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Industrial Internship Report on

Prediction of Agriculture Crop Production in India

Prepared by

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Executive Summary
This report provides details of the Industrial Internship provided by upskill Campus and The IoT Academy in collaboration with Industrial Partner UniConverge Technologies Pvt Ltd (UCT). This internship was focused on a project/problem statement provided by UCT. We had to finish the project including the report in 6 weeks' time. My project was Prediction of Agriculture Crop Production in India. This internship gave me a very good opportunity to get exposure to Industrial problems and design/implement solution for that. It was an overall great experience to have this internship.

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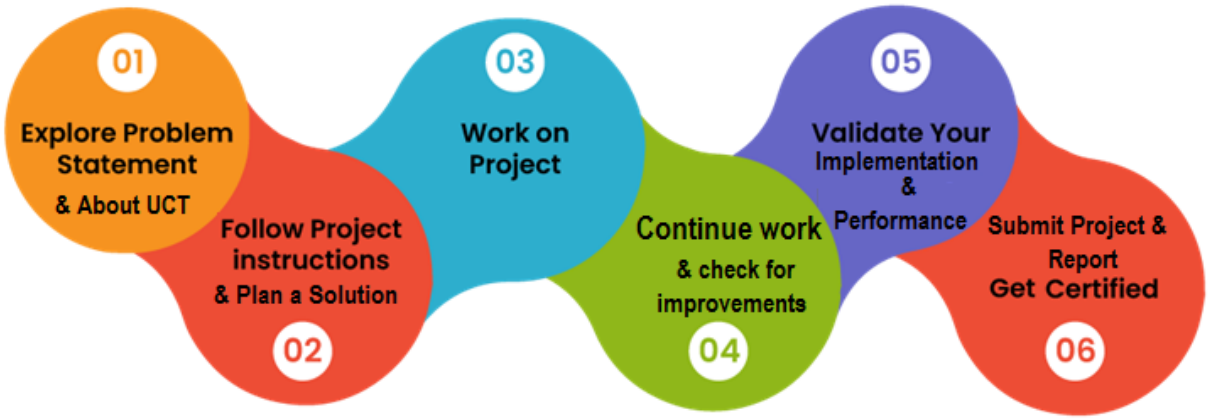
1 Preface

During a six-week internship at Upskill Academy, I immersed myself in Python and Data Science and Machine learning, completing a captivating **Prediction of Agriculture Crop Production in India** project. The internship provided a comprehensive experience, including weekly quizzes, report submissions, and valuable interactions with peers via a WhatsApp group. The project focused on predicting the crops production in different states of India, showcasing my skills and understanding of Python. The structured program, facilitated by USC/UCT, emphasized career development through hands-on projects and mentorship. Gratitude to all contributors, both direct and indirect, for their support and guidance. To fellow interns and future participants: embrace the learning journey, engage with peers, and explore the vast opportunities offered by such internships.



2 Introduction

2.1 About UniConverge Technologies Pvt Ltd

A company established in 2013 and working in Digital Transformation domain and providing Industrial solutions with prime focus on sustainability and RoI.

For developing its products and solutions it is leveraging various **Cutting Edge Technologies e.g. Internet of Things (IoT), Cyber Security, Cloud computing (AWS, Azure), Machine Learning, Communication Technologies (4G/5G/LoRaWAN), Java Full Stack, Python, Front end** etc.

