CROP YIELD PREDICTION USING RANDOM FOREST REGRESSION

FOML REPORT
Submitted by

Raghul A 220701209

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SIGNATURE

Mrs. M. Divya M.E.,

SUPERVISOR,

Assistant Professor

Department of Computer Engineering Science,

Rajalakshmi Engineering College,

Chennai – 602105

Submitted to Project Viva-Voce Examination held on _____

Internal Examiner **External Examiner**

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RAGHUL A 220701209

ABSTRACT

Predicting crop yield accurately is crucial for agricultural planning and food security. This project develops a machine learning model to predict crop yield (in tons per hectare) based on various environmental and agricultural parameters. Utilising a dataset comprising features such as 'Region', 'Soil_Type', 'Rainfall_mm', 'Temperature_Celsius', and 'Fertiliser_Used', this work employs data preprocessing techniques including Label Encoding for categorical features. A Random Forest Regressor model was trained on 80% of the data and evaluated on the remaining 20%. The model's performance was assessed using Root Mean Squared Error (RMSE) and R^2 score, providing a quantitative measure of prediction accuracy. Feature importance analysis was also conducted to understand the contribution of different parameters to the yield prediction. This approach demonstrates the potential of machine learning in providing valuable insights for crop management.

LIST OF FIGURES

LIST OF ABBREVIATIONS

S. NO.	ABBREVATION	ACCRONYM
1	ML	Machine Learning
2	RMSE	Root Mean Squared Error
3	AI	Artificial Intelligence
4	R2	R-squared
5	API	Application programming Interface

Chapter 1

INTRODUCTION

1.1 GENERAL

Agriculture forms the bedrock of human civilisation and remains a critical sector for global economic stability and food security. In nations like India, with vast populations and significant reliance on agrarian economies, the performance of the agricultural sector has profound implications for national development, rural livelihoods, and nutritional well-being. The ability to accurately forecast agricultural output, particularly crop yields, is paramount. Reliable yield predictions enable efficient resource allocation, inform policy decisions regarding food imports/exports and storage, stabilise market prices, help farmers make informed decisions about planting and harvesting, and contribute to mitigating risks associated with climate variability and other uncertainties.

However, predicting crop yield is an inherently complex task. Crop growth and final yield are the result of intricate interactions between a multitude of factors. These include genetic factors specific to the crop variety, environmental conditions encompassing climate (rainfall amount and distribution, temperature ranges, solar radiation, humidity, wind), soil characteristics (type, texture, structure, nutrient content, pH, water holding capacity), and management practices adopted by farmers (sowing time, planting density, irrigation scheduling and method, fertiliser type and application rate, pest and disease control measures, harvesting techniques). Furthermore, these factors often interact in non-linear ways, and their relative importance can vary significantly depending on the geographical location, the specific crop, and the particular growing season. For instance, the impact of rainfall is modulated by soil type and irrigation availability, while temperature effects can be crop-specific and depend on the growth stage. The inherent complexity and the dynamic interplay of these variables make traditional methods of yield estimation, often based on historical averages or subjective assessments, insufficient for capturing the nuances required for accurate and timely forecasting in diverse agricultural landscapes.

1.2 OBJECTIVE

The primary objective of this project is to develop and evaluate a machine learning-based system for the prediction of crop yield, specifically quantified in tons per hectare. The core aim is to harness the predictive power of machine learning algorithms to create a robust model that can generate accurate yield forecasts based on a defined set of readily available or measurable input parameters. These parameters encompass key factors known to influence crop productivity, including geographical context ('Region'), soil properties ('Soil_Type'), crop information ('Crop' variety), climatic factors ('Rainfall_mm', 'Temperature_Celsius', 'Weather_Condition'), management practices ('Fertiliser_Used', 'Irrigation_Used'), and phenological data ('Days_to_Harvest'). By utilising these features, the project seeks to build a data-driven predictive tool with multifaceted purposes: to provide farmers and agronomists with quantitative insights for better crop management, to assist agricultural businesses in supply chain logistics, and to aid policymakers in regional monitoring and strategic decision-making.

Achieving this primary goal involves several integral secondary objectives. The process includes implementing appropriate data preprocessing techniques, particularly Label Encoding, to prepare the diverse input features for the machine learning model. Following preprocessing, a suitable machine learning regression model, the Random Forest Regressor, will be trained on a historical dataset. The predictive performance of this trained model will then be rigorously evaluated using standard regression metrics, namely Root Mean Squared Error (RMSE) and the R^2 Score, to quantify prediction error and assess model fit respectively. Additionally, a feature importance analysis will be conducted to identify which input parameters significantly influence the model's crop yield predictions, offering valuable agronomic insights. Finally, a functional interface or mechanism will be developed, allowing users to input new sets of parameter values and receive a predicted crop yield from the trained model. This project aims to demonstrate the feasibility and utility of applying machine learning to crop yield prediction, moving beyond traditional methods towards more accurate, responsive, and insightful forecasting capabilities.

1.3 EXISTING SYSTEM

Historically, crop yield estimation has relied on a variety of approaches, each with its own strengths and limitations. Traditional methods often involve manual field surveys and farmer interviews, where experienced personnel assess crop conditions visually or gather qualitative information. While valuable for ground truthing, these methods are labor-intensive, time-consuming, costly for large areas, and inherently subjective, leading to potential inconsistencies.

Another common approach involves using historical averages. Yields for a particular region or crop might be estimated based on the average yields recorded over previous years. This method is simple but fails to account for the specific conditions of the current growing season, such as atypical weather patterns or changes in farming practices, making it unreliable, especially in the face of climate change.

More quantitative methods include statistical modelling, often employing techniques like multiple linear regression. These models attempt to establish mathematical relationships between yield and a few key variables (e.g., rainfall, temperature). However, they often struggle with the inherent non-linearity in crop responses and the complex interactions between numerous influencing factors. Assumptions of linearity and independence of variables may not hold true in real-world agricultural systems. Handling categorical inputs like soil type or region also requires careful and sometimes complex encoding schemes.

