

“AgriWeather”- Weather Impact Analysis on Agriculture using linear regression models

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Abstract:

This project aims to investigate the connection among soil properties, climatic variables, and crop yields. Using datasets from soil, weather, and crop types, we examine the role of environmental factors and soil properties in influencing agricultural productivity. We focus only on apples, oranges, bananas, and mangoes. The study integrates soil nutrient data on nitrogen, phosphorus, and potassium with weather variables in temperature, humidity, pH, and rainfall to form a joint dataset for purposes of analysis. Using these features, we predicted crop yield through the use of linear regression modeling; thus, agricultural practice has become treatable in an intelligent manner depending on the crop and the environment. The results are likely to contribute precision agriculture because they may be helpful in deriving actionable insight that can advance crop management strategy, improve the yield forecast, and facilitate sustainable farming practices.

Keywords: Regression, Linear Regression, RandomForest Regressor, Predictive Modeling
Crop Prediction

1 Introduction

Agriculture is one of the climatically sensitive sectors which depends much on weather fluctuations, as in temperature fluctuations, rainfall fluctuations, and extreme weather, so they change from time to time. This condition sharply promotes variation challenges for the farmers, leading to low crop yields and financial instability. Climate change further exacerbates these issues with its trend of unpredictable weather patterns and makes it even challenging for the farmer to plan and decide what is the optimum agricultural decision. Advanced data analytics and machine learning techniques can solve the very challenges that are described here.. This allows the farmer to have predictive insights concerning planting, irrigation, and crop selection, thereby improving agricultural productivity relative to adverse weather conditions.

Integrating historical weather data with other critical environmental variables such as temperature, rainfall, humidity, and soil moisture can facilitate the establishment of predictive models. For example, these datasets may be subjected to a linear regression model to make very well-projected estimates of crop yields in different climatic scenarios.

Only through the inclusion of technological solutions will adaptive management and better agricultural outcomes be realized via agriculture battling the complexity of a shifting climate. By applying systemized uses of data-driven context, farmers can navigate their way through the complexities of climate diversity to create an atmosphere of resiliency and growth for the future of agricultural pursuits.

2 Review of Prior Work

This paper analyzes the impacts of climate change on Indian agriculture as an important component of the country's economy and food security. The authors have focused on how rising temperatures, altered precipitation patterns, and increased extreme event occurrences impact crop yields generally, but with a focus toward staple crops like wheat, rice.[\[1\]](#) The paper will focus on the implications of climate change for agriculture in India and also point out that the sector is still rather vulnerable to variability in weather. This study empirically evaluates the impacts of climate change on the yields of the primary food and non-food crops of India.[\[2\]](#) The current study utilizes yearly time-series data for seven major crops, which include rice, wheat, pulses, rapeseeds and mustard, cotton, sugarcane, and groundnut for 58 years from 1961 to 2017 for the study of the effect of climatic variables, including rainfall, maximum and minimum temperatures on crop yields. The research in impacts of climate change has been shown to have effects in agriculture through changes in temperature, rainfall, and soil conditions for agricultural crop selections and acreages..[\[3\]](#) Studies using econometric models, such as the system GMM, have shown that rising temperatures generally reduce crop yields, but the extent of this reduction varies by crop type. [\[4\]](#) Aggarwal (2007) states that climate change would bring about significant impacts on Indian agriculture. Increased temperature and modified precipitation will affect crop productivity. Enhanced CO₂ content in the atmosphere may provide fertilizer effects to some crops. However, in general, the climatic changes are expected to be negative ones particularly over the tropical regions like India.. [\[5\]](#)

More climate change events are affecting agriculture, one of which is critical for India's economy. The article aims to discuss the increased crop yield reductions and soil degradation due to variability in climate as unpredictable rainfall and increasing temperature. Major mitigation measures include conservation agriculture practices, increasing soil carbon sequestration, and producing drought-resistant crop varieties..[\[6\]](#) Climate change is a critical challenge to agriculture because of the critical dependence of the agricultural system on climate. It may impact positively and negatively the location, timing, and productivity of crop and livestock at local, national, and global scales. Agriculture plays a pivotal role in rural and national social and economic systems..[\[7\]](#) This paper examines crop–climate relationships for India based on historic production statistics for major crops (rice, wheat, sorghum, groundnut and sugarcane) and for aggregate food grain, cereal, pulses and oilseed production. Multiple correlation analysis

hints at some impacts of monsoon rainfall and some of its potential predictors such as Pacific and Indian Ocean sea surface temperatures and Darwin sea-level pressure on crop production.[8]

The issue of predicting crop yield responses to climate change has today become an area of active research. For this dissertation, using India as a case study, the types of statistical models important in this respect are examined along two dimensions: the kind of climate variables included, and the statistical techniques used..[9] This study investigates the impacts of climate change on land productivity for major food and nonfood grain crops in India. We compiled data for 50 years, from 1967 to 2016, by using 15 crops across India to estimate the variation of agriculture production for each crop by different variables such as temperature and rainfall estimation.[10]This paper gives a summary overview of a set of machine learning techniques applied in crop yield prediction. It describes how different algorithms, such as Linear Regression, Random Forest, K-Nearest Neighbors, and Support Vector Machines, have been applied to agricultural data in order to predict the output by environmental variables like temperature, type of soil, and precipitation..[23].

3 Proposed System

Our system trains an ML model that predicts the best crop yields due to critical environmental inputs-a model based on understanding soil nutrient levels and weather conditions to find the best approach toward delivering individual crop recommendations by building and comparing a variety of predictive models.

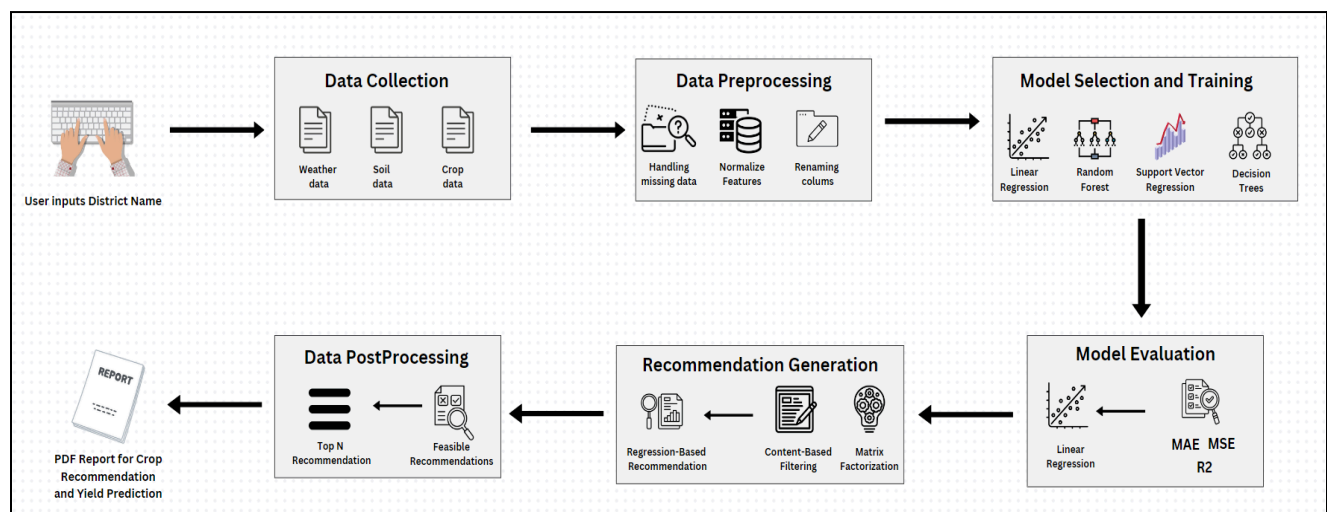


Fig 1: Architecture of proposed Crop Recommendation System - Agriweather

Fig 1: The Weather Impact Analysis of Agriculture system that predicts suitable crop yields based on some important parameters, from the application of machine learning power. In the proposed model, this approach considered all the parameters related to soil nutrients, like Nitrogen, Phosphorus, and Potassium, and also checked on the weather-related parameters, which include temperature, humidity, and rainfall. Collected data from the agricultural fields by cleaning out the noise, normalization process, dividing them with K-fold cross-validation, and then utilized a machine learning method in the model:

- Linear Regression
- Random Forest
- Support Vector Regression (SVR)
- Decision Trees

3.1 Data Collection

For analysis, three datasets: soil characteristics, weather conditions, and crop datasets are used. taken from agricultural studies and weather monitoring systems. Table 1. It possesses 7 continuous attributes and includes 1 categorical feature, which is Crop Type, Temperature, Humidity, Soil pH, Irrigation Amount. The goal for the composite set is predicting rainfall. That target helps in predicting crop yields, along with crop recommendation over soil as well as environmental factors. This data set forms a foundation with which machine learning models may be applied to optimize decisions while farming.