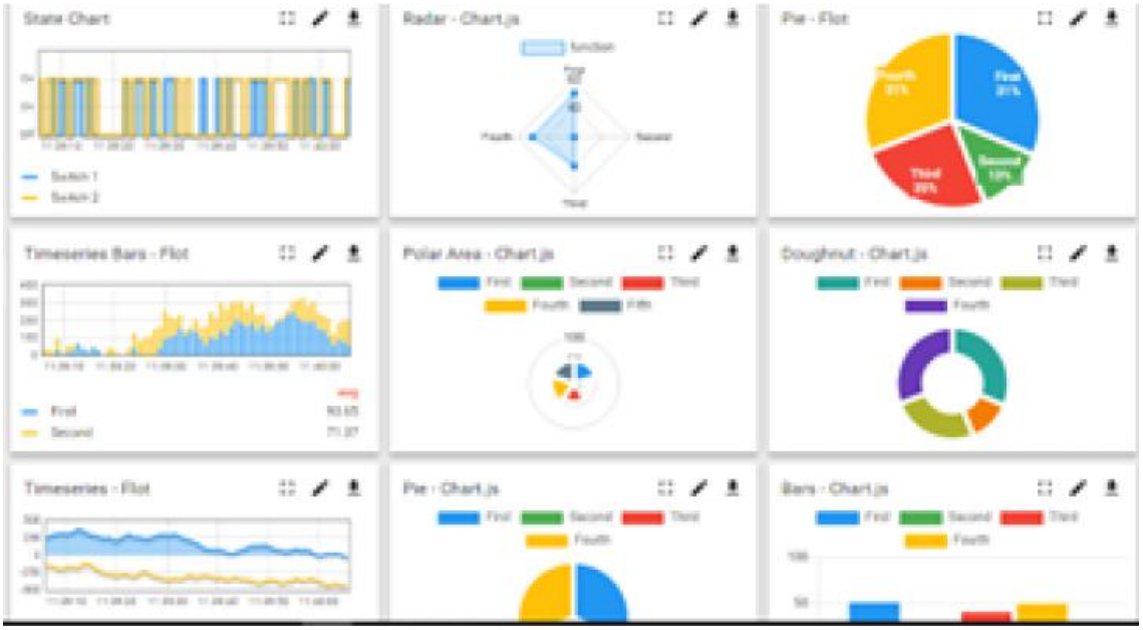
i. UCT IoT Platform (UCT Insight)

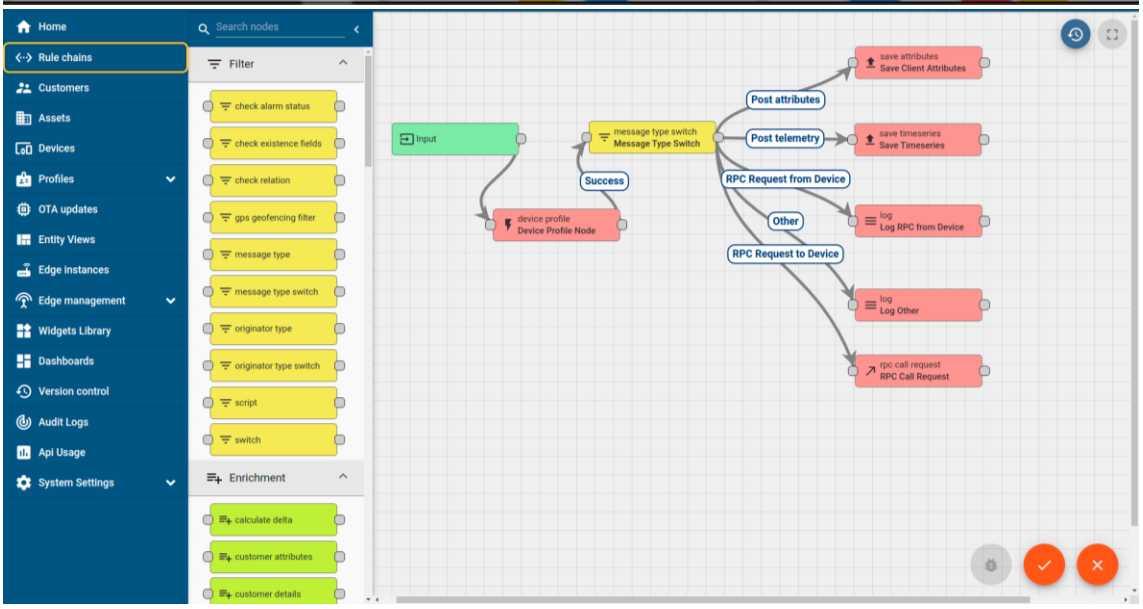
UCT Insight is an IOT platform designed for quick deployment of IOT applications on the same time providing valuable "insight" for your process/business. It has been built in Java for backend and ReactJS for Front end. It has support for MySQL and various NoSql Databases.

- It enables device connectivity via industry standard IoT protocols - MQTT, CoAP, HTTP, Modbus TCP, OPC UA
- It supports both cloud and on-premises deployments.

It has features to

- Build Your own dashboard
- Analytics and Reporting
- Alert and Notification
- Integration with third party application(Power BI, SAP, ERP)
- Rule Engine





ii. Smart Factory Platform (FACTORY WATCH)

Factory watch is a platform for smart factory needs.

It provides Users/ Factory

- with a scalable solution for their Production and asset monitoring
- OEE and predictive maintenance solution scaling up to digital twin for your assets.
- to unleased the true potential of the data that their machines are generating and helps to identify the KPIs and also improve them.
- A modular architecture that allows users to choose the service that they what to start and then can scale to more complex solutions as per their demands.