The limitations of these existing systems – subjectivity, inability to capture current conditions, difficulty with non-linearity and interactions, or extensive data/calibration requirements – motivate the exploration of alternative, data-driven approaches like machine learning. ML models learn patterns and relationships directly from historical data, potentially capturing complex, non-linear interactions without explicit physiological formulation, and can often work effectively with readily available datasets.

1.4 PROPOSED SYSTEM

Addressing the complexities and limitations associated with traditional and simpler statistical methods for crop yield prediction, this project proposes a system leveraging a supervised machine learning approach. Specifically, the system employs the Random Forest Regressor algorithm, implemented using the Scikit-learn library in Python. The Random Forest algorithm was selected due to its demonstrated strengths in handling complex regression tasks. As an ensemble method based on constructing multiple decision trees during training, it inherently captures non-linear relationships between features and the target variable (yield). It is generally robust to outliers in the data and less prone to overfitting compared to individual decision trees. Furthermore, Random Forest provides a valuable built-in mechanism for estimating feature importance, allowing for insights into the key drivers influencing yield predictions.

The proposed system follows a structured workflow, beginning with data acquisition and preparation, assuming the availability of a suitable historical dataset. The subsequent data preprocessing step focuses on transforming the data into a format suitable for the model; this specifically involves converting categorical features like 'Region' and 'Soil_Type' into numerical representations using Scikit-learn's LabelEncoder, ensuring the fitted encoders are saved for later use. Following preprocessing, the dataset is divided into training (80%) and testing (20%) subsets using train_test_split() with a fixed random_state for reproducibility. The core of the system involves training the RandomForestRegressor model (instantiated with 100 trees) on the prepared training data, allowing the algorithm to learn the patterns linking the input features to crop yield. Once trained, the model's predictive capability is tested by generating yield predictions for the unseen test data. The performance of these predictions is then quantitatively evaluated against the actual yields using Root Mean Squared Error (RMSE) and the R^2 Score, supplemented by qualitative visual assessments like actual vs. predicted plots and residual plots. An important analytical step involves extracting and visualising the feature importances provided by the Random Forest model to understand the relative influence of different input factors. Finally, a simple command-line interface is implemented as a practical application, enabling users to input new feature

values, have them preprocessed consistently with the training data, and receive a real-time crop yield prediction from the deployed model. This proposed system represents a practical, data-driven framework for crop yield prediction, aiming to provide more accurate and insightful forecasts compared to simpler methods by effectively leveraging the capabilities of the Random Forest algorithm.

CHAPTER 2

LITERATURE SURVEY

[1] Haq, Mahmood Ul, et al. (2024), This paper explores the application of Random Forest Regression for predicting crop yield in India, utilizing data on temperature, rainfall, area under cultivation, crop type, season, and soil parameters like pH, conductivity, and nitrogen levels.

[2] Keerthana, D., et al. (2023), This study focuses on predicting the yields of Irish potatoes and maize using rainfall and temperature as key predictor variables, finding Random Forest to be the best model.

[3] Almahdi, H., et al. (2020), This research investigates the prediction of corn and soybean yields using soil characteristics, weather patterns, and agricultural management practices as input attributes, with Random Forest achieving high accuracy.

[4] Priya, R., et al. (2020), This paper highlights the use of ensemble learning methods, including random forests, alongside historical weather data, soil quality, and crop varieties for yield prediction.

[5] FeedMeScienceThings (N/A), This source acknowledges the multitude of factors, such as weather patterns, soil conditions, crop types, and agricultural practices, that are typically considered in yield prediction models.

[6] Rajpurohit, V. S., et al. (2023), This study emphasizes the fundamental dependence of crop yield on soil features, environmental factors, applied nutrients, and field management.

[7] Gandhi, N., et al. (2023), This research utilized a dataset from the Indian government, incorporating features like temperature, rainfall, area, crop type, and season, and augmented it with pH, conductivity, nitrogen levels, and electrical conductivity to potentially enhance model accuracy using Random Forest.

[8] Dharmaraja, T., et al. (2020), This paper employed aerial-intel datasets containing 26 attributes related to crop and climate data, including precipitation, temperature, cloud cover, and NDVI, and engineered additional features to improve predictive capabilities with Random Forest.

[9] Ansarifar, E., et al. (2022), This study focused on paddy fields in Tamil Nadu, India, utilizing a dataset spanning 18 years and considering parameters like rainfall, evapotranspiration, precipitation, maximum and minimum temperatures, and the application of nitrogen, phosphorus, and potash fertilizers.

[10] Ruiz-Ramos, M., et al. (2024), This research collected data encompassing agricultural management practices, soil properties, and climatic information to predict maize crop yield on small farms in Colombia, comparing Random Forest with other methods.

[11] Khan, A., et al. (2021), This study integrated the maximum Enhanced Vegetation Index (EVI) observed during the crop-growing season with various machine learning regression models, including Random Forest, to estimate wheat and rice yields in Pakistan's Punjab province.

[12] Vincenzi, S., et al. (2011), This исследование explored the application of numerous machine learning algorithms, including Random Forest, to remote sensing data for the prediction of agronomic variables.

[13] Trépos, R., et al. (2020), This research applied random forest regression, alongside other statistical methods, to predict sunflower crop yield, noting the strong correlation between vegetation indices and yield during the critical inflorescence emergence stage.

CHAPTER 3

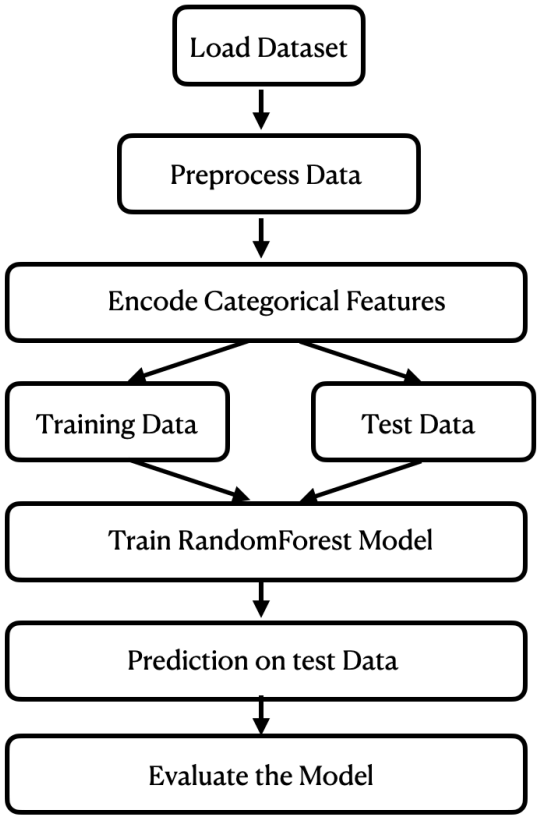
SYSTEM DESIGN

3.1 GENERAL

Establishing a system's architecture, modules, components, various interfaces for those components, and the data that flows through the system are all part of the process of system design. This gives a general idea of how the system operates.

