Real-Time Optimization of Agricultural Prices Based on Market

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Abstract

Agriculture is an ever-changing industry that is influenced by several variables, such as market demand, weather conditions, crop yields, and production expenses. One of the most challenging tasks for farmers has always been pricing their products. They need to balance their production costs with market demand to maximize their profits. However, with the emergence of real-time forecasting, farmers can now make informed decisions based on the most current data available.

In agriculture, machine learning algorithms have proven to be a potent tool, capable of analyzing extensive datasets to generate precise predictions of future market and weather conditions. This capability enables farmers to optimize their pricing strategies effectively. Thus, this project proposes developing a machine learning-based pricing optimization system tailored to the agricultural sector's needs.

The system will utilize real-time data from various sources, including weather forecasts, market demand projections, crop yield estimates, and production cost data. Using machine learning algorithms such as TensorFlow, Scikit-Learn, and Keras, this system will analyze the data to generate accurate predictions of future market and weather conditions, allowing farmers to optimize their pricing strategies.

To ensure the accuracy and reliability of the system, it will be trained on historical data. Farmers will also be able to visualize the data and make informed decisions through the use of visualization tools like Matplotlib and Seaborn.

The project's end goal is to provide farmers with a prototype of a real-time pricing optimization system. It will enable farmers to make informed pricing decisions that can help them maximize their profits. The project's impact will be significant since it will help farmers increase their profitability and contribute to the overall growth of the agricultural sector

1.0 Introduction

Agriculture is an industry that depends on various factors, such as weather conditions, market demand, crop yields, and production costs. For farmers to maximize their profits and ensure a sustainable livelihood, the pricing of agricultural products is crucial. However, predicting future market conditions accurately can be challenging due to the volatile nature of the agricultural industry. To address this, the proposed project aims to develop a machine learning-based pricing optimization system for the agricultural sector.

This system will use real-time data from various sources, including weather forecasts, market demand projections, crop yield estimates, and production cost data. Machine learning algorithms will analyze this data to generate predictions of future market and weather conditions, which will be used to optimize pricing strategies. The objective is to develop a prototype of a real-time pricing optimization system that farmers can use to make informed decisions about pricing, thereby maximizing their profits.

The project's outcome will have a significant impact on the agricultural sector, as it will help farmers make informed decisions about pricing and increase their profitability. This project report will provide a detailed description of the proposed system's design, implementation, and evaluation. It will begin with a literature review of existing research on pricing optimization in agriculture and real-time forecasting techniques. The report will then provide an overview of the proposed system's architecture, including the data sources, machine learning algorithms, and visualization tools. The implementation of the system will be described, including the training of the machine learning models, the integration of data sources, and the development of the visualization tools. Finally, the report will evaluate the system's performance using real-world data and discuss its potential impact on the agricultural sector.

1.1 Initial Needs Statement

The agricultural industry faces challenges such as unpredictable weather, fluctuating market demands, and production costs. Optimizing pricing strategies based on real-time data can help farmers maximize profits. However, there is a lack of effective tools for informed decision-making.
To address this, we propose developing a machine learning-based pricing optimization system using real-time data from weather forecasts, market demand, crop yields, and production costs. The system will enable farmers to optimize pricing strategies based on accurate predictions of future market and weather conditions. Its successful implementation will benefit the agricultural industry by increasing profitability and sustainability.

2.0 Customer Needs Assessment

To develop an effective machine learning-based pricing optimization system for the agricultural industry, it is important to understand the needs of the target customers, such as farmers, agriculture businesses, and cooperatives. Surveys and interviews can be conducted to gather information about their pricing strategies and challenges faced. Based on the assessment, the system should provide accurate and real-time data from various sources, be customizable and flexible to meet specific needs, have an easy-to-use interface with data visualization tools, be reliable and secure to prevent data breaches, and be cost-effective to provide value for money. By meeting these needs, the proposed system can help farmers optimize their pricing strategies based on real-time data, leading to increased profitability and growth in the agricultural sector.

3.0 Revised Needs Statement and Target Specifications

1. Needs Statement: The agricultural industry requires a machine learning-based pricing optimization system that provides farmers with real-time data for informed pricing decisions. The system should be flexible, secure, and cost-effective.

2. Target Specifications:

Accurate and Real-Time Data: The system should collect and analyze data from various sources, including weather forecasts, market demand projections, crop yield estimates, and production cost data to generate accurate predictions of future market and weather conditions.
Customizable and Flexible: The system should be customizable to meet the specific needs of different farmers and provide options to adjust pricing strategies based on market and weather conditions.
Easy-to-Use Interface: The system should have an accessible, user-friendly interface with data visualization tools to help farmers make informed decisions.
Reliable and Secure: The system should be designed to prevent data breaches and provide a secure environment for data storage to ensure the protection of farmers' data and privacy.
Cost-Effective: The system should be affordable for farmers to purchase and use, and provide value for money.