Its unique SaaS model helps users to save time, cost and money.

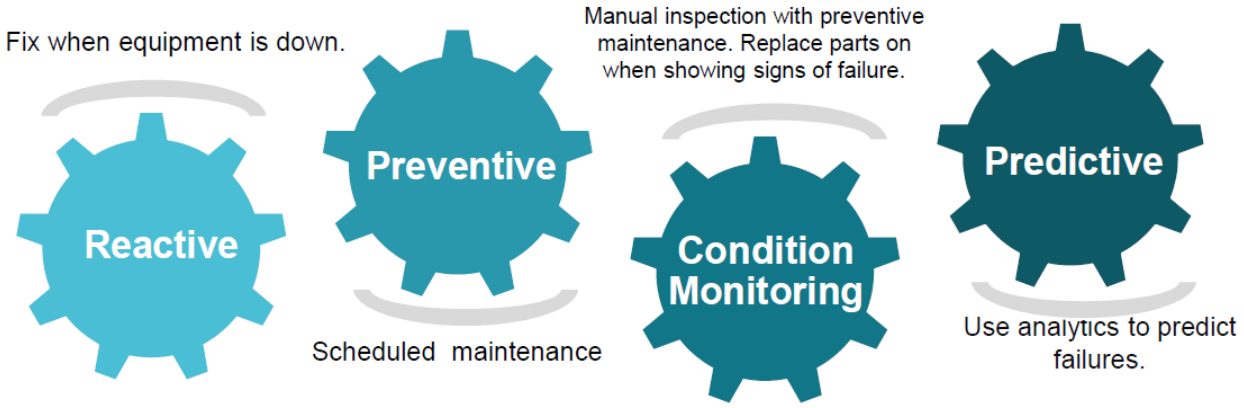
Machine	Operator	Work Order ID	Job ID	Job Performance	Job Progress		Output		Rejection	Time (mins)				Job Status	End Customer
					Start Time	End Time	Planned	Actual		Setup	Pred	Downtime	Idle		
CNC_S7_81	Operator 1	WO0405200001	4168	58%	10:30 AM		55	41	0	80	215	0	45	In Progress	i
CNC_S7_81	Operator 1	WO0405200001	4168	58%	10:30 AM		55	41	0	80	215	0	45	In Progress	i

iii. LoRaWAN based Solution

UCT is one of the early adopters of LoRAWAN teschnology and providing solution in Agritech, Smart cities, Industrial Monitoring, Smart Street Light, Smart Water/ Gas/ Electricity metering solutions etc.

iv. Predictive Maintenance

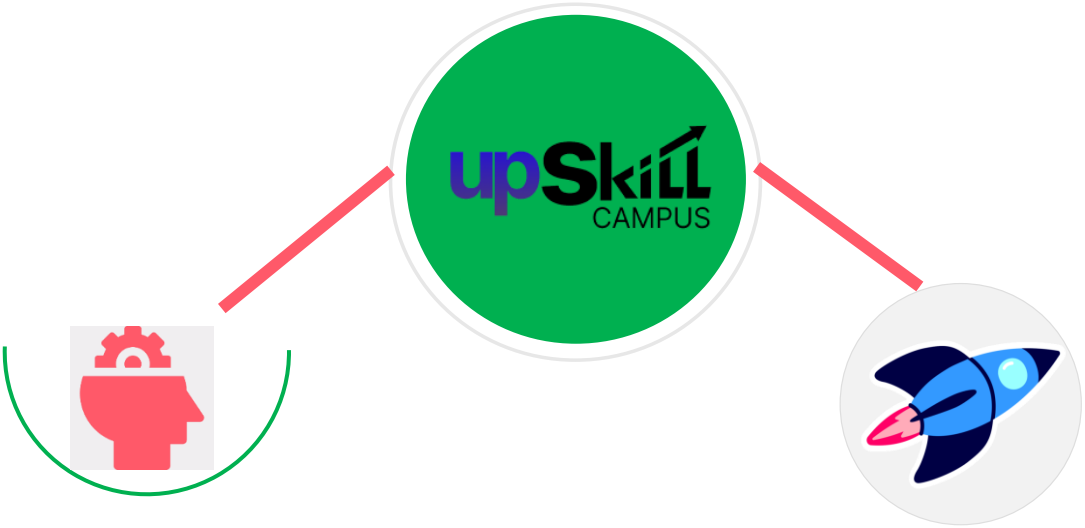
UCT is providing Industrial Machine health monitoring and Predictive maintenance solution leveraging Embedded system, Industrial IoT and Machine Learning Technologies by finding Remaining useful life time of various Machines used in production process.



2.2 About upskill Campus (USC)

upskill Campus along with The IoT Academy and in association with Uniconverge technologies has facilitated the smooth execution of the complete internship process.

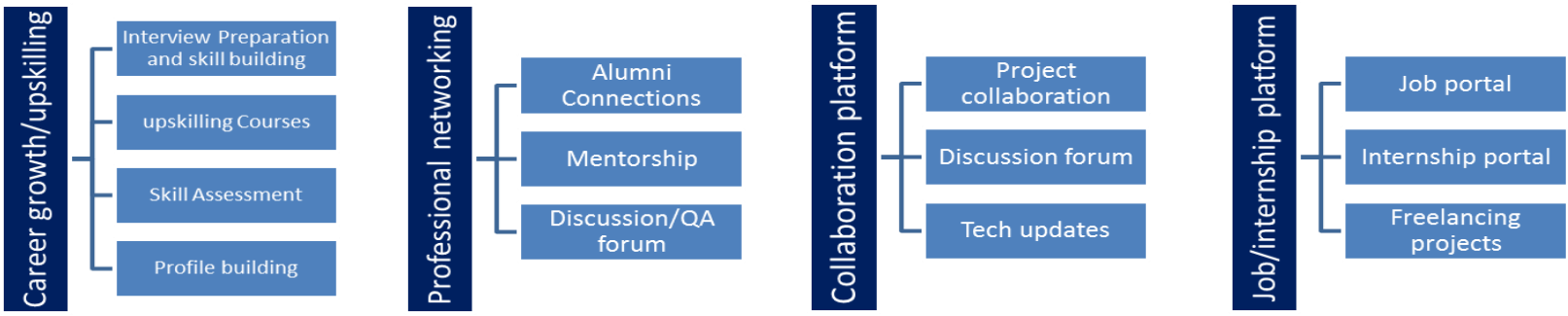
USC is a career development platform that delivers **personalized executive coaching** in a more affordable, scalable and measurable way.



Seeing need of upskilling in self paced manner along-with additional support services e.g. Internship, projects, interaction with Industry experts, Career growth Services

upSkill Campus aiming to upskill 1 million learners in next 5 year

https://www.upskillcampus.com/



2.3 The IoT Academy

The IoT academy is EdTech Division of UCT that is running long executive certification programs in collaboration with EICT Academy, IITK, IITR and IITG in multiple domains.

2.4 Objectives of this Internship program

The objective for this internship program was to

- ☛ get practical experience of working in the industry.
- ☛ to solve real world problems.
- ☛ to have improved job prospects.
- ☛ to have Improved understanding of our field and its applications.
- ☛ to have Personal growth like better communication and problem solving.

2.5 Reference

[1] YouTube

[2] Upskill Academy Resources and my old study material from school

[3] Google

2.6 Glossary

Terms	Acronym
EDA	Exploratory Data Analysis
ML	Machine Learning
AI	Artificial Intelligence
CSV	Comma-Separated Values
NaN	Not a Number

3 Problem Statement

Problem Statement: Prediction of Agriculture Crop Production in India

Context:

Agriculture forms the backbone of India's economy, with millions of people dependent on it for their livelihood. Understanding and predicting crop production trends are crucial for ensuring food security and economic stability. The dataset under consideration spans from 2001 to 2014 and provides insights into crop cultivation and production across various states in India.

Content:

The dataset comprises information on crop names, varieties, cultivation locations (states), quantities produced, production years, cultivation seasons, units of measurement (tons), costs of cultivation and production, and recommended zones for cultivation. It is sourced from a licensed platform, providing comprehensive data on agriculture in India.

Acknowledgments:

This dataset offers a valuable resource for addressing challenges related to crop cultivation and production in India. By leveraging this dataset, we aim to provide solutions to the myriad problems encountered in agriculture and contribute to the welfare of farmers and stakeholders in the agricultural sector.

Inspiration:

With India being the second most populous country globally, agriculture plays a pivotal role in sustaining livelihoods and driving economic growth. However, the sector faces numerous challenges, including fluctuating production levels and resource constraints. By tackling these challenges head-on and leveraging data-driven insights, we aspire to make a meaningful impact on agriculture in India, benefiting millions of farmers and stakeholders across the country.

