

<u>Project Report: Crop Production Analysis In India</u>

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Introduction:

Agriculture plays a pivotal role in India's economy, employing a significant portion of its population and contributing substantially to its GDP. Understanding and analyzing crop production data is crucial for policymakers, researchers, and stakeholders to make informed decisions regarding agricultural policies, resource allocation, and food security initiatives. This report delves into the analysis of agricultural crop production in India, leveraging a comprehensive dashboard titled "CROP PRODUCTION OF INDIA" created using Power BI Desktop. By examining key metrics, trends, and patterns in crop production, this report aims to provide valuable insights into the dynamics of India's agricultural sector.

Through visualization and interpretation of data, this report seeks to uncover trends, identify high-performing regions, and offer recommendations for optimizing agricultural productivity. By harnessing the power of data analytics, stakeholders can drive sustainable growth, enhance food security, and foster economic development in the agricultural sector of India.

Acknowledgements:

We acknowledge the contributions of the Unified Mentor team and express gratitude for their guidance and support throughout the project.

This report serves as a foundational analysis of crop production of India, providing a roadmap for further exploration and actionable insights to drive business success.

Method:

1. Data Collection:

The analysis is based on a dataset containing information on crop production in India, including variables such as State_Name, District_Name, Crop_Year, Season, Crop, Area, and Production. The dataset was obtained from reliable sources such as government agricultural departments or research institutions.

2. Data Preparation:

Prior to analysis, the dataset underwent preprocessing steps to clean and format the data. This involved handling missing values, encoding categorical variables, and ensuring data consistency and integrity..

3. Dashboard Creation:

Using Power BI Desktop, a comprehensive dashboard titled "CROP PRODUCTION OF INDIA" was developed to visualize and analyze the crop production data. The dashboard comprises various visualizations, including bar charts, line charts, pie charts, and maps, to effectively communicate insights.

4. Machine Learning Model Development:

To enhance the predictive capabilities of the analysis, a machine learning model was trained using the Random Forest algorithm. The model utilizes features such as crop type, season, and area to predict crop production with high accuracy.

5. Analysis and Visualization:

The dashboard provides an overview of key performance indicators such as total production, crop varieties, and area used for cultivation. It also presents visualizations to analyse production trends over time, compare production volumes across states and districts, and assess spatial distribution of production.

6. Insights and Recommendations:

The analysis of the dashboard visualizations and machine learning predictions yielded insights into the dynamics of crop production in India. These insights were used to formulate recommendations for policymakers, researchers, and stakeholders to enhance agricultural productivity, address challenges, and promote sustainable development in the agricultural sector.

Key Points:

- **1. Dashboard Overview:** The "CROP PRODUCTION OF INDIA" dashboard provides a comprehensive view of crop production metrics in India, including total production, crop varieties, and cultivation area.
- **2. Performance Indicators:** performance indicators such as total production, the number of crop varieties, and the total cultivation area are prominently displayed, offering a snapshot of India's agricultural landscape.
- 3. State-Wise Production: Kerala emerges as the leading state in crop production, followed by Andhra Pradesh, Tamil Nadu, and others. This highlights the importance of regional analysis in understanding production dynamics.
- **4. District-Wise Production:** Top-performing districts are ranked based on production volume, enabling stakeholders to identify areas of high productivity and potential areas for improvement
- **5. Trends Over Time:** The analysis of production trends over time reveals patterns and fluctuations in crop production, providing insights into factors influencing production dynamics.
- **6. Spatial Distribution:** Geospatial analysis visualizes production volume by state, allowing stakeholders to assess spatial distribution and identify regions contributing significantly to overall production.
- **7. Machine Learning Predictions:** The integration of a Random Forest machine learning model enhances predictive capabilities, enabling accurate predictions of crop production based on factors such as crop type, season, and cultivation area