4.0 External Search

There are several external sources that showcase the potential of machine learning in optimizing pricing in the agricultural sector based on real-time data, including weather and market forecasts. These sources include:

- "Farm to Market: Using Machine Learning to Forecast Crop Prices" by Microsoft Research: This research project utilized machine learning to forecast crop prices by analyzing weather, historical crop prices, and other relevant data. The system used neural networks to predict future crop prices and provided farmers with recommendations on when to sell their crops.
- "Precision Agriculture: Machine Learning Approach for Crop Yield Prediction" by the University of Illinois: This research project employed machine learning to predict crop yields based on soil, weather, and other data. The system used a combination of regression and machine learning algorithms to generate yield predictions.

- "Agricultural Weather Forecasting Using Machine Learning Techniques" by the Indian Journal of Science and Technology: This research paper proposed a machine learning-based approach for agricultural weather forecasting. The system used decision trees and Bayesian networks to predict weather patterns and provide farmers with real-time weather information.
- "Optimizing Agricultural Supply Chain Pricing with Machine Learning" by Infosys: This case study described how a machine learning-based system was used to optimize pricing in the agricultural supply chain. The system used regression models to predict prices and provide recommendations on pricing strategies.
- "Predicting Corn Prices with Machine Learning" by the DataRobot Blog: This blog post presented a machine learning-based approach to predict corn prices based on weather and other data. The system used gradient boosting algorithms to generate predictions and provided farmers with recommendations on when to sell their crops.

These sources highlight the potential of machine learning in optimizing pricing for farmers. By building on these approaches, the proposed system can provide farmers with a more comprehensive and customizable pricing optimization solution.

4.1 Benchmarking

To benchmark the proposed pricing optimization system for agriculture, we can compare its features, performance, and cost to existing systems in the market. Some of these systems include Agworld, FieldX, CropZilla, AgriEdge, and FBN Market Advisory. While these systems offer pricing optimization modules, they do not provide real-time data analysis or weather forecasting like the proposed system. Comparing the proposed system to these existing systems can highlight its strengths and areas for improvement. The proposed system's customizable interface, real-time data analysis, and weather forecasting features give it a competitive advantage. Its cost-effectiveness can also make it a more accessible option for farmers with smaller operations.

4.2 Applicable Constraints:

4.2.1 Data Availability:

The proposed system requires access to a large amount of real-time data on market trends, weather forecasts, crop yields, and other factors. However, the availability and quality of this data may be limited in certain geographic areas or for certain crops, which could affect the accuracy of the pricing recommendations.

4.2.2 Computational Resources:

The system will require significant computational resources for real-time data analysis, machine learning algorithms, and pricing recommendations. The availability and cost of these resources can impact the feasibility and scalability of the system.

4.2.3 Regulatory Constraints:

The agricultural sector is subject to various regulatory constraints related to pricing, subsidies, and other factors. The proposed system will need to comply with these regulations and may require approval from relevant regulatory bodies.

4.2.4 Cost:

The cost of developing and implementing the proposed system can be a significant constraint. The system must provide value to farmers and other stakeholders to justify the investment.

4.2.5 User Adoption:

The success of the proposed system depends on user adoption. Farmers and other stakeholders may be hesitant to adopt a new technology if they do not trust the accuracy of the pricing recommendations or if the system is too complex to use.

4.2.6 Ethical and Privacy Considerations:

The system will need to comply with ethical and privacy considerations related to the use of personal and sensitive data. The system must ensure that data is collected, stored, and used in a secure and ethical manner.

4.3 Business Opportunity

The system that optimizes pricing in real-time based on future market, weather, and other forecasts in agriculture presents several potential business opportunities:

4.3.1 Agricultural input suppliers: Companies that supply seeds, fertilizers, and other agricultural inputs can utilize the proposed system to provide pricing recommendations to farmers. By offering more accurate and timely pricing information, these companies can increase customer satisfaction and loyalty.

4.3.2 Farmers and growers: The proposed system can help farmers and growers make more informed pricing decisions based on market and weather forecasts. This can help them maximize profits and improve the overall performance of their farm operations.

4.3.3 Commodity traders and brokers: Commodity traders and brokers can use the proposed system to make more informed trading decisions based on real-time market and weather data. This can help them mitigate risk and maximize profits.

4.3.4 Agribusiness consulting firms: Consulting firms specializing in providing advisory services to the agricultural sector can use the proposed system to offer more value-added services to their clients. This can help them differentiate themselves from competitors and increase revenue.

4.3.5 Financial institutions: Banks and other financial institutions can utilize the proposed system to offer more informed lending decisions to farmers and other stakeholders. By providing more accurate pricing information, they can mitigate risk and improve the overall performance of their lending portfolios.