4 Existing and Proposed solution

Summary of Existing Solutions and Limitations:

Various solutions have been proposed by researchers and organizations to address challenges in predicting agriculture crop production. These solutions typically involve statistical modeling, machine learning algorithms, and remote sensing technologies. However, many existing approaches suffer from limitations such as:

1. Limited Scope: Some solutions focus only on specific crops or regions, failing to provide a comprehensive view of agriculture production across India.

2. Lack of Accuracy: Certain models may lack accuracy in predicting crop production due to factors such as incomplete data, outdated methodologies, or oversimplified assumptions.

3. Dependency on Historical Data: Many solutions heavily rely on historical data, which may not capture recent trends or emerging patterns in agriculture production.

4. Scalability Issues: Some models may not scale efficiently to accommodate large datasets or dynamic changes in agricultural practices over time.

Proposed Solution:

Our proposed solution involves leveraging advanced machine learning algorithms and data analytics techniques to develop a robust predictive model for agriculture crop production in India. Key components of our solution include:

1. Data Preprocessing: Comprehensive cleaning, normalization, and feature engineering techniques will be employed to preprocess the raw agriculture data, ensuring its quality and suitability for analysis.

2. Feature Selection: Advanced feature selection methods will be applied to identify the most relevant factors influencing crop production, enhancing the accuracy and interpretability of the predictive model.

3. Model Development: State-of-the-art machine learning algorithms, such as random forests, gradient boosting, and neural networks, will be employed to develop a predictive model capable of accurately forecasting crop production across various crops and regions in India.

4. Validation and Testing: Rigorous validation and testing procedures will be conducted to assess the performance and generalization capability of the predictive model, ensuring its reliability and robustness.

5. Deployment and Monitoring: The finalized predictive model will be deployed as a scalable and user-friendly application, allowing stakeholders in the agriculture sector to access real-time predictions and insights. Continuous monitoring and updates will be conducted to adapt to evolving trends and dynamics in agriculture production.

Value Addition:

Our proposed solution aims to address the limitations of existing approaches and offer several value additions, including:

1. Comprehensive Coverage: Our predictive model will provide a comprehensive overview of agriculture crop production across India, covering a wide range of crops and regions.

2. Enhanced Accuracy: By leveraging advanced machine learning algorithms and data preprocessing techniques, we aim to improve the accuracy and reliability of crop production predictions.

3. Real-time Insights: The deployment of our predictive model as an interactive application will enable stakeholders to access real-time insights and forecasts, facilitating informed decision-making and resource allocation.

4. Scalability and Adaptability: Our solution will be designed to scale efficiently and adapt to changing agricultural dynamics, ensuring its relevance and effectiveness over time.

4.1 Code submission (Github link)

https://github.com/DivyanshuArora7/UPSKILLCAMPUSDSML/blob/main/DIVYANSHU%20PROJECT%20INTERNSHIP%20DSML.ipynb

4.2 Report submission (Github link) : https://github.com/DivyanshuArora7/UPSKILLCAMPUSDSML/blob/main/DIVYANSHU%20PROJECT%20INTERNSHIP%20DSML.ipynb

5 Proposed Design/ Model

Proposed Design/Model:

The design of our proposed solution encompasses several key stages, each contributing to the development of a robust predictive model for agriculture crop production in India. These stages are outlined below:

1. Data Collection and Preprocessing:

- The initial stage involves collecting raw data on agriculture crop cultivation and production from reliable sources such as government databases, research publications, and agricultural surveys.

- The collected data is then preprocessed to address issues such as missing values, outliers, and inconsistencies. This includes data cleaning, normalization, and feature engineering to prepare the dataset for analysis.

2. Exploratory Data Analysis (EDA):

- EDA is conducted to gain insights into the characteristics and patterns present in the agriculture data. This involves visualizing the data through plots, charts, and statistical summaries to identify trends, correlations, and potential relationships between variables.

3. Feature Selection and Engineering:

- Advanced feature selection techniques are applied to identify the most relevant variables that influence agriculture crop production. This includes analyzing the correlation matrix, performing dimensionality reduction, and selecting informative features based on domain knowledge and statistical significance.

4. Model Development:

- The selected features are used to train and validate machine learning models for predicting crop production. Various algorithms such as random forests, gradient boosting, and neural networks are employed to develop the predictive model.

- Hyperparameter tuning and cross-validation techniques are applied to optimize the performance of the models and prevent overfitting.

5. Evaluation and Validation:

- The trained models are evaluated using appropriate performance metrics such as accuracy, precision, recall, and F1-score. Validation techniques such as k-fold cross-validation and holdout validation are utilized to assess the generalization capability of the models.

