Community mapping- Prediction of crops based on environmental conditions

In [157…
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from xgboost import XGBClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.feature_selection import RFECV
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split,RandomizedSearchCV,KFold
from sklearn.metrics import accuracy_score,confusion_matrix,ConfusionMatrixDisplay,classification_report,precis
from matplotlib.colors import LinearSegmentedColormap
import plotly.express as px
from imblearn.over_sampling import RandomOverSampler
import warnings
warnings.filterwarnings("ignore")
```

In [158…
```
crops = pd.read_csv("vijayawada_guntur_soil_climate_data_subset.csv")
```

In [159…
```
crops.shape[0]
```

Out[159… 150

In [160…
```
crops.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 6 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   Latitude            150 non-null    float64
 1   Longitude           150 non-null    float64
 2   Soil_Type           150 non-null    object 
 3   Precipitation (mm)  150 non-null    int64  
 4   Temperature (Â°C)   150 non-null    float64
 5   class               150 non-null    object 
dtypes: float64(3), int64(1), object(2)
memory usage: 7.2+ KB
```

In [161…
```
crops.describe()
```

Out[161…

	Latitude	Longitude	Precipitation (mm)	Temperature (Â°C)
count	150.000000	150.000000	150.000000	150.000000
mean	16.114753	80.517522	147.106667	30.764667
std	0.385490	0.291412	79.038955	5.254492
min	15.507179	80.005062	0.000000	22.300000
25%	15.779216	80.247478	84.500000	25.875000
50%	16.082545	80.556001	150.500000	30.600000
75%	16.474560	80.757838	215.500000	35.500000
max	16.782953	80.990054	291.000000	40.000000

List of Attributes within the dataset

In [162…
```
columns = [column for column in crops]
print(columns)
```

```
['Latitude', 'Longitude', 'Soil_Type', 'Precipitation (mm)', 'Temperature (Â°C)', 'class']
```

In [163…
```
categorical=pd.DataFrame(columns=['Categorical Columns','Unique Values'])
object_columns=list(crops.columns[crops.dtypes=='O'])
for columns in object_columns:
    unique_val= crops[columns].unique()
    categorical= pd.concat([categorical, pd.DataFrame({'Categorical Columns': [columns], 'Unique Values': [uniq
categorical
```

Out[163…

	Categorical Columns	Unique Values
0	Soil_Type	[Clay Loam, Alluvial Soil, Sandy Loam, Red Soil]
1	class	[Rice, Chilli, Maize, Turmeric, Sugarcane, Mil...

In [164…
```
Continuous=pd.DataFrame(columns=['Continuous Columns','Unique Values'])
nonobject_columns=list(crops.columns[crops.dtypes!='O'])
for columns in nonobject_columns:
    unique_val= crops[columns].unique()
    Continuous = pd.concat([Continuous, pd.DataFrame({'Continuous Columns': [columns], 'Unique Values': [unique_
Continