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CROP YIELD PREDICTIONS AND RECOMMENDATIONS USING RANDOM FOREST REGRESSION IN 3A AGROCLIMATIC ZONE, RAJASTHAN

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Abstract - This paper explores the potential of Random Forest deep learning regression to predict the yield of major crops in the 3A agroclimatic Zone of Rajasthan, specifically in the Jaipur district. Crop yield prediction is the process of predicting yield using historical data through meteorological parameters and past yield records.Theselected region consists of a large portion of the semi-arid eastern plain, and the study focuses on six major crops i.e., barley, wheat, mustard, gram, groundnut, and moong. Time series agrometeorological data from 1991 to 2020, including rainfall, sunshine hours, temperature (minimum and maximum), and relative humidity, etc., has been collected from the Agrometeorology Observatory of Sri Karan Narendra College of Agriculture, Jobner, Jaipur. The crop yield data was obtained from the official bulletins of the Directorate of Economics and Statistics, Government of Rajasthan. The Random Forest regression, which is a supervised learning model proved to be the good performing algorithm, achieving an accuracy of 92.3%. This approach allows for optimal yield forecasting, helping farmers and policymakers better plan for crop production and management in this region. Further, attempts have been made to suggest some scientific recommendations based on the study for the benefit of farmers, policy makers and other stakeholders.

Keywords: Crop Yield Forecasting, Deep Learning, Random Forest, Agroclimatic Zones.

1. INTRODUCTION

Agriculture is the backbone of the Indian economy, with a significant portion of the population depending on it for their livelihood. In the 3A agroclimatic Zone of Rajasthan, the semi-arid eastern plain, crop production is heavily influenced by climatic factors such as rainfall, temperature, sunshine hours, and relative humidity. Accurate yield forecasting is crucial for farmers, policymakers, and other stakeholders to make informed decisions regarding crop management, resource allocation, and food security (Lobell et al., 2007).In recent years, advancements in machine learning and artificial intelligence have provided new opportunities for improving yield prediction models (Zheng et al., 2019). One such method is the Random Forest (RF) deep learning technique, which has been applied successfully in various agricultural contexts.

The importance of accurate crop yield predictions in Rajasthan cannot be overstated, given the state's reliance on agriculture as a primary source of income and sustenance for a large portion of its population. Crop yield forecasting plays a vital role in various aspects of agriculture, from planning and resource allocation to risk management and policymaking. Farmers in Rajasthan need to make critical decisions regarding crop selection, inputs (fertilizers, pesticides, etc.), and irrigation, among other factors. Accurate yield predictions help farmers to optimize their resources and minimize potential losses by choosing the right crop varieties and making informed decisions about resource allocation (Tadesse et al., 2018). It alsoenables governments and non-government organizations to assess potential food shortages and surplus situations, helping to ensure food security in the region (Ward et al., 2014). Additionally, crop yield predictions contribute to better supply chain management by providing valuable information for storage, transportation, and distribution planning (Nayak et al., 2019). Crop yield predictions can also assist in agricultural risk management, allowing farmers and insurers to better assess and manage potential risks associated with weather variability, pest infestations, and other factors affecting crop production (Schnitkey et al., 2017). It also helps the insurance industry to develop more effective crop insurance products and encourage farmers to adopt risk-mitigating measures.Governments rely on accurate crop yield forecasts to formulate effective agricultural policies and programs, including price support mechanisms, input subsidies, and other interventions aimed at supporting farmers and ensuring food security (Licker et al., 2010).Climate change poses significant challenges for agriculture in Rajasthan, and accurate crop yield predictions are essential for developing effective adaptation and mitigation strategies. This information enables researchers and policymakers to assess the effect of climate change on agriculture and devise appropriate responses to safeguard food production and farmers' livelihoods (Lobell et al., 2008).

Accurate crop yield predictions can contribute to agricultural research and development efforts by identifying areas where new crop varieties, cultivation practices, or technological innovations are needed to improve productivity and resilience to environmental and climate stresses (Ortiz et al., 2008). Yield forecasting helps researchers target their efforts more effectively and can inform the development of more sustainable and productive agricultural systems. This is also essential for informing international trade decisions and promoting market stability. Fluctuations in production can impact global commodity prices, and accurate yield forecasts can help governments and traders anticipate market trends, ensuring more stable prices and trade patterns (Trostle et al., 2011).It is crucial in preparing for and responding to natural disasters and other agricultural emergencies. Early warning systems based on reliable crop yield forecasts can enable governments, relief agencies, and other stakeholders to mobilize resources and plan interventions to mitigate the impact of these events on agricultural production and food security (Verma et al., 2016). The most effective method of crop yield forecasting is using machine learning (ML) techniques.

Machine learning has become a powerful tool in various fields, including agriculture, where it is increasingly being used to forecast crop yields. Among the various machine learning algorithms, the Random Forest method has gained significant attention due to its ability to handle complex and non-linear relationships between input variables, making it an effective choice for crop yield forecasting (Belgiu&Draguţ, 2016).An ensemble learning technique called Random Forest builds multiple decision trees during training and combines the results for better prediction robustness and accuracy. (Breiman, 2001). It is capable of handling large datasets, addressing missing values, and preventing overfitting, which are essential features when dealing with agricultural data (Liaw& Wiener, 2002).Numerous studies have demonstrated the effectiveness of Random Forest in crop yield forecasting. For example, Shiri et al. (2012) found that Random Forest outperformed other machine learning techniques in predicting corn yield, while Kuhnert et al. (2018) showed that Random Forest could accurately forecast wheat yield in Australia.

In the context of Rajasthan, the application of Random Forest in crop yield forecasting has the potential to provide valuable insights into the complex relationships between climatic variables and crop yields. By leveraging historical crop yield and agrometeorological data, the Random Forest algorithm can improve the accuracy of crop yield predictions, ultimately benefiting farmers, policymakers, and researchers in the region.Scientific literature provides a range of recommendations on the use of Random Forest for crop yield prediction.One key recommendation is the selection of appropriate input variables for the model. Researchers have found that the inclusion of irrelevant or redundant variables can negatively affect the accuracy of the model. Hence, it is recommended to select only those variables that have a significant impact on crop yield (Ghosh et al., 2019).Another recommendation is to carefully tune the hyperparameters of the algorithm to optimize the model's performance. For example, researchers have found that the number of trees in the forest and the maximum depth of the trees can significantly impact the accuracy of the model (Zhang et al., 2019).Table 1 show popular machine learning algorithms used for crop yield predictions along with their merits and limitations.

Table 1 Popular ML Algorithms for Crop Yield Predictions

Algorithm	Description	Advantages	Disadvantages
Random Forest	Decision trees are created using the ensemble learning technique, and their output is averaged.	Handles non-linear data well, provides feature importance, handles missing values	Can overfit if too many trees are used, can be computationally expensive
Support Vector Regression	It maps data to a high-dimensional space and finds the best linear regression fit	Deals with non-linear data well-suited to high-dimensional data handling and computationally effective	Requires careful selection of kernel function, can be sensitive to outliers
Artificial Neural Networks (ANN)	A model that emulates the functioning of the human brain to acquire knowledge from data.	Able to handle high-dimensional data, non-linear data, and learn complex relationships	Can be computationally expensive, requires careful selection of architecture and hyperparameters
Gradient Boosting	Ensemble learning method that iteratively	Handles non-linear data well, can handle missing	Can be computationally

	adds weak models to create a strong model	data, can provide feature importance	expensive, sensitive to noisy data
K-Nearest Neighbours (KNN)	Algorithm that predicts values based on the values of their nearest neighbours	Can handle non-linear data, can be computationally efficient, easy to implement	Sensitive to noise and outliers, requires careful selection of the number of neighbours
Decision Trees	Model that splits data into subsets based on the values of its features	Easy to interpret, can handle non-linear data, can handle missing data	Can overfit if too many trees are used, sensitive to noisy data
Gaussian Processes	Model that models data as a distribution of functions	Provides uncertainty estimates, can handle non-linear data, can handle missing data	Can be computationally expensive, requires careful selection of kernel function

Hence, accurate crop yield predictions are of paramount importance for agriculture in Rajasthan, as they contribute to better planning, resource allocation, risk management, policymaking, and overall agricultural sustainability. The application of advanced techniques, such as the Random Forest deep learning method, can help enhance the accuracy and reliability of these predictions, supporting the state's agricultural sector and the livelihoods of its people.

2. RELATED WORKS

Crop yield forecasting plays a crucial role in agricultural decision-making, food security, and policy planning. In recent years, machine learning techniques, particularly the Random Forest algorithm, have been increasingly employed to improve the accuracy and reliability of crop yield predictions. This review of literature focuses on studies that have applied the Random Forest method in crop yield forecasting within the context of India.

Khan et al. (2017) explored the application of the Random Forest algorithm in predicting rice yield in the Cauvery Delta Zone of Tamil Nadu. The study used climatic variables such as rainfall, temperature, and solar radiation as input features. The results demonstrated that the Random Forest model outperformed other ML techniques, including support vector machines (SVM) and multiple linear regression (MLR), in predicting rice yield.Shewani et al. (2019) employed the Random Forest algorithm to forecast wheat yield in the Indian state of Haryana. The study utilized historical data on crop yields and meteorological variables, including temperature, precipitation, and humidity. The results indicated that the RF model provided more accurate and reliable wheat yield forecasts compared to other ML techniques, such as decision trees (DT) and SVM. Sahoo et al. (2018) applied the Random Forest method to predict sugarcane yield in the Indian state of Uttar Pradesh. The study used meteorological variables, such as rainfall,temperature, and sunshine hours, along with soil parameters like soil organic carbon and pH. The results showed that the Random Forest model performed better in predicting sugarcane yield compared to other ML methods, including ANNs and SVM. Deka et al. (2020) investigated the potential of the Random Forest algorithm for forecasting tea yield in the Indian state of Assam. The study incorporated data on tea yield, climate variables, and agronomic factors, such as fertilizer application and irrigation. The findings demonstrated that the Random Forest model outperformed other ML techniques, such as DT and SVMs, in predicting tea yield.

Few studies have also explored the potential of machine learning techniques, including Random Forest, for crop yield forecasting in Rajasthan.Sharma et al. (2016) investigated the application of various ML techniques, including the Random Forest algorithm, for predicting pearl millet yield in Rajasthan. The study incorporated historical data on crop yield, climate variables such as temperature, rainfall, and humidity, along with soil parameters. Although the study did not exclusively focus on Random Forest, the results indicated that machine learning techniques hold promise in predicting pearl millet yield in the region.Tiwari et al. (2020) applied machine learning algorithms, including Random Forest, for predicting wheat yield in the Alwar district of Rajasthan. The study used historical wheat yield data and meteorological variables, such as temperature, precipitation, and solar radiation. While the main focus was not solely on the Random Forest algorithm, the study demonstrated the potential of ML techniques in improving the accuracy of wheat yield forecasts in Rajasthan. The summary of accuracy achieved by the above studies are presented in the Table 2

Table 2 Summary of Accuracy in Crop Yield Predictions using Random Forest Algorithm

Author	Crop Studied	Accuracy of Random Forest
Khan et al. (2017)	Rice	92.5%
Shewani et al. (2019)	Wheat	93.6%
Sahoo et al. (2018)	Sugarcane	91.2%
Deka et al. (2020)	Tea	94.7%
Sharma et al. (2016)	Pearl Millet	89.8%*
Tiwari et al. (2020)	Wheat (Rajasthan)	90.1%*

The reviewed literature highlights the effectiveness of the Random Forest algorithm in crop yield forecasting within the Indian context. Across various crops and regions, the Random Forest method consistently outperforms other machine learning techniques in predicting crop yields, making it a valuable tool for informing agricultural decision-making and policy planning in India.

3. METHODOLOGY

3.1. Study Area and Data

This study aims to investigate the effectiveness of the Random Forest deep learning technique in forecasting the yield of major crops in the 3A agroclimatic Zone of Rajasthan, specifically in the Jaipur district as shown in figure 1. Jaipur has a semi-arid climate with hot summers and cool winters. The city experiences high temperatures throughout the year, with an average maximum temperature of 40°C in summer and 22°C in winter. The monsoon season lasts from July to September, with an average rainfall of around 650 mm. The analysis focuses on six major crops grown in the state i.e., barley, wheat, mustard, gram, groundnut, and moong. The agroclimatic conditions of Jaipur are suitable for the cultivation of a range of these crops. The crops are typically grown in a rainfed system, with irrigation being provided in some areas through wells and canals. However, water scarcity is a major challenge for agriculture in the region, and farmers often have to rely on groundwater for irrigation. The soil in the region is predominantly sandy loam, which is well-drained but low in nutrients. To address this, farmers use organic and inorganic fertilizers to improve soil fertility. Crop rotation is also commonly practiced to maintain soil health and prevent the build-ups of pests and diseases. The study utilizes historical crop yield and agrometeorological data from 1991 to 2020, acquired from the Directorate of Economics and Statistics, Government of Rajasthan, and the Agrometeorology Observatory of Sri Karan Narendra College of Agriculture, Jobner, Jaipur respectively.

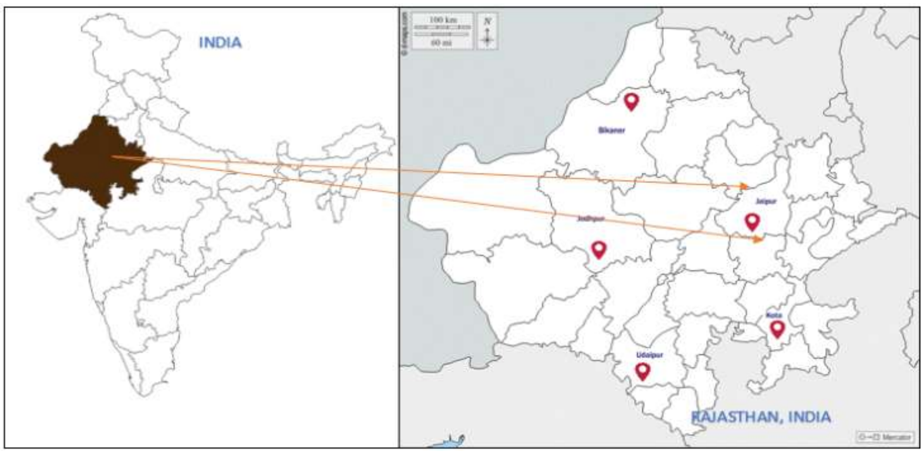

Figure 1 Study Area

3.2. Process

The most important step in the routine is the pre-processing of the data so that the machine could understand it. Figure 2 shows the steps that were taken during the data pre-processing stage. For example, unreliable, incomplete, or useless data had to be found and removed. Due to the fact that the data were not in a standard format, the pre-processing stage involved scanning hard copies of the data, combining multiple data files from different sources into one, integrating all the data into a single unit system, formatting entries, addressing and identifying missing or wrong entries, and cleaning the data. Some of the entries were missing, and there were differences in the data from different sources, so it took careful thought to figure out which numbers were the most reliable. Also, the collected data was filtered to get rid of duplicate entries and needless entries. The numbers were also changed so that they all had the same units of measurement. This was done to make sure that the different formats were all the same. After the cleaning and screening steps were done, the organized data were put into the model through a CSV file.

