CROP YIELD ANALYSIS AND FORECASTING

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1. Abstract

This project aims to comprehensively analyze and forecast crop yields by leveraging a rich combination of historical agricultural data and advanced analytical techniques. The core objective is to systematically identify and model the most significant factors influencing crop productivity across various regions. These factors include key climatic parameters such as rainfall patterns and temperature fluctuations, as well as region-specific agricultural practices, water resource management, and the availability of critical inputs like fertilizers and irrigation infrastructure. By doing so, the project seeks to unravel the complex interdependencies between environmental conditions and agricultural performance.

Through rigorous data exploration and preprocessing, the study first establishes a clear understanding of temporal trends and spatial variability in crop yields over the years. This is followed by the application of multiple modeling strategies, combining both classical and modern machine learning methods. Specifically, the project integrates advanced Machine Learning (ML) techniques such as Random Forest Regressors and ensemble models alongside traditional approaches like Linear Regression and Time-Series analysis. These models collectively utilize historical yield records, target-encoded categorical variables, and a suite of environmental and resource-based features to predict future yield outcomes with improved accuracy.

The analysis highlights that while some crops demonstrate pronounced sensitivity to climatic changes, particularly variations in rainfall and temperature, other crops are more substantially influenced by local farming techniques and the efficiency of resource utilization, such as water storage levels and irrigation practices. This insight underscores the importance of context-aware modeling that accommodates both environmental and human-managed variables.

To further refine predictions, the project employs feature engineering and model validation strategies, including year-based train-test splitting and feature prediction using simpler regression models when direct measurements are unavailable for the forecast period. The results reveal that different models perform better in different contexts: in certain states, linear models capture the underlying trends effectively, whereas in others, tree-based models like Random Forests excel due to their ability to model non-linear interactions.

Ultimately, the findings of this study aim to contribute to the broader goal of supporting data-driven, informed decision-making within the agricultural ecosystem. By providing reliable forecasts and uncovering actionable patterns, this work aspires to help policymakers, farmers, and stakeholders in planning and optimizing agricultural practices, ensuring better food security and resource management for the future.

2. Introduction

Agriculture is a cornerstone of the Indian economy, providing livelihood to a significant majority of the population. It is intricately linked to national development, food security, and rural employment. The performance of this sector influences not only farmers, but also a wide spectrum of stakeholders including government agencies, private enterprises, and supply chain intermediaries. In such a context, accurately predicting crop yield becomes a critical tool for decision-making in agricultural planning, policy formulation, and resource management.

Agriculture continuously seeks innovative methods to boost productivity and ensure food security. The convergence of data analytics, machine learning, and deep learning has emerged as a transformative force in this pursuit. In the context of India, where agriculture is highly sensitive to climatic and environmental variations, leveraging data-driven techniques for crop yield prediction has become increasingly vital.

Additionally, regional variations in farming practices and irrigation infrastructure introduce further complexity. The datasets used in this study reflect these real-world conditions by capturing daily agro-meteorological variables like maximum and minimum temperatures, rainfall, and water reservoir levels, along with corresponding crop yields across different states and time intervals.
By evaluating the predictive accuracy of these models, the study aims to identify the most effective algorithms and features influencing crop output. Ultimately, this research aspires to enhance the precision of agricultural forecasting and support more informed and timely agricultural decision-making through the integration of machine learning and domain-specific insights.
Topics Covered in the First Two Weeks

During the initial phase of the internship, we were introduced to a diverse set of foundational and technical topics, including:
• Power BI: Basics of data visualization and dashboard creation.
• Streamlit: Create interactive web app.
• Research Project Introduction: Overview of project scope, objectives, and expected outcomes.
• Introduction to Machine Learning and Deep Learning.
• Prompt Engineering & Generative AI: Fundamentals of crafting effective prompts and understanding AI outputs.
• Text Analytics: Introduction to NLP techniques for extracting insights from textual data

3. Project Objective

• To analyse historical agricultural data to identify key factors influencing crop yield, including temperature, rainfall, and regional practices.
• To develop predictive models using Machine Learning and Deep Learning techniques for accurate crop yield forecasting.
• To compare the performance of various algorithms (e.g., Linear Regression, Random Forest, XGBoost) and determine the most effective model for yield prediction.
• To illustrate the impact of environmental and climatic variables on crop productivity and provide actionable insights for farmers and policymakers.
• To demonstrate how data-driven forecasting can support strategic planning in agriculture, such as crop selection, resource allocation, and market readiness.