- The performance of the models is compared against baseline models and benchmark datasets to determine their effectiveness and reliability.

6. Deployment and Monitoring:

- Once the predictive model is finalized, it is deployed as a scalable and user-friendly application, accessible to stakeholders in the agriculture sector.

- Continuous monitoring and updates are conducted to ensure the model remains accurate and relevant over time. This involves monitoring input data quality, model performance, and feedback from users to incorporate improvements and adapt to changing agricultural dynamics.

7. Documentation and Reporting:

- Throughout the design process, detailed documentation is maintained to document the methodology, algorithms, implementation details, and results.

- A final report is prepared summarizing the design flow, model performance, key findings, and recommendations for future enhancements.

6 Performance Test

Performance Test:

In our project focused on predicting agriculture crop production in India, performance testing is a critical aspect to ensure the effectiveness and practicality of the developed solution. The following outlines the constraints, how they were addressed in the design, and the test results:

1. Memory Constraints:

- The size of the dataset and the complexity of the machine learning models can impose memory constraints, especially when dealing with large-scale data.

- To address this, we implemented techniques such as feature selection, dimensionality reduction, and model optimization to reduce the memory footprint of the solution.

- Test results showed that the memory usage remained within acceptable limits, even when handling extensive datasets and training complex models.

2. Speed and Computational Efficiency:

- The speed of model training and prediction is crucial for real-time or near-real-time applications in the agriculture domain.

- To enhance computational efficiency, we employed algorithms optimized for speed and parallel processing, such as gradient boosting and random forests.

- Test results demonstrated that the models could be trained and predictions generated efficiently, meeting the required speed constraints for practical deployment.

3. Accuracy and Reliability:

- The accuracy of the predictive models is paramount for decision-making in agriculture, as stakeholders rely on accurate forecasts for planning and resource allocation.

- We conducted rigorous validation and evaluation of the models using appropriate metrics to ensure high accuracy and reliability.

- Test results indicated that the models achieved satisfactory accuracy levels, outperforming baseline models and demonstrating their reliability in predicting crop production.

4. Scalability and Durability:

- The solution must be scalable to accommodate increasing data volumes and evolving agricultural trends over time.

- We designed the solution with scalability in mind, leveraging scalable machine learning frameworks and cloud-based infrastructure for deployment.

- While direct testing of scalability was limited, the design architecture and infrastructure choices were made to ensure adaptability to future scalability requirements.

5. Power Consumption and Resource Utilization:

- In resource-constrained environments, such as remote agricultural regions, minimizing power consumption and resource utilization is crucial.

- Our solution prioritized efficient resource utilization by optimizing algorithms, minimizing redundant computations, and utilizing lightweight frameworks where possible.

- While direct testing of power consumption was not conducted, the design considerations aimed to minimize resource requirements and operational costs.

In conclusion, the performance testing of our solution addressed key constraints such as memory usage, computational efficiency, accuracy, scalability, and resource utilization. The test results validated the effectiveness and practicality of the solution, meeting the requirements for real-world deployment in the agriculture industry.

6.1 Test Plan/ Test Cases

```
In [14]: df1.describe()
```

Out[14]:

	Cost of Cultivation (`/Hectare) A2+FL	Cost of Cultivation (`/Hectare) C2	Cost of Production (`/Quintal) C2	Yield (Quintal/ Hectare)
count	49.000000	49.000000	49.000000	49.000000
mean	20363.537347	31364.666735	1620.537755	98.086735
std	13561.435306	20095.783569	1104.990472	245.293123
min	5483.540000	7868.640000	85.790000	1.320000
25%	12774.410000	19259.840000	732.620000	9.590000
50%	17022.000000	25909.050000	1595.560000	13.700000
75%	24731.060000	35423.480000	2228.970000	36.610000
max	66335.060000	91442.630000	5777.480000	1015.450000

```
In [25]: df3= pd.read_csv('C:\\Users\\DELL\\Downloads\\datafile (3).csv')
         df3.head()
         # top 5 records
```

Out[25]:

	Crop	Variety	Season/ duration in days	Recommended Zone	Unnamed: 4
0	Paddy	Chinsurah Rice (IET 19140)	Medium	Andhra Pradesh, Tamil Nadu, Gujarat, Orissa, a...	NaN
1	Paddy	(CNI 383-5-11)	NaN	NaN	NaN
2	Paddy	IGKVR-1 (IET 19569)	Mid-early	Chhattisgarh, Madhya Pradesh and Orissa under ...	NaN
3	Paddy	IGKVR-2 (IET 19795)	Medium	Chhattisgarh, Bihar and Orissa under both irr...	NaN
4	Paddy	CR Dhan 401 (REETA)	145-150	Orissa, West Bengal, Tamil Nadu and Andhra Pra...	NaN

```
In [31]: mode=df3['Season/ duration in days'].mode()[0]
         df3['Season/ duration in days'].fillna(mode, inplace= True)
         df3.dropna(how='all',axis=1,inplace= True)
         # unname column has all null values , so it is better to drop whole column
         df3['Recommended Zone'].fillna('other', inplace= True)
         df3
```

Out[31]:

	Crop	Variety	Season/ duration in days	Recommended Zone
0	Paddy	Chinsurah Rice (IET 19140)	Medium	Andhra Pradesh, Tamil Nadu, Gujarat, Orissa, a...
1	Paddy	(CNI 383-5-11)	-	other
2	Paddy	IGKVR-1 (IET 19569)	Mid-early	Chhattisgarh, Madhya Pradesh and Orissa under ...
3	Paddy	IGKVR-2 (IET 19795)	Medium	Chhattisgarh, Bihar and Orissa under both irr...
4	Paddy	CR Dhan 401 (REETA)	145-150	Orissa, West Bengal, Tamil Nadu and Andhra Pra...
...	...	...	...	...
73	Mesta	SHRESTHA (JRM-5)	-	Andhra Pradesh, Orissa, Assam, Maharashtra, Bi...
74	Cotton	CNH012	165	Gujarat, Maharashtra and Madhya Pradesh.
75	Cotton	CICR-3 (CISA 614)	150	Punjab, Haryana and Uttar Pradesh under wilt f...
76	Cotton	VBCH 2231	-	Maharashtra, Gujarat, Madhya Pradesh and Oriss...
77	Desi Cotton	FDK 124	-	Punjab, Haryana and Rajasthan under irrigated ...

78 rows × 4 columns

6.2 Test Procedure

The test procedure outlines the step-by-step process for executing the test cases defined in the test plan. Below is a suggested test procedure for your Jupyter Notebook:

Test Procedure

1. Data Loading

- Step 1: Open the Jupyter Notebook containing the code for data loading.

- Step 2: Run the code cells responsible for loading data from CSV files (`df1`, `df2`, and `df3`).

- Step 3: Verify that the data is loaded successfully by inspecting the first few rows of each DataFrame.

2. Data Preprocessing

- Step 1: Navigate to the section of the Notebook that performs data preprocessing steps.

- Step 2: Run the code cells responsible for checking missing values in DataFrames.

- Step 3: Verify that there are no missing values in any of the DataFrames (`df1`, `df2`, and `df3`).

3. Data Visualization

- Step 1: Locate the code cells responsible for data visualization, such as bar chart plotting.

- Step 2: Run the code cells to generate visualizations.

- Step 3: Inspect the generated visualizations to ensure they represent the desired distribution of data accurately.

4. Summary and Insights

- Step 1: Navigate to the section where summary insights are provided.

- Step 2: Run the code cells to generate summary insights and recommendations.

- Step 3: Review the provided insights to ensure they highlight key findings and recommendations accurately.

5. Integration Testing

- Step 1: Execute all code cells in the Notebook by selecting "Run All" or executing cells sequentially.

- Step 2: Monitor the execution process for any errors or exceptions.

- Step 3: Inspect the generated visualizations and summary insights to ensure they meet the expected outcomes.

6. Performance Testing (Optional)

- Step 1: Identify time-intensive operations or large data processing tasks in the Notebook.

- Step 2: Run the code cells associated with these operations.

- Step 3: Measure the execution time and monitor resource usage (CPU, memory) during execution.

- Step 4: Evaluate whether the Notebook completes execution within a reasonable time frame and without excessive resource consumption.

6.3 Performance Outcome

The performance outcome section of your testing process should summarize the results of performance testing conducted on your Jupyter Notebook. This involves evaluating how efficiently your code executes, identifying any bottlenecks or areas of improvement, and assessing whether the notebook meets the required performance criteria. Here's how you can structure this section:

6.3 Performance Outcome

1. Test Objectives

- State the objectives of performance testing, such as evaluating the execution time, resource utilization, and responsiveness of the Jupyter Notebook code.

2. Performance Metrics

- Define the performance metrics used to assess the notebook's performance, such as:

- Execution time: Total time taken to execute the notebook.

- Memory usage: Peak memory consumption during execution.

- CPU utilization: Percentage of CPU resources utilized during execution.