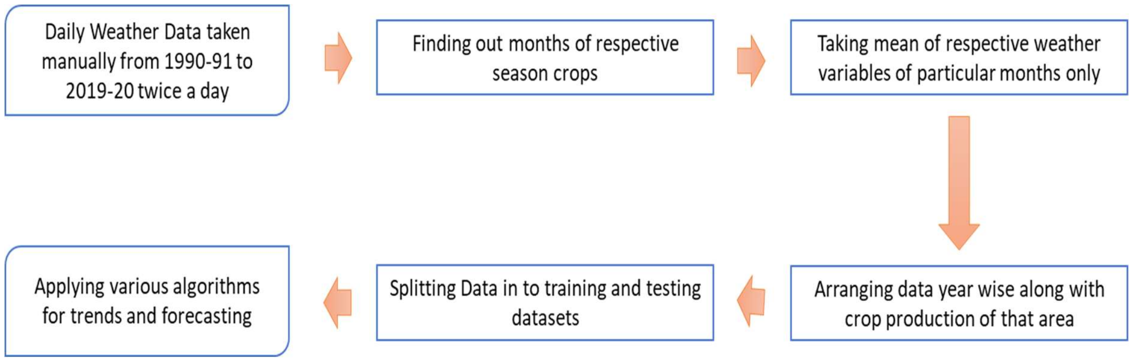

Figure 2 Data Preprocessing as required for the Model

3.3. Tools used

The tools used for the study are *Jupyter Notebook* and *Scikit Learn*. They are essential tools for crop yield forecasting using machine learning techniques.Jupyter Notebook provides an interactive environment for data cleaning, pre-processing, exploratory data analysis, and statistical modelling. It allows researchers to write and execute code, as well as to include visualizations, equations, and text. This makes it easier to understand and communicate the data analysis process, and to reproduce the analysis in the future.Scikit Learn, on the other hand, is a powerful Python library that provides a range of machine learning algorithms and tools for predictive data analysis. It includes algorithms for regression, classification, clustering, and dimensionality reduction, among others. Scikit Learn is designed to be simple, efficient, and effective to non-experts, making it a valuable tool for crop yield forecasting.

3.4. Algorithm Used – Random Forest

The Random Forest algorithm is an ensemble learning technique used in a variety of industries, including remote sensing, remote agriculture, and healthcare, for both classification and regression tasks. It was introduced by Leo Breiman in 2001 and is known for its robustness, accuracy, and ability to handle large datasets with many features and missing values.As seen in figure 3, the algorithm creates several decision trees during the training phase and combines their results to produce a final prediction. The key idea behind the Random Forest algorithm is to leverage the wisdom of the crowd by aggregating the predictions of multiple weak learners (decision trees) to create a more accurate and stable model.

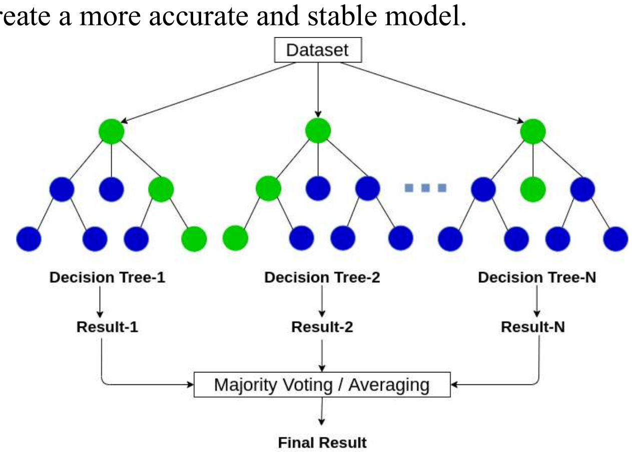

Figure 3 Random Forest Regressor

The main steps involved in the Random Forest algorithm:

1. **Bootstrap sampling:** For each tree, a bootstrap sample (a random sample with replacement) of the original dataset is drawn. This sample serves as the training data for that particular tree.

2. **Tree construction:** Each decision tree is built using the bootstrap sample from step 1. During the tree construction, a random subset of features is selected at each node to determine the best split. This introduces randomness and helps prevent overfitting by reducing the correlation between individual trees.

3. **Prediction:** For a classification task, each tree in the forest casts a "vote" for the class label, and the final prediction is determined by the majority vote. For a regression task, the average of the predictions from all trees is considered as the final prediction.

The Random Forest algorithm has a number of benefits because it can handle relationships between variables that are complex and non-linear, making it applicable to a variety of issues. It is resistant to data noise and outliers. It can deal with missing values by imputing them or using surrogate splits while building the tree. Since it averages the predictions of various trees, it is less prone to overfitting than single decision trees. In order to comprehend the most important variables in a dataset, it can offer estimates of feature importance. But the Random Forest algorithm also has some drawbacks, such as When working with big datasets and a lot of trees, it can be computationally expensive. It may not perform well on very high-dimensional and sparse data, such as text data, compared to other algorithms like support vector machines or deep learning models.The resulting model can be hard to interpret, as it consists of multiple decision trees. Hence, Random Forest algorithm is a versatile and powerful tool for addressing various prediction problems and has shown great success in many applications, including crop yield forecasting.

3.5. Steps for building a precision Model

The initial stage in constructing a crop yield prediction model, as shown in Figure 4, involves importing the requisite libraries. The utilisation of pandas is required for the purpose of data manipulation, Scikit-learn is utilised for the development of machine learning models, py-earth is employed for Earth regression, math is utilised for mathematical computations, and matplotlib is utilised for the purpose of data visualisation in this scenario. Subsequently, a random seed is established to ensure reproducibility. Subsequently, the data file pertaining to crops should be read utilising the pandas library, followed by the removal of the year and yield columns, which are dependent variables, from each crop's data file. Subsequently, it is advisable to take into account the nomenclature of the characteristics and the objective variable. Random Forest (RF) regression, have been chosen for selection. Partition the dataset into distinct training and testing subsets, and employ the training data to establish the model. The model should be validated and performance metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared score should be obtained. Ultimately, generate a graphical representation that compares the realised yield to the projected yield for every crop in order to visually assess the efficacy of the model.