4.Methodology

In this project, we focused on **predicting agricultural yield** using weather and reservoir features, following a structured data science and machine learning workflow.

Below, we describe in detail the process, tools, and methods used from data preparation to model evaluation.

Data Collection & Understanding

- The primary dataset was provided by our mentor, containing **crop yield data for multiple crops**, daily weather variables (temperature, rainfall), and reservoir data (water level, FRL, live storage) across multiple states in India for several years.
- The data covered multiple crops (e.g., rice, wheat, gram, mustard, etc.) and included thousands of records per crop and state.

Data Preparation & Cleaning

- Cleaned column names and standardized formats.
- Converted date columns to datetime objects and extracted useful temporal features like **year** and **week number**.
- Removed rows with missing critical values to ensure model reliability.
- Merged all crop Datasets and then created separate DataFrames for states.

Feature Engineering

- Created additional features to enrich model inputs:
    - **avg_temp**: mean of yearly max and min temperatures.
    - **Target encoding of crop_name**: replacing categorical crop names with their mean yield in training data.
    - **Interaction features**: experimented with manually multiplying reservoir level and categorical features to capture relationships.
- Explored correlations to identify important features.

Model Selection & Rationale

We focused on classical ML models that are:

- Easy to interpret,
- Robust to nonlinear relationships,
- Require minimal data preprocessing.

Models used:

Linear Regression:

- Used as a baseline model to capture simple linear dependencies between yield and features.

Random Forest Regressor:

- Selected for its ability to handle non-linearities and feature interactions.
- Naturally robust to multicollinearity and outliers.

We trained models separately for each state to account for regional differences.

Data Splitting & Validation Strategy

- Sorted data chronologically by year to avoid data leakage.
- Split each state dataset into:
  - **Training data:** first 80% of years.
  - **Testing data:** remaining 20% of years.
- Avoided random shuffling to maintain temporal order, simulating real-world prediction where future data is unseen.

For additional realism:

- Built separate regressors (e.g., LinearRegression) to predict test set features (avg_temp, rainfall, etc.) **only using year as input**.
- Used these predicted features instead of true test features when predicting yield — mimicking deployment where future weather data isn't known.

Model Training & Evaluation

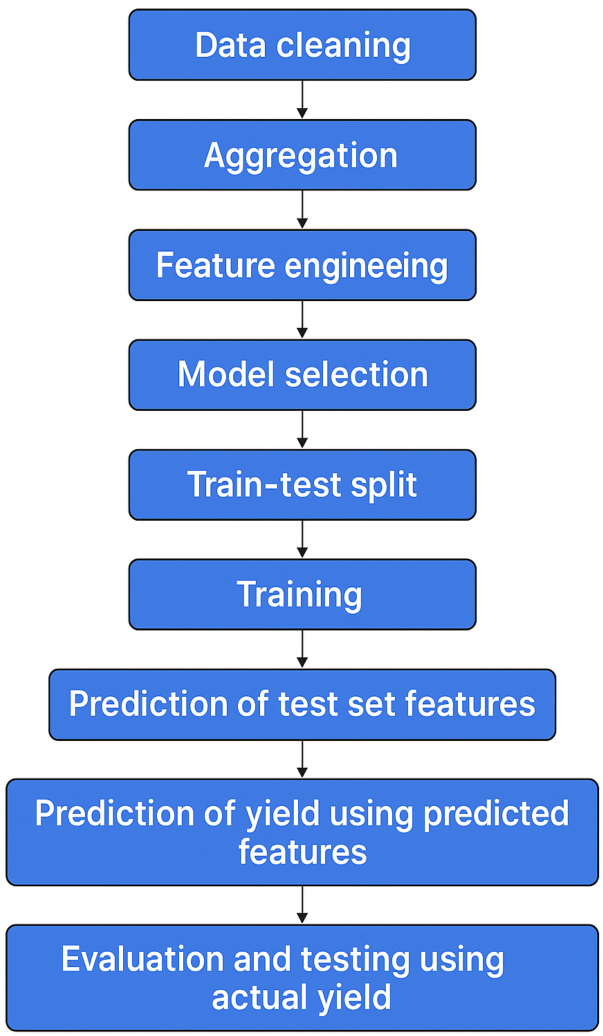
- For Random Forest: tuned number of trees, fixed random_state for reproducibility.
- Experimented with different combinations of feature set to get the best performing features.
- Evaluated models on both training and test data using:
  - RMSE (Root Mean Squared Error)
  - R^2 score (Coefficient of Determination)

This helped assess not only how well models fit the training data but also their generalization capability.

Tools & Libraries

- Python (Jupyter / Colab)
- pandas & numpy (data manipulation)
- sklearn (models and metrics)
- matplotlib & seaborn (visualizations)

Summary Flow-Chart

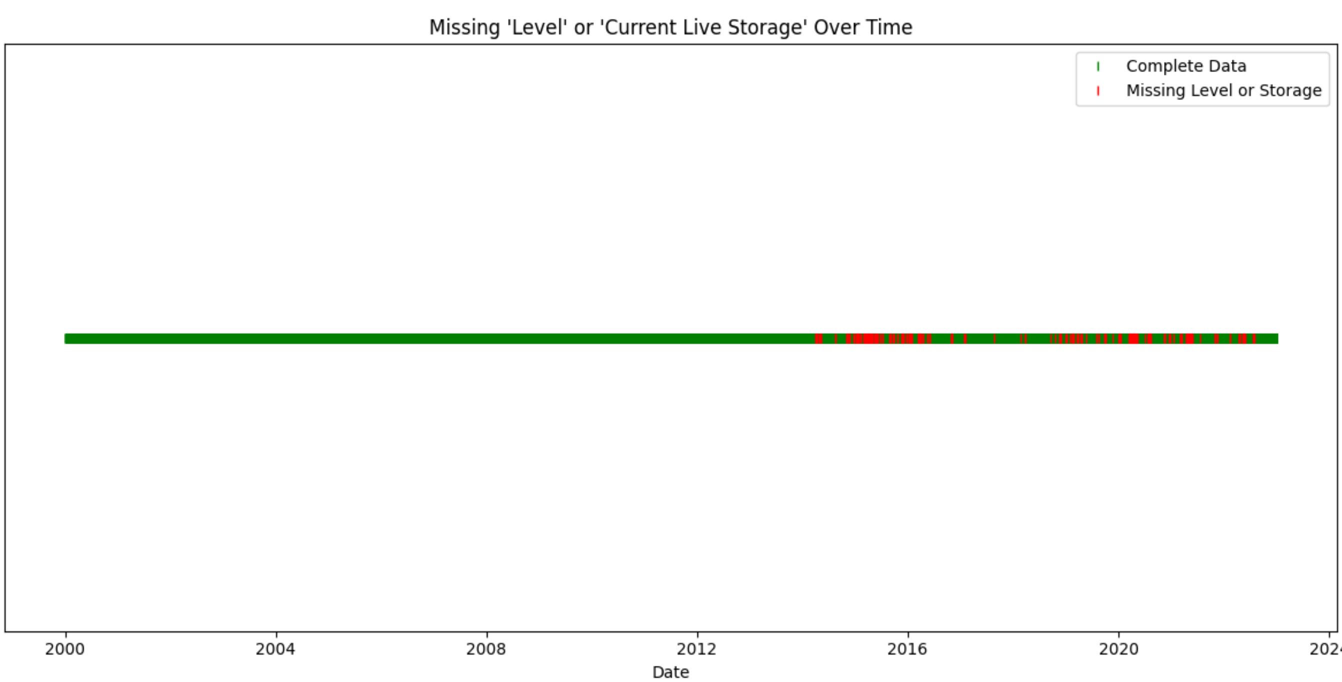


5.Data Analysis and Results

Missing values and Duplicates(Potato Dataset):

During data analysis, we checked for missing values across all columns. Most features had complete data except for Level and Current Live Storage, which had 382 missing entries each. This is likely due to occasional gaps in reservoir data reporting. Since these features are important for downstream modeling, appropriate imputation strategies (such as using mean, median, or model-based imputation) can be considered in future steps to handle these missing values effectively. No duplicate rows were found, ensuring data consistency.

```
Missing values per column:
 state_name                     0
crop_name                      0
apy_item_interval_start        0
temperature_recorded_date      0
state_temperature_max_val      0
state_temperature_min_val      0
state_rainfall_val             0
yield                          0
FRL                            0
Live Cap FRL                   0
Level                        382
Current Live Storage         382
dtype: int64
Number of duplicate rows: 0
```



Summary Statistics:

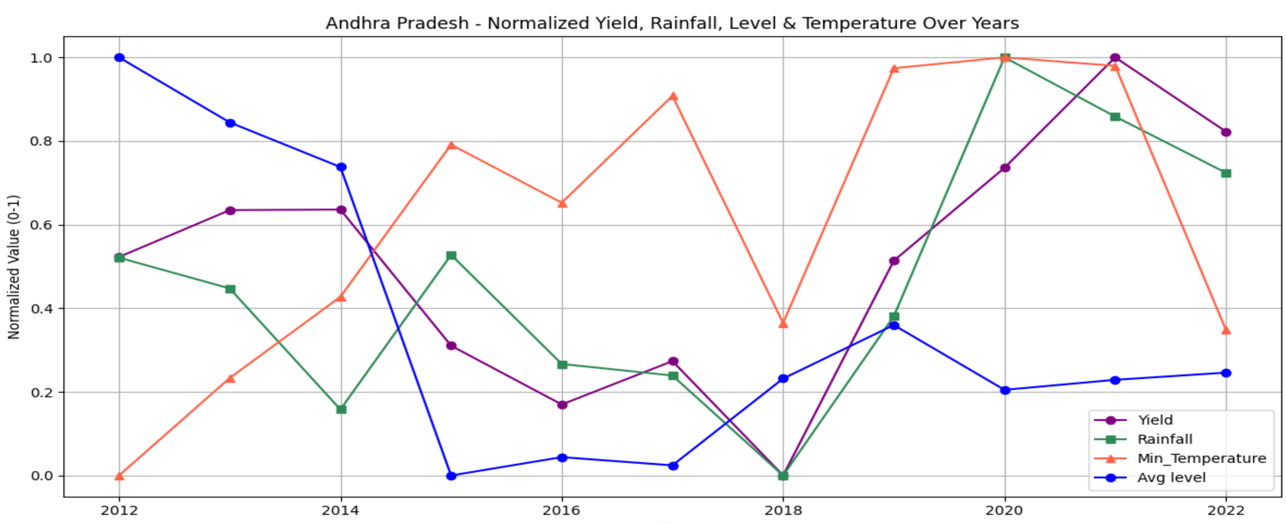
The dataset contains 47,848 records covering agricultural and climatic data from 2000 to 2022. Temperature values vary widely, with maximum temperatures ranging from about 11 °C to nearly 48 °C and minimum temperatures from -0.5 °C to around 29 °C, reflecting seasonal and regional diversity. Rainfall shows high skewness, with a median close to zero and a maximum value near 187 mm, indicating many dry days interspersed with occasional heavy rainfall. Yield values range from about 4 to 36, with a mean of roughly 16, suggesting moderate variability across crops and years. Reservoir features like FRL and Level also exhibit broad ranges, highlighting differences in storage capacity and water availability across states and years. Overall, the statistics reveal significant variability, which is essential context for model building and analysis.

```
Summary statistics of the dataset:
       apy_item_interval_start  state_temperature_max_val  \
count             47848.000000               47848.000000
mean               2014.045645                  33.566005
std                   5.432290                   5.031233
min                2000.000000                  11.110000
25%                2010.000000                  31.070000
50%                2015.000000                  33.420000
75%                2019.000000                  36.560000
max                2022.000000                  47.510000

      state_temperature_min_val  state_rainfall_val         yield  \
count              47848.000000        47848.000000  47848.000000
mean                  17.305670            3.262658     16.346552
std                    5.572399            6.542797      8.407129
min                   -0.500000            0.000000      3.975090
25%                   13.420000            0.000000      8.409210
50%                   18.490000            0.310000     15.056890
75%                   21.790000            3.770000     22.558860
max                   28.920000          186.990000     35.916140

                FRL  Live Cap FRL         Level  Current Live Storage
count  47848.000000  47848.000000  47466.000000          47466.000000
mean     341.616405      1.515693    330.989787              0.752887
std      148.469866      0.867089    148.225816              0.628405
min      135.136667      0.198465     64.960000              0.000000
25%      183.210000      0.523000    177.213125              0.244333
50%      348.926000      1.539062    338.858500              0.576688
75%      461.933333      1.866600    421.389800              1.099721
max      597.731875      2.898000    824.960000              4.327000
```

