

The background of the slide features a wide-angle photograph of a rural landscape. In the foreground, there's a lush green field with some dark spots, possibly crops or animals. In the middle ground, the field continues across rolling hills. On the right side, several white wind turbines stand tall against a sky filled with large, fluffy white clouds. The overall scene is bright and suggests a peaceful, modern agricultural setting.

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# CROP PREDICTION SYSTEM



# Introduction

The Crop Prediction System predicts suitable crops using soil, weather, and historical data, helping farmers optimize yields and adopt sustainable practices.

# objectives



## 1. Enhance Agricultural Decision-Making

Assist farmers in choosing the most suitable crops based on environmental and soil conditions.

## 2. Efficient Resource Utilization

Minimize resource wastage (water, fertilizer, seeds) by optimizing crop selection.

## 3. Boost Agricultural Productivity

Increase yield by providing data-driven crop recommendations.

# objectives



## 4. Leverage Data for Accuracy

Use historical and real-time datasets (e.g., soil type, rainfall, temperature) to make precise predictions.

## 5. Support Sustainable Farming

Promote sustainable agricultural practices by aligning crop choices with ecological conditions.

## 6. Simplify User Experience

Design a system that is user-friendly for farmers with minimal technical expertise.

# objectives



## 7. Improve Profitability

Help farmers maximize profits by predicting high-demand crops suited to the region.

## 8. Enable Real-Time Analysis

Incorporate live data updates (e.g., weather conditions) for dynamic recommendations.

## 9. Address Regional Challenges

Tackle issues such as drought, over-irrigation, or pest infestations through predictive insights.

## 10. Promote Smart Agriculture

Integrate the system into broader smart agriculture initiatives for long-term benefits.

# DATASET

	A	B	C	D	E	F	G	H	I	J
1	Crop	Crop_Year	Season	State	Area	Production	Annual_Rainfall	Fertilizer	Pesticide	Yield
2	Areca nut	1997	Whole Year	Assam	73814	56708	2051.4	7024878	22882.34	0.796087
3	Arhar/Tur	1997	Kharif	Assam	6637	4685	2051.4	631643.3	2057.47	0.710435
4	Castor seed	1997	Kharif	Assam	796	22	2051.4	75755.32	246.76	0.238333
5	Coconut	1997	Whole Year	Assam	19656	126905000	2051.4	1870662	6093.36	5238.052

# LOADING AND EXPLORING CROP YIELD DATA

```
▶ data=pd.read_csv('/content/crop_yield.csv')  
print(data.head())
```

→

	Crop	Crop_Year	Season	State	Area	Production	\
0	Arecanut	1997	Whole Year	Assam	73814.0	56708	
1	Arhar/Tur	1997	Kharif	Assam	6637.0	4685	
2	Castor seed	1997	Kharif	Assam	796.0	22	
3	Coconut	1997	Whole Year	Assam	19656.0	126905000	
4	Cotton(lint)	1997	Kharif	Assam	1739.0	794	

	Annual_Rainfall	Fertilizer	Pesticide	Yield
0	2051.4	7024878.38	22882.34	0.796087
1	2051.4	631643.29	2057.47	0.710435
2	2051.4	75755.32	246.76	0.238333
3	2051.4	1870661.52	6093.36	5238.051739
4	2051.4	165500.63	539.09	0.420909

# INSPECTING THE LAST FEW ROWS OF DATA

```
▶ print(data.tail())
```

```
→      Crop  Crop_Year   Season          State    Area \
19684  Small millets  1998  Kharif      Nagaland  4000.0
19685        Wheat    1998  Rabi       Nagaland  1000.0
19686        Maize   1997  Kharif  Jammu and Kashmir  310883.0
19687        Rice    1997  Kharif  Jammu and Kashmir  275746.0
19688        Wheat   1997  Rabi   Jammu and Kashmir  239344.0
```

```
Production  Annual_Rainfall  Fertilizer  Pesticide    Yield
19684        2000            1498.0     395200.00  1160.00  0.500000
19685        3000            1498.0     98800.00   290.00  3.000000
19686      440900           1356.2    29586735.11  96373.73  1.285000
19687        5488            1356.2    26242746.82  85481.26  0.016667
19688      392160           1356.2    22778368.48  74196.64  1.261813
```

```
[32] print(data.shape)
```

```
→ (19689, 10)
```