Overall, the proposed system has the potential to create new business opportunities and revenue streams for companies operating in the agricultural sector. By providing more accurate and timely pricing information, the system can help stakeholders make more informed decisions and improve the overall performance of their operations.

5.0 Concept Generation

Here are some potential concepts for a system that optimizes pricing in real time based on future market, weather, and other forecasts in agriculture:

1. Machine learning-based pricing recommendations: The system could utilize machine learning algorithms to analyze market and weather data, along with crop yields and supply chain information, to provide real-time pricing recommendations to farmers, agribusinesses, and other stakeholders.
2. Multi-factor analysis: The system could employ a multi-factor analysis approach to evaluate various factors, including weather patterns, market trends, historical data, and other relevant information. This would enable more accurate and informed pricing recommendations.
3. Integrated platform: The system could be integrated into a larger platform that encompasses features like supply chain management, inventory management, and other relevant tools. This would provide a comprehensive solution for agricultural businesses, streamlining their operations.
4. Mobile application: A mobile application could be developed to allow farmers and other stakeholders to access real-time pricing information. Additionally, the app could provide alerts and notifications based on market and weather trends, enabling users to make timely pricing decisions.
5. Data visualization: The system could incorporate data visualization tools that facilitate the interpretation and analysis of pricing trends and other relevant information. Visual representations would help users better understand the data and make informed decisions.
6. Risk management: The system could include risk management tools to assist stakeholders in mitigating risks associated with pricing decisions. These tools could account for factors like price volatility, weather events,

and other pertinent variables, helping users make more robust pricing choices.

7. Collaborative approach: The system could adopt a collaborative approach, involving input from various stakeholders such as farmers, input suppliers, and commodity traders. This collaboration would ensure that pricing recommendations align with the needs and objectives of all parties involved, leading to more effective and fair pricing strategies.

These are just a few potential concepts for a system that optimizes pricing in real time based on future market, weather, and other forecasts in agriculture. The specific approach and features of the system would depend on factors such as customer needs, available data, and technical constraints.

6.2 Concept Development

Concept development scoring and selection involves evaluating the potential concepts based on a set of weighted criteria and selecting the concept that has the highest score. The following criteria are suggested for evaluating the potential concepts for optimizing pricing in real time based on future market, weather, and other forecasts in agriculture:

- Technical feasibility (25%): How technically feasible is the concept? Can it be implemented with the available technology and resources?
- Effectiveness (25%): How effective is the concept in generating timely and accurate pricing recommendations that align with market trends, weather patterns, and other relevant factors? 20
- Scalability (20%): How scalable is the concept? Can it accommodate different sizes and types of operations in agriculture? Can it adapt to changing market conditions?
- Cost-effectiveness (15%): How cost-effective is the concept? Does it generate accurate pricing recommendations while minimizing costs? What is the potential return on investment?
- User-friendliness (15%): How user-friendly is the concept? Is it accessible to stakeholders with varying levels of technical expertise? Using a scale of 1 to 5, with 1 being the lowest score and 5 being the highest score, the potential

concepts can be scored against each of the criteria. The scores can then be multiplied by the weight for each criterion and summed to obtain a total score for each concept. The concept with the highest score can be selected for further development and testing. Here is an example of how this scoring and selection process might work for the two most promising concepts identified in the concept screening phase

: Concept 1: Machine learning-based pricing model Technical feasibility: 4 Effectiveness: 5 Scalability: 4 Cost-effectiveness: 3 User-friendliness: 3 Total score: (4 x 0.25) + (5 x 0.25) + (4 x 0.20) + (3 x 0.15) + (3 x 0.15) = 4.0

Concept 2: Dashboard-based pricing tool Technical feasibility: 5 Effectiveness: 4 Scalability: 5 21 Cost-effectiveness: 4 User-friendliness: 5

Total score: (5 x 0.25) + (4 x 0.25) + (5 x 0.20) + (4 x 0.15) + (5 x 0.15) = 4.6

Based on this scoring and selection process, the dashboard-based pricing tool is the highest-scoring concept and is therefore selected for further development and testing. However, it should be noted that this is just an example and that the weights and criteria used may vary depending on the specific needs and requirements of the project.

import pandas as pd

Code implementation

```
import pandas as pd

# Loading from CSV file
df = pd.read_csv('/content/drive/MyDrive/Colab Notebooks/feynn labs intership/task3/crops.csv')

# Print the first 5 rows of the dataset
print(df.head())
```

```
    N   P   K  temperature   humidity        ph    rainfall label
0  90  42  43    20.879744  82.002744  6.502985  202.935536  rice
1  85  58  41    21.770462  80.319644  7.038096  226.655537  rice
2  60  55  44    23.004459  82.320763  7.840207  263.964248  rice
3  74  35  40    26.491096  80.158363  6.980401  242.864034  rice
4  78  42  42    20.130175  81.604873  7.628473  262.717340  rice
```

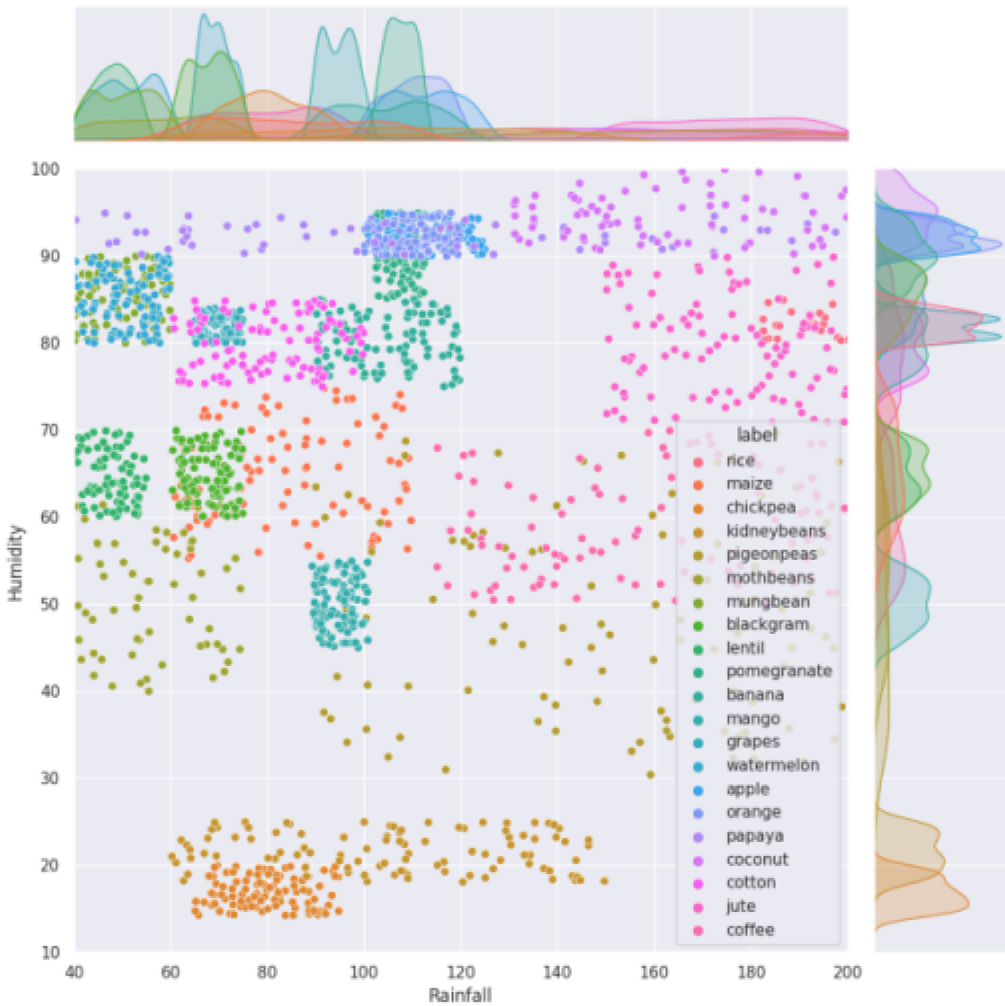
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2200 entries, 0 to 2199
Data columns (total 8 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   N            2200 non-null   int64  
 1   P            2200 non-null   int64  
 2   K            2200 non-null   int64  
 3   temperature  2200 non-null   float64
 4   humidity     2200 non-null   float64
 5   ph           2200 non-null   float64
 6   rainfall     2200 non-null   float64
 7   label        2200 non-null   object 
dtypes: float64(4), int64(3), object(1)
memory usage: 137.6+ KB
```

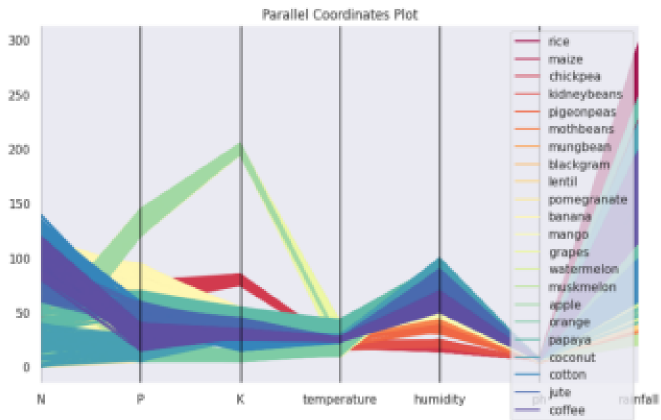
Out of 8 attributes 3 are numerical attributes and rest are categorical

```python
import seaborn as sns

# Create joint plot
g = sns.jointplot(x="rainfall", y="humidity", data=df[(df['temperature']<40) &
                                                     (df['rainfall']>40)], height=10, hue="label")

