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Crop Yield Prediction at District Level in India Using Machine Learning

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Abstract
The Indian economy relies heavily on agriculture. Computing crop yield at a finely differentiated spatial level is a complicated task because of varied and regional diversity of India and the interaction of different factors affecting the crop yield. Using the historical agricultural data, a machine learning framework for crop yield prediction is proposed at a district level in this paper. The dataset consists of multi-year agricultural data generated by considering attributes of crop, area, season and geographic data. Different machine learning methods refer to The yield variation is modeled using Random Forest, Extreme Gradient Boosting (XGBoost), and Multi-Layer Perceptron (MLP). In addition to that, Root Mean Squared Error, Mean Absolute Error and coefficient of determination (R^2) regression metrics are implemented. A temporal data-splitting approach is used for training and testing. The model uses a past year's data for training and a future year's data for testing. Tree-based models are able to perform well in modelling non- linear data among all models. Additional methods of explainable artificial intelligence are applied to explanation analysis. An analysis was done of the Feature Importance which showed that features like crop, area, season, etc are important.

Keywords: Machine Learning, XGBoost, Random Forest, Multi-Layer Perceptron, Explainable AI, SHAP, Agricultural Data Analysis

INTRODUCTION

Agriculture is one of the important components of the Indian economy because it supports and employs a sizeable segment of the population. Moreover, it is essential for the country's food security. In agricultural planning, market functioning and policy, estimation of crop yield is very important. Crop yield prediction continues to be a difficult task as well. Because large yield variation is found at finer geographic levels one might expect that it is useful to use the district level. Moreover, the conditions are extremely variable at the regional and individual level. Therefore, an able system is developed that can adapt to these conditions and yield results useful to an individual. Otherwise, there will be preparation of inaccurate crop yield leading to gap between supply and demand, insta- bility in price and inefficient utilization of resources. Most of the existing systems for prediction of crop yield are based on historical data and trends.

Furthermore, a majority of the research considers entire state as a single geographic unit which does not account for the variation at a smaller level. Due to the enormous agricultural data available nowadays, machine learning became a popular tool for the development of prediction systems. Machine learning models are capable of identifying intricate relationships and hidden patterns in order to create

scalable and improved predictive systems.

This paper gives crop yield prediction for different districts of India using Indian agriculture data of several years. The dataset contains information about crop type, area cultivated, season and other location-specific attributes. The implemented work takes a temporal data-splitting strategy where a model is trained on previous year data and tested on future years.

A. Background and Motivation

Increasing demand for food due to population growth, scarce resources, and climate variabilities are creating a need for precision oriented and localized crop yield prediction systems. In order to make right decisions on crop choice, resource application and supply chain management, farmers, policy makers and stakeholder need district wide precise information.

Machine Learning techniques allow one to move beyond the limitations of traditional approaches with data-driven al- gorithms. The Random Forest, Extreme Gradient Boosting (XGBoost), and Multi-Layer Perceptron (MLP) have given promising results for complex nonlinear data. The implementa- tion of explainable artificial intelligence (XAI) methods further helps in interpreting model predictions, which increases the usability and trustworthiness of machine learning techniques applied to agriculture.

B. Problem Statement

Getting a fine-grained crop yield prediction remains a chal- lenge even with sophisticated techniques offered by machine learning. The models proposed recently face problems like inability to interpret them, regional model diversity, temporal variability, high computation costs, and misbehaviours. A lot of methodologies involve making random splits within the data. However, in the real world, we wish to forecast future data.

Moreover, it is hard to develop a universal and consistent predicting system as agriculture data sets are subject to vari- ation because they are based on different crop types, seasons and geo-location. Consequently, it is keenly felt the need for a machine learning framework which is scalable and easy to understand that can predict the crop yield at the district level accurately and reliably.

C. Objectives and Scope

The goal of this study is to develop a machine learning- based framework for district-level crop yield assessment from historical data. The model should be easy to understand and trustworthy in order to make useful predictions on the crop.