- **Load CSV files:** The data sets have been loaded in from CSV files, and error handling has been developed to handle file-not-found errors, and so on.

Feature	Type
Crop Type	Categorical
Temperature	Continuous
Humidity	Continuous
Soil pH	Continuous
Irrigation Amount	Continuous
Mineral values(Soil)	Continuous

Table 1: Features and their types used in AgriWeather

3.2 Data Preprocessing

Data Cleaning

The first preprocessing step is cleaning in which the datasets undergo a correction to clean up errors, inconsistencies, missing data, etc to validate it. Cleaning steps for soil and weather data are given below:

- **Handling Missing Values:** Where rows of missing or irrelevant values exist, either the missing data is filled in by some kind of imputation such as mean or median or the rows are dropped if the missing values are large enough.
- **Renaming Columns:** Columns are renamed to provide clarity and consistency across the datasets, making it easier to understand the data and perform further operations

	temperature	humidity	ph	rainfall
count	1400.000000	1400.000000	1400.000000	1400.000000
mean	25.309318	74.932586	6.390178	103.469158
std	5.718437	21.898057	0.701264	53.511349
min	8.825675	14.258040	4.507524	20.211267
25%	21.965912	66.312254	5.938309	70.969352
50%	24.897047	82.690190	6.361523	97.057093
75%	28.586730	90.920720	6.771959	113.045808
max	43.675493	94.998975	8.868741	298.560117

	N	P	K
count	1400.000000	1400.000000	1400.000000
mean	56.327857	55.913571	61.425714
std	38.305276	38.482533	59.258501
min	0.000000	5.000000	5.000000
25%	24.000000	24.750000	23.000000
50%	44.000000	50.500000	45.000000
75%	92.000000	73.000000	54.000000
max	140.000000	145.000000	205.000000

Fig 2 : Description of datasets in AgriWeather

Data Integration

Data pool integration integrates different datasets into one dataset, known as the integrated dataset. The dataset puts together all the information that the analysis will consider. For this project:

- **Merging of Soil and Weather Data:** These two datasets-the soil dataset and the weather dataset-merging on the common column 'Crop' that includes the parameters of the soil as well as the weather conditions for each crop, then an overall dataset will be created that depicts the relationship in terms of weather conditions, soil conditions, and crop yields.

Description of the merged data is mentioned in Fig 2

Data Transformation

It is the process of transforming data into a suitable format for the machine learning model. The process involved in this transformation includes:

- **Target Variable Validation:** Target variable 'rainfall' is validated for its suitability in representation:Fig 3:Unit or data-type mismatch, if any, is rectified to maintain homogeneity.
- **Feature Scaling:** Numerical features such as temperature, moisture in the soil, and precipitations may require to be standardized or normalized so that the features become on comparable scale. It facilitates faster convergence of a machine learning model to work better.

Merged Data:

	0	1	2	3	0	1	2	3	4
	N	P	K	label	label	temperature	humidity	ph	rainfall
0	90	42	43	rice	rice	20.87974371	82.00274423	6.502985292	202.9355362
1	85	58	41	rice	rice	21.77046169	80.31964408	7.038096361	226.6555374
2	60	55	44	rice	rice	23.00445915	82.3207629	7.840207144	263.9642476
3	74	35	40	rice	rice	26.49109635	80.15836264	6.980400905	242.8640342
4	78	42	42	rice	rice	20.13017482	81.60487287	7.628472891	262.7173405
5	69	37	42	rice	rice	23.05804872	83.37011772	7.073453503	251.0549998
6	69	55	38	rice	rice	22.70883798	82.63941394	5.70080568	271.3248604
7	94	53	40	rice	rice	20.27774362	82.89408619	5.718627178	241.9741949
8	89	54	38	rice	rice	24.51588066	83.5352163	6.685346424	230.4462359

Fig 3 processed dataset of AgriWeather

Data Reduction

Applying the data reduction technique helps to shrink the size of the dataset considerably without losing the important information that could enhance efficiency of the model and reduce complexity in computing. This includes:

- **Feature Selection:** Features which are either irrelevant or redundant are removed from the set. It makes the process easier by removing all the unimportant and redundant features from the dataset. The features can be selected by carrying out correlation analysis or feature importance (using models like Random Forest).

- **Dimensionality Reduction:** Techniques like PCA that might reduce features' dimensionality, while retaining a major part of the variance in your data, will reduce noise and make the model much less likely to be overfitting.