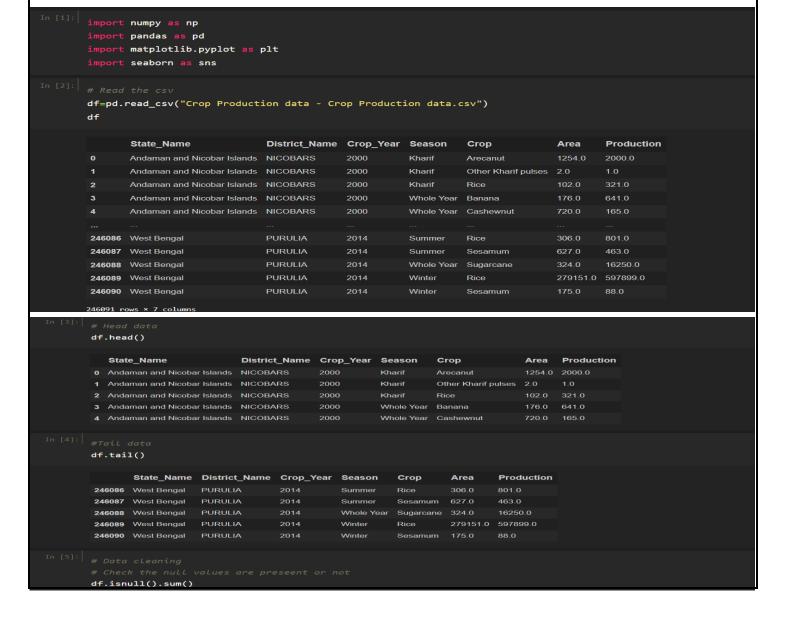
- **8.** Insights and Recommendations: Insights derived from dashboard analysis and machine learning predictions inform actionable recommendations for policymakers, researchers, and stakeholders to optimize agricultural productivity, address challenges, and promote sustainable development in the agricultural sector.
- **9. Data-Driven Decision Making:** The project underscores the importance of data-driven approaches in informing strategic decision-making and driving business growth.

Recommendations:

- Targeted Interventions: Identify regions with low crop production and implement targeted interventions such as improved access to irrigation, better seeds, and enhanced agricultural extension services to boost productivity.
- Technology Adoption: Encourage the adoption of modern agricultural technologies such as precision farming, drone technology, and IoT-based monitoring systems to optimize resource use and improve yields.
- Crop Diversification: Promote crop diversification initiatives to reduce dependence on a few staple crops and enhance resilience to climate change and market fluctuations.
- Capacity Building: Invest in capacity building programs to empower farmers with knowledge and skills on sustainable agricultural practices, crop management techniques, and post-harvest management.
- Infrastructure Development: Prioritize infrastructure development in rural areas, including roads, storage facilities, and market linkages, to improve access to markets and reduce post-harvest losses.
- Research and Innovation: Foster collaboration between research institutions, academia, and the private sector to develop innovative solutions for enhancing agricultural productivity, disease resistance, and climate resilience.

- Policy Support: Formulate supportive policies and incentives to promote sustainable agricultural practices, including organic farming, conservation agriculture, and agroforestry.
- Data-driven Decision Making: Emphasize the importance of data-driven decision-making by providing access to reliable agricultural data, analytics tools, and training programs for policymakers and agricultural stakeholders.
- Public-Private Partnerships: Foster partnerships between the public and private sectors to leverage resources, expertise, and technology for sustainable agricultural development and value chain integration.
- Community Engagement: Encourage community participation and involvement in agricultural development initiatives through farmer cooperatives, self-help groups, and community-based organizations.