The specific objectives are as follows:

- **Development of a Machine Learning Based System for Crop Prediction:** To design and implement a system that can predict the yield value using a multi-year dataset.
- **Comparison and Optimisation of Models:** To assess and compare the performance of Random Forests, XG- Boost, and MLP in modelling complex destinies.
- **Ensure Realistic Evaluation:** As an illustration, develop scripts that utilize past data for training models while relying on future data for testing.
- **Enhance Interpretability:** Use Explainable AI tech- niques including feature importance analysis to determine the major contributing factors for crop yield.
- **Achieve High Prediction Accuracy:** Assessing model performance using regression metrics (RMSE, MAE & R- squared) to achieve high prediction accuracy and practical applicability.

LITERATURE REVIEW

The yield prediction of crops have long been an established area of research as it helps to increase

agricultural production and enhance evidence-based policy decisions. Past methods largely relied on statistical tools and past data. The estimation of crop yields was attempted by the correlation of old records. While these methods were helpful in the beginning, they were unable to deal with the complex variability in the data. As data science started becoming more complex, machine learning techniques started being used for agricultural forecasts. A couple of algorithms became the top-ranking choices for the modeling of increasing non-linearity issues as well as that of better performance on tabular data.

These models performed significantly better than older statistical methods when tested on large agricultural datasets with high diversity. Gradient boosting approaches, other than XGBoost, have recently gained popularity for yield forecast- ing. XGBoost is an algorithm that enhances the performance of weak learners to lessen the prediction errors. It is effective yet computationally efficient. XGBoost can efficiently handle large amounts of categorical and numerical data which is why it is used in agriculture. Moreover, the use of Multi-Layer Per- ceptrons, a deep learning approach, has also been investigated for modelling crop yield data. Although these architectures improve flexibility in learning subtle relationships between inputs and outputs, effective tuning of hyperparameters is essential. Additionally, you need sufficient data for training. A lot of architectures fail to do well, when they are sparse and heavily.

METHODOLOGY / FLOW CHART

A. System Overview

The suggested method uses a structured pipeline to forecast agricultural yield through machine learning. Data collection from a publicly accessible agricultural dataset is the first step in the process, which is then followed by feature modification and preprocessing. Several machine learning models are then trained using the prepared data. In order to comprehend the im- pact of various variables on yield, interpretability approaches are used and model predictions are assessed.

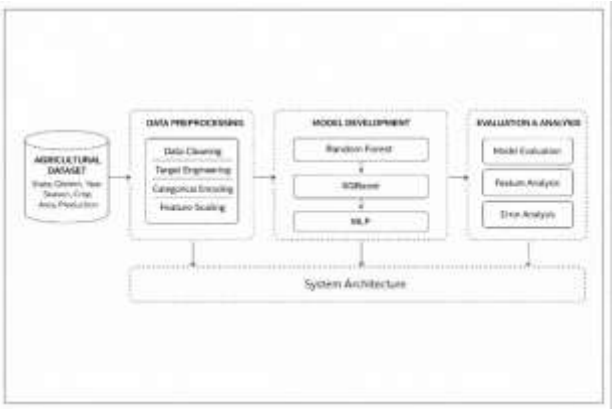


Fig. 1: Proposed System Architecture for Crop Yield Prediction

B. Dataset Description

The project uses data gathered from different sources comprising of different statistics and reports. This includes state name, district name, crop year, season, crop, area and production. The dataset containing raw data is modified into the preferred form that can aid in accurately predicting the yield from area and production. Formula:

$$\text{Yield} = \frac{\text{Production}}{\text{Area}}$$

Feature Name	Description	Data Type
State_Name	Name of the state where crop is cultivated	Categorical
District_Name	District-level geographical location	Categorical
Crop_Year	Year of crop production	Numerical
Season	Agricultural season (Kharif, Rabi, etc.)	Categorical
Crop	Type of crop cultivated	Categorical
Area	Cultivated area (in hectares)	Numerical
Production	Total crop production (in tonnes)	Numerical
Yield	Crop yield (Production / Area)	Numerical

