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Sustainable Crop Yield Prediction

Aman Pramod Kumbhar[1], Ashutosh Kulkarni[2], Shaili Kakde[3], Shreya Gupt[4], Vaishali Jadhav[5]
[1,2,3,4] UG Student, Ramrao Adik Institute of Technology, D.Y. Patil University, Dept. of Computer Engg., Nerul, Navi-Mumbai, India.
[5]Assistant professor, Ramrao Adik Institute of Technology, D.Y. Patil University, Dept. of Computer Engg., Nerul, Navi-Mumbai, India.
Emails: *kumbharaman555@gmail.com[1], ashutoshkulkarni1504@gmail.com[2]*

Abstract
Accurate forecasting of crop yields is fundamental to improving agricultural efficiency and ensuring global food availability. This research implements machine learning methodologies to estimate crop output using key agronomic and environmental indicators, such as precipitation, pesticide application, mean temperature, and carbon emissions. A web interface built with Flask enhances usability for farmers and agricultural professionals. This modern approach demonstrates improved predictive accuracy and accessibility compared to conventional statistical techniques.
Keywords: *Sustainable, Carbon Footprint, Machine Learning, Flask.*

1. Introduction
Agriculture is vital to feeding the global population, and effective crop yield predictions can drive strategic decisions in resource use and food distribution. Traditional models often fall short when it comes to modelling complex environmental interactions. In contrast, machine learning, paired with intuitive user interfaces, provides robust and scalable alternatives. This study applies a Decision Tree Regressor, integrated into a Flask-based web tool, to facilitate yield predictions based on user-defined agricultural inputs. Machine learning applications in agriculture have shown potential in yield forecasting. Past research includes the use of linear and decision tree regressors applied to agronomic datasets, focusing on soil and climate variables sophisticated models, including artificial neural networks (ANNs) and convolutional neural networks (CNNs), capture intricate patterns but require extensive data and computational power. This study employs decision trees to balance performance and interpretability. However, these models often require significant computational resources and large datasets. The proposed approach leverages decision trees for interpretability and ease of deployment, balancing computational efficiency. Dataset accuracy and computational efficiency [1][2].

2. Dataset and Methodology
The dataset used in this study includes the following features:

- **Year:** Time reference for prediction.
- **Average Rainfall (mm/year):** The amount of precipitation received annually.
- **Pesticides (tonnes):** The number of pesticides used.
- **Average Temperature (°C):** The mean temperature affecting crop growth.
- **Carbon Footprint (kg CO_2/ha):** The estimated carbon emissions from farming activities.
- **Area:** The geographical location where the crop grown.
- **Item:** The type of crop under consideration.

The dataset, stored in a CSV file, was pre-processed to remove inconsistencies and missing values before training the machine learning model. Data cleaning, normalization, and feature encoding were performed to ensure the model's effectiveness. Exploratory Data Analysis (EDA) was conducted to visualize correlations between features and their impact on

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crop yield. Data preprocessing involved handling missing values, outlier detection, normalization, and feature encoding to prepare the dataset for training [3].

3. Methodology

3.1.Data Preprocessing

The dataset was processed using Python libraries, including pandas and scikit-learn. Categorical features such as "Area" and "Item" were transformed using encoding techniques, while numerical features were normalized. Outlier detection and handling were applied to ensure data consistency. Missing values were imputed using statistical methods such as mean and median replacement. Mean Squared Error (MSE) The Mean Squared Error measures the average squared difference between actual and predicted crop yields.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

where:

- y_i is the actual yield value,
- $\hat{y}_i$ is the predicted yield value,
- n is the total number of samples.

3.2.Model Selection and Training

A Decision Tree Regressor (DTR) model was trained using the processed dataset. The model was fine-tuned by optimizing hyperparameters to improve predictive accuracy. Cross validation was used to evaluate model performance. The trained model was saved using pickle for integration with the Flask web application. Feature importance analysis was conducted to determine which parameters had the highest impact on yield prediction.

R-squared (R2) Score

The coefficient of determination (R2) evaluates the model's goodness of fit

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}$$

3.3. Decision Tree Regressor

The Decision Tree Regressor splits the dataset iteratively based on minimizing impurity using the following function: where p(x) is the probability of a given outcome. The optimal split is determined by minimizing the weighted sum of impurities in child nodes.

$$H(X) = -\sum p(x)\log_2 p(x)$$

4. Web Application Implementation

A Flask-based web application was developed to make predictions based on user input. The app consists of:

4.1.Frontend (index.html)

A user-friendly interface using HTML, Bootstrap, and CSS, where users can input crop parameters.