Code:



```
df.isnull().sum()
 State_Name
 District_Name
 Season
 Area
 Production
                3730
production = df['Production'].mean()
df['Production'].fillna(production, inplace=True)
df.isnull().sum()
 District_Name
 Season
df.isnull().sum()
 State_Name
 District Name
 Season
                0
 Production
df.shape
df.columns
 Index(['State_Name', 'District_Name', 'Crop_Year', 'Season', 'Crop', 'Area',
       'Production'],
      dtype='object')
df.describe()
       Crop_Year
                    Area
                                Production
count 246091.000000 2.460910e+05 2.460910e+05
mean 2005.643018 1.200282e+04 5.825034e+05
                  5.052340e+04 1.693599e+07
std 4.952164
min 1997.000000 4.000000e-02 0.000000e+00
 25% 2002.000000 8.000000e+01 9.100000e+01
     2006.000000 5.820000e+02 7.880000e+02
 50%
 75%
      2010.000000
                    4.392000e+03 8.000000e+03
      2015.000000
                    8.580100e+06 1.250800e+09
print(df['Crop'].nunique())
print(df['Season'].nunique())
df['Crop'].value_counts()
```

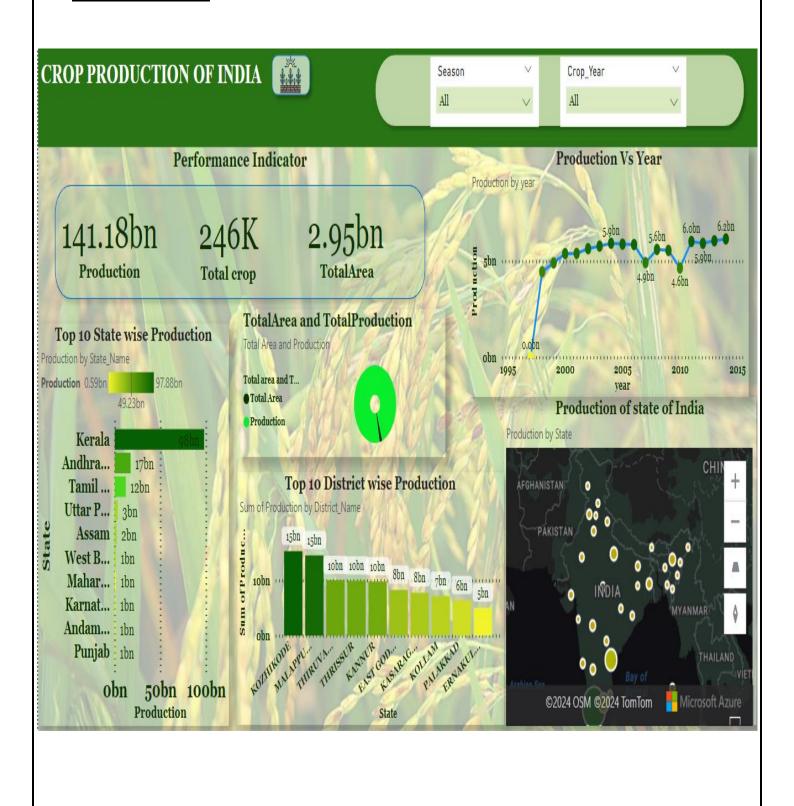
```
df['Crop'].value_counts()
                        15104
  Maize
                        13947
  Moong(Green Gram)
                        10318
  Urad
                         9850
                         9046
  Sesamum
  Coffee
  Peach
  Other Dry Fruit
  Name: Crop, Length: 124, dtype: int64
df['Season'].unique()
        dtype=object)
df['State_Name'].unique()
  array(['Andaman and Nicobar Islands', 'Andhra Pradesh', 'Arunachal Pradesh', 'Assam', 'Bihar', 'Chandigarh',
           'Chhattisgarh', 'Dadra and Nagar Haveli', 'Goa', 'Gujarat',
           'Haryana', 'Himachal Pradesh', 'Jammu and Kashmir', 'Jharkhand',
          'Karnataka', 'Kerala', 'Madhya Pradesh', 'Maharashtra', 'Manipur',
'Meghalaya', 'Mizoram', 'Nagaland', 'Odisha', 'Puducherry',
'Punjab', 'Rajasthan', 'Sikkim', 'Tamil Nadu', 'Telangana',
          'Tripura', 'Uttar Pradesh', 'Uttarakhand', 'West Bengal'],
         dtype=object)
 df.info()
  RangeIndex: 246091 entries, 0 to 246090
  Data columns (total 7 columns):
                      Non-Null Count Dtype
   0 State_Name 246091 non-null object
1 District_Name 246091 non-null object
                     246091 non-null int64
246091 non-null object
   2 Crop_Year
       Season
                       246091 non-null float64
  dtypes: float64(2), int64(1), object(4)
  memory usage: 13.1+ MB
if df.duplicated().any():
     print("Duplicate rows are present.")
     print("No duplicate rows are present.")
 No duplicate rows are present.
max_thresold=df['Production'].mean()+3*df['Production'].std()
min_thresold=df['Production'].mean()-3*df['Production'].std()
print(max_thresold,min_thresold)
 51390460.233226016 -50225453.34872411
df1=df[(df['Production']>min_thresold)&(df['Production']<max_thresold)]
df1.reset_index(drop=True,inplace=True)
df1.shape
 (245753, 7)
```

```
plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
plt.scatter(df1.index, df1['Production'], color='blue', label='Filtered Production')
plt.xlabel('Index')
plt.ylabel('Production')
plt.title('Filtered Production Data ')
plt.legend()
plt.subplot(1, 2, 2)
plt.boxplot(df1['Production'], vert=True)
plt.ylabel('Production')
plt.title('Filtered Production Data')
plt.tight_layout()
plt.show()
            Filtered Production Data
                                                                          Filtered Production Data
               100000
Index
     50000
                         150000
                                    200000
productiondata = df1['Production'].values
maxval = df1['Production'].max()
normalize_production = productiondata / maxval
plt.figure(figsize=(8, 20))
plt.scatter(normalize_production,df1['Crop'])
plt.title('Crop vs Production')
plt.xlabel('Production')
plt.ylabel('Crop')
plt.xticks(rotation=90)
plt.show()
```

```
data_netpro = df1.groupby('Crop_Year')['Production'].sum()
       years =df1['Crop_Year'].unique()
       max_netpro=data_netpro.max()
       data_netpro = np.array(data_netpro)
       data_netpro = data_netpro/max_netpro
       plt.scatter(years, data_netpro, color='green')
       plt.title('Year vs Net Production 2000-2014')