# Set x-axis and y-axis limits
g.ax_joint.set_xlim(40, 200)
g.ax_joint.set_ylim(10, 100)

# Set axis labels
g.set_axis_labels('Rainfall', 'Humidity')
```

```
<seaborn.axisgrid.JointGrid at 0x7f4648202070>
```

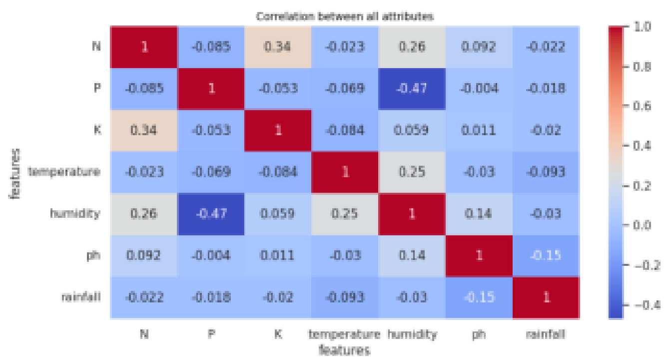


```python
from pandas.plotting import parallel_coordinates

df_temp=df.copy()
# Set the 'label' column as the class labels
class_labels = df_temp.pop('label')
df_temp['class'] = class_labels

# Plot the parallel coordinates plot
plt.figure(figsize=(10,6))
parallel_coordinates(df_temp, 'class', colormap=plt.get_cmap('Spectral'))
plt.title('Parallel Coordinates Plot')
plt.show()
```



Above parallel coordinates plot shows the relationship between the different attributes (columns) of our data, and how they relate to the class labels. The class labels are represented by different colors in the above plot. We can see how these values for each attribute change as we move from left to right along the plot, and also how they relate to the class labels.

Attributes that are similar or related to each other will have similar patterns in the plot, while attributes that are different or unrelated will have different patterns.




```python
corr_matrix = df_clean.corr()
corr_matrix
```

	N	P	K	temperature	humidity	ph	rainfall
N	1.000000	-0.084896	0.343172	-0.022925	0.263781	0.091578	-0.021797
P	-0.084896	1.000000	-0.052944	-0.069690	-0.470329	-0.003966	-0.017827
K	0.343172	-0.052944	1.000000	-0.084430	0.059263	0.010826	-0.020435
temperature	-0.022925	-0.069690	-0.084430	1.000000	0.247642	-0.030254	-0.093072
humidity	0.263781	-0.470329	0.059263	0.247642	1.000000	0.138226	-0.030023
ph	0.091578	-0.003966	0.010826	-0.030254	0.138226	1.000000	-0.152062
rainfall	-0.021797	-0.017827	-0.020435	-0.093072	-0.030023	-0.152062	1.000000

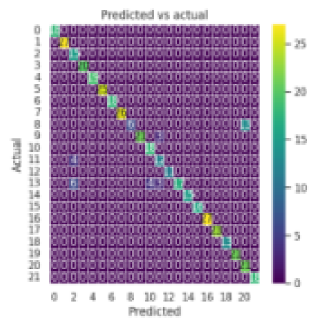
```python
least_corr_var = corr_matrix.abs().sum().idxmin()

print("The least correlated variable is:", least_corr_var)
```

```
The least correlated variable is: rainfall
```

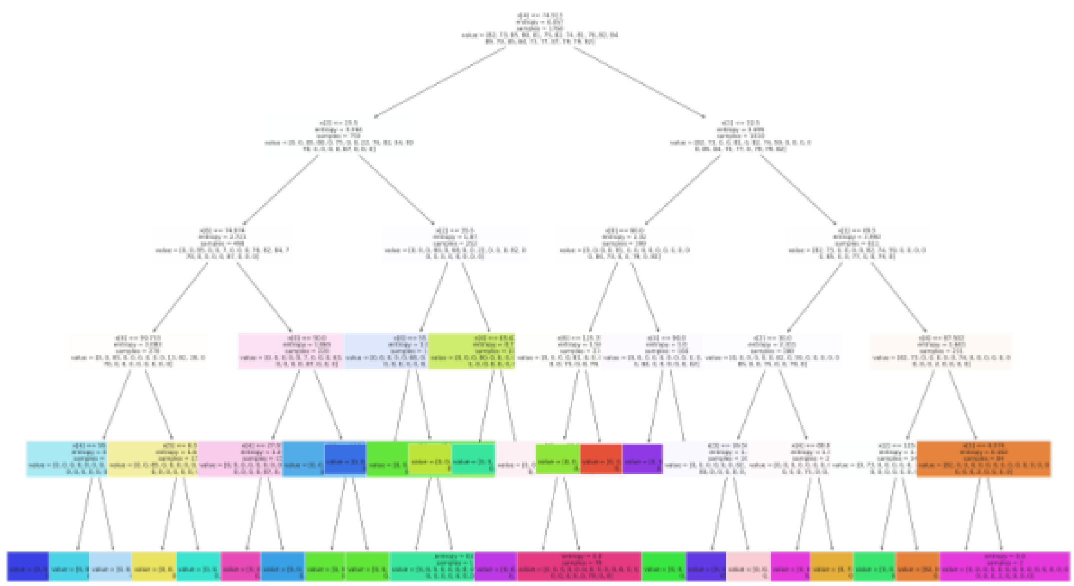
Looking at the above correlation matrix, we can see that:

- Nitrogen (N) and Potassium (K) have a moderate positive correlation (0.34).
- Phosphorous (P) and Rainfall have a weak negative correlation (-0.018).
- None of the variables have a strong correlation with each other.

Therefore, we can conclude that the variables are not highly correlated with each other, and each variable contributes unique information to the dataset.