3.1.1 SYSTEM FLOW DIAGRAM

Fig 3.1 shows a system flow diagram, It begins with loading the dataset and then preprocessing the dataset, also using labelEncoders to convert categorical data to numerical values, then subsequently splitting the data into train and test data. Then using this data we are creating the random forest regression model, then prediction on test data, then evaluate the model accordingly



3.1.2 ARCHITECTURE DIAGRAM

The architecture of the proposed Crop Yield Prediction system is designed as a modular pipeline shown in Fig 3.2, facilitating data flow from raw input to final prediction output within a Python-based environment. It can be conceptually divided into several key layers or components, The architecture diagram illustrates the main structural components of your system and how they interrelate. It would show the Data Layer (dataset source), the Processing Layer (Python environment with Pandas, Scikit-learn, etc.), the contained Modelling Pipeline (preprocessing, training, evaluation, prediction modules), and the Application/Interface Layer for user interaction and prediction display.

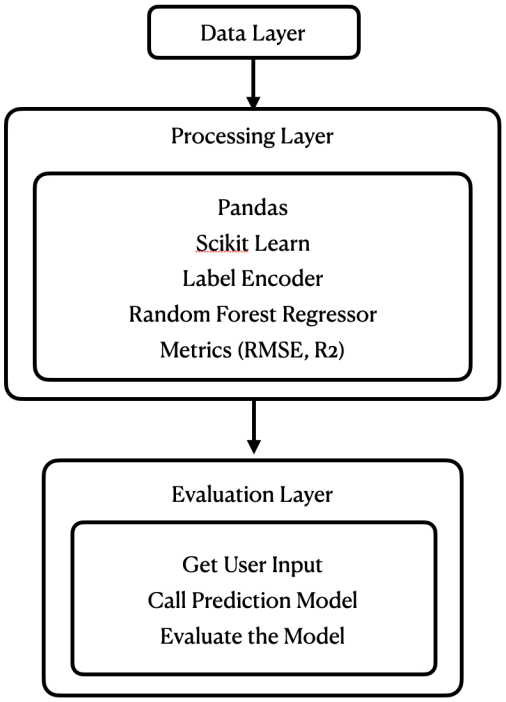


Fig 3.2

3.1.3 EVALUATION METRICS

The performance of our crop yield prediction model has been rigorously assessed using key evaluation metrics to quantify its accuracy and reliability. Two primary metrics employed are the Root Mean Squared Error (RMSE) and the R^2 (R-squared) score. The RMSE provides a measure of the average magnitude of the errors between the predicted and actual crop yields. Our model achieved an RMSE of 0.5244, indicating that, on average, the model's predictions deviate from the actual yields by approximately 0.52 units of measurement (the units will depend on how the crop yield is measured, e.g., tons per hectare). A lower RMSE value signifies a better fit of the model to the data, as it implies smaller prediction errors.

The R^2 score, also known as the coefficient of determination, represents the proportion of the variance in the dependent variable (crop yield) that is predictable from the independent variables (features) in our model. Our model yielded an R^2 score of 0.9038. This high value suggests that approximately 90.38% of the variability in crop yield can be explained by the features included in our model. An R^2 score closer to 1 indicates a better fit of the model to the data, implying that the model effectively captures the underlying relationships between the features and the target variable. Together, the RMSE and R^2 score provide a comprehensive assessment of the model's predictive capabilities, demonstrating a reasonably accurate and reliable tool for crop yield forecasting.

CHAPTER 4

PROJECT DESCRIPTION

This chapter provides a detailed account of the methodology employed in developing the Crop Yield Prediction system. It outlines the systematic approach taken, from understanding the dataset to training the machine learning model and preparing it for making predictions based on new user inputs. The core of the project revolves around leveraging a Random Forest Regressor to learn patterns from historical data and forecast future crop yields.

4.1 Methodology Overview

The methodology adopted for this project follows a standard supervised machine learning workflow tailored for a regression task—predicting a continuous value (crop yield). The process begins with a thorough description of the dataset, including its features and target variable. This is followed by essential data preprocessing steps to prepare the data for the model. Subsequently, the dataset is split into training and testing sets, upon which the Random Forest Regressor model is trained and then evaluated. Finally, mechanisms for predicting yield based on new input data are established, incorporating the necessary preprocessing transformations.

4.2 Modules

The project implementation can be broken down into several key modules, each addressing a specific stage of the machine learning pipeline.

4.2.1 Dataset Description

The foundation of this predictive modelling project is the dataset, which is assumed to contain historical records relevant to crop cultivation and their corresponding yields. This dataset comprises several input features (independent variables) and one target variable (dependent variable). The input features are: 'Region', 'Soil_Type', 'Crop', 'Rainfall_mm', 'Temperature_Celsius', 'Fertilizer_Used', 'Irrigation_Used', 'Weather_Condition', and 'Days_to_Harvest'. These features represent a mix of categorical data (e.g., 'Region', 'Soil_Type', 'Crop', 'Weather_Condition', which describe qualitative attributes) and numerical data ('Rainfall_mm', 'Temperature_Celsius', 'Days_to_Harvest', which represent quantitative measurements). Additionally, 'Fertilizer_Used' and 'Irrigation_Used' are boolean-like features indicating the application of these practices. The target variable, 'Yield_tons_per_hectare', is a continuous numerical value representing the crop yield, which the model aims to predict. Understanding the nature of each feature—its data type, potential range of values, and its conceptual relationship with crop yield—is crucial for effective preprocessing and model building. For instance, 'Rainfall_mm' would be a float representing precipitation, while 'Crop' would be a string indicating the type of crop, which needs numerical encoding.