# GETTING DETAILED INFORMATION

```
▶ print(data.info())
→ <class 'pandas.core.frame.DataFrame'>
RangeIndex: 19689 entries, 0 to 19688
Data columns (total 10 columns):
 #   Column            Non-Null Count  Dtype  
--- 
 0   Crop              19689 non-null    object  
 1   Crop_Year         19689 non-null    int64  
 2   Season            19689 non-null    object  
 3   State             19689 non-null    object  
 4   Area              19689 non-null    float64 
 5   Production        19689 non-null    int64  
 6   Annual_Rainfall  19689 non-null    float64 
 7   Fertilizer        19689 non-null    float64 
 8   Pesticide         19689 non-null    float64 
 9   Yield              19689 non-null    float64 
dtypes: float64(5), int64(2), object(3)
memory usage: 1.5+ MB
None
```

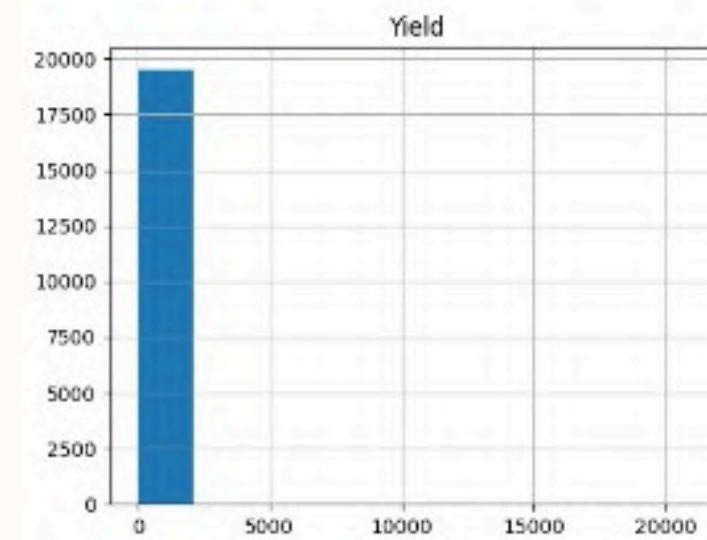
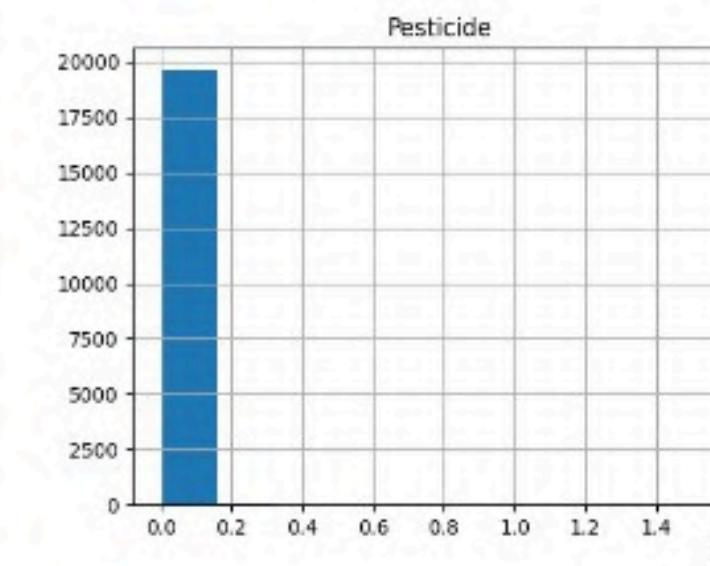
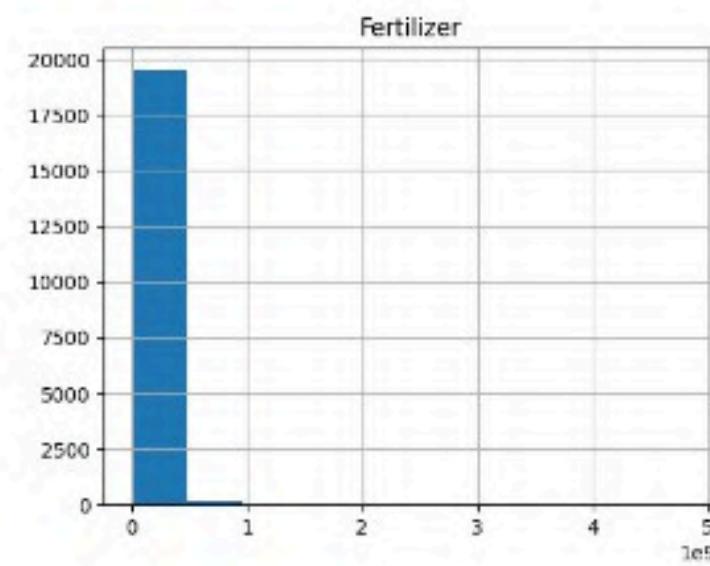
