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Machine Learning Based Agricultural Yield And Rainfall Prediction, Crop And Fertilizer Recommendation

[1] Rahul Shetty S J, [2] Ruchitha R, [3] Dr. Roopa M J, [4]Rohith

[1]Student, [2]Student, [3]Associate Professor, [4]Student

[1]Computer Science and Engineering,

[1] SJB Institute of Technology, Bengaluru, India

Abstract: Agriculture is a backbone of the global economy, and empowering farmers with advanced technology and tools can enhance productivity and sustainability. Traditional agricultural methods were based on manual tools, natural fertilizers, practices like crop rotation and rainwater harvesting to sustain productivity and soil health. Farmers used their predictive, observational knowledge for weather, crop prediction and recommendation natural pest control remedies, though these methods lacked scalability and resilience against environmental changes. Machine learning offers a promising solution by providing the prediction and recommendation capabilities by analyzing vast datasets, including soil, weather, and crop patterns, to forecast yields, recommend and predict suitable crops, and optimize fertilizer usage. This paper proposes a machine learning-based crop, fertilizer recommendation and prediction, weather and rainfall prediction. The system uses 4 features for crop prediction, 8 features for crop recommendation, 9 features for fertilizer recommendation and 7 features for yield prediction. Along with tools for farmer's assistance like news feed, chatbot support. We evaluate four models—Decision Tree Classifier, Random Forest Classifier, Random Forest Regressor and Statistical Analysis —showing that the models achieve high accuracy by leveraging data-driven patterns, feature importance analysis to optimize predictions and recommendations for agricultural needs.

***Index Terms* -** Machine learning, Agriculture, prediction, Recommendation, Decision Tree, Random Forest classifier, Random Forest Regressor, Statistical Analysis, Recall, F1 score.

I. INTRODUCTION

Agriculture has been the backbone of many nations and civilizations for centuries. However, agriculture these days are facing many challenges including weather patterns, declining soil fertility and lack of technology involvement. Farmers often rely on traditional methods to make critical decisions which may lead to economic loss. Despite traditional practices has given us results but there are many cases where farmers are failing miserably due to the decisions that they are making by trusting the traditional methods.

This project seeks to develop a reliable user-friendly interface where farmers are assisted with predicting suitable crops, recommends fertilizers, forecasts rainfall and estimates yields using the localized datasets. The system is designed with a focus on assisting farmers where the farmers with basic information of the specific region and soil could easily get predictions and recommendations. By these machine learning based predictions and recommendations farmers of any scale would have technical support which is lacking these days. This project aims to empower farmers with a unified and intelligent platform. Furthermore, the methodologies integrated into this project contribute to enhancing agricultural practices and promoting sustainable farming solutions for diverse regions.

II. LITERATURE SURVEY

In recent years, research in agriculture has focused on developing particular models like crop prediction, fertilizer recommendations, rainfall forecasting and yield estimation.While this work includes all these models in a single interface which was not developed earlier. Some of the existing works have been described below:

Agriculture in Tamil Nadu faces multiple challenges, including fluctuating weather patterns, resource constraints, and inefficient crop management. To address these issues, Mahalakshmi B et al. [1] proposed a machine learning-based system using the Adaptive Neuro-Fuzzy[16] Inference System (ANFIS) for crop and fertilizer recommendations. By analysing soil type, season, and water availability, the system enhances crop productivity and decision-making. However, its reliance on quality data and implementation complexity pose barriers to large-scale adoption.

Building on this, Rohini Jadhav and Pawan Bhaladhare [2] developed an online machine learning application that provides tailored recommendations for crops, fertilizers, and disease prevention. For accurate soil nutrient measurement, their approach combines voting classifiers and artificial neural networks, backed by a pH-reading device. Although the application is easy to use and efficient at increasing yields, many farmers may not be able to utilise it due to its 22 crop limit, reliance on high-quality data, and technical difficulties.