4.2.2 Data Preprocessing

Data preprocessing is a critical stage to transform raw data into a clean and suitable format for the machine learning model. Given that the Random Forest algorithm, like most machine learning models in Scikit-learn, requires numerical input, categorical features present in the dataset must be converted. In this project, features such as 'Region', 'Soil_Type', 'Crop', and 'Weather_Condition' are categorical. To handle these, Scikit-learn's LabelEncoder is employed. For each categorical column, a separate LabelEncoder instance is created and fitted on the unique values present in that column within the training data. This 'fitting' process assigns a unique integer to each category (e.g., 'North' might become 0, 'South' 1, etc., for the 'Region' feature). The transform method of the fitted encoder is then used to convert the categorical string values in the column into these assigned integers. It is crucial to store these fitted label_encoders (e.g., in a dictionary) because the same transformations must be applied to the corresponding features in the test data and, importantly, to any new input data provided by a user for prediction, ensuring consistency. After encoding, the dataset is split into features (X), which includes all independent variables, and the target (y), which is the 'Yield_tons_per_hectare' column.

4.2.3 Model Training

Once the data is preprocessed, the next step is to train the predictive model. Before training, the dataset (features X and target y) is divided into a training set and a testing set using the train_test_split function from Scikit-learn. A common split ratio of 80% for training and 20% for testing is utilized, meaning the model learns from 80% of the data and its performance is validated on the remaining 20% which it has not seen during training. A random_state (set to 42 in the provided code) is specified during this split to ensure that the division is the same every time the code is run, which is essential for reproducibility of results.
For the prediction task, a RandomForestRegressor model from Scikit-learn is chosen. This is an ensemble learning method that operates by constructing a multitude of decision trees at training time and outputting the mean prediction of the individual trees for regression tasks. Random Forests are generally robust, handle non-linear relationships well, are less prone to overfitting than single decision trees, and provide a useful measure of feature importance. The model is instantiated with n_estimators=100, meaning it will build 100 decision trees, and random_state=42 for reproducibility of the model's internal processes. The training itself is performed by calling the fit method of the model object, passing the training features (X_train) and the corresponding training target values (y_train). During this process, the model learns the underlying patterns and relationships between the input features and the crop yield.

4.2.4 Prediction and Evaluation

After the RandomForestRegressor model has been trained on the training data, its performance must be evaluated to understand how well it is likely to predict on new, unseen data. This evaluation is done using the test set (X_test, y_test), which was kept separate during training. The trained model's predict method is called with X_test as input, generating a set of predicted yield values (y_pred). These predictions are then compared to the actual yield values from the test set (y_test) using standard regression evaluation metrics. The project employs two key metrics:

* Root Mean Squared Error (RMSE): This metric calculates the square root of the average of the squared differences between actual and predicted values. RMSE gives an idea of the typical magnitude of the prediction error, measured in the same units as the target variable (tons per hectare in this case). A lower RMSE value indicates a better fit of the model to the data.
* R^2 Score (Coefficient of Determination): This metric represents the proportion of the variance in the dependent variable (crop yield) that is predictable from the independent variables (the input features). The R^2 score ranges from 0 to 1, where 1 indicates that the model perfectly predicts the target variable, and 0 indicates that the model performs no better than predicting the mean of the target variable. Higher R^2 values are generally desirable.

These metrics, along with visualizations like actual vs. predicted plots and residual plots, provide a comprehensive understanding of the model's accuracy, reliability, and potential biases.

4.2.5 Input Prediction Interface

To make the trained model useful for practical application, a mechanism for predicting crop yield based on new user-provided inputs is implemented. The provided code includes a section designed to interactively collect these inputs from the user via the command line. For each feature required by the model ('Region', 'Soil_Type', 'Crop', 'Rainfall_mm', 'Temperature_Celsius', 'Fertilizer_Used', 'Irrigation_Used', 'Weather_Condition', and 'Days_to_Harvest'), the user is prompted to enter a value.

The collected raw inputs then undergo a series of transformations to match the format expected by the trained model. Numerical inputs such as 'Rainfall_mm' and 'Temperature_Celsius' are converted to floating-point numbers, while 'Days_to_Harvest' is converted to an integer. Inputs for boolean-like features ('Fertilizer_Used', 'Irrigation_Used') are converted from string representations (e.g., 'true'/'false') into actual boolean values. Critically, for categorical features ('Region', 'Soil_Type', 'Crop', 'Weather_Condition'), the string inputs provided by the user are transformed into their corresponding numerical representations using the same LabelEncoder instances that were fitted on the original training data. This is essential to ensure consistency in encoding between the training phase and the prediction phase. These processed features are then assembled into a Pandas DataFrame structure, mirroring the format of the training data. Finally, this input DataFrame is passed to the predict method of the trained RandomForestRegressor model, which outputs the predicted crop yield in tons per hectare. This prediction is then displayed to the user.