Fig. 2: Description of the Dataset

C. Data Preprocessing and Feature Engineering

The dataset was preprocessed for the quality and consistency of data for further processing For instance, values with null production and zero cultivated area, which provides a value of production that is ultimately zero, are deleted. A new value that represented the invincible was named NaN and then dropped. One-hot encoding was used to encode the categorical vari- ables – state name, district name, crop category, and season. One-hot Encoding creates dummy variables for the different values of the categorical attributes. This enables the models to process the categorical data unbiasedly and also assists in not

incorrectly interpreting the data.

The final data consisted of numerical and one-hot encoded categorical features for the models to learn from. Therefore, models can leverage the data's spatial, temporal, and agricul- tural diversity in prediction of crops.

D. Temporal Data Splitting

Subjects were randomly divided the subjects into training and testing sets at a ratio of 7:3. The gesture was classified using all hand features. The binary features that were available were changed to 7*6 and the other 26 features were computed for the N 21 bits. Wilson and his colleagues employed eight users for recognition. Boosting evaluated usage and cross- validation techniques because of the features set.

E. Model Development

Three machine learning models were used for crop yield prediction:

- **Random Forest:** An ensemble learning method, the random forest takes the strength of many decision trees and builds them up.
- **Extreme Gradient Boosting (XGBoost):** The simple intuitive nature of the algorithm, internally caching objects to avoid redundant calculations, makes gbm particularly effective on large datasets.
- **Multi-Layer Perceptron (MLP):** The MLP is an ex- ample of feedforward neural network and it is capable of learning the non-linear relationship using more than one hidden layers to model the relation between input features and yield.

The prepared dataset was used to train each model after applying appropriate preprocessing techniques like feature scaling wherever required.

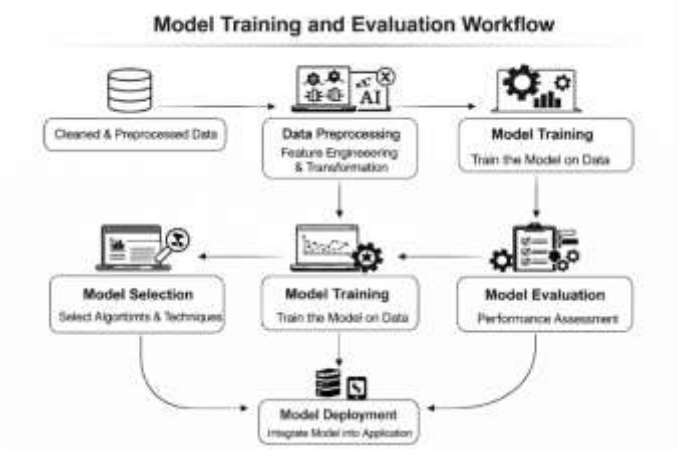


Fig. 3: Model Training And Workflow

F. Model Evaluation

The evaluation of the models was done with standard regression metrics:

- **Root Mean Squared Error (RMSE):** Measures the size of the error in prediction.
- **Mean Absolute Error (MAE):** Indicates the average dissimilarity between the predicted and actual values.
- **Coefficient of Determination (R^2):** Indicates the vari- ance in the dependent variable that can be explained by the independent variables.

They reflect both accuracy and reliability of the model's predictions.

G. Explainability and Feature Analysis

There was the implementation of the explainable artificial intelligence technique to enhance the model transparency. SHAP (Shapley Additive Explanations) was used to determine how individual features influenced the prediction of the model. This analysis will show what affects the yield of the crops the most. For example, what crops affect it the most, how much area is cultivated and so on. Hence, the impact of these parameters goes beyond just the numerical prediction.