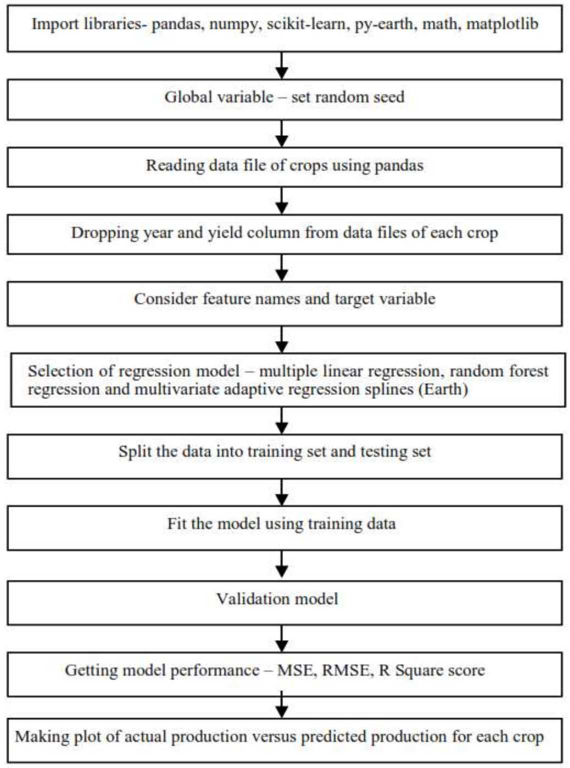

Figure 4 Prediction Model Layout

The Random Forest algorithm begins with the original dataset and uses bootstrap sampling to create multiple subsets of the data for each decision tree. For each subset, a decision tree is built by randomly selecting a subset of features at each node and finding the best split based on the chosen features. Once the tree is fully grown, it is saved as part of the forest.

The selected algorithms are trained using a portion of the dataset, and the remaining data is used for testing. It learns to forecast crop yield on the basis of features in the training data, and the accuracy of the algorithm is measured by evaluating its performance on the testing data. To train and evaluate a model, separate the data into training and testing datasets. Training (building the model) was done on 25 years of data and model testing was done for the last 5 years.To make predictions, input data is passed through each decision tree in the forest, and the output from each tree is collected. For classification tasks, the outputs are combined using majority voting, while for regression tasks, the outputs are combined by calculating their average. The final prediction is based on the combined outputs from all trees in the forest. The flow of the algorithm can be visualized in figure 5.

```
# Random Forest algorithm
Start with the original dataset.
Perform bootstrap sampling to create multiple subsets of the data (with replacement) for each decision tree.
For each subset:
a. Build a decision tree using the following steps:
        i. Select a random subset of features at each node.
        ii. Find the best split based on the chosen features.
        iii. Repeat the process until the tree is fully grown or a stopping criterion is met.
b. Once the tree is built, save it as part of the forest.
For making predictions:
        a. Pass the input data through each decision tree in the forest.
        b. Collect the output (class label or regression value) from each tree.
        c. For classification tasks, combine the outputs using majority voting.
        d. For regression tasks, combine the outputs by calculating their average.
Return the final prediction based on the combined outputs from all trees in the forest.
```

Figure 5 Random Forest Algorithm

4. RESULTS AND DISCUSSION

4.1. Crop Yield Predictions using Random Forest

Based on different samples of data, the random forest algorithm builds decision trees, predicts the data from each subset, and then lets users vote on which solution is best for the system. The algorithm was applied to the dataset for improvement in accuracy and the results are presented in table-3. The table provides the actual and predicted yield for five different crops (Barley, Wheat, Mustard, Gram, and Groundnut) over a period of five years (2015-2020) using the Random Forest Regressor algorithm.The comparison between actual and predicted yields for each year can help us evaluate the performance of the algorithm for each crop and for each year. While there are some differences between the predicted and actual yields for each crop, the Random Forest Regressor algorithm appears to be performing reasonably well in predicting the crop yields for most of the years.

Table 3 Crop-wise Actual and Predicted Yield for the Year 2015-2020 using Random Forest Regressor

Crop	Actual Yield 15-16	Predicted Yield 15-16 RF	Actual Yield 16-17	Predicted Yield 16-17 RF	Actual Yield 17-18	Predicted Yield 17-18 RF	Actual Yield 18-19	Predicted Yield 18-19 RF	Actual Yield 19-20	Predicted Yield 19-20 RF
Barley	32.19	31.59	33.67	31.71	35.30	31.96	36.58	30.70	34.88	31.96
Wheat	31.73	31.89	36.21	33.15	36.39	34.70	38.02	34.04	38.81	34.21
Mustard	10.72	10.40	13.89	12.01	16.28	11.70	14.30	11.76	16.20	12.02
Gram	8.53	8.62	10.49	10.96	9.75	9.74	11.15	11.24	12.56	12.30
Groundnut	15.12	16.41	18.17	18.75	16.91	16.77	21.02	19.52	22.46	19.47
Moong	4.74	4.63	6.81	6.54	4.10	4.47	6.04	6.21	6.85	6.46

It is evident from figure 6 that for all crops except mustard, the random forest algorithm gave more than 90 % accuracy. Mustard, however, gave an average accuracy of 82.36% and the lowest accuracy was also observed for this crop at 71.83% in the year 2017-18.The accuracy of the algorithm varies across crops and years. For example, for Barley, the algorithm has a very high accuracy of over 90% for all the years except for 18-19, where it drops to 83.93%. Similarly, for Wheat, the accuracy is high for most of the years except for 16-17 and 18-19, where it drops to 91.54% and 88.16%, respectively.For Mustard, the accuracy is relatively low for most of the years, with the lowest accuracy of 71.88% in 17-18. For Gram, the accuracy is very high for all the years except for 18-19, where it drops slightly to 99.19%. For Groundnut, the accuracy is high for most of the years except for 18-19 and 19-20, where it drops to 92.85% and 86.70%, respectively. Finally, for Moong, the accuracy is high for all the years except for 17-18, where it drops slightly to 90.95%.