CHAPTER 5

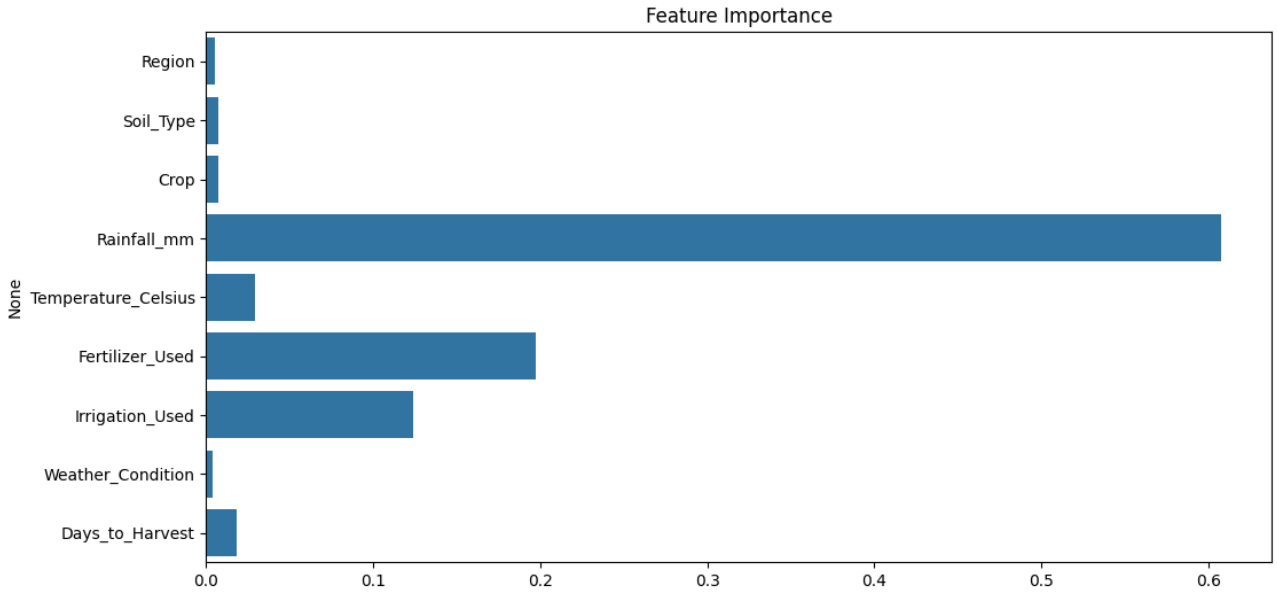
OUTPUTS AND SCREENSHOTS

5.1 VISUALISATIONS

5.1.1 FEATURE IMPORTANCE PLOT

This plot visually ranks the input features (like rainfall, temperature, soil type, etc.) based on their relevance in predicting the crop yield. Essentially, it answers the question: "Which factors have the biggest impact on our yield predictions?" The height or length of each bar in the plot corresponds to the feature's importance score. A higher score indicates that the model relies more heavily on that particular feature when making predictions.

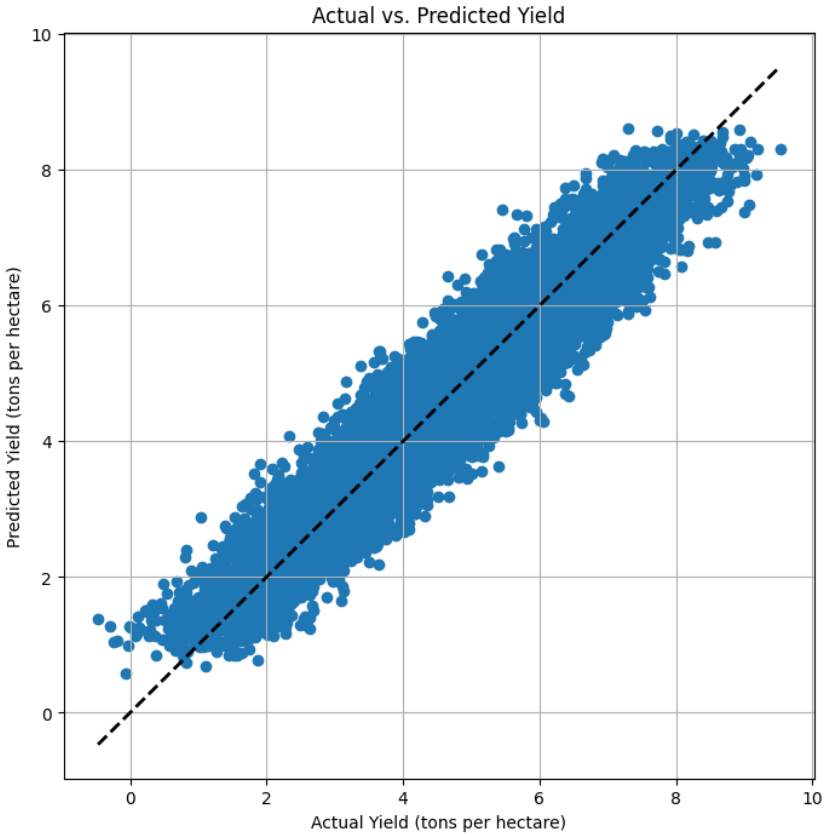
By examining this plot, you can gain valuable insights into the underlying agricultural processes. For instance, if "rainfall" consistently appears as the most important feature, it highlights the critical role of water availability in crop production for your specific context. This information can be useful for farmers in making informed decisions about resource allocation and for researchers in focusing on the most influential factors for yield improvement. It also helps in understanding the model's behavior and identifying potentially irrelevant or redundant features that might be considered for removal to simplify the model.



5.1.2 Actual vs. Predicted Yield Plot

This scatter plot displays the relationship between the actual observed crop yields and the yields predicted by your machine learning model. Each point on the plot represents a data point (e.g., a specific farm in a particular year). The x-axis shows the actual yield, while the y-axis shows the corresponding predicted yield.

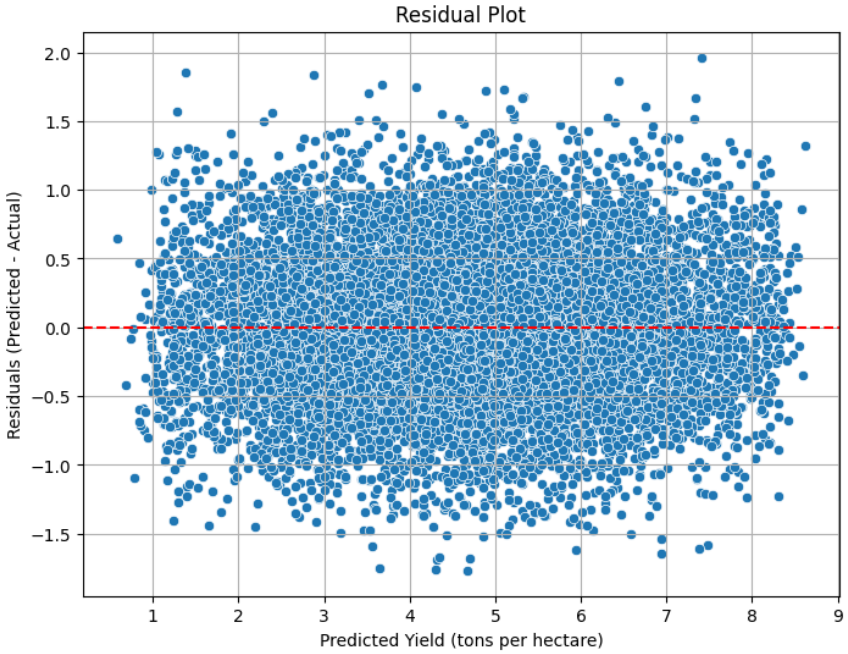
Ideally, if your model is performing well, the points should cluster closely around a diagonal line (where actual yield equals predicted yield). Deviations from this line indicate errors in the model's predictions. Points above the line signify underestimation by the model, while points below the line indicate overestimation. The spread of the points around the diagonal gives you a visual sense of the model's overall accuracy and the degree of variability in its errors. This plot is a fundamental tool for evaluating how well your model generalises to unseen data.