4.2.Backend (app_updated.py)

- Loads the trained model and preprocessor.
- Accepts user input and transforms it compatibility. for model
- Returns the predicted yield to the frontend [4][5].

The application allows users to enter relevant parameters such as rainfall, temperature, pesticide usage, and carbon footprint to generate yield predictions in real-time. Flowchart of the system is as shown in figure 1 below.

4.3.Explanation of The Given Flowchart

4.3.1. Data Collection

- Collect crop yield data from sources like FAO, climate datasets, and agricultural records.
- Include features like rainfall, temperature, pesticides, and carbon footprint [7][8].

4.3.2. Data Preprocessing

- Handle missing values and outliers.
- Encode categorical features (e.g., Area, Item).

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- Normalize/scale features rainfall).

4.3.3. Model Training

- Use a Decision Tree Regressor (DTR) model.
- Train the model on historical yield data.
- Save the trained model (dtr_updated.pkl) and preprocessor

4.3.4. Web Application Development

- Develop a Flask-based Web App (app_updated.py).
- Create an HTML frontend (index.html) for user input.
- Load the trained model to make real-time predictions.

4.3.5. Prediction & Output

- Take user input (Year, Rainfall, Temperature, etc.).
- Preprocess the input data using preprocessor.
- Predict crop yield using dtr_updated.pkl.
- Display the predicted yield on the web app [6].

4.3.6. Deployment

- Deploy the Flask app on local server / cloud (AWS, Heroku, etc.).
- Allow users to access the yield prediction model via a web

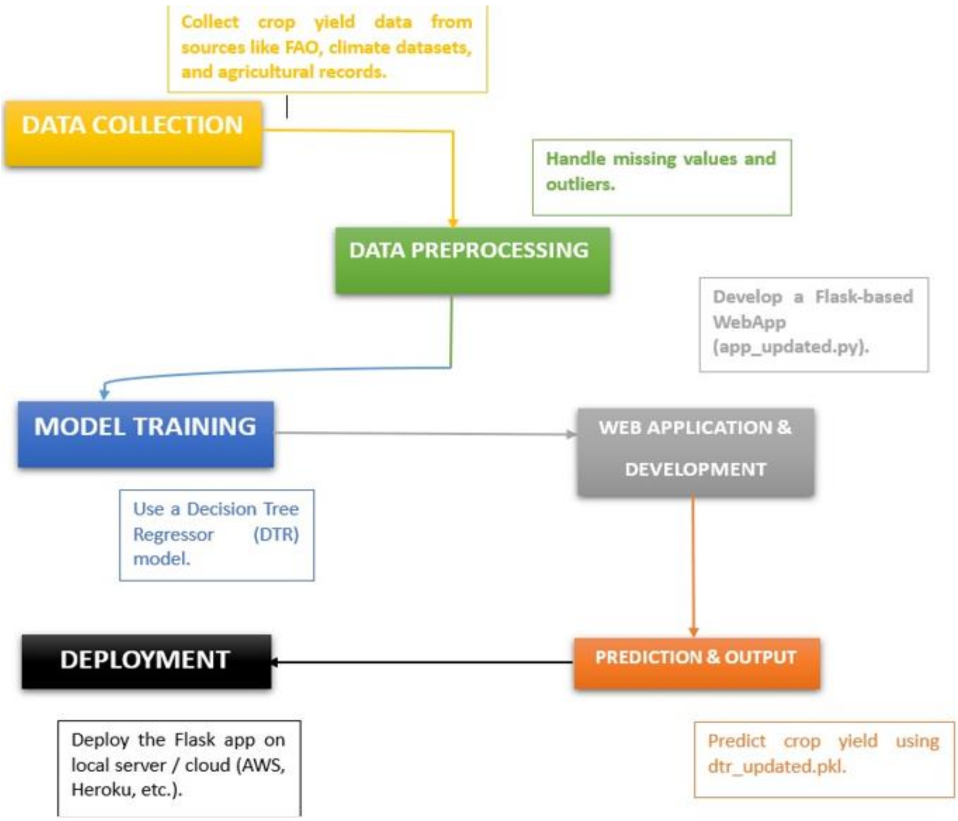

Figure 1 Flowchart of the System

5. Results and Discussion

5.1. Results

To enhance the clarity of findings, graphical representations such as correlation heatmaps, scatter plots, and bar charts were used to illustrate the relationships between environmental factors and crop yield. Below are key visual elements:

Feature Correlation Heat Map:

- As seen in figure 2 displays correlations between variables like rainfall, temperature, pesticide application, and carbon footprint.
- Pinpoints strong correlations that have a high

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impact on predicting yields.