H. Error Analysis

Moreover, apart from overall model evaluation analysis was done for errors at district level. To find the regions where the model fails to deliver accurate predictions, the prediction errors were grouped by district.

The study reveals that there are data issues and external factors such as climate change impact or bad farming that may influence predictions.

Result and Analysis

This section presents the experimental results obtained from the implemented machine learning models and provides a detailed analysis of their performance in predicting crop yield.

A. Model Performance Evaluation

To evaluate the effectiveness of the proposed approach, The provided dataset was used to train and evaluate three machine learning models: Random Forest, Extreme Gradient Boosting (XGBoost), and Multi-Layer Perceptron (MLP). Regression measures such as Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and coefficient of determination (R^2) were used to evaluate the models.

Table I provides a summary of the models' comparative outcomes. With the lowest error values and

greatest R2 score among the assessed models, XGBoost performed the best, demonstrating its greater capacity to grasp intricate connec- tions in the data. Strong performance was also shown by Random Forest, which produced accurate predictions with a somewhat greater error than XGBoost. Because of the large dimensionality of the encoded features and the little number of training iterations, the MLP model, on the other hand, performed quite poorly.

TABLE I: Model Performance Comparison

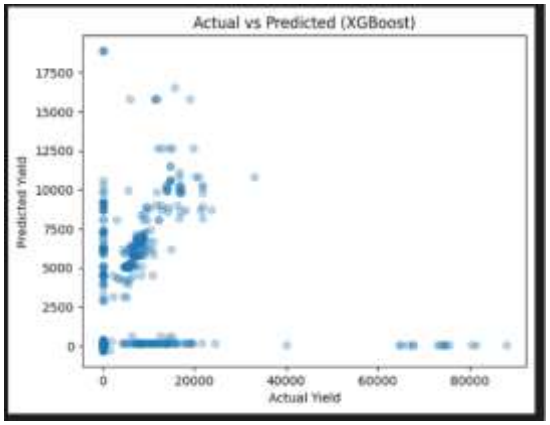
Model	RMSE	MAE	R^2
Random Forest	1207.89	45.15	0.118
XGBoost	1204.52	46.46	0.123
MLP	1219.71	82.18	0.101

B. Prediction Analysis

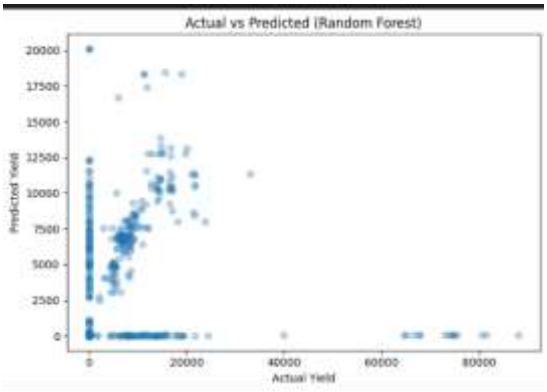
The projected and actual yield values were compared in order to further evaluate the model's performance. The comparison demonstrates the ability of tree-based models, especially XGBoost, to closely track the real yield value trend across several samples. This suggests that non-linear patterns found in agricultural data may be effectively learned by these algorithms.

However, the MLP model showed more deviations in some areas, indicating that it had trouble efficiently generalizing over all districts. When applied to high-dimensional, sparse tabular datasets without much adjustment, this behavior is consistent with neural networks.

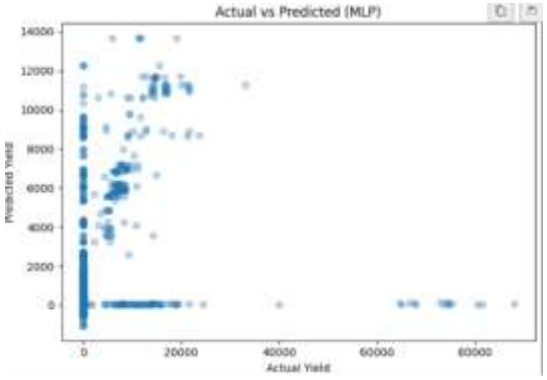
In addition, outliers and extreme values in yield negatively influenced the prediction accuracy of all models. Unlike neural networks, ensemble-based methods were more robust to these variations.