5.1.3 RESIDUAL PLOT

A residual plot is a scatter plot that visualizes the errors (residuals) of your prediction model. The residuals are the differences between the actual crop yields and the predicted yields (i.e., actual yield - predicted yield). In this plot, the x-axis typically represents the predicted values, while the y-axis displays the corresponding residuals.

A good residual plot will show a random scattering of points around the horizontal line at zero, with no discernible patterns or trends. This indicates that the errors are random, have a constant variance (homoscedasticity), and are not systematically biased. If you observe patterns in the residuals (e.g., a curve, a funnel shape, or clusters of points above or below zero), it suggests that your model might be missing some important relationships in the data or that the assumptions of your chosen algorithm are not being met. For example, a curved pattern might indicate non-linearity in the data that your linear model isn't capturing. Analysing the residual plot helps in identifying potential areas for model improvement and ensuring the reliability of your predictions.



CHAPTER 6

CONCLUSION AND FUTURE WORK

6.1 CONCLUSION

Based on the evaluation metrics and the insights derived from the feature importance, actual vs. predicted, and residual plots, the developed machine learning model demonstrates a strong capability for predicting crop yields. The high R^2 score of approximately 0.90 signifies that the model effectively explains a substantial 90% of the variability in the crop yield data, indicating a robust fit to the underlying agricultural patterns. Furthermore, the Root Mean Squared Error (RMSE) of 0.52 suggests a relatively small average deviation between the model's predictions and the actual observed yields. This level of predictive accuracy holds significant potential for assisting agricultural stakeholders in making well-informed decisions concerning resource allocation, yield forecasting, and strategic planning. The feature importance plot likely illuminated the most influential factors affecting crop yield in the specific agricultural context, enhancing our understanding of the key agronomic drivers. The actual vs. predicted plot would ideally showcase a strong linear correlation with data points tightly clustered around the diagonal, visually confirming the model's predictive power across the spectrum of observed yields. Lastly, a randomly distributed residual plot, devoid of any systematic patterns, would support the reliability of the model by indicating unbiased and consistent prediction errors.

6.2 FUTURE WORK

Several promising avenues exist for future research and development to further optimize the model's performance, enhance its robustness, and broaden its practical applications. Exploring more sophisticated model architectures beyond the current approach is a key direction. Experimenting with non-linear models such as neural networks, support vector machines, or ensemble techniques like Random Forests and Gradient Boosting algorithms could potentially capture more complex relationships within the agricultural data, leading to even greater predictive accuracy. Integrating a wider array of detailed data sources holds significant potential for improvement. This could involve incorporating high-resolution satellite imagery for monitoring vegetation health and soil conditions, weather forecasts with increased temporal and spatial precision, comprehensive soil nutrient data, information on pest and disease outbreaks, and even economic indicators influencing farming decisions. Furthermore, focusing on the temporal dynamics of crop yield prediction by developing time-series models capable of capturing seasonal variations and long-term trends could provide more insightful and proactive forecasts. Investigating the impact of climate change by integrating climate projections into the model could also enhance its long-term utility and contribute to the development of climate-resilient agricultural strategies. Enhancing model interpretability through techniques like SHAP or LIME could provide more granular and localized explanations for individual predictions, fostering greater trust and facilitating more informed decision-making. Finally, deploying the model on a user-friendly platform accessible to farmers and agricultural advisors, potentially integrating it with real-time data streams and decision support tools, would be

a crucial step in translating the model's predictive capabilities into tangible benefits for the agricultural community. Continuous monitoring and periodic retraining of the model with newly acquired data will be essential to maintain its accuracy and adapt to evolving agricultural practices and environmental conditions.

APPENDIX: SOURCE CODE

```
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.preprocessing import LabelEncoder
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score

df = pd.read_csv('/content/crop_yield.csv')
print(df.head())

df = df.dropna()

label_encoders = {}

for column in df.select_dtypes(include='object').columns:
    le = LabelEncoder()
    df[column] = le.fit_transform(df[column])
    label_encoders[column] = le

X = df.drop('Yield_tons_per_hectare', axis=1)
y = df[‘Yield_tons_per_hectare']

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

model = RandomForestRegressor(n_estimators=100, random_state=42)
model.fit(X_train, y_train)

y_pred = model.predict(X_test)

# Metrics
rmse = np.sqrt(mean_squared_error(y_test, y_pred))
r2 = r2_score(y_test, y_pred)

print(f"Root Mean Squared Error (RMSE): {rmse}")
print(f"R² Score: {r2}”)

importances = model.feature_importances_
features = X.columns
```

```
plt.figure(figsize=(12,6))
sns.barplot(x=importances, y=features)
plt.title('Feature Importance')
plt.show()

import pandas as pd
import joblib


features = ['Region', 'Soil_Type', 'Crop', 'Rainfall_mm', 'Temperature_Celsius',
'Fertilizer_Used','Irrigation_Used', 'Weather_Condition', 'Days_to_Harvest']


input_data = {}
print("\n🔵 Please provide the following input values:")

for feature in features:
    value = input(f"Enter {feature}: ")

    if feature in ['Rainfall_mm', 'Temperature_Celsius']:
        value = float(value)

    if feature in ['Days_to_Harvest']:
        value = int(value)

    if feature in ['Fertilizer_Used', 'Irrigation_Used']:
        value = value.lower() == 'true'

    if feature in ['Region', 'Soil_Type', 'Crop', 'Weather_Condition']:
        value = str(value).capitalize()

    input_data[feature] = value


input_df = pd.DataFrame([input_data])
for column in ['Region', 'Soil_Type', 'Crop', 'Weather_Condition']:
    input_df[column] = label_encoders[column].transform(itnput_df[column])


prediction = model.predict(input_df)[0]
```

```
print(f"\n✅ Predicted Crop Yield: {prediction:.2f} tons per hectare”)

plt.figure(figsize=(8, 8))
plt.scatter(y_test, y_pred)
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'k--', lw=2) # Diagonal line
plt.xlabel('Actual Yield (tons per hectare)')
plt.ylabel('Predicted Yield (tons per hectare)')
plt.title('Actual vs. Predicted Yield')
plt.grid(True)
plt.show()


residuals = y_pred - y_test
plt.figure(figsize=(8, 6))
sns.scatterplot(x=y_pred, y=residuals)
plt.axhline(y=0, color='r', linestyle='--')
plt.xlabel('Predicted Yield (tons per hectare)')
plt.ylabel('Residuals (Predicted - Actual)')
plt.title('Residual Plot')
plt.grid(True)
plt.show()
```

