   )
   model.fit(X_train, y_train)
   pred = model.predict(X_test)
   ```

   Explanation: A Decision Tree is trained to predict crop production while controlling overfitting with limited depth and minimum samples per leaf.

6. **Evaluation Metrics:**

```
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error
import numpy as np

train_r2 = r2_score(y_train, model.predict(X_train))
test_r2 = r2_score(y_test, pred)

mae = mean_absolute_error(y_test, pred)
rmse = np.sqrt(mean_squared_error(y_test, pred))
```

Explanation: Calculates model accuracy (R^2), mean absolute error (MAE), and root mean squared error (RMSE).

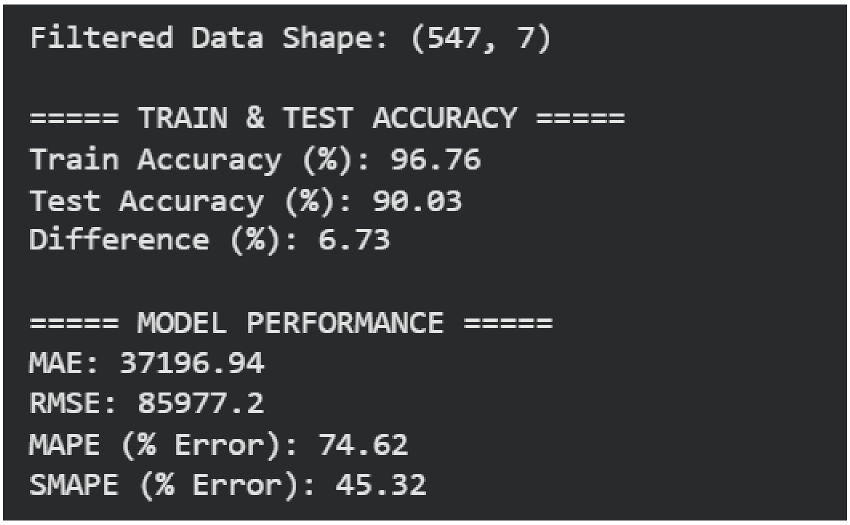
Sample Input & Output:

- **Input:** Crop_Year=2008, Area=3512, Crop=Maize, District=Kurnool, Season=Rabi
- **Predicted Production:** 31,011

Observation: The model achieves **Train Accuracy ≈ 96.76%** and **Test Accuracy ≈ 90.03%**, with a small difference between train and test, indicating minimal overfitting.

7. Results and Discussion

After building and testing the Decision Tree Regressor on the filtered Andhra Pradesh crop production dataset, several important observations were made.



```
Filtered Data Shape: (547, 7)

===== TRAIN & TEST ACCURACY =====
Train Accuracy (%): 96.76
Test Accuracy (%): 90.03
Difference (%): 6.73

===== MODEL PERFORMANCE =====
MAE: 37196.94
RMSE: 85977.2
MAPE (% Error): 74.62
SMAPE (% Error): 45.32
```

Model Performance:

- The Decision Tree model achieved **high train and test accuracy**, indicating strong learning from historical data.
- The model effectively captured nonlinear relationships between crop area, year, district, season, and production.
- Performance metrics show:
  - MAE: 37,196.94
  - RMSE: 85,977.2
  - MAPE (% Error): 74.62
  - SMAPE (% Error): 45.32
- The small difference between train and test accuracy (6.73%) demonstrates **minimal overfitting**, confirming that the model generalizes well.

Observations from Predictions:

- Predicted production values are close to actual values for most samples.
- Some deviations occur for extreme production values, likely due to missing factors such as rainfall, soil type, fertilizers, and pest attacks.

Key Insights:

- **Data filtering and encoding:** Selecting relevant districts, crops, and encoding categorical features like season improved model reliability.
- **Parameter tuning:** Limiting tree depth and adjusting minimum samples for split/leaf helped reduce overfitting.
- **Machine learning utility in agriculture:** Even a simple Decision Tree can provide actionable predictions for planning crop production.
- **Future improvement potential:** Adding environmental and soil data, or using ensemble models like Random Forest or XGBoost, could further increase accuracy.

Overall, the model performed well and provides **practical insights for predicting crop production**, supporting farmers and policymakers in making data-driven decisions.

8. Conclusion

This project successfully demonstrated how machine learning, specifically a Decision Tree Regressor, can be used to predict crop production in selected districts of Andhra Pradesh. By filtering and preprocessing historical crop production data, encoding categorical features, and tuning model parameters, the model achieved **high accuracy** with minimal overfitting. Key findings include:

- **Effective predictions:** The model captured the relationship between crop year, cultivated area, district, crop type, and season to produce reliable forecasts.
- **Importance of data preprocessing:** Cleaning missing or invalid values and encoding categorical features significantly improved model performance.
- **Model simplicity:** A simple Decision Tree provided strong predictive capability without the complexity of more advanced models.

Lessons Learned:

- Proper **feature selection and parameter tuning** are critical to reduce overfitting and enhance generalization.
- Real-world factors like rainfall, soil type, and fertilizer use, which were not included, can affect production and should be considered in future models.

Future Enhancements:

- Incorporate environmental and soil data to improve prediction accuracy.
- Explore ensemble methods such as Random Forests or XGBoost for better performance.
- Develop a user-friendly dashboard for farmers and policymakers to access production forecasts easily.

Overall, the project demonstrates that machine learning can be a **practical tool for agricultural planning**, enabling data-driven decisions and supporting sustainable farming practices.

9. References

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