(a) XGBoost



(b) Random Forest



(C) MLP

Fig. 4: Actual vs Predicted Yield Comparison Across Models

C. Classification-Based Interpretation

The continuous yield numbers were divided into three classes—low, medium, and high yield—to improve inter- pretability. This conversion makes it easier to comprehend model predictions and makes practical interpretation easier.

To assess categorization performance, a confusion matrix was created. The majority of cases are accurately classified by the model, according to the results, with only a few small misclassifications between nearby categories like medium and high yield. This implies that even while the model functions well generally, it is still difficult to discern between yield ranges that are closely linked.

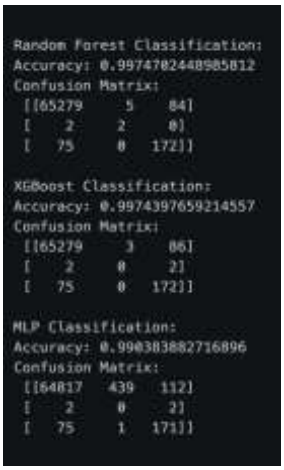


Fig. 5: Confusion Matrix for each

D. Feature Importance and Explainability

SHAP (Shapley Additive Explanations) was utilized for feature significance analysis in order to comprehend the con- tribution of various attributes. The findings show that factors including crop variety, farmed area, and seasonal conditions have a big impact on output. Additionally, the study shows that various characteristics have variable degrees and directions of effect on predictions.

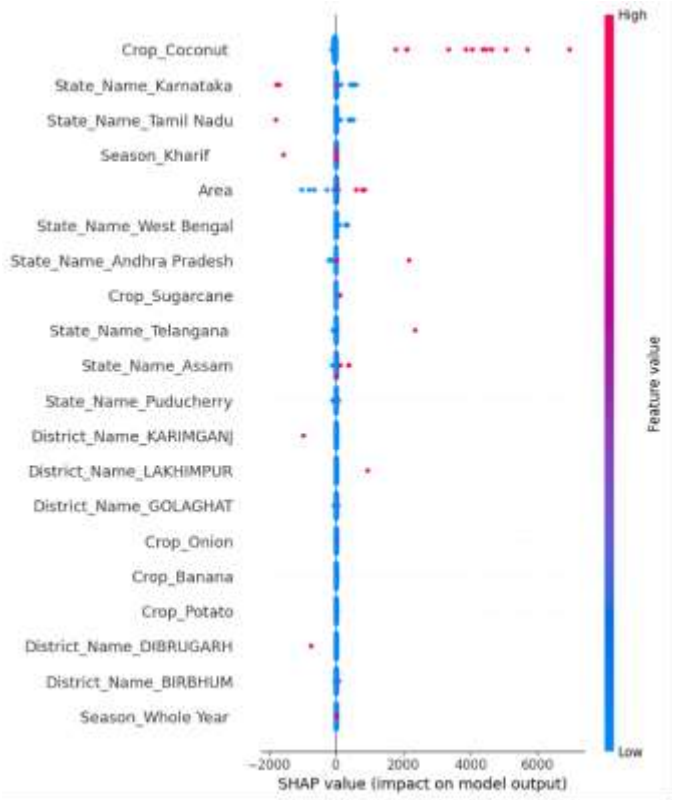


Fig. 6: SHAP Analysis

E. Error Analysis

To investigate the differences in model performance be- tween several districts, an error analysis was carried out. The findings indicate that some districts have larger predic- tion errors, which might be the consequence of insufficient representation in the dataset, inconsistent data patterns, or environmental variability.