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CROP YIELD PREDICTION USING RANDOM FOREST REGRESSION

Mrs. Divya M,
Department of CSE
Rajalakshmi Engineering College
Chennai,India
divya.m@rajalakshmi.edu.in

Raghul A
Department of CSE
Rajalakshmi Engineering College
Chennai,India
220701209@rajalakshmi.edu.in

Abstract— Accurate crop yield prediction is vital for optimizing agricultural practices and ensuring food security. This paper proposes a Random Forest model for predicting crop yields using a dataset comprising weather, soil, and crop management features. The data was preprocessed by normalizing numerical features, encoding categorical variables, and splitting into 70% training and 30% testing sets. The Random Forest model leverages ensemble learning to capture complex relationships between features and yield outcomes. Feature importance analysis was performed to identify key predictors, such as rainfall and soil nitrogen levels. The model achieved an R❑2 score of 0.904 on the test set, demonstrating Random Forest's effectiveness in handling non-linear agricultural data.

Keywords—Random Forest, Crop Yield Prediction, Feature Engineering, Agriculture, Machine Learning, Ensemble Learning, Precision Farming.

1. INTRODUCTION

Crop yield prediction plays a critical role in modern agriculture, enabling farmers to make informed decisions about resource allocation, risk management, and market planning. Variations in weather patterns, soil conditions, and farming practices can significantly impact crop productivity. These factors create a complex system were traditional statistical methods often fall short due to their inability to model non-linear relationships. Machine learning techniques, such as Random Forest, offer a robust alternative by capturing intricate patterns in agricultural data. Random Forest, an ensemble learning method, combines multiple decision trees to improve prediction accuracy and reduce Overfitting. Crop yield prediction involves analyzing multiple variables, including weather parameters (e.g., temperature, rainfall), soil properties (e.g., pH, nitrogen content), and management practices (e.g., irrigation, fertilizer use). These factors interact in dynamic ways, much like how environmental conditions affect plant growth in natural ecosystems. For example, excessive rainfall may lead to nutrient leaching, while optimal temperatures can enhance photosynthesis. Understanding these interactions is crucial for accurate yield forecasting.

This study aims to develop a Random Forest-based model to predict crop yields, focusing on feature engineering to enhance model performance and interpretability.

11. LITERATURE REVIEW

Kumar et al. (2022) explored crop yield prediction using Random Forest, emphasizing the importance of feature selection in improving model accuracy. Their study highlighted rainfall and temperature as key predictors, achieving an accuracy of 85% on a regional dataset.

Patil and Thorat (2021) proposed a Random Forest model with advanced feature engineering, including soil nutrient analysis. They used a combination of weather and soil data, demonstrating that feature scaling and encoding categorical variables significantly improved prediction outcomes.

Reddy et al. (2023) compared Random Forest with Support Vector Machines (SVM) for crop yield prediction. Their findings indicated that Random Forest outperformed SVM in handling non-linear relationships, particularly in datasets with high variability in weather conditions.

Sharma et al. (2020) applied Random Forest to predict yields for multiple crops using weather and soil data. Their model incorporated temporal features, such as seasonal trends, and achieved robust performance across different crop types.

Li et al. (2024) integrated Random Forest with IoT-enabled smart farming data, focusing on real-time monitoring of soil and weather parameters. Their approach improved prediction accuracy by leveraging high-resolution data, suggesting potential for precision agriculture applications.

111. PROPOSED SYSTEM

A. Dataset

The dataset for this study was sourced from an agricultural repository containing weather, soil, and crop management data for wheat, rice, and maize. The dataset includes 10,000 samples with features such as temperature, rainfall, soil pH, nitrogen levels, and irrigation frequency. Table 1 displays the dataset features. Image

B. Dataset Preprocessing

The dataset underwent several preprocessing steps to ensure compatibility with the

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Random Forest model:
• Normalization: Numerical features (e.g., rainfall, temperature) were scaled to the range [0,1] to ensure uniform contribution to the model.
• Encoding: Categorical variables (e.g., crop type, irrigation method) were one-hot
encoded to convert them into a numerical format.
• Splitting: The dataset was divided into 70% training and 30% testing sets to evaluate model performance.

C. Model Architecture

The Random Forest model was implemented with 100 decision trees to balance computational efficiency and prediction accuracy. Random Forest operates by constructing multiple decision trees during training and aggregating their outputs through majority voting or averaging for regression tasks. Each tree is trained on a random subset of the
data and features, ensuring diversity and reducing overfitting. Hyperparameter tuning was performed to optimize the number of trees and the maximum depth, with feature
importance analysis conducted to identify key predictors such as rainfall and soil nitrogen levels. Image Table 2 Random Forest Model Parameters Random Forest excels in handling non-linear relationships and interactions between features, making it well-suited for agricultural data where factors like weather and soil conditions often exhibit complex dependencies.