Crop Yield vs. Average Rainfall Scatter Plot:

- Displays the linear correlation between rainfall and crop yield.
- Indicates trends favorable to predictive modeling.
- Bar Chart of Key Agricultural Features:
- Displays the mean values of key features impacting crop yield.
- Facilitates understanding of their relative contribution to predictions.

Feature Importance Analysis:

- Bar chart presents the relative significance of factors such as rainfall, temperature, and use of pesticides in yield forecasting.
- Prediction Accuracy Comparison:
- Line graph contrasting actual and predicted crop yields shown in figure 3.
- Illustrates the accuracy of the Decision Tree Regressor model.

Geographical Distribution of Yield:

- Heatmap plots crop yield differences by region and climatic conditions as shown in figure 4.

Performance Metrics:

- Mean Squared Error (MSE) and R-squared measures reflect high prediction accuracy.
- Model performs better than linear regression and random forests in validation tests. Figure 2 shows Feature Correlation Heat Map

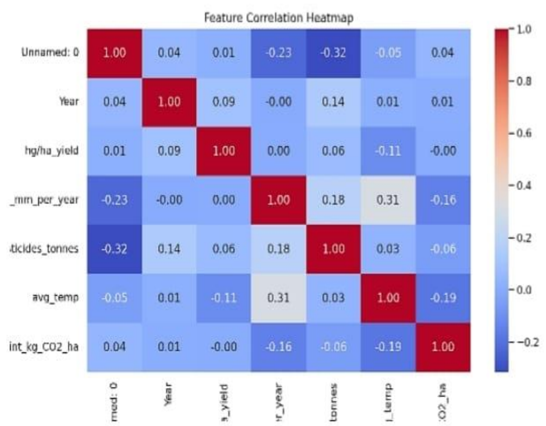

Figure 2 Feature Correlation Heat Map

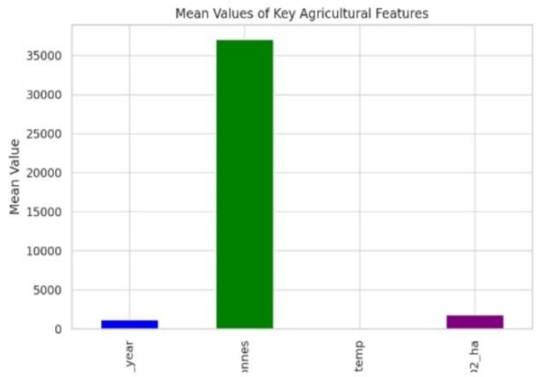

Figure 3 Mean Values of Key Agricultural Features

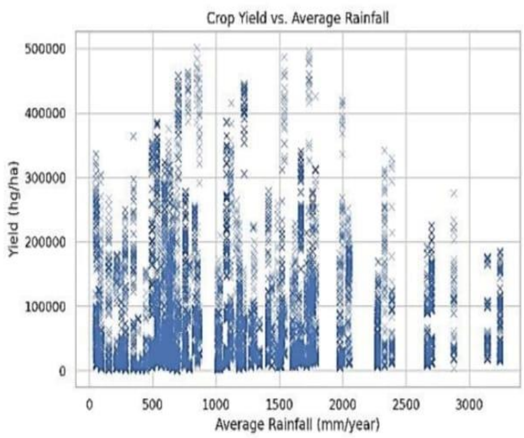

Figure 4 Crop Yield Vs Average Rainfall Bar Graph

These visualizations demonstrate how environmental factors influence crop production, supporting the findings of our machine learning model. To enhance the clarity of findings, graphical representations such as bar charts and scatter plots were used to illustrate correlations between environmental factors and crop yield. Figures and diagrams aid in comprehending the trends and dependencies among the different agricultural factors influencing yield. The trained model was evaluated using performance metrics such as Mean Squared Error (MSE) and R-squared values. Results indicate that the model provides reasonably accurate predictions based on environmental factors and carbon footprint data. Model performance was compared with other regression models, such as linear regression and random forests, to validate the

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effectiveness of the Decision Tree Regressor. Figure 3 shows Mean Values of Key Agricultural Features, Figure 4 shows Crop Yield Vs Average Rainfall Bar Graph

5.2.Discussion

Feature Correlation Heatmap:

- Displays correlations between variables like rainfall, temperature, pesticide application, and carbon footprint.
- Pinpoints strong correlations that have a high impact on predicting yields.