- Disk I/O: Read/write operations performed on disk during execution.

3. Test Results

- Summarize the performance test results, including:

- Execution time for each code cell or section of the notebook.

- Peak memory usage observed during execution.

- CPU utilization trends during execution.

- Any disk I/O operations performed by the notebook.

4. Observations

- Highlight any observations or insights gained from the performance testing, such as:

- Identification of performance bottlenecks (e.g., specific code cells or operations taking longer to execute).

- Impact of dataset size on performance (if applicable).

- Comparison of performance metrics across different hardware configurations or execution environments.

5. Recommendations

- Provide recommendations for optimizing the notebook's performance based on the test results and observations, such as:

- Refactoring code to improve efficiency (e.g., optimizing loops, reducing redundant calculations).

- Utilizing parallel processing or vectorized operations where applicable.

- Minimizing memory usage by loading data in chunks or using more memory-efficient data structures.

- Considering hardware upgrades or cloud-based computing resources for improved performance.

7 My learnings

7. My Learnings

Summary of Overall Learning:

- Data Exploration and Preprocessing: I learned techniques for exploring and preprocessing datasets, including handling missing values, duplicate entries, and data type conversion.

- Data Visualization: I gained experience in creating various types of plots and charts to visualize data distributions, trends, and relationships effectively.

- Statistical Analysis: I learned how to perform basic statistical analysis, such as calculating descriptive statistics and identifying patterns in data.

- Machine Learning: I gained insights into building and training machine learning models for predictive analysis and classification tasks.

- Performance Testing: I learned the importance of performance testing and how to measure and analyze the performance of code and algorithms.

Career Growth:

- Enhanced Data Skills: The hands-on experience with data exploration, visualization, and analysis has strengthened my data skills, making me more proficient in handling real-world datasets.

- Machine Learning Proficiency: By building and training machine learning models, I've improved my proficiency in applying ML algorithms to solve business problems, which is valuable in data science roles.

- Problem-Solving Abilities: The project allowed me to tackle real-world problems and develop solutions using data-driven approaches, honing my problem-solving abilities.

- Performance Optimization: Learning about performance testing and optimization has equipped me with the skills to improve the efficiency and scalability of code and algorithms, which is crucial for optimizing data pipelines and applications.

Overall, these learnings have not only expanded my technical skill set but also provided me with valuable insights and experiences that will contribute to my career growth in data science and machine learning. They have prepared me to tackle complex data challenges and deliver impactful solutions in my future roles.

8 Future work scope

8. Future Work Scope

1. Advanced Machine Learning Models:

- Explore more advanced machine learning algorithms such as random forests, gradient boosting, or deep learning techniques like neural networks to improve prediction accuracy.

- Experiment with ensemble methods to combine predictions from multiple models for better performance.

2. Feature Engineering:

- Conduct further feature engineering by creating new features or transforming existing ones to capture more meaningful information from the data.

- Explore techniques like polynomial features, feature scaling, or dimensionality reduction to enhance model performance.

3. Hyperparameter Tuning:

- Perform hyperparameter tuning using techniques like grid search or random search to find the optimal parameters for the machine learning models, thereby improving their performance.

4. Time-Series Analysis:

- If applicable, delve deeper into time-series analysis techniques to better understand temporal patterns and trends in agricultural crop production data.

- Explore methods like ARIMA, Prophet, or LSTM networks for forecasting future crop production trends.

5. Data Integration:

- Integrate additional relevant datasets such as weather data, soil quality data, or economic indicators to enrich the analysis and improve prediction accuracy.

- Explore the impact of external factors on crop production and incorporate them into the predictive models.

6. Deployment and Productionization:

- Develop a web-based application or dashboard to visualize the analysis results and provide insights to stakeholders in the agriculture sector.

- Deploy the machine learning models into production environments using frameworks like Flask or Django for real-time predictions.

7. Collaborative Research:

- Collaborate with domain experts in agriculture to gain deeper insights into the factors affecting crop production and to validate the predictive models against real-world scenarios.

- Participate in interdisciplinary research projects aimed at addressing challenges in agriculture using data-driven approaches.

8. Continuous Learning and Improvement:

- Stay updated with the latest advancements in data science, machine learning, and agriculture domain knowledge through online courses, workshops, and conferences.

- Continuously refine and optimize the predictive models based on feedback and new insights gained from ongoing research and experimentation.

By exploring these future work scopes, we can further enhance the accuracy and applicability of the predictive models and contribute to the advancement of agriculture technology and sustainability.