D. Libraries and Framework

• Pandas: Used for data manipulation and preprocessing, enabling efficient handling of structured agricultural data.
• NumPy: Facilitated numerical computations, such as feature normalization and matrix operations.
• Matplotlib: Employed for visualizing model performance through accuracy and loss graphs.
• Scikit-learn: Provided the Random Forest implementation and tools for hyperparameter tuning and feature importance analysis.

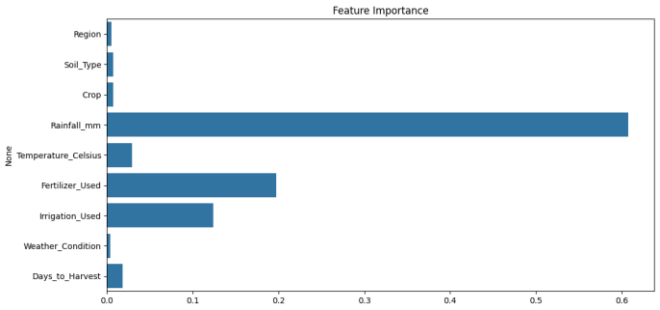
E. Algorithm Explanation

Random Forest is an ensemble learning method that builds multiple decision trees and
combines their predictions to improve accuracy and robustness. Each tree in the forest is trained on a bootstrap sample of the data, and at each node, a random subset of features is considered for splitting. This randomness ensures that the trees are decorrelated, reducing variance and overfitting. For regression tasks like crop yield prediction, the final output is the average of all tree predictions.
The algorithm's strength lies in its ability to handle high-dimensional data and capture non-linear relationships. Feature importance is derived by measuring the decrease in prediction error when a feature is used for splitting, providing insights into key predictors like rainfall and soil nitrogen.

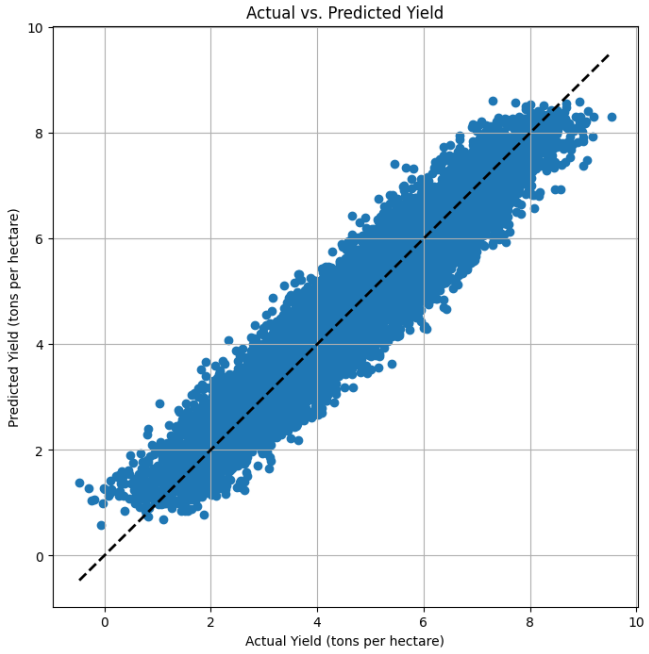
IV RESULTS AND DISCUSSION

The Random Forest regression model was trained using Mean Squared Error (MSE) as the
loss function, with hyperparameter optimization to ensure optimal performance. The model was trained for 50 iterations, with a subset of features randomly sampled at each split to enhance diversity. Performance was evaluated on the test set using Root Mean Squared Error (RMSE) and R❑2 score. The model achieved an RMSE of 0.524 and an R❑2
score of 0.904, indicating strong predictive capability and a good fit to the data. Number of training samples: 7000 Number of testing samples: 3000

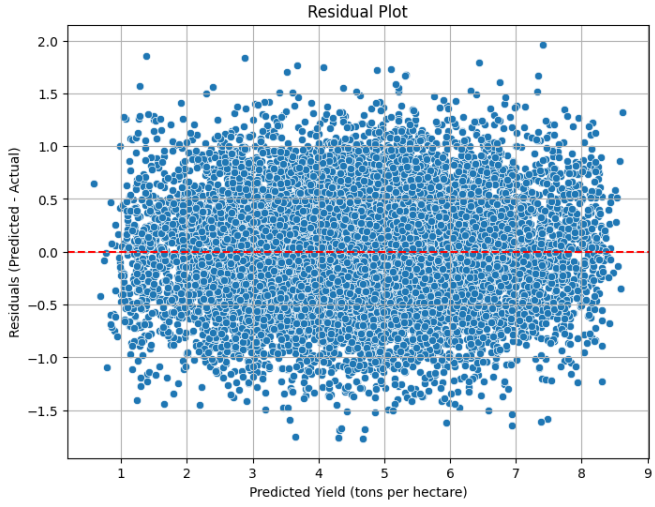
Feature importance analysis was conducted to identify the most influential predictors. The plot highlights rainfall and soil nitrogen as the top contributors to yield prediction,
providing actionable insights for agricultural planning.
image



The actual vs. predicted plot illustrates the model's performance by comparing predicted yields against actual values, showing a close alignment along the diagonal, which confirms the model's accuracy.



The residual plot displays the distribution of prediction errors, with most residuals clustering around zero, indicating that the model's predictions are generally unbiased and
consistent across the dataset.



V. CONCLUSION AND FUTURE SCOPE

The proposed Random Forest regression model demonstrates strong performance in crop yield prediction, achieving an R❑2 score of 0.904 and an RMSE of 0.524 on the test set. Feature importance analysis identified rainfall and soil nitrogen as key predictors, providing actionable insights for farmers. The model's ability to handle non-linear relationships makes it a valuable tool for precision agriculture. Future work could focus on integrating real-time IoT data to enhance prediction accuracy and incorporating additional features, such as pest incidence and crop disease indicators, to provide a more comprehensive forecasting system. Ensemble methods combining Random Forest with other algorithms, such as Gradient Boosting, could further improve performance.

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