Trends:

The above plots illustrate key temporal trends in the dataset from 2000 to 2022.

- The top plot shows clear seasonal cycles in daily average maximum and minimum temperatures, highlighting regular annual fluctuations with higher max temperatures peaking around mid-year and lower min temperatures in cooler months.
- The middle plot displays daily average rainfall, which is highly variable with sharp spikes, capturing the sporadic and monsoon-driven nature of rainfall in India.
- The bottom plot presents daily average yield, aggregated across crops, which shows relatively smoother step-like trends over time, reflecting long-term changes in agricultural productivity. Together, these plots help in understanding the seasonality, variability, and potential factors influencing crop yield over the years.



The above chart shows the normalized trends (scaled between 0 and 1) of yield, rainfall, minimum temperature, and average reservoir level in Andhra Pradesh from 2012 to 2022. We observe fluctuations in yield roughly aligning with changes in rainfall and temperature, while average reservoir levels show a declining trend initially and stabilize later. This visualization helps explore potential relationships and seasonal impacts of climatic and water storage variables on agricultural yield over the years.

Comparative analysis of models

Comparing performance of Linear Regression and Random Forest models tested using actual random test features.

State	LR Train RMSE	LR Train R^2	LR Test RMSE	LR Test R^2	RF Train RMSE	RF Train R^2	RF Test RMSE	RF Test R^2
Uttarakhand	1.583138	0.887347	1.646568	0.883942	0.249097	0.997211	0.687708	0.979755
Uttar Pradesh	1.742486	0.963755	1.818623	0.962261	0.401013	0.998080	1.019810	0.988133
Chhattisgarh	0.460810	0.933399	0.466045	0.931195	0.083273	0.997825	0.224716	0.984003
West Bengal	1.771452	0.967269	1.775435	0.967109	0.419865	0.998161	1.078628	0.987860
Andhra Pradesh	1.672503	0.874421	1.698052	0.871731	0.271357	0.996694	0.628160	0.982447
Jharkhand	0.409126	0.969718	0.422939	0.968140	0.095489	0.998350	0.277078	0.986326
Karnataka	0.918453	0.972216	0.908613	0.973086	0.267703	0.997640	0.712759	0.983438
Telangana	1.408565	0.891958	1.447935	0.888519	0.252960	0.996515	0.644023	0.977945
Rajasthan	0.289818	0.919311	0.287629	0.921742	0.044570	0.998092	0.117705	0.986894
Madhya Pradesh	0.440958	0.726663	0.438265	0.730158	0.063497	0.994332	0.167924	0.960385
Gujarat	0.303580	0.851027	0.298526	0.857417	0.054341	0.995227	0.142135	0.967678
Maharashtra	0.167746	0.896734	0.167160	0.899790	0.034631	0.995599	0.091609	0.969903
Tamil Nadu	0.989472	0.989035	0.964188	0.989344	0.192415	0.999585	0.510851	0.997009
Odisha	0.060912	0.980900	0.061269	0.981614	0.010577	0.999424	0.026625	0.996528

Comparing performance of Linear Regression and Random Forest models tested using predicted test features predicted by simple linear regression models.