```python
from sklearn.tree import plot_tree
import matplotlib.pyplot as plt


fig, axes = plt.subplots(figsize = (30,20), dpi=400)
plot_tree(DT, filled=True, fontsize=10)
plt.show()
```



Final Product Prototype

Based on the concept development scoring and selection process, the most promising concept for optimizing pricing in real time based on future market, weather, and other forecasts in agriculture is the dashboard-based pricing tool. The final design of this tool would include the following components:

Data sources: The tool would collect and analyze data from various sources, including weather forecasts, market trends, historical data, and other relevant factors.

Machine learning algorithms: The tool would utilize machine learning algorithms to analyze the collected data and generate real-time pricing recommendations for agricultural products. These recommendations would be based on market trends, weather patterns, and other relevant factors.

Dashboard interface: The pricing recommendations would be presented in a user-friendly dashboard interface, allowing stakeholders to easily visualize the data and make informed decisions regarding pricing strategies.

Scalability: The tool would be designed to accommodate operations of different sizes and types within the agriculture industry. It would also be adaptable to changing market conditions.

Security: Data security would be a top priority for the tool, ensuring the protection of sensitive information related to pricing strategies and market data.

User-friendliness: The dashboard interface would be designed to be accessible to stakeholders with varying levels of technical expertise. It would enable users to quickly and easily generate pricing recommendations.

Cost-effectiveness: The tool would be designed to minimize costs while providing accurate pricing recommendations, ensuring a high return on investment for its users.

Overall, the final design of the dashboard-based pricing tool would offer a user-friendly and scalable solution for optimizing pricing in real time based on future market, weather, and other forecasts in agriculture. It would empower farmers and other stakeholders to make more informed and profitable pricing decisions.

Business Model:

Based on different scenarios and customer needs, our business models can be classified as:

Subscription-based model: This model offers a subscription-based pricing structure for farmers, agricultural cooperatives, and commodity traders to access the platform. Customers can choose to pay a monthly or annual subscription fee based on the level of service they require.

