Yield Prediction and Analysis

About Dataset

This dataset encompasses agricultural data for multiple crops cultivated across various states in India from the year 2011 till 2020. The dataset provides crucial features related to crop yield prediction, including crop types, crop years, cropping seasons, states, areas under cultivation, production quantities, annual rainfall, fertilizer usage, pesticide usage, and calculated yields.

Data Fields

- Crop: The name of the crop cultivated.
- Crop_Year: The year in which the crop was grown.
- Season: The specific cropping season (e.g., Kharif, Rabi, Whole Year).
- State: The Indian state where the crop was cultivated.
- Area: The total land area (in hectares) under cultivation for the specific crop.
- Production: The quantity of crop production (in metric tons).
- Annual_Rainfall: The annual rainfall received in the crop-growing region (in mm).
- Fertilizer: The total amount of fertilizer used for the crop (in kilograms).
- Pesticide: The total amount of pesticide used for the crop (in kilograms).
- Yield: The calculated crop yield (production per unit area).

Importing Libraries

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

Importing Agriculture Crop Yield Dataset and Initial Observations

<pre>data = pd.read_csv('crop_yield.csv') data.head()</pre>									
	Crop	Crop_Year	Season	State	Area	Production			
\									
0	Arecanut	2011	Kharif	Puducherry	60.0	77			
				_					
1	Bajra	2011	Kharif	Puducherry	11.0	29			
2	Bajra	2011	Summer	Puducherry	20.0	51			
3	Banana	2011	Kharif	Puducherry	266.0	3263			
4	Black pepper	2011	Kharif	Puducherry	11.0	5			

Annual_Rainfall Fertilizer Pesticide Yield 0 1434.5875 10051.20 19.80 1.280000 1 1434.5875 1842.72 3.63 2.640000 2 1434.5875 3350.40 6.60 2.550000 3 1434.5875 44560.32 87.78 10.903333 4 1434.5875 1842.72 3.63 0.450000								
dat	a.tail()							
Pro	Crop duction \	Crop_Year	Se	eason Sta	ate	Area		
901		2018	Winter	Odis	sha 6	5778.0	417672	
901	8 Urad	2018	Autumn	Odis	sha 13	3720.0	3583	
901	9 Urad	2018	Summer	0dis	sha 4	571.0	2336	
902	0 Urad	2018	Winter	Odis	sha 39	560.0	13123	
902	1 Wheat	2018	Summer	Odis	sha	147.0	268	
901 901 901 902 902	8 16 9 16 0 16	35.9 109 35.9 22 35.9 74 35.9 64	tilizer 99391.6 25384.0 41416.2 16632.0 23843.4	Pesticide 2372.30 4802.00 1599.85 13846.00 51.45	57.58 0.33 0.46 0.35	ield 34545 36667 59091 52759		
data.shape								
(9022, 10)								

We understand that our data has 9022 rows and 10 features to work with

```
data.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9022 entries, 0 to 9021
Data columns (total 10 columns):
#
                      Non-Null Count
    Column
                                      Dtype
     -----
0
                      9022 non-null
                                      object
     Crop
    Crop_Year
1
                      9022 non-null
                                      int64
2
     Season
                      9022 non-null
                                      object
3
     State
                      9022 non-null
                                      object
4
    Area
                      9022 non-null
                                      float64
 5
                      9022 non-null
     Production
                                      int64
 6
     Annual Rainfall 9022 non-null
                                      float64
```

```
7 Fertilizer 9022 non-null float64
8 Pesticide 9022 non-null float64
9 Yield 9022 non-null float64
```

dtypes: float64(5), int64(2), object(3)

memory usage: 705.0+ KB

This information tells us that, out of the 10 features in our dataset 3 are object type else all are numerical data