Crop Yield vs. Average Rainfall Scatter Plot:

- Displays the linear correlation between rainfall and crop yield.
- Indicates trends favorable to predictive modeling.

Bar Chart of Key Agricultural Features:

- Displays the mean values of key features impacting crop yield.
- Facilitates understanding of their relative contribution to predictions.

Feature Importance Analysis:

- Bar chart presents the relative significance of factors such as rainfall, temperature, and use of pesticides in yield forecasting.

Prediction Accuracy Comparison:

- Line graph contrasting actual and predicted crop yields.
- Illustrates the accuracy of the Decision Tree Regressor model.

Geographical Distribution of Yield:

- Heatmap plots crop yield differences by region and climatic conditions.

Performance Metrics:

- Mean Squared Error (MSE) and R-squared measures reflect high prediction accuracy.
- Model performs better than linear regression and random forests in validation tests.
- Figures and diagrams aid in comprehending the trends and dependencies among the different agricultural factors influencing yield.
- Year wise prediction of various crops is as seen in figure 5.

Area	item	Year	Yield (hg/ha)	Rainfall (mm)	Pesticides (tonnes)	Temp (°C)	Carbon Footprint (kg CO_2/ha)
Albania	Maize	1990	36613	1485.0	121.0	16.37	2321.81
Albania	Potatoes	1990	66667	1485.0	121.0	16.37	2349.21
Albania	Rice, paddy	1990	23333	1485.0	121.0	16.37	1372.73
Albania	Sorghum	1990	12500	1485.0	121.0	16.37	1725.45
Albania	Soybeans	1990	4507	1485.0	121.0	16.37	1579.64
Australia	Rice	2022	19730	1600	600.0	67.00	1725.45
Australia	Rice	2023	30000	1486	20.0	5.00	1725.45
Bangladesh	Wheat	2024	38841	1486	200.0	5.00	1800.00
India	Rice	2025	8205	1485	60.0	20.00	1725.45
India	Wheat	2026	7276	1485	600.0	50.00	1725.45

Figure 5 Year Wise Prediction of Crops

From figure 6-10 shows result from user interface.