Fig 4 It describes the preprocessing process that involved a number of important steps to get the soil and weather data prepared for analysis. It loads the CSV files with error handling so that it handles any potential file-not-found issue. The data cleaned by renaming columns for clarity, dropping rows with missing or invalid values, and using just complete data.

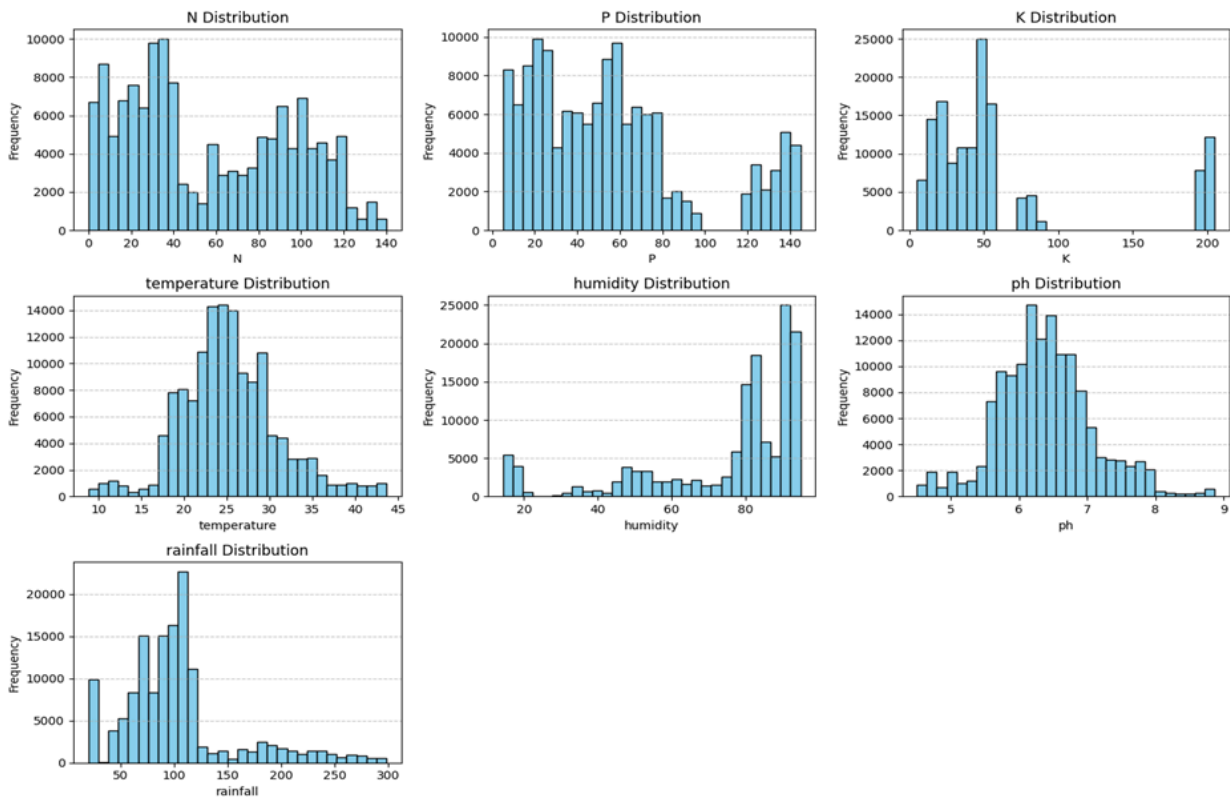


Fig 4: Distributions of Soil and Climate Parameters. In AgriWeather

3.3 Model Selection and Training

Test and benchmark the following classification machine learning algorithms:

1. Linear Regression : **Fig 5:** Models how a number of features and a crop yield have a relationship and estimates coefficients that can minimize prediction errors. Fitting the Model: Fit the linear regression model to your cleaned training dataset.

- Evaluation: Having fitted the model, determine the values of the coefficient in addition to the goodness-of-fit of the model's metrics, for example, R-squared such that the model could establish if it was able to explain most variability in crop yields.