data.describe(in	clude='all')	.Т					
Crop Crop_Year Season State Area Production Annual_Rainfall Fertilizer Pesticide Yield	9022.0 Na 9022 9022.0 Na 9022.0 Na 9022.0 Na 9022.0 Na 9022.0 Na 9022.0 Na	55 aN	top Rice NaN narif Karnataka NaN NaN NaN NaN	NaN	159062 17051337 1435 25052366 53458	mean NaN 5.182997 NaN NaN 2.678774 7.986588 5.353493 5.189199 8.906243 2.457035	\
F.00		std	min		25%		
50% \ Crop		NaN	NaN		NaN	NaN	J
Crop_Year	2.58	32179	2011.0	201	13.0	2015.0)
Season		NaN	NaN		NaN	NaN	J
State		NaN	NaN		NaN	NaN	J
Area	630033.7	76956	0.8	1036	5.25	7000.0)
Production	270796230.0	70602	0.0	105	52.5	11117.5	5
Annual_Rainfall	785.52	27676	301.3	95	6.2	1235.6	5
Fertilizer	99436190.08	34488	120.768	163052.9	9676 11	100093.175	5
Pesticide	212682.69	96615	0.264	347.5	925	2335.53	3
Yield	923.0	14095	0.0	0.683	3333	1.1255	5
Crop Crop_Year Season	75% NaN 2017.0 NaN		max NaN 2020.0 NaN				

```
State
                        NaN
                                      NaN
Area
                    56567.5
                               10216517.0
Production
                  108095.75
                             6200900000.0
Annual Rainfall
                     1593.9
                                   5649.1
Fertilizer
                 8878633.35
                             1754788960.0
                              3780111.29
Pesticide
                   18940.05
Yield
                   2.699125
                                  21105.0
data.isnull().sum()
Crop
                   0
Crop_Year
                   0
                   0
Season
State
                   0
                   0
Area
Production
                   0
Annual Rainfall
                   0
Fertilizer
                   0
Pesticide
                   0
Yield
                   0
dtype: int64
```

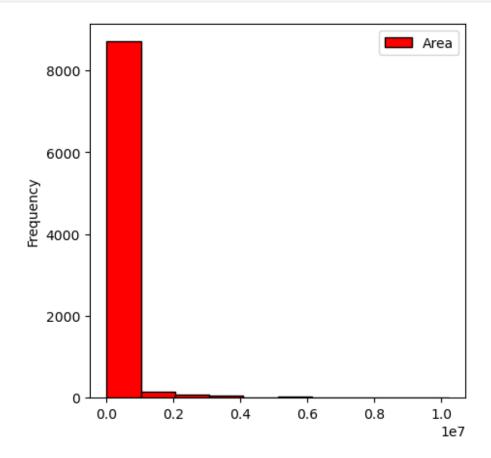
This shows that our data has no null values in it

data.head()										
	Crop Cr	op_Year	Se	eason	State	Area	Production			
0	Arecanut	2011	Kharif	Р	uducherry	60.0	77			
1	Bajra	2011	Kharif	Р	uducherry	11.0	29			
	-				_					
2	Bajra	2011	Summer	Р	uducherry	20.0	51			
3	Banana	2011	Kharif	Р	uducherry	266.0	3263			
4	Black pepper	2011	Kharif	Р	uducherry	11.0	5			
0	Annual_Rainfall 1434.5875	Fertili 10051		sticide 19.80	Yield 1.280000					
1 2	1434.5875	1842	.72	3.63	2.640000					
3	1434.5875 1434.5875	3350 44560		6.60 87.78	2.550000 10.903333					
4	1434.5875	1842	.72	3.63	0.450000					

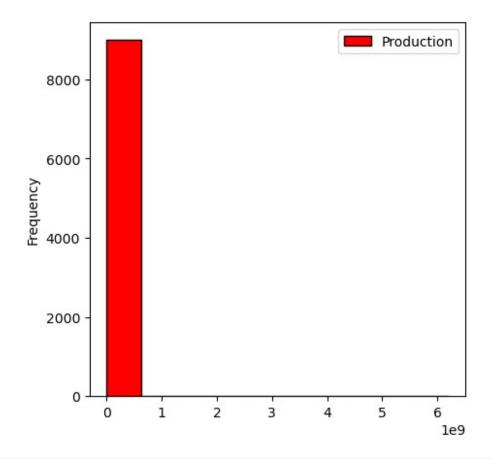
Exploratory Data Analysis

```
data['Area'].plot(kind='hist',figsize=(5,5),color='red',edgecolor='bla
ck')
```