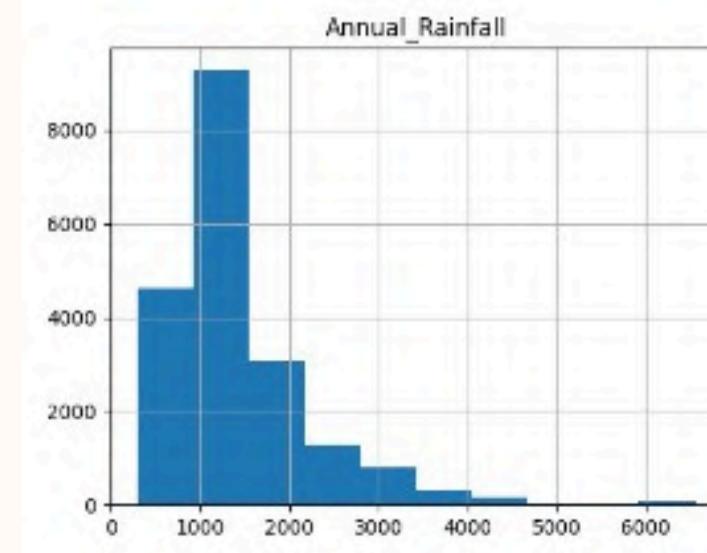
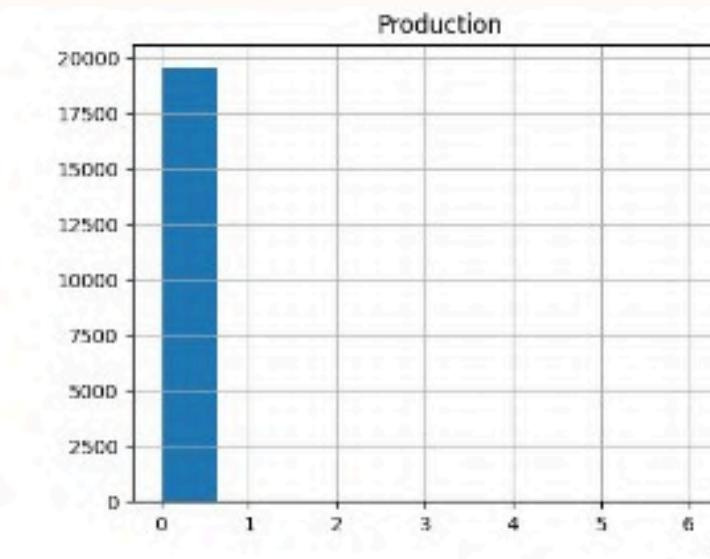
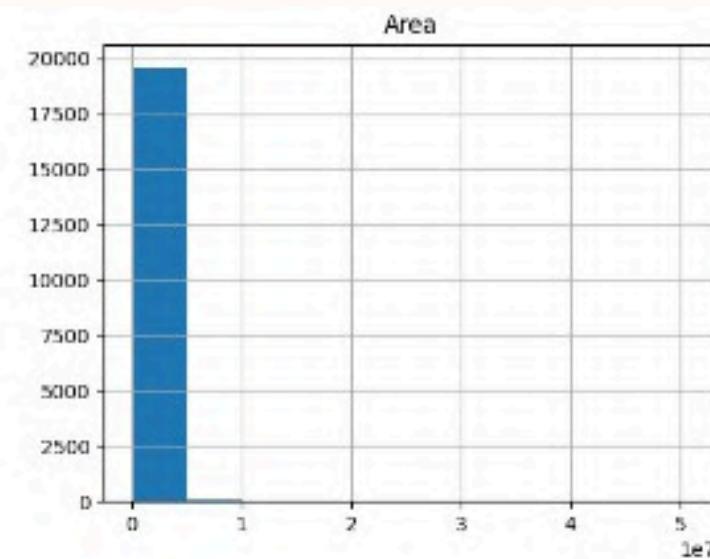
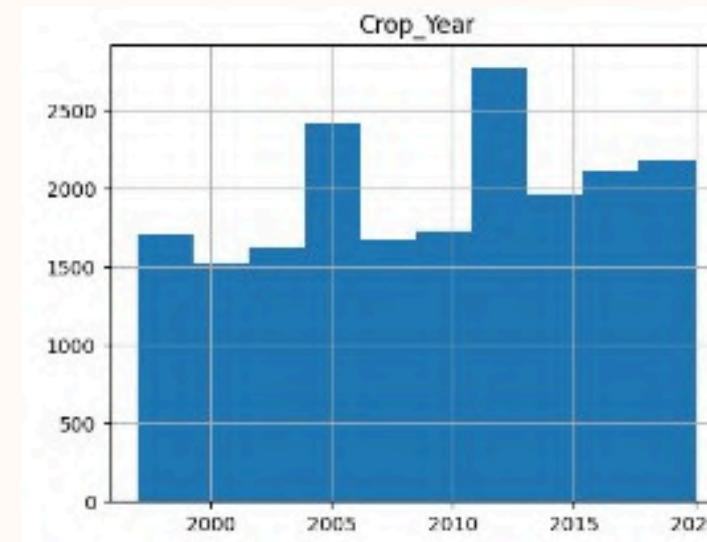
# CHECKING FOR MISSING VALUES

```
▶ print(data.isna().sum())
```

```
→   Crop          0  
    Crop_Year     0  
    Season        0  
    State         0  
    Area          0  
    Production    0  
    Annual_Rainfall 0  
    Fertilizer    0  
    Pesticide     0  
    Yield          0  
dtype: int64
```