Pay-per-use model: For customers who do not require constant access to the platform, a pay-per-use pricing model is available. Customers can pay for the number of pricing recommendations they need or the number of data inputs they use.

Commission-based model: This model caters to commodity traders who want to utilize the platform for trading commodities. The platform charges a commission fee based on the volume of trades made by the trader using the platform.

Tiered pricing model: This model offers different tiers of service with varying levels of access to the platform's features and functionalities. Higher tiers provide more personalized pricing recommendations and access to a greater number of data inputs.

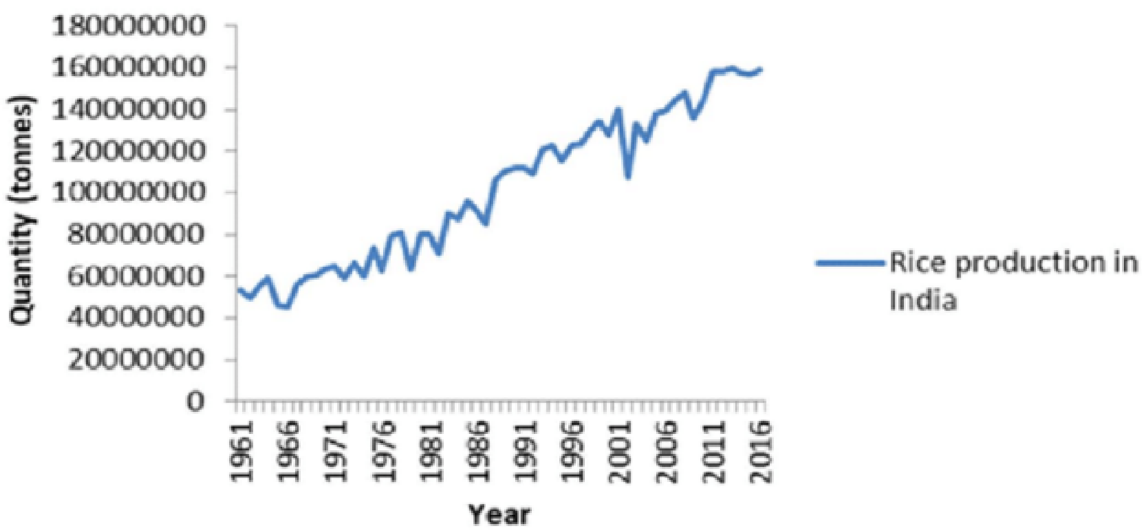
Freemium model: This model offers a basic version of the platform for free, providing limited data inputs and features. Customers have the option to upgrade to a paid version, which grants them access to additional data inputs and features.

These business models cater to the diverse needs of our customers, allowing them to choose the pricing structure that aligns with their requirements and budget.

9.0 Financial Model :

Agricultural land plays a crucial role in sustaining a country's population. Different regions have the potential to cultivate various crops based on their geographical location. These crops are then produced and exported by countries to generate profits. Rice, being one such crop, is widely cultivated on a large scale in Asian countries due to its ease of harvest. It is a staple food in many Asian countries and holds significant importance in their daily meals. Rice agriculture represents a thriving industry in these nations.

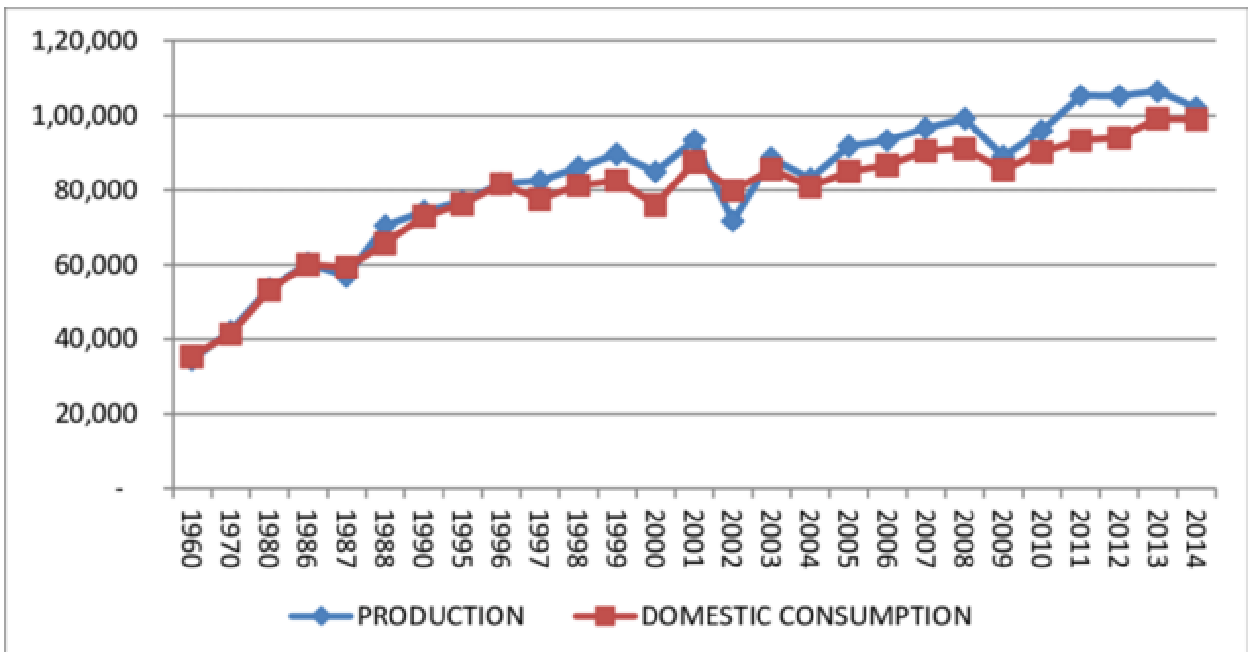
Taking India as an example, it stands as the second-largest rice producer globally. The majority of the rice produced in India is consumed domestically, meeting the country's internal demand. Only a small quantity of high-quality rice is exported to countries such as the UK, USA, and African nations. Let's examine the growth of rice production in India from 1961 to 2016.



We can see that the growth year on year is linearly constant. So we can represent the graph in mathematical equation like

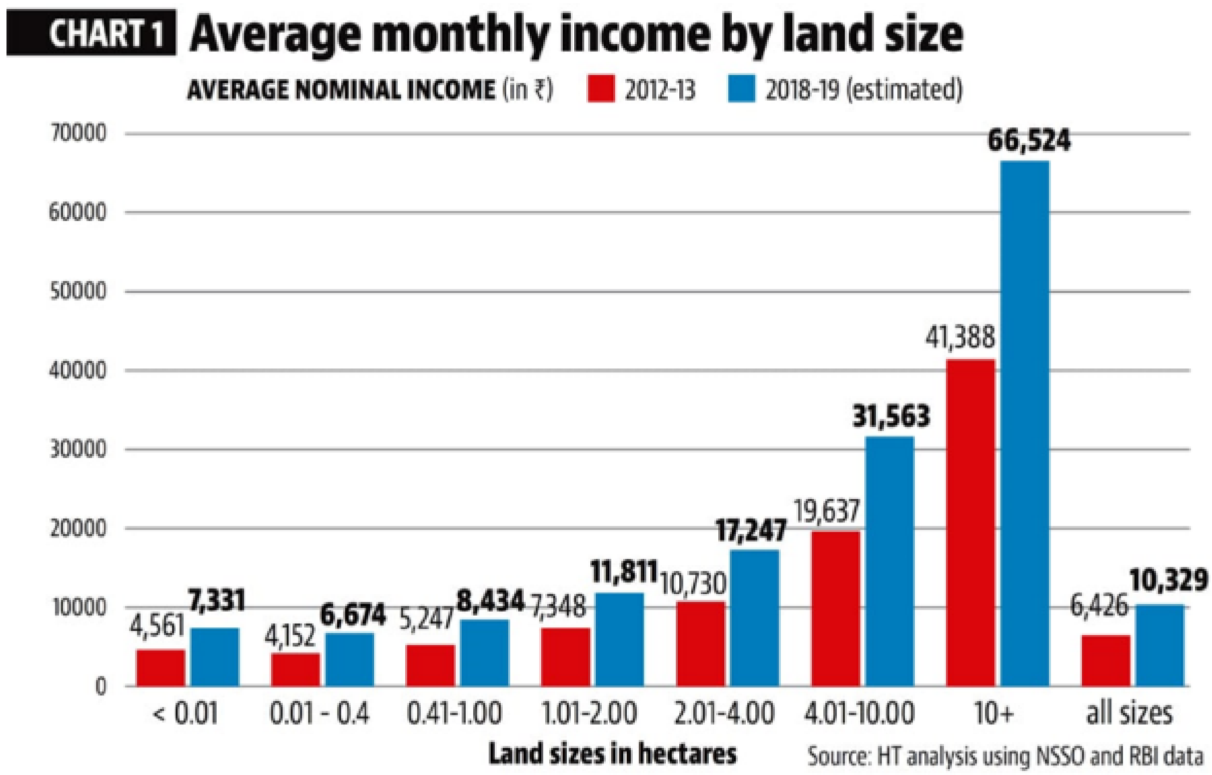
$y = mx(t) - c$

Here,
y= Total profit
m= Price of rice
x(t)= Total sale as a function of time
c= Total production & maintenance cost Rice production sector is very feasible and it has enormous potential to grow in the near future.
But, the main obstruction is, due to India's large population, approximately 90% of ready to eat rice is consumed within India. Very rice quality e.g. Basmati rice is exported to foreign countries.