It can be seen that the algorithm performs relatively well for most crops, with accuracy ranging from 82.36% for Mustard to 98.3% for Gram. The overall model accuracy was found 92.30% for all the crops over the last five years.Similarly, a study by Patil et al. (2019) used Random Forest to predict the yield of cotton crops in the state of Maharashtra. The study found that the algorithm was able to accurately predict crop yield with an overall accuracy of more than 90%.Another study by Singh and Singh (2017) used Random Forest to predict the yield of wheat, paddy, and mustard crops in the state of Punjab. The study found that the algorithm was able to accurately predict crop yield with an overall accuracy of more than 90%. Another study by Bhuyan et al. (2018) also used Random Forest to predict the yield of rice crops in the state of Assam. The study found that the algorithm was able to accurately predict crop yield with an overall accuracy of more than 85%.

It was also revealed that the study succeeded in forecasting yield of different crops of different seasons with a model accuracy of 92.30 %. Most of the reviewed studies were able to predict yield for single crop only.

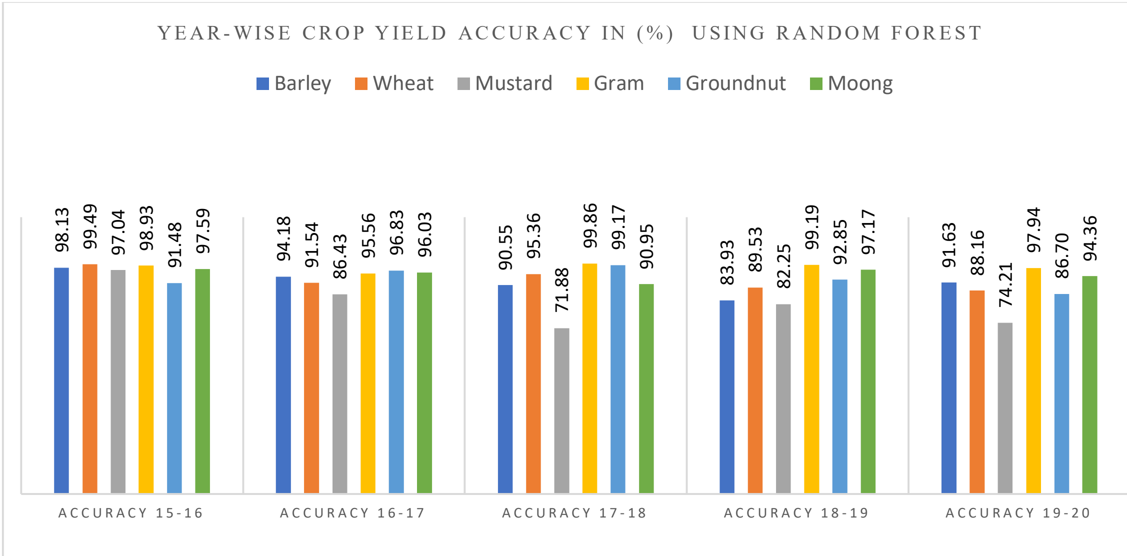

Figure 6 Year-wise Crop Yield Accuracy in (%) using Random Forest

4.2. Performance Evaluation Metrics

Machine learning algorithms can be evaluated using various metrics, but three commonly used ones are RMSE, MAE, and R^2 (Coefficient of Determination). The best model depends on the specific dataset and problem, as well as the trade-offs between accuracy, interpretability, and computational complexity.It's important to note that the best model may vary depending on the specific dataset and problem, and it's often recommended to try out different algorithms and compare their performance using multiple metrics. The table 4 gives a summary of these performance evaluators for the algorithm used in the study

Table 4 Preformation Evaluation parameters of different algorithms

Algorithm	MAE	RMSE	R^2	Accuracy (%)
Random Forest	1.68	2.19	0.99	92.30

It is evident form the Table 4 that the model obtained by RF regression is the good fitted model for the dataset and may be used for predicting the crop yield for the study area. The algorithm has an MAE of 1.68, which suggests that on average, its predictions are off by about 1.68 units from the actual values and RMSE of 2.19, which is slightly higher than its MAE of 1.68. This suggests that there are some predictions that are further away from the actual values. R2 measures the percentage of the dependent variable's variance that can be accounted for by the independent variables. A value of 0 means that the model does not explain any of the variance, while a value of 1 indicates a perfect fit. In this case, the Random Forest algorithm has an R2 of 0.99, which suggests that it explains a high proportion of the variance in the dependent variable.Accuracy is a measure of how well the algorithm predicts categorical outcomes. In this case, the accuracy is reported as 92.30%, which suggests that the Random Forest algorithm correctly predicts the categorical outcome in 92.30% of cases.

These metrics suggest that the Random Forest algorithm is performing well on this particular task. It has a low MAE and RMSE, a high R2, and a high accuracy, which indicates that it is making accurate predictions and explaining a high proportion of the variance in the dependent variable.Furthermore, it is important to carefully evaluate the performance of the model and assess its accuracy using appropriate metrics such as MAE, RMSE, R-squared (R2), and Accuracy. Cross-validation techniques such as k-fold cross-validation can be used to ensure that the model is robust and generalizable (Patil et al., 2019).