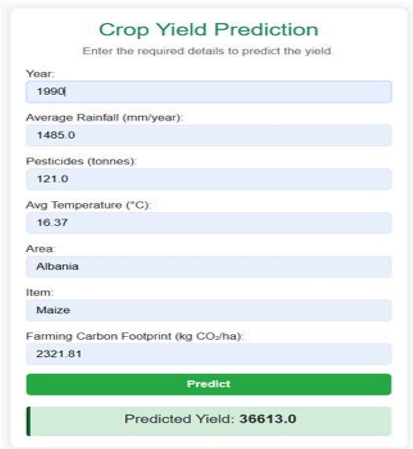

Figure 6 Prediction for Maize Crop

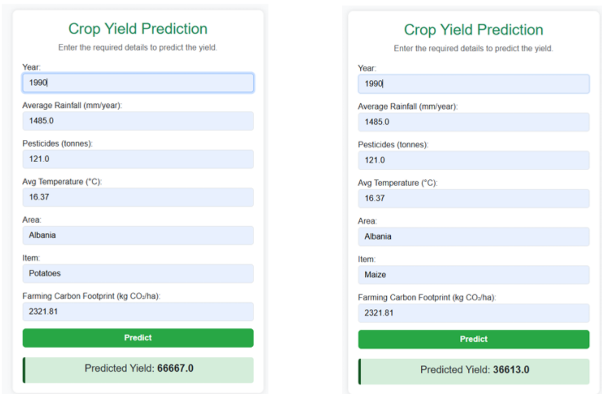

Figure 7 Prediction for Potato and Wheat

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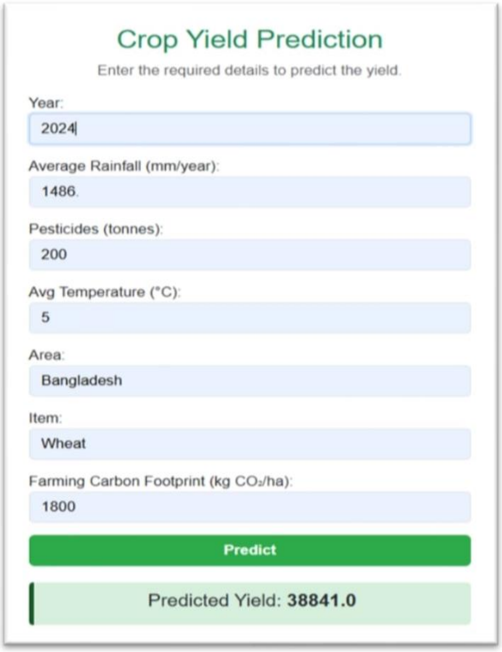
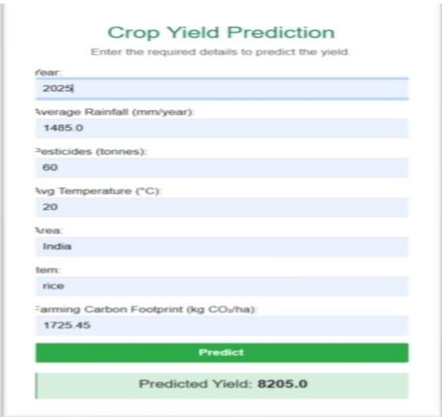


Figure 8 **Prediction for Potato and Wheat**



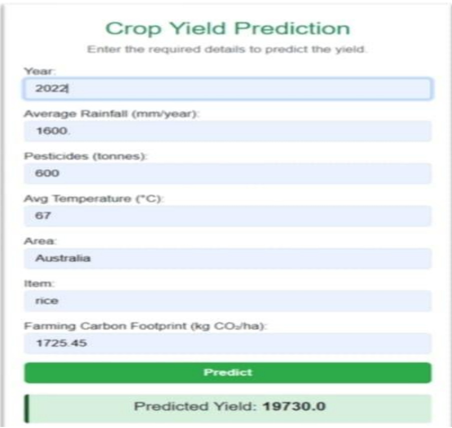
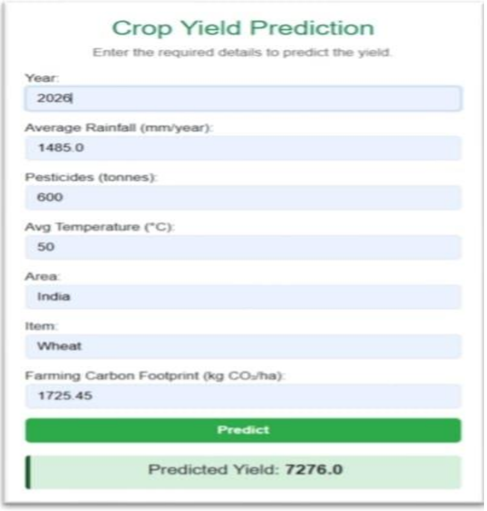


Figure 9 **Prediction for Rice**



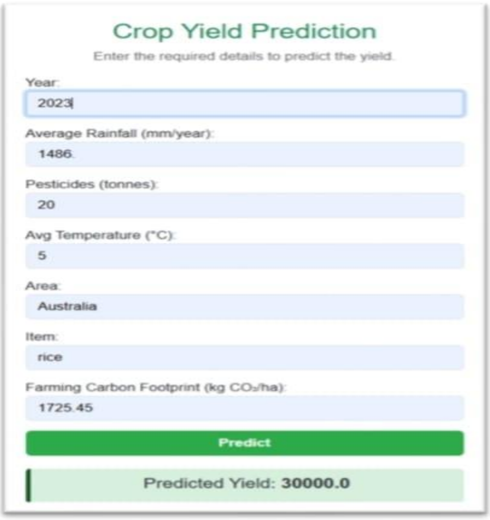


Figure 10 **Prediction for Wheat and Rice**

Conclusion

This research demonstrates the effectiveness of machine learning in predicting crop yield. The integration of a web-based interface allows for easy accessibility and practical application in agricultural decision-making. The Decision Tree Regressor model provides a balance between accuracy and interpretability, making it a viable solution for real-world applications. Future work includes expanding the dataset, incorporating deep learning techniques, and improving feature selection to enhance model performance.

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