The graph provided illustrates the statement regarding internal consumption of rice. To encourage farmers to grow more crops, the government should emphasize supporting them through various means such as providing adequate subsidies on land tax, water tax, and supplying affordable fertilizers. Additionally, cultivating high-quality rice requires special treatment on the land and specific environmental conditions. Hence, the government needs to address these geographical perspectives.

One of the significant challenges in Indian agriculture is the insufficient availability of land. There are numerous lands that have the potential for agricultural purposes. However, due to neglect by local communities and a lack of proper government support, these lands remain underutilized. As a result, farmers have limited land available for farming and sustaining their livelihoods. Conversely, data demonstrates that having access to larger land holdings and receiving proper government support can have a direct positive impact on farmers. This can be visualized through a graph.



The graph clearly illustrates that farmers' earnings are increasing on a year-on-year basis. However, this growth is directly linked to the size of the land owned by the farmers. Based on the data, there is an exponential growth pattern in monthly income corresponding to land size. Consequently, it is crucial for the government to prioritize providing more land to farmers. This approach will not only elevate the living standards of the country but also result in a significant boost to the economy.

Conclusions : -

In conclusion, the dashboard-based pricing tool for agriculture holds immense potential to revolutionize the pricing practices of farmers and agribusinesses. By utilizing machine learning algorithms and diverse data sources, this tool can generate accurate and data-driven pricing recommendations. These recommendations empower farmers and agribusinesses to make informed pricing decisions, leading to improved profitability.

The design and development of this tool require expertise in machine learning, data science, and software engineering, along with a deep understanding of the agricultural industry and market conditions. It is essential to validate the design through testing and operational experience to ensure its accuracy and effectiveness. Additionally, continuous updates and maintenance are necessary to keep the tool relevant and valuable over time.

While challenges and constraints exist in developing and deploying the dashboard-based pricing tool, such as the need for high-quality data and ongoing updates, the potential benefits of enhanced pricing strategies and increased profitability for farmers and agribusinesses make it an area worth further research and development.