# HISTOGRAM

```
▶ import matplotlib.pyplot as plt  
numeric_cols = data.select_dtypes(include=['int64', 'float64'])  
numeric_cols.hist(figsize=(20, 15))  
plt.show()
```



# SCALING

```
▶ from sklearn.preprocessing import MinMaxScaler\n\n# Assuming 'data' is your dataframe\nscaler = MinMaxScaler()\n\n# Select columns to scale based on your dataset\ncolumns_to_scale = ['Area', 'Production', 'Annual_Rainfall', 'Fertilizer', 'Pesticide']\n\n# Scale and transform the data\ndata[columns_to_scale] = scaler.fit_transform(data[columns_to_scale])\n\n# View the scaled data\nprint(data.head())
```

	Crop	Crop_Year	Season	State	Area	Production	\
0	Arecanut	1997	Whole Year	Assam	0.001453	8.964274e-06	
1	Arhar/Tur	1997	Kharif	Assam	0.000131	7.405944e-07	
2	Castor seed	1997	Kharif	Assam	0.000016	3.477711e-09	
3	Coconut	1997	Whole Year	Assam	0.000387	2.006086e-02	
4	Cotton(lint)	1997	Kharif	Assam	0.000034	1.255138e-07	

	Annual_Rainfall	Fertilizer	Pesticide	Yield
0	0.279953	0.001453	0.001453	0.796087
1	0.279953	0.000131	0.000131	0.710435
2	0.279953	0.000016	0.000016	0.238333
3	0.279953	0.000387	0.000387	5238.051739
4	0.279953	0.000034	0.000034	0.420909

# ENCODING

```
[38] from sklearn.preprocessing import LabelEncoder

# Create encoder instance
encoder = LabelEncoder()

# Specify categorical columns in your dataset
categorical_cols = ['Crop', 'Season', 'State'] # Update with your actual categorical column names

# Encode each categorical column
for col in categorical_cols:
    data[col] = encoder.fit_transform(data[col])

# View the transformed data
print(data.head())
```

→	Crop	Crop_Year	Season	State	Area	Production	Annual_Rainfall	＼
0	0	1997	4	2	0.001453	8.964274e-06	0.279953	
1	1	1997	1	2	0.000131	7.405944e-07	0.279953	
2	8	1997	1	2	0.000016	3.477711e-09	0.279953	
3	9	1997	4	2	0.000387	2.006086e-02	0.279953	
4	11	1997	1	2	0.000034	1.255138e-07	0.279953	

	Fertilizer	Pesticide	Yield
0	0.001453	0.001453	0.796087
1	0.000131	0.000131	0.710435
2	0.000016	0.000016	0.238333
3	0.000387	0.000387	5238.051739
4	0.000034	0.000034	0.420909

# CREATING YIELD CATEGORIES

```
[44] # Create categories for Yield (e.g., low, medium, high)
      bins = [0, 2, 5, 10] # Adjust based on the distribution of your target variable
      labels = ['Low', 'Medium', 'High']
      data['Yield_Category'] = pd.cut(data['Yield'], bins=bins, labels=labels)
```

# MODEL TRAINING AND EVALUATION

```
▶ # Define features and target
  X = data.drop(['Yield', 'Yield_Category'], axis=1) # Features
  y = data['Yield_Category'] # Target (categorical 'Yield_Category')

  # Split data
  X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.1, random_state=42)

  # Train the model
  dt_classifier = DecisionTreeClassifier(random_state=42)
  dt_classifier.fit(X_train, y_train)

  # Make predictions
  y_pred = dt_classifier.predict(X_test)

  # Evaluate the model
  accuracy = accuracy_score(y_test, y_pred)
  print(f"Accuracy: {accuracy}")
  print(classification_report(y_test, y_pred))
```

```
→ Accuracy: 0.9310344827586207
          precision    recall  f1-score   support

           High       0.85      0.87      0.86      119
            Low       0.96      0.97      0.97     1387
        Medium       0.79      0.76      0.78      263

   accuracy         0.93      0.93      0.93     1769
  macro avg       0.87      0.87      0.87     1769
weighted avg       0.93      0.93      0.93     1769
```

# MAKING PREDICTIONS

```
new_input = pd.DataFrame({  
    'Crop': [1], # Encoded value for 'Wheat'  
    'Crop_Year': [2022], # Year of the crop  
    'Production': [5000], # Production value  
    'Area': [73814], # Area of the farm  
    'Annual_Rainfall': [2051.4], # Annual Rainfall  
    'Fertilizer': [7024878], # Fertilizer value  
    'Pesticide': [22882.34], # Pesticide value  
    'Season': [1], # Encoded value for 'Kharif'  
    'State': [2] # Encoded value for 'Maharashtra'  
}, index=[0]) # Adding an index  
  
# Get the columns used during training  
training_columns = X_train.columns  
  

```



Prediction for the new input: Low

# Conclusion

The Crop Prediction System uses AI and ML to help farmers select suitable crops, improve yields, and promote sustainable farming. It addresses agricultural challenges and supports climate-resilient practices, enhancing productivity and food security.





A wide-angle photograph of a tobacco field at dusk or night. The foreground is filled with the dark green, broad leaves of tobacco plants. In the background, a dark, silhouetted forest line is visible against a very dark, almost black sky. The overall atmosphere is moody and atmospheric.

Thank You!