This finding suggests that although the model performs well overall, prediction accuracy may be impacted by regional variances and outside variables. These findings are crucial for enhancing the robustness of the model and directing future improvements.

Furthermore, the analysis indicates that adding more de- tailed characteristics like temperature fluctuations, rainfall patterns, and soil type could further lower prediction mistakes. Adding such region-specific characteristics to the dataset could help the model better represent local agricultural circum-stances and produce predictions that are more accurate.

District Name	Error Value
FATEHGARH SAHIB	3286.38
FAZILKA	2920.62
PATHANKOT	2865.38
KAPURTHALA	2730.47
PATIALA	2319.19

Fig. 7: Errors Found

F. Key Findings

The following is a summary of the main findings from the experimental analysis:

1. Of all the models, XGBoost had the greatest prediction performance.
2. Consistent findings with somewhat greater error levels were produced by Random Forest.
3. Because of its inability to handle high-dimensional data, MLP performed worse.
4. The most important factors were found to be crop type, farmed area, and season.
5. The influence of geographical variations was demon- strated by the variation in prediction errors between districts.

Overall, the findings show that machine learning mod- els—especially those based on trees—are useful for predicting crop yields at the district level and can offer insightful infor- mation for agricultural decision-making.

Discussion and Summary

The results from an experiment have revealed that the ML techniques for predicting crop yield at the district level have proven effective. The three model comparison illustrated that tree-based models are better suited for this kind of structured agricultural data than neural network-based models. Based on the individual model performance parameters, it is evident that XGBoost has outperformed the other models on all evaluation measures. XGBoost can perform well in a relatively high- dimensional feature space because it can model non-linear relationships. The boosting characteristics enable the model to learn from errors in successive iterations. In addition, owing to the presence of categorical and numerical features in the dataset whose interactions are rather complex, the modeling of such dependencies by XGBoost is better suited.

Random Forest model shows satisfactory performance and stable predictions across the region. The technique provides reliable analysis with credible results since being an ensemble structure that helps in variance reduction and overfitting. Though its performance is slightly lesser than that of the XGboost model in capturing data patterns, the error values of Random Forest models are slightly on the higher side.

The performance of MLP model is comparatively less due to the dataset. Using one hot encoding for the categorical features such as district and crop, the dataset consists of high dimensional sparse features MLP.

Based on our observation, yield is majorly determined by the crop type, area, and season. This is in harmony with practical insights, since they affect the yield directly. The addition of interpretability also adds relevance to the model. It creates a sense of worthiness in the prediction created through the model.

The overall results indicate suitability of machine learning models that marks especially the ensemble-

based models for crop yield prediction. The proposed framework's predictive model performance and interpretability makes it worthy of a real-world implementation. Further, the resources can assist in upgrading the model in the future with newer features and advanced models.

Conclusion and Future Work

This study used historical agricultural data to offer a ma- chine learning-based framework for forecasting crop produc- tion at the district level in India. The suggested method sought to capture regional differences in agricultural production by utilizing characteristics including crop type, cultivated area, season, and geographic data. By training models on historical data and testing on upcoming observations, a temporal data- splitting approach was used to guarantee realistic evaluation. Regression-based assessment measures were used to de- velop and compare three machine learning models: Random Forest, Extreme Gradient Boosting (XGBoost), and Multi- Layer Perceptron (MLP). The results of the experiment in- dicated that Random Forest and XGBoost performed the best, with MLP exhibiting relatively lesser accuracy because to its
inability to handle high-dimensional structured data.

Even with encouraging outcomes, there are still certain restrictions. Environmental elements that can have a big impact on crop output, such temperature, rainfall, and soil quality, are not specifically included in the dataset.

Overall, the suggested approach shows that data-driven agricultural planning may be supported and district-level crop production prediction can be successfully accomplished by combining machine learning with interpretability methodolo- gies.

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