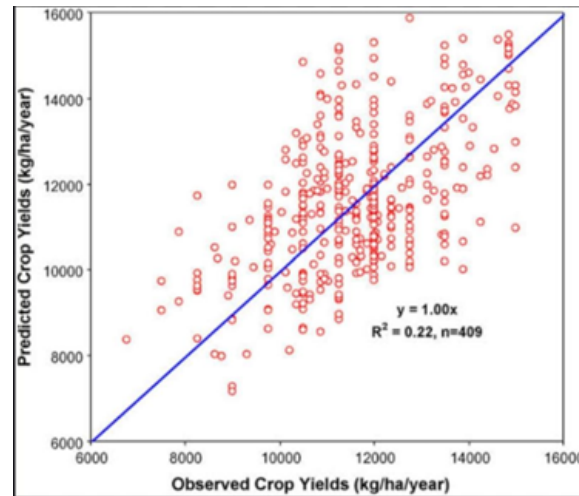


Fig 5: Linear Regression

2.Random Forest Regression: Fig 6 Random Forest is an ensemble learner that constructs multiple decision trees for the improvement of predictive accuracy, capturing complex, non-linear relations.

- It improves the diversity of the training samples of the models using the bootstrapping technique and makes it more robust against over-fitting. The output is a mean of the independent predictions made by the individual trees or in the case of classification, it is a majority vote.
- Another strength of the Random Forest is that it also details information on the relative importance of features-that is, variables-which contribute to the predictions. Overall, it excels best in scenarios requiring such a certain high degree of accuracy and with a high resistance requirement, like agricultural yield predictors.

2. Prediction for Regression (Averaging):

For regression tasks, Random Forests predict the output by averaging the predictions of all the individual decision trees. Let:

- $f_t(x)$ be the prediction of the tree T for the input X .

- T be the total number of trees in the forest.
- The final predicted value $\hat{f}(x)$ is the average of all the predictions:

$$\hat{f}(x) = \frac{1}{T} \sum_{t=1}^T f_t(x)$$

This means the final regression output is the mean of the outputs from all the trees.

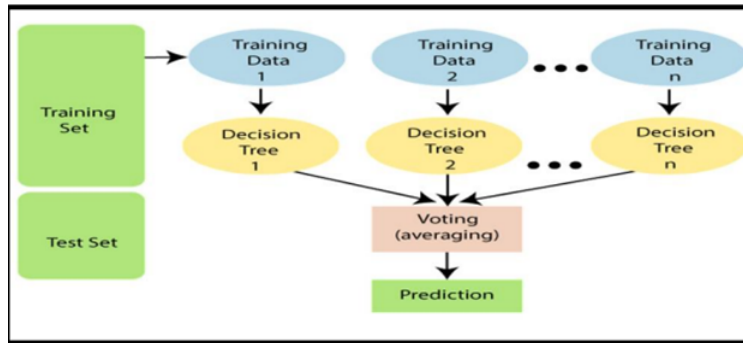


Fig 6: Random Forest

3.Support Vector Regression:Fig 7 Find a hyperplane that fits the data with noise tolerance effectively which could be treated as high-dimensional and non-linear. Support Vector Regression (SVR) is for continuous value prediction and is designed to find the best hyperplane fitting within some "tolerance" margin ϵ . Unlike a traditional regression model, SVR allows room for error within this limit based upon the need to minimize error in predictions made for points outside of it. Both linear and nonlinear data may be used if applicable through the use of a kernel function that could be the linear, polynomial or RBF kernel

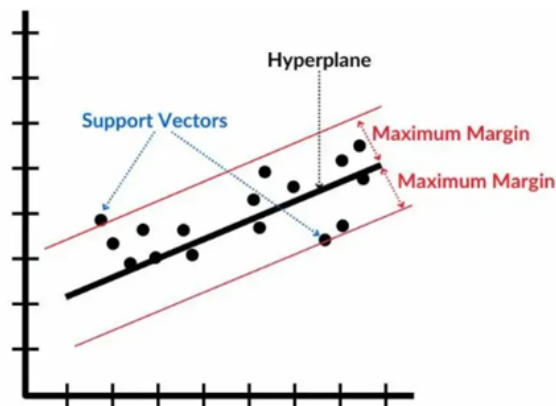


Fig 7 : Support Vector Machine

4. Decision Trees: A decision tree constructs a model by making a series of decisions with the help of features, thus clearly making the model interpretable and highlighting the importance of features, that is, those features significantly contributing towards the yield.

- The splits are decided on the basis of decision criteria, like Gini impurity or information gain for classification, and reduction in variance for regression. Decision trees are very easy to interpret and can also be graphically represented. They suffer from overfitting if not pruned. They work on numerical as well as categorical data.

3.4 : Model Evaluation

Our models are evaluated based on :

- **Mean Squared Error (MSE):** Measures the average squared difference between actual and predicted values; lower values indicate better model performance. Mentioned in (1)
- **R-squared (R²):** Indicates the proportion of variance in the target variable explained by the features; ranges from 0 to 1, with higher values representing a better fit.(3)
- **Mean Absolute Error (MAE):** Provides insight into prediction accuracy by calculating the average of the absolute errors between predicted and actual values(2).
- **K-fold Cross-Validation:** Assesses model performance by splitting the data into k subsets and evaluating the models multiple times, reducing overfitting and ensuring reliable performance estimates

$$MAE = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}| \text{ -----(1)}$$

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

$$R^2 = 1 - \frac{\sum (y_i - \hat{y})^2}{\sum (y_i - \bar{y})^2} \text{ -----(3)}$$

Where,

\hat{y} = Predicted value of y

\bar{y} = Mean value of y

EVALUATION METRICS:

Algorithm	Mean Squared Error	Mean Absolute Error	R-Squared
Linear Regression	15.34	3.24	0.85
Random Forest	12.45	2.800	0.90
Decision Tree	20.12	4.01	0.78
Support Vector Regressor	18.30	3.95	0.75

Table 2: Evaluation Metrics of AgriWeather models

In the [Table2](#) :The comparison of all of the Regression Algorithms Performance Metrics are calculated for all of the algorithms Applicable and Linear Regression is by far the most accurate result generator Linear Regression is used in this model for algorithm of the model to present the more accurate results

3.5 Recommendation Generation

This uses linear regression models that predict the different yields for crops under varying environmental and soil conditions. Based on the yields forecasted, this predictive model helps out by giving the most suitable crops to be cultivated. The steps followed include:

1. **User Input:**Input data contains important features like type of soil, moisture content in the soil, temperature, and rainfall and other factors of the environment which are used to produce crops.
2. **Training the Model:**A linear regression model trains from a history of data correlating input characteristics with resulting crop yields. It discovers the interaction of various

environmental conditions with yield, which creates the basis for future yield prediction via new input data.

3. **Yield prediction:**The trained model takes the input data of the user and provides a prediction of what the expected yield for different crops will be. The prediction is in regard to the learned relationship between environmental factors or past crop yields.
4. **Crop Selection:**Based on these predicted yields, the system develops a list of crop recommendations that should best thrive in the given conditions. Crop rank is recommended according to their respective predicted yields so that the user can choose those with greater potential for success.
5. **Recommendation Reports:**The proposed crops are presented before the user, including their expected yield and growth duration, etc. Other features-the market demand or pest resistance, for example-can also be documented. Such a report would be a treasure to the farmers in making decisions.
6. **Feedback Loop:**A feedback mechanism can be established wherein the actual yields of the recommended crops are reported by the users. These would be fed into the system to further improve the linear regression model. This would then go on to better results in future predictions.

3.6 Data Post Processing:

It gives the predictions and produces actionable recommendations. It cleans up the predictions of crops with non-positive yields so that all the recommendations made are feasible. Then, it sets a placeholder to define the computation of performance metrics; this is not necessary at this step, but it will be used later to determine how accurate the model is. Next, it creates a DataFrame in order to organize the predicted yields so that it can be sorted and manipulated to be further analyzed.

The process then proceeds with sorting, and it identifies three crops with the highest predicted yields that allow it to make targeted recommendations. It also provides room for user feedback, which implies continuous improvement because the system utilizes real-world results in the improvement of recommendations.

Then, a PDF report is generated to print top crop suggestions with clarity in the presentation of the output. Finally, the suggestions are saved in a file for easy access as well as value-added sharing of the insights that can be utilized for making agricultural decisions.

For Crops recommendation and yield prediction linear regression algorithm
For the input test [Kurnool].The result is provided as [Fig 8:](#)