       plt.ylabel('Production')
       plt.xlabel('Year')
       plt.xticks(np.arange(2000, 2014, 2))
       plt.grid(True)
       plt.show()
                                Year vs Net Production 2000-2014
   1.0
   0.8
   0.6
   0.4
   0.2
   0.0
                           2000
                                     2002
                                                2004
                                                          2006
                                                                     2008
                                                                               2010
                                                                                          2012
                                                            Year
       season_production=df1.groupby('Season')['Production'].mean()
       season production
        Season
Autumn
Kharif
Rabi
                   52126.460218
37819.545581
12676.573566
185957.467642
        Summer
Whole Year
           er 72500.801536
: Production, dtype: float64
      ax = sns.barplot(x='Season', y='Production', data=season_production.reset_index())
      plt.xlabel('season')
      plt.ylabel('Average production')
      plt.title('season vs average production')
       for p in ax.patches:
           ax.annotate(format(p.get_height(), '.1f'),
                       (p.get_x() + p.get_width() / 2., p.get_height()),
                       ha='center', va='center',
                       xytext=(0, 9),
                       textcoords='offset points')
                                         season vs average production
    175000
    150000
Average production
    125000
    100000
                                                                                                      72500.8
     75000
                                   52126.5
     50000
                                                    37819.5
     25000
                   15251.8
                                                                     12676.6
                                                                                     Milotes
             0
                                     4500ill
                                                                     cylinet
                                                                                                       Whitet
                     PATERINE
                                                       230
                                                             season
```

```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error
df1.head(3)
   State_Name
                           District_Name Crop_Year Season Crop
                                                                            Area Production
• Andaman and Nicobar Islands NICOBARS
                                         2000
                                                                            1254.0 2000.0
 1 Andaman and Nicobar Islands NICOBARS
                                         2000
                                                    Kharif
                                                            Other Kharif pulses 2.0
2 Andaman and Nicobar Islands NICOBARS
                                         2000
                                                    Kharif
data_encoded = pd.get_dummies(df.drop(columns=['State_Name', 'District_Name', 'Crop_Year', 'Crop']), columns
X = data_encoded.drop(columns=['Production'])
y = data_encoded['Production']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
model = RandomForestRegressor(random_state=42)
model.fit(X_train, y_train)
  RandomForestRegressor(random_state=42)
In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.
train_preds = model.predict(X_train)
 test_preds = model.predict(X_test)
train_rmse = mean_squared_error(y_train, train_preds)
test_rmse = mean_squared_error(y_test, test_preds)
print("Train RMSE:", train_rmse)
print("Test RMSE:", test_rmse)
 Train RMSE: 52978381939011.125
 Test RMSE: 207551213835908.3
new_data = X_test.iloc[[0]]
prediction = model.predict(new_data)
print("Predicted Production:", prediction)
 Predicted Production: [621.72964762]
```