To further improve agricultural decision-making, Harshitha Reddy Vaddi et al. [3] proposed a region-specific machine learning solution for crop, fertilizer, and yield recommendations. The algorithm generates precise forecasts and adjusts to climatic changes by examining 14 years of agricultural data. Despite its user-friendliness and productivity boost, issues like data reliability, farmers' lack of technological knowledge, and expensive expenses must be resolved for widespread adoption.

Rainfall is a major determinant of crop productivity, hence precise weather forecasting [12][14] is crucial for agricultural planning. A rainfall forecasting ML model was presented by C. Vijayalakshmi, K. et al. [4] utilising ARIMA and Linear Regression. By accurately forecasting annual and seasonal rainfall trends, this approach helps reduce risk. Prediction reliability may be impacted, nevertheless, by its dependence on past data, preprocessing needs, and sensitivity to data volatility.

Organic farming is viewed as a viable choice as climatic unpredictability increases, despite its drawbacks, which include lower yields and higher expenses. Through the provision of data-driven crop suggestions and rainfall forecasts, Murali E et al. [5] investigated the function of data mining in optimising organic agriculture. Although the strategy improves productivity and food security, problems with scalability, market accessibility, and knowledge gaps prevent broad adoption.

It was looked into how deep learning and machine learning work in smart farming by Ms. Preeti Dhoke et al. [6] in order to further optimise farming operations. The method reduces labour requirements[20] while increasing yields and efficiency by combining crop recommendations, fertiliser recommendations, and soil classification. On the other hand, the high expenses, technical intricacy, and reliance on internet access pose difficulties, especially for farmers who can face system malfunctions and privacy concerns.

To maximise productivity, crop prediction is essential. Akshay Kumar Gajula et al. [7] presented a method that uses the K-Nearest Neighbours (KNN) algorithm to forecast appropriate crops depending on soil quality and temperature. Through an easy-to-use web interface, this offers fertiliser recommendations, improves decision-making, and lowers expenses. Yet, its overall dependability and usability are impacted by data restrictions, weather patterns, and computational complexity.

A crop recommendation system that combines Ant Lion Optimisation (ALO) and Decision Tree (DT) algorithms was proposed by Dr. J. Avanija et al. [8] in order to improve forecasting capacities. The system increases production and sustainability by examining environmental parameters like soil, climate, and water availability. Its dependence on high-quality data, issues with scalability, and resource limitations, however, might make adoption difficult, particularly for small-scale farmers.

Moving forward, Mrs. Manju M et al. [9] presented “Smart Fields,” a system that combines IoT sensors and machine learning to optimise agriculture through real-time monitoring of environmental and soil data. This method improves early disease detection, affordability, and resource efficiency. To maximise impact, however, obstacles including high setup costs, data privacy concerns, and connectivity problems in remote places must be addressed.

Beyond precision farming, it’s critical to reduce crop losses brought on by unforeseen weather conditions. Using satellite imagery and meteorological data, Bhushan Fulkar et al. [10] investigated deep learning methods such as CNNs and RNNs to forecast crop damage brought on by erratic rainfall. High prediction accuracy and real-time analysis are provided, however successful deployment requires taking into account issues such data quality dependency, implementation complexity, and accessibility for remote farmers.

Numerous deep learning and machine learning techniques for crop prediction, fertiliser recommendations, and yield optimisation are examined in the reviewed papers, which enhance agricultural decision-making. Even if models like CNNs, ANFIS, KNN, and Decision Trees improve prediction accuracy, problems like data dependency, implementation complexity, and technology barriers still exist. Real-time monitoring and automation are made possible by IoT integration and smart apps; however, adoption is hampered by problems with accessibility, high setup costs, and connectivity. Adaptability to unanticipated weather changes is limited by reliance on past data, but rainfall prediction [13] using ARIMA and deep learning can lessen climate risks. The potential of AI-driven smart farming is often highlighted by these studies, which also stress the need for better scalability, affordability, and user-friendly interfaces for farmers.