State	LR Train RMSE	LR Train R^2	LR Test RMSE	LR Test R^2	RF Train RMSE	RF Train R^2	RF Test RMSE	RF Test R^2
Uttarakhand	3.050504	0.871694	0.712182	0.958732	0.039830	0.998325	0.295978	0.982849
Chhattisgarh	0.121900	0.949905	0.618529	0.891795	0.002989	0.998771	0.677984	0.881394
West Bengal	3.699386	0.957748	0.878195	0.992971	0.162505	0.998144	1.763023	0.985888
Jharkhand	0.184052	0.971026	0.148013	0.928788	0.009374	0.998524	0.202175	0.902730
Karnataka	0.759944	0.971073	1.295533	0.970228	0.046510	0.998230	1.388033	0.968102
Rajasthan	0.056365	0.942937	0.129117	0.890229	0.000783	0.999208	0.060204	0.948816
Madhya Pradesh	0.152771	0.709419	0.547404	0.445695	0.002670	0.994921	0.192569	0.805003
Gujarat	0.052286	0.914362	0.221269	0.490499	0.001168	0.998087	0.200743	0.537764
Maharashtra	0.020882	0.915420	0.036566	0.882064	0.000723	0.997070	0.144693	0.533329
Tamil Nadu	1.101848	0.986548	0.544978	0.995123	0.034081	0.999584	0.598605	0.994644
Odisha	0.003076	0.987176	0.012952	0.301620	0.000092	0.999618	0.010285	0.445409

Actual test features vs Predicted test features of Rajasthan for 2021

	Actual Value	Predicted Value
avg_temp	28.140000	26.087362
state_rainfall_val	0.140000	1.931910
Level	279.644000	284.743750
FRL	287.252000	287.252000
Current Live Storage	0.451574	0.728505
crop_encoded	1.251720	1.251720

Actual yield vs Predicted yield

Crop-wise across states

	crop_name	State	yield	Predicted Yield
0	gram	Chhattisgarh	0.693304	0.955106
1	gram	Gujarat	1.691451	1.099751
2	gram	Jharkhand	1.202375	0.998426
3	gram	Karnataka	0.671894	0.598654
4	gram	Madhya Pradesh	1.614275	1.151620
5	gram	Maharashtra	1.030654	0.765881
6	gram	Odisha	0.702796	0.618480
7	gram	Rajasthan	1.075413	0.907155
8	gram	Tamil Nadu	0.926280	0.824060
9	gram	Uttarakhand	0.787872	0.827735
10	gram	West Bengal	1.245962	1.033128
11	masoor	Chhattisgarh	0.710361	0.342319
12	masoor	Jharkhand	0.859635	0.736243
13	masoor	Madhya Pradesh	1.057188	0.714615
14	masoor	Odisha	0.470337	0.414680
15	masoor	Rajasthan	1.317518	1.043778
16	masoor	Uttarakhand	0.890343	0.719279
17	masoor	West Bengal	0.865374	0.760473
18	potato	Chhattisgarh	6.718750	5.221069
19	potato	Jharkhand	7.305450	6.567597
20	potato	Karnataka	16.360702	14.811667
21	potato	Tamil Nadu	23.386947	22.737142
22	potato	Uttarakhand	12.218719	11.307472
23	potato	West Bengal	29.878287	31.324976
24	rapeseed &mustard	Chhattisgarh	0.510415	0.494861
25	rapeseed &mustard	Gujarat	1.933926	1.518604
26	rapeseed &mustard	Jharkhand	0.811379	0.816629
27	rapeseed &mustard	Madhya Pradesh	1.550358	1.229001
28	rapeseed &mustard	Maharashtra	0.328988	0.346819
29	rapeseed &mustard	Rajasthan	1.628265	1.440817
30	rapeseed &mustard	Tamil Nadu	0.235114	0.241568
31	rapeseed &mustard	Uttarakhand	0.924425	0.815565
32	rapeseed &mustard	West Bengal	1.219520	0.938837
33	rice	Jharkhand	2.515670	1.501949
34	rice	Karnataka	2.540047	2.506189
35	wheat	Chhattisgarh	1.462655	1.398062
36	wheat	Gujarat	3.195756	2.971460
37	wheat	Jharkhand	2.135435	1.482597
38	wheat	Karnataka	1.225168	0.847122
39	wheat	Madhya Pradesh	3.526995	3.032108
40	wheat	Maharashtra	1.767831	1.260650
41	wheat	Rajasthan	3.892101	3.641733
42	wheat	Uttarakhand	3.006383	2.334568
43	wheat	West Bengal	2.964734	2.353336