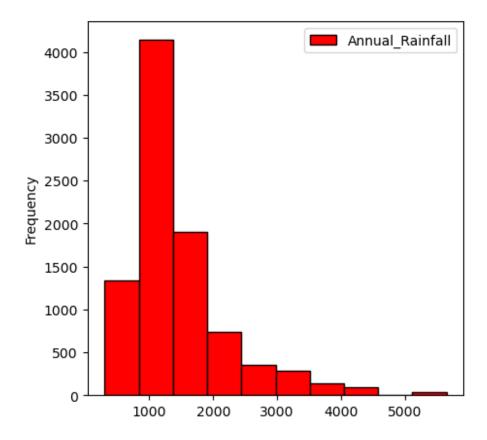
```
plt.legend()
plt.show()
```



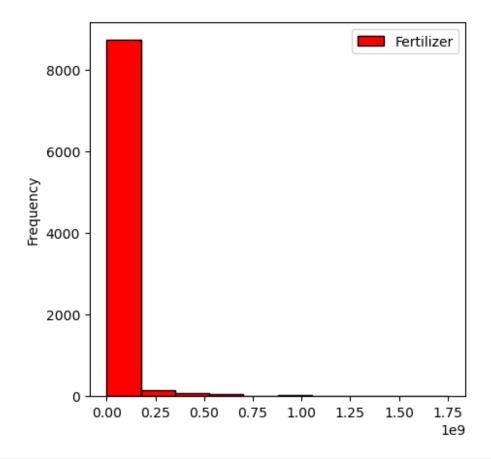
```
data['Production'].plot(kind='hist',figsize=(5,5),color='red',edgecolo
r='black')
plt.legend()
plt.show()
```



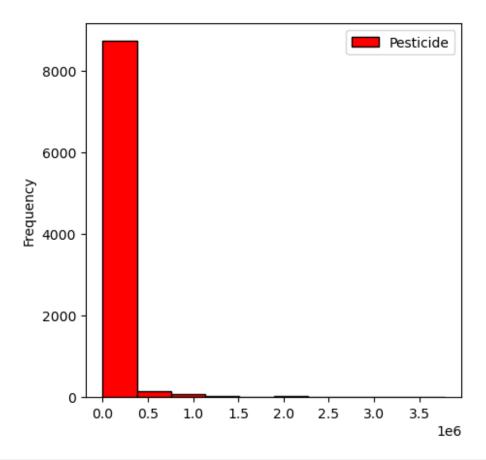
```
data['Annual_Rainfall'].plot(kind='hist',figsize=(5,5),color='red',edg
ecolor='black')
plt.legend()
plt.show()
```



```
data['Fertilizer'].plot(kind='hist',figsize=(5,5),color='red',edgecolo
r='black')
plt.legend()
plt.show()
```



```
data['Pesticide'].plot(kind='hist',figsize=(5,5),color='red',edgecolor
='black')
plt.legend()
plt.show()
```



```
from sklearn.model selection import train test split
from sklearn.linear model import LinearRegression
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from sklearn.metrics import mean_squared_error, r2_score
# List of categorical and numerical columns
categorical_columns = ['Crop', 'Season', 'State']
numerical columns = ['Crop Year', 'Area', 'Annual Rainfall',
'Fertilizer', 'Pesticide']
# Encoding categorical variables using one-hot encoding
data encoded = pd.get dummies(data, columns=categorical columns,
drop first=True)
# Standardizing numerical features
scaler = StandardScaler()
data encoded[numerical columns] =
scaler.fit transform(data encoded[numerical columns])
# Normalizing the target variable (Yield)
target scaler = MinMaxScaler()
data encoded['Yield'] =
target_scaler.fit_transform(data_encoded[['Yield']])
```

```
# Splitting features and target variable
X = data encoded.drop(columns=['Yield']) # Features
y = data encoded['Yield'] # Target
# Train-test splitting
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)
# Trainning the Linear Regression model
model = LinearRegression()
model.fit(X train, y train)
# Making predictions
y pred = model.predict(X test)
# Model eEvaluation
r2 = r2 score(y test, y pred)
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
# Print evaluation metrics
print(f"R2 Score: {r2:.4f}")
print(f"Mean Squared Error (MSE): {mse:.4f}")
print(f"Root Mean Squared Error (RMSE): {rmse:.4f}")
R<sup>2</sup> Score: 0.8541
Mean Squared Error (MSE): 0.0004
Root Mean Squared Error (RMSE): 0.0191
sorted indices = np.argsort(y test)
y_test_sorted = y_test.iloc[sorted_indices]
y pred sorted = y pred[sorted indices]
# Plotting the Actual vs. Predicted with Fit Line
plt.figure(figsize=(8, 6))
plt.plot(y_test_sorted, y_pred sorted, color='blue', label='Fit Line')
plt.scatter(range(len(y_test_sorted)), y_test_sorted, color='red',
label='Actual Values', alpha=0.6)
plt.scatter(range(len(y pred sorted)), y pred sorted, color='green',
label='Predicted Values', alpha=0.6)
plt.xlabel("Index")
plt.vlabel("Yield (Normalized)")
plt.title("Fit Line for Linear Regression")
plt.legend()
plt.grid(True)
plt.show()
```