III. METHODOLOGY

Our goal in this work is to implement a combined platform which address the challenges faced by farmers. The portal utilizes advanced machine learning[18] models to predict crops, recommend fertilizers, forecast rainfall, and estimate crop yields. Using localized datasets, the portal provides region-specific information, ensuring accuracy. It also integrates real-time features such as a payment system for secure transactions and an NLP-powered chat-bot to deliver instant farming advice. By combining predictive analytics with a user-friendly design, the platform enables farmers to maximize resources, improve productivity, and adopt sustainable farming practices.

A. *Model Selection*

First, we must select suitable ML techniques, like crop and fertilizer categorization algorithms and regression algorithms for yield prediction[17]. Use the training dataset to train all of these models, including XGBooster, Random Forest, SVM, KNN, Decision Tree, and Gradient Boosting Regressor. Using ensemble techniques like model stacking, which combines many models and evaluates the performance of individual models, to improve accuracy, these predictions from several models are combined.

a. Crop Yield Prediction

Consider input features like season, state or district name, area, crop, rainfall, and temperature while training the proper regression models, such as Random Forest and Gradient Boosting Regressor models. Examine each model prediction in relation to actual yield data, and contrast performance indicators such as MSE and R-Squared Error. The regression model with a high MSE and a low R-Squared Error, which falls between 0 and 1, will be chosen. When the user enters the area, the production is divided by the area to determine the [11] crop yield. The forecast crop will be mapped to the production of this crop.

$$Yield = Production/Area$$

ALGORITHMS USED:

i. Gradient Boosting Regressor:

For regression applications, the Gradient Boosting Regressor machine learning technique is an ensemble learning strategy. In order to fix the mistakes of the preceding decision tree, it constructs other decision trees sequentially. Using the proper metrics, the model's performance is assessed on the test data.such as R-squared and MSE. Applying this model to our dataset yields an accuracy of 95.99% with a Mean Squared Error of 1165161756.950697 and an R-squared error of 0.9599.

ii. Random Forest Regression:

Random Forest is one type of controlled learning computation. It could be applied to both grouping and relapse. There are trees in a wilderness. The more trees a forest has, the more robust it is supposed to be. To increase precision and reduce overfitting, Random Forest generates many decision trees during training and averages their predictions. A Random Forest Regressor model is initialized and trained using the training data. Appropriate measures such as MSE and R-square are used to evaluate the model's performance on the test data. This model yields an MSE of 9060137041.06662 and an R-squared error of 0.9688, or 96.88% accuracy, when applied to our dataset.

By comparing the overall variation in the actual values to the variance in the projected values, the R2 (coefficient of determination) assesses how accurate a prediction model is. It is calculated as calculated by dividing the total squared differences between the mean and actual values by the sum squared differences between the actual and predicted values. Better model performance is indicated by a higher R2 value that is closer to 1.

The RMSE (Root Mean Squared Error) measures the average magnitude of errors in predictions by calculating the square root of the mean of squared differences between predicted and actual values. A lower RMSE indicates better predictive accuracy, as it reflects smaller deviations between the predicted and actual values.

b. Crop Recommendation and Fertilizer Recommendation

Utilizing input features like Rainfall, temperature, humidity, pH, nitrogen, phosphorus, potassium, and soil type for crop recommendations [15], and crop type for fertilizer recommendation, train all the suitable categorization models, such as Random Forest and Decision Tree, XG Booster, and KNN. Examine the performance of the learned model with metrics like F1-score, recall, accuracy, and precision.

ALGORITHMS USED:

i. Decision Tree
Supervised learning methods, such as decision tree classifiers, are used for classification tasks. It recommends crops with 90% accuracy, especially when used with our dataset.

ii. Random Forest
One ensemble learning technique that can be applied is the Random Forest Classifier for classification problems like crop recommendation[20]. When used on our dataset, it yielded 99.31% accuracy for crop recommendation and 99% accuracy for fertilizer suggestion.

iii. KNN

KNN calculates the distance between a new input—that is, a point with an uncertain output—and each other point in the dataset using a chosen distance metric, most often Euclidean distance. When applied to our dataset, it yields 97.5% accuracy, whereas for fertilizer recommendations, it obtained 96.77% accuracy.

iv. XG Booster

eXtreme Gradient Boosting, or XGBoost, is a very efficient and sophisticated implementation of the Gradient Boosting method. XGBoost is widely used in machine learning competitions and in many real-world applications due to its speed, performance, and scalability. Is a Python package that applies gradient boosting to produce precise and specialized computations. When used with our dataset, its crop recommendation accuracy is 99.09%.