Crop-wise across years

	crop_name	year	yield	Predicted Yield
0	gram	2004	0.626860	0.618480
1	gram	2018	1.008188	0.824798
2	gram	2019	1.039189	0.900636
3	gram	2020	1.123991	0.920867
4	gram	2021	1.137153	0.926313
5	gram	2022	1.108544	0.927649
6	masoor	2004	0.397120	0.414680
7	masoor	2018	0.819200	0.708152
8	masoor	2019	0.816920	0.677634
9	masoor	2020	0.914734	0.735954
10	masoor	2021	0.910728	0.722406
11	masoor	2022	1.205086	0.715014
12	potato	2018	13.724845	13.361661
13	potato	2019	15.525360	15.503793
14	potato	2020	16.351722	14.723173
15	potato	2021	17.109432	17.059317
16	potato	2022	18.293028	17.433595
17	rapeseed &mustard	2017	0.342920	0.345954
18	rapeseed &mustard	2018	1.076504	0.865820
19	rapeseed &mustard	2019	1.096448	0.960139
20	rapeseed &mustard	2020	1.157538	0.950945
21	rapeseed &mustard	2021	1.100306	0.952986
22	rapeseed &mustard	2022	1.100691	0.945838
23	rice	2018	2.476320	2.524485
24	rice	2019	2.755020	2.517498
25	rice	2020	2.245620	2.502406
26	rice	2021	2.558790	2.493603
27	rice	2022	2.589446	1.998462
28	wheat	2018	2.157894	1.784618
29	wheat	2019	2.514777	2.165283
30	wheat	2020	2.680861	2.172770
31	wheat	2021	2.601702	2.158983
32	wheat	2022	2.624035	2.148369

6.Conclusion

In this project, we explored the use of machine learning models—specifically **Random Forest** and **Linear Regression**—to predict crop yield based on features like average temperature, rainfall, reservoir level, and crop-specific encoding.

The dataset covered multiple Indian states over several years, enabling state-level models.

From our analysis:

- **Random Forest and Linear Regression both showed strengths in different states**:
    - For states like *Rajasthan*, *Odisha*, and *Tamil Nadu*, Random Forest achieved lower test RMSE and higher R^2, indicating better predictive performance.
    - In contrast, Linear Regression performed competitively and sometimes better in states like *Gujarat*, *West Bengal*, and *Jharkhand*, where simpler linear relationships between features and yield were more prominent.
- Overall, both models achieved reasonably high R^2 scores on training data (often >0.90), but test performance varied by state, likely due to differences in data distribution, crop diversity, and climatic variability.
- For some larger and more variable states (e.g., Uttar Pradesh, Andhra Pradesh, Telangana), the models struggled, likely due to higher data variability and complex crop-climate interactions.

We also observed:

- **Predicted test features** (using time-based regressions) were reasonably close to actual features, as seen in Rajasthan's comparison table.
- Target encoding of the crop name feature improved model performance by capturing crop-specific yield tendencies.
- The Random Forest model provided feature importance insights, helping identify reservoir variables like level, Current Live Storage had the most impact on yield predictions

7.Appendices

github.com/TheGiftedExplorer/yield-prediction