Dashboard:



Future Scope:

- Big Data Integration: Harness the power of big data analytics by integrating data from multiple sources such as satellite imagery, weather forecasts, soil health data, and market trends to develop comprehensive decision support systems for farmers and policymakers.
- Precision Agriculture: Embrace precision agriculture technologies including remote sensing, drones, and IoT sensors to enable real-time monitoring of crops, soil conditions, and weather patterns, leading to more efficient resource utilization and sustainable crop management practices.
- Climate Resilience: Develop strategies and technologies to enhance the
 resilience of crops to climate change-induced stresses such as drought, floods,
 and extreme temperatures, including the breeding of climate-resilient crop
 varieties and the adoption of climate-smart agricultural practices.
- Digital Agriculture Platforms: Invest in the development of digital agriculture platforms and mobile applications that provide farmers with access to timely information, advisory services, market linkages, and financial services, empowering them to make informed decisions and improve productivity.
- Vertical Farming and Urban Agriculture: Explore the potential of vertical farming, hydroponics, and urban agriculture to address urban food security challenges and reduce the environmental footprint of agriculture by maximizing crop yields in limited space and reducing transportation costs.
- Sustainable Supply Chains: Strengthen sustainable supply chains by promoting traceability, transparency, and ethical sourcing practices, ensuring fair remuneration for farmers, and minimizing the environmental impact of agricultural production and distribution.
- Capacity Building and Extension Services: Invest in capacity building programs, vocational training, and extension services to equip farmers, agrientrepreneurs, and rural youth with the skills and knowledge needed to adopt modern agricultural practices, agribusiness management, and value chain development.
- Policy Support and Regulatory Framework: Enact supportive policies,
 regulatory frameworks, and incentives that foster innovation, investment, and

entrepreneurship in the agricultural sector, while ensuring social equity, environmental sustainability, and food sovereignty.

Conclusion:

the analysis of crop production in India reveals key insights into production trends, regional variations, and predictive modeling. By leveraging data-driven analytics and machine learning, we've gained a deeper understanding of agricultural dynamics. Looking ahead, embracing innovation and evidence-based strategies can drive sustainable growth and resilience in India's agricultural sector.

In essence, the analysis presented in this report serves as a foundation for informed decision-making, collaboration, and collective action towards a resilient, productive, and equitable agricultural sector in India. By harnessing the power of data and technology, we can address the challenges facing agriculture and unlock new opportunities for growth, prosperity, and resilience in the years to come.