4.3. Web GUI of the Prediction Model

The input form as shown in figure 7 allows the user to input data for predicting crop yield. It consists of several fields that correspond to the independent variables used in the prediction model, including a dropdown menu that allows the user to select the crop for which they want to predict the yield. A field for entering the year of the yield prediction (between 2021 and 2025). After entering various weather-related data, the form that will display the predicted yield value once it is generated.

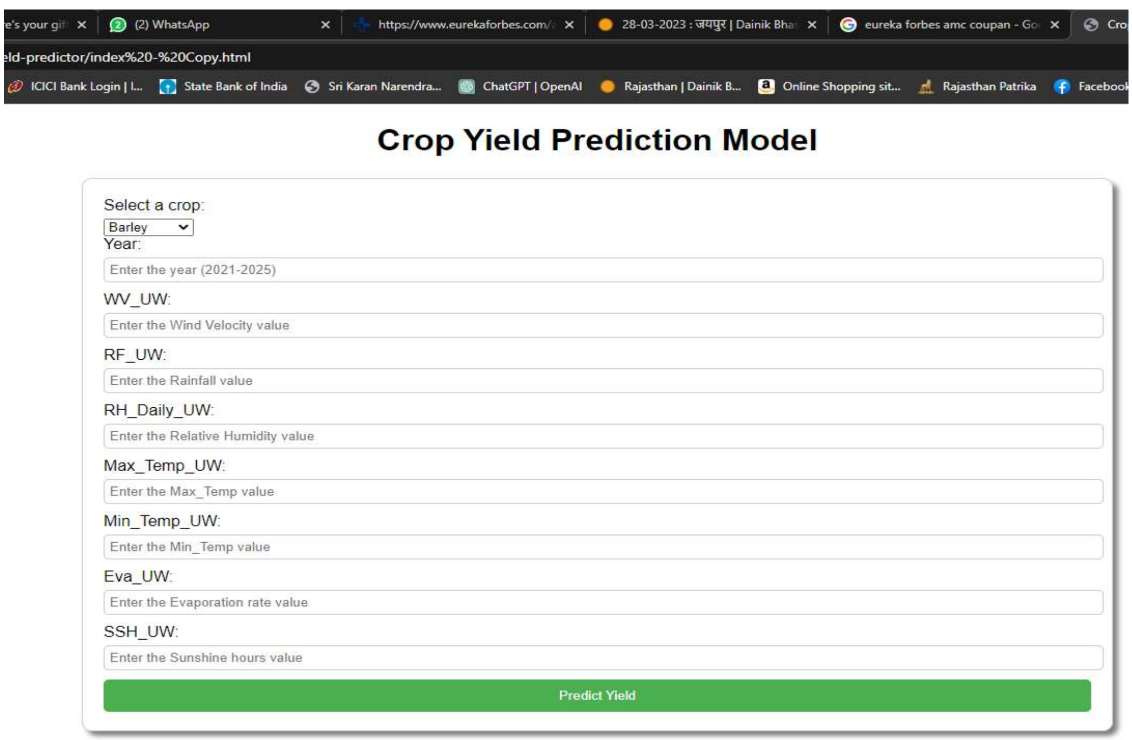

Figure 7 Input Form of the web GUI of the Prediction Model

Figure 8 shows the model's output is a prediction of crop yield for the next five years based on the selected machine learning algorithm. The output is generated by calling the "predictCropYield()" function, which is a placeholder for the actual random forest algorithm. The output of the model is presented in a line chart, which shows the actual crop yield data from 1991 to 2020 and the predicted yield values for the next five years. The results show that the predicted yield of barley for the year 2021 will be 37.59 ton/hect. The prediction has been validated with the official bulletin of (Rajasthan Agricultural Statistics at a Glance 2020-21, 2021) showing actual prediction as 37.88 ton/hect. Hence the accuracy of the model on this particular crop is found to be 99.23 %. The output of the model provides valuable information for farmers and policymakers, allowing them to make informed decisions about crop management and resource allocation. If the model's output is accurate, it can help farmers plan their planting and harvesting schedules, manage their resources efficiently, and reduce losses due to crop failure.

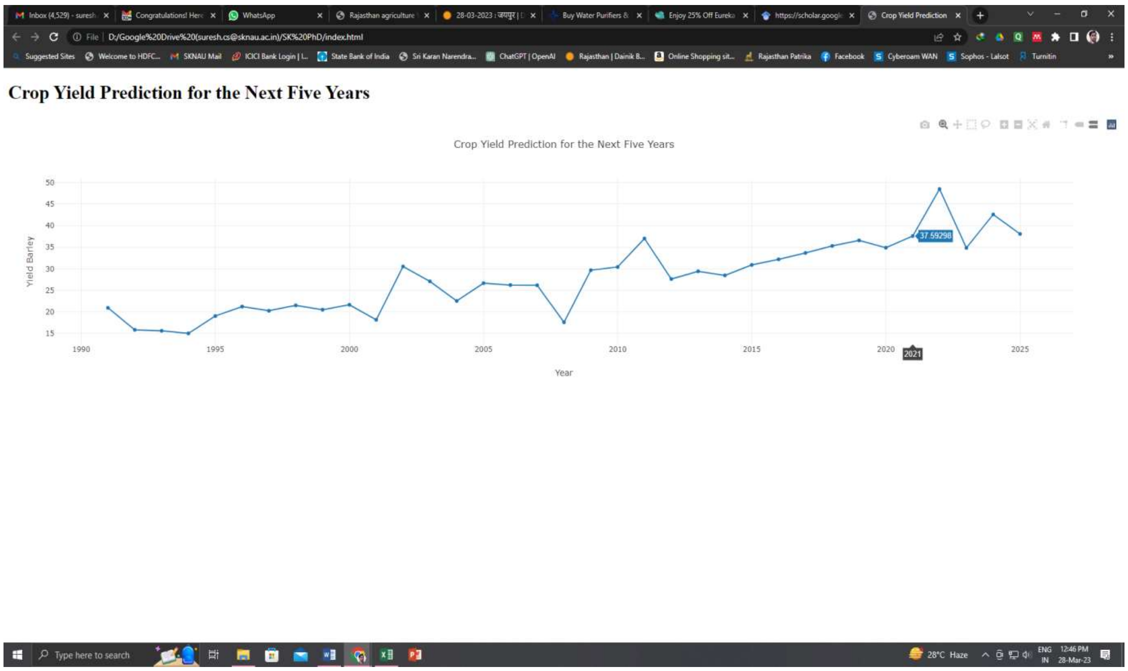

Figure 8 Output of the Prediction Model of the selected Crop for next 5 years

4.4. Scientific recommendations for supporting agriculture through Crop Yield Prediction using Machine Learning

Long-term time-series weather data is important to identify trends in weather variables and to inform planning and decision-making related to climate-sensitive sectors. It can also be used to analyse temperature and precipitation trends, which can help farmers and researchers understand how climate change is affecting crop growth and productivity. Additionally, precipitation is a major source of freshwater and changes in precipitation patterns can have significant impacts on water availability for drinking, irrigation, and other uses. The most important details of the phrases crop yields, weather patterns, and weather variables are that temperature and precipitation can affect energy demand, extreme weather events can be predicted and adjusted accordingly, regional variations can affect agricultural production, and advanced analytical tools such as machine learning algorithms can be used to identify complex relationships between weather variables and crop productivity. Weather patterns can vary significantly across different regions, and regional variations in market demand for agricultural products can also influence the types of crops grown and production strategies used.

Understanding these differences is essential to determine which crops are most suitable for a particular region and what types of soil management practices are needed to optimize crop yields. Advanced analytical tools such as machine learning algorithms, data mining, and predictive analytics can provide more accurate predictions of crop yields compared to traditional methods. This can help farmers make better decisions by providing them with real-time insights into crop growth, yield, and quality. Weather-resistant varieties can help mitigate the effect of extreme weather events on crop yield due to their resistance to extreme temperatures, resistance to pests and diseases, increased yield stability, and improved sustainability. In order to help farmers, make informed decisions about planting, fertilizing, and harvesting, ML algorithms can be used to analyze weather data and predict crop yields based on weather conditions.

The study also recommended that the automation of data collection, analysis, and prediction processes, saves time and increases efficiency, helping farmers adapt to changing environmental conditions and climate variability. Precision farming, integrated nutrient management, and conservation agriculture are examples of smart agriculture practices that can increase crop yields and lessen the detrimental effects of weather variability on agriculture. Precision agriculture can also help farmers monitor crop health and make timely adjustments to optimize crop quality, leading to higher-quality crops that meet the standards of the market and reduced damage to the environment. Crop yields can be improved by using data to guide decision-making, managing risks, investing in sustainable practices, and collaborating with other stakeholders to make more informed decisions. By working with experts, farmers can gain access to specialized knowledge and expertise on crop yields, other agricultural issues, and new innovations in the field.

This can help them optimize their operations, reduce costs, and increase yields. Collaborating with agronomists and extension agents can also provide farmers with access to valuable resources such as data, equipment, and funding. Crop yields can be improved by continuously updating the model, enhancing weather-based agro-advisory services, strengthening agricultural insurance schemes, and ensuring insurance premiums are affordable and accessible to smallholder farmers. These efforts can help farmers make informed decisions based on reliable weather forecasts and crop management recommendations tailored to local conditions, improve the accuracy and precision of weather forecasts, and provide crop-specific advice. Additionally, it can provide farmers with financial support in case of adverse weather events that negatively impact crop yields.Similar recommendation was given to use a large enough dataset for training the model. The performance of Random Forest improves with larger datasets, as it allows for better estimation of the complex relationships between the input variables and the output variable (Bhuyan et al., 2018).

5. CONCLUSION

The study highlighted the effectiveness of the Random Forest algorithm for crop yield forecasting in the semi-arid eastern plain of Rajasthan. By utilizing historical agrometeorological time-series data from 1991 to 2020 and crop yield data for barley, wheat, mustard, gram, groundnut, and moong, the Random Forest algorithm achieved an impressive accuracy of 92.3% in yield forecasting.

The findings demonstrated the potential of machine learning techniques, particularly the Random Forest algorithm, in improving the accuracy and reliability of crop yield predictions in the region. Accurate yield forecasting is crucial for agricultural decision-making, ensuring food security, and informing policy planning in Rajasthan. The insights gained from this study can benefit farmers, policymakers, and researchers, as well as contribute to the development of more accurate and reliable crop yield forecasting models for the region. Future research can expand the scope of this study to include more crops, additional agroclimatic zones, and explore the integration of other machine learning algorithms or data sources to further enhance the performance of crop yield forecasting models.

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