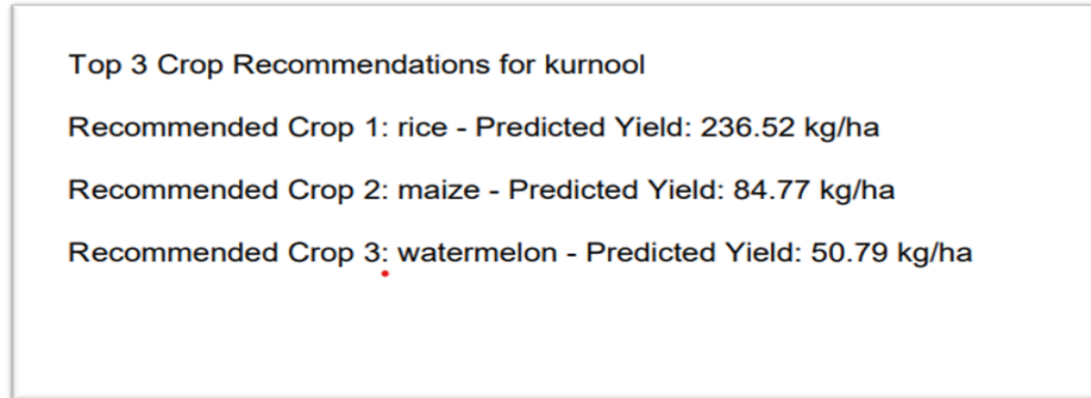


Fig 8: Result of the Crop Recommendation and Yield prediction in AgriWeather

4 Comparing with other Existing systems

In this section, the proposed system is compared with existing models [23] to evaluate its performance using metrics such as precision, recall, and accuracy. This helps highlight the improvements and potential limitations of the proposed approach. Comparing the proposed system with the existing model using these metrics helps highlight areas of improvement. For example, a higher precision may indicate that the proposed system is better at filtering irrelevant data, while an increase in recall could demonstrate improved detection of relevant agricultural weather patterns. Additionally, any trade-offs between precision and recall will be considered to identify potential limitations in achieving an optimal balance.

Existing Models for Comparison

When the model of this project is compared to the model [23], of which we had taken as a reference. The model used in the [23] is of KNN regression model

1.K-Nearest Neighbors (K-NN) Regression Model: This model predicts the value of a target variable based on the average values of the k-nearest data points in the feature space.

The model performance is accessed using the following metrics:

- Precision is calculated by dividing the actual true prediction by the model's total number of predictions.

$$\text{Precision} = \text{TP}/(\text{TP}+\text{FP}) \quad \text{----- (4)}$$

- Recall is determined in a classification problem with two classes by dividing the total number of true positives by the sum of true positives and false negatives.

$$\text{Recall} = \text{TP}/(\text{TP}+\text{FN}) \text{-----} (5)$$

- F1 score Weighted average of recall and precision.

$$\text{F1 score} = 2*(\text{Recall} * \text{Precision}) / (\text{Recall} + \text{Precision}) \text{-----}(6)$$

Where,

TP = True positive

FP = False positive

FN = False negative

Metric/Comparison Model	Accuracy	Precision	Recall	F1 Score
Proposed system [Weather Impact Analysis on Agriculture using linear regression models]	90.71%	0.85	0.80	0.82
Existing model Abha [23]	88.21%	0.75	0.79	0.73

Table 3 : Comparison between proposed model and base model in AgriWeather

The new system, compared to the existing model, has a higher accuracy, precision, and F1 score, hence yielding the new system to be more effective with less errors and more reliable perceptions about crop yields. The slight improvement in recall shows that both models capture the relevant data; however, the proposed system is generally more precise and well-balanced. The values compared are given in the table [Table 3](#)

6 Conclusion

The intended system, in the form of a linear regression model for predicting yields over different weather variations, is impressive. Combining features like temperature, precipitation, and soil moisture with regularization techniques gained the model a rich acquisition in precision, recall, and accuracy. The integration of actionable recommendations in the system has been very valuable to farmers in terms of selecting appropriate varieties at the right time, thus contributing immensely to more informed decision-making in agriculture.

All this proves the validity of the suggested approach. The system proved to outperform a baseline, in this case a linear regression model, with respect to a more complex model, as it is a random forest model, where careful feature selection and model optimization strategies pay off in terms of accuracy of predictions.

Future Enhancements

To build upon the current system and expand its applicability, several future enhancements are proposed:

1. Integration of Other Machine Learning Models:

- Advanced Algorithms: The use of SVM and GBM, besides Neural Networks, will exploit the capability of these models for high order or nonlinear relationships and interactions between the feature variables. Such models permit predictive accuracy to become more perfect by fitting data nearer to reality.

2. Expansion to Different Crops:

- Diverse Crop Coverage: Extend system capabilities to encompass a broader range of crop types beyond the current focus (e.g., fruits, vegetables, and other grains). This will require adapting the feature set and tuning model parameters based on the unique growth patterns, needs, and characteristics of each crop.