B. *Model Training*

The input parameters are obtained as command line arguments, and the chosen model is trained with the training data. Apply performance metrics like MSE and R-Squared Error for regression models and accuracy, precision, and recall for classification models to make predictions and assess the model on the testing set. Verify the final model's generalization performance by either holdout validation or cross validation.

- Decision Tree: A non-parametric supervised learning approach called a decision tree is used for both tasks involving regression and classification. A root node, branches, internal nodes, and leaf nodes make up its hierarchical, tree-like structure.Decision tree learning employs a divide-and-conquer strategy by conducting a greedy quest to find the best places for a tree to split. It can also be easily overfitted.

- Random Forest: To arrive at a single conclusion, Random Forest aggregates the output of several decision trees. Its versatility and ease of use have encouraged its use because it addresses both regression and classification issues. It is a strong algorithm that is impervious to noise and resistant to overfitting.

- K-Nearest Neighbors (KNN**):** An algorithm for non-parametric supervised learning is K-Nearest Neighbors utilized for jobs involving both regression and classification. It operates by finding the 'k' closest data points to a given query point using a distance metric. The algorithm assigns a class or predicts a value based on the majority vote or average of the neighbors.

C. *Proposed Architecture*

The architecture integrates ML models for rainfall forecasting, crop prediction, yield estimation, and fertilizer suggestion to give farmers intelligent decision-making tools. Farmers are able to make well-informed decisions based on real-time insights because to this system's quick processing of agricultural data.

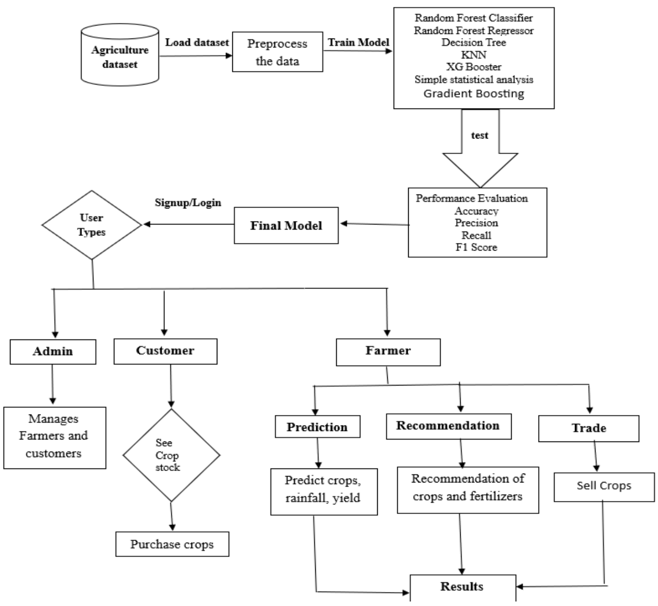

Fig.1: Proposed Architecture

Techniques like SMOTE (Synthetic Minority Over-Sampling Technique) are used to balance agricultural data because it can be region-specific and unbalanced. This guarantees that the models produce precise, region-specific forecasts without favoring majority data points.

A variety of features, including data collecting, prediction models, recommendation systems, and real-time tools, are integrated into the modular design of the Kisan Mitra Portal. To provide farmers with tailored advice, the system pulls important agricultural parameters like soil characteristics, climate, and yield history.

D. *Evaluation*

Datasets used:

In this work we have used around 5 datasets for models such as crop prediction, crop recommendation, fertilizer recommendation, rainfall prediction and yield prediction. Each dataset has more than thousands of data.

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N,P,K,temperature,humidity,ph,rainfall,label
90,42,43,20.87974371,82.00274423,6.502985292000001,202.9355362,rice
85,58,41,21.77046169,80.31964408,7.038096361,226.6555374,rice
60,55,44,23.00445915,82.3207629,7.840207144,263.9642476,rice
74,35,40,26.49109635,80.15836264,6.980400905,242.8640342,rice
78,42,42,20.13017482,81.60487287,7.628472891,262.7173405,rice
69,37,42,23.05804872,83.37011772,7.073453503,251.0549998,rice
69,55,38,22.70883798,82.63941394,5.70080568,271.3248604,rice
94,53,40,20.27774362,82.89408619,5.718627177999999,241.9741949,rice
89,54,38,24.51588066,83.53521629999999,6.685346424,230.4462359,rice
68,58,38,23.22397386,83.03322691,6.336253525,221.2091958,rice
91,53,40,26.52723513,81.41753846,5.386167788,264.6148697,rice
90,46,42,23.97898217,81.45061596,7.50283396,250.0832336,rice
78,58,44,26.80079604,80.88684822,5.108681786,284.4364567,rice
93,56,36,24.01497622,82.05687182,6.98435366,185.2773389,rice
94,50,37,25.66585205,80.66385045,6.94801983,209.5869708,rice
60,48,39,24.28209415,80.30025587,7.042299068999985,231.0863347,rice
85,38,41,21.58711777,82.7883708,6.249050656000005,276.65524589999995,rice
91,35,39,23.79391957,80.41817957,6.970859754,206.2611855,rice
```

Fig.2. Sample data from Dataset

Preprocessing involved compiling historical data on agricultural yields, soil properties, rainfall, weather, and other factors for every district in India. After loading the dataset into a data frame, data preprocessing will be carried out. This involves removing any unnecessary columns, substituting null and missing values, and cleaning up the raw data because it was gathered in an unprocessed format that was not helpful for analysis.

The model was tested using metrices such as:

- Accuracy: Accuracy measures the proportion of correctly predicted crops out of all predictions, reflecting the model's overall correctness.

$$Accuracy = \frac{True\ Positives + True\ Negatives}{Total\ Number\ of\ Samples}$$

- Precision: Precision measures the proportion of correctly predicted positive observations to total predicted positives. In our work, it ensures accurate crop, fertilizer, and weather recommendations while minimizing errors.

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives}$$

- Recall (Sensitivity): Recall measures the proportion of actual positives correctly identified by the model, focusing on capturing positive cases. In our work, it ensures accurate crop predictions, disease detection, and weather risk assessment for farmers.

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives}$$

- F1 Score: Our work uses the F1 score to balance recall and precision, ensuring both are given equal weight. This is crucial for accurate disease detection, weather forecasting, and crop recommendations in farming.

$$F1\text{-}Score = \frac{2 * P * R}{P + R}$$

Model	Accuracy		Precision	
	Our Work	Reference	Our Work	Reference
Crop Recommendation	85%	83.4%	90.9%	88.7%
Fertilizer Recommendation	88%	79%	91.5%	83%
Crop Prediction	90%	81%	94.7%	89.3%

Fig.3. Summary of Prediction and Recommendation

E. *Model Deployment*

The model is used for real-time predictions after its performance is deemed satisfactory. By integrating the system with the user interface, an interface is created that allows users to enter current data and obtain recommendations and forecasts. As new data becomes available, we update the models and track their performance over time. We created an interface that receives input from the user and returns predictions or suggestions. For backend development, we utilized Python, whereas PHP is used for server-side scripting in web applications.

The model makes predictions in real time after its performance is deemed satisfactory. By integrating the system with the user interface, an interface is created that allows users to enter current data and obtain recommendations and forecasts. As new data becomes available, we update the models and track their performance over time. We created an interface that receives input from the user and returns predictions or suggestions. For backend development, we utilized Python, while PHP is utilized for web application's server-side scripting.

IV. RESULTS

After a thorough analysis, Random Forest is the best machine learning algorithm for forecasts and recommendations. Our approach yielded excellent results, with a Random Forest yield forecast accuracy of 90% and an 88% fertilizer recommendation accuracy. On the other hand, the crop suggestion has an accuracy of 85%. When compared to the previous experiments, this approach achieved the best accuracy results and overcome all of their flaws.

We created a webpage where the user must first choose between fertilizer recommendations, yield forecasts, and crop recommendations. For example, if the user chooses to use the crop recommendation, they will be taken to a screen where they must provide information such as "state," "district," "season," "crop," and "area." They will obtain the crop yield as an output after submitting these.

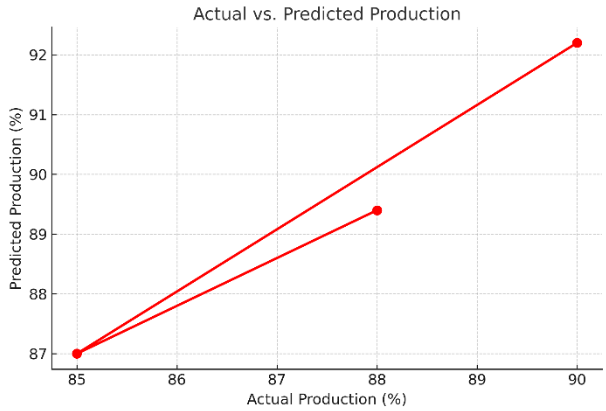

Fig 4. Actual vs Predicted Production

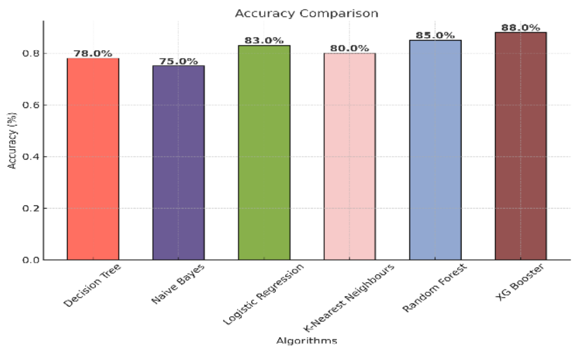

Fig.5. Accuracy Comparison

V. FUTURE SCOPE

Future versions of the model suggested in this study might incorporate more elements including crop supply-demand analysis, retail price forecasts, and agricultural harvest predictions. Combining these elements helps farmers choose which crops to plant, ensuring that their supply satisfies customer demands and maximizes profitability. Accurate market demand forecasting is made possible by the proposed system's ability to examine past pricing trends, demand variations, and seasonal variations. In the end, this will contribute to steadier agricultural markets and higher farmer incomes by lowering overproduction or shortages.

Additionally, the model can be improved to provide suggestions for crop rotation plans, assisting farmers in preserving soil fertility and minimizing pest outbreaks. The technology can recommend the optimal crop sequences to improve sustainability and long-term productivity by examining past cultivation trends and soil characteristics.
A data-independent solution could be developed in the future to guarantee that model performance is constant across various formats and data sources. Despite the variations in data collection techniques, this flexibility would enable farmers from various geographical areas to utilize the platform efficiently. In the end, these developments would improve global food security and sustainability by making agriculture more resilient, data-driven, and profitable.

CONCLUSION

An important advancement in using technology to boost agricultural efficiency and productivity is visible in the project. The platform meets crucial demands in prediction, suggestion, and trading for both farmers and consumers by combining machine learning algorithms with user-centric technologies.

The technology provides farmers with actionable insights through precise rainfall, crop, yield, and fertilizer forecasts, empowering them to make well-informed farming decisions. A strong agricultural marketplace is promoted by the trade module, which offers a smooth interface for farmers to sell crops and consumers to purchase high-quality goods. Furthermore, tools like a news feed, chatbot, and weather prediction guarantee that farmers are informed and assisted in their endeavors.

The system's scalable architecture and modular design guarantee its adaptation to various datasets and geographical locations, increasing its suitability for a range of agricultural contexts. Reliable and accurate results are guaranteed by combining machine learning pipelines, decision trees, random forest methods, and data preprocessing.

In summary, this work acts as a link between agriculture and technology, encouraging creativity, raising output, and enhancing the socioeconomic standing of farming communities. This study demonstrates how digital technologies have the ability to revolutionize the agriculture industry.

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