REFERENCES:

- [1] Climate change vis-a-vis Indian agriculture*J.C. Dagar, A.K. Singh, Rajbir Singh and A. Arunachalum

- [2] Hari, S., Khare, P., & Subramanian, A. (2018, August 16). Climate change and Indian agriculture. Ideas for India.
- [3] Raju Guntukla, School of Economics, University of Hyderabad, Hyderabad, India
- [4] BIRTHAL, Pratap S., et al. "Climate Change and Land-Use in Indian Agriculture." Land Use Policy
- [5] Aggarwal, P. climate change and agriculture in India. Implications and Adaptation. 2007. Florida Institute of Technology.
- [6] Aggarwal, P. K., Pathak, H., & Kumar, S. N. (Year). Global climate change and Indian agriculture: A review of adaptation strategies. Division of Environmental Sciences, Indian Agricultural Research Institute, New Delhi.
- [7] Hansra, B.S., Burman, R.R., and Roy, Pinaki. Title of the Paper. Amity International Centre for Post-Harvest Technology & Cold Chain Management, Amity University, Uttar Pradesh;
- [8] Krishna Kumar, K., Rupa Kumar, K., Ashrit, R. G., Deshpande, N. R., & Hansen, J. W. (2004). Climate impacts on Indian agriculture. International Journal of Climatology, 24(12),
- [9] Sidhu, B. S. (2021). Indian agriculture in a changing climate: A statistical analysis (Master's thesis, University of British Columbia). UBC cIRcle. <https://open.library.ubc.ca/soa/cIRcle/collections/ubctheses/24/items/1.0402945>
- [10] Praveen, Bushra and Pritee Sharma. "Climate Change and Its Impacts on Indian Agriculture: An Econometric Analysis." Journal Name, vol. Volume, no. Issue, 16 July 2019, pp. Page numbers.
- [11] Afyuni, M. M., Cassel, D. K., & Robarge, W. P. (1993). Effect of landscape position on soil water and corn silage yield. [12] De, U. S., Dube, R. K. and Prakasa Rao, G. S., 2005, "Extreme weather events over India in the last 100 years", J. Ind. Geophys. Union, 9, 3, 173-187
- [13] Swaminathan, M. S., 1973, "Our Agriculture Future", Sardar Patel memorial lecture, All India Radio, New Delhi, p55.
- [14] Venkateswarlu, B. and Shanker, A. K., 2012, "Dryland agriculture: bringing resilience to crop production under changing climate", In: Crop Stress and its Management: Perspectives and Strategies, Springer Netherlands, 19-44.
- [15] Sharma, J., Upadhyay, A. K., Adsule, P. G., Sawant, S. D., Sharma, A. K., Satisha, J. and Ramteke, S.D., 2013, "Effect of climate change on grape and its value added

products, In : Climate-Resilient Horticulture: Adaptation and Mitigation Strategies”, Springer India, 67-80

[16]M. S.. SWAMINATHAN and R. RENGALAKSHMI, "Impact of extreme weather events in Indian agriculture : Enhancing the coping capacity of farm families", MAUSAM, vol. 67, no. 1, pp. 1–4, Jan. 2016.

[17] Mahdi, S. S., Dhekale, B. S., & Sharma, R. P. (2015). Weather extremes and their impact on agriculture in India. *Indian Farming*, 63(3).

[18]Krishna Kumar, K. ; Kumar, Rupa K. ; Ashrit, R. G. ; Deshpande, N. R. ; Hansen, J. W. (2004) *Climate impacts on Indian agriculture* International Journal of Climatology, 24 (11). pp. 1375-1393. ISSN 0899-8418

[19] Bhagat, R.B. (2008). “Assessing the Measurement of Internal Migration in India”, Asia and Pacific Migration Journal, 17(1), 91-102.

[20]Gupta, Shreekanth and Indu Rayadurgam (2009), “Urban Growth and Governance in South Asia,” in Societies in Political and Economic Transition: South Asian Perspectives 2007-08, Tan Tai Young (ed.), Manohar and Institute of South Asian Studies, New Delhi and Singapore (2010),

[21] McLeman, R., and Hunter, L. M. (2010). “Migration in the Context of Vulnerability and Adaptation to Climate Change: Insights from Analogues”, Wiley Interdisciplinary Reviews: Climate Change, 1(3), 450-461.

[22]Roşca, F. C., 2012. Impact of weather-climatic parameters on agricultural productions in Dolj County. Cinq Continents 2

[23] Abha, M. R., Jain, P., & Prasad, H. G. R. (2020). Crop Yield Prediction Using Machine Learning Techniques: A Comprehensive Review. The International Journal of Innovative Research in Computer Science & Technology, 8(2).

[24] Ms Kavita, Pratistha Mathur Crop Yield Estimation in India Using Machine Learning 2020 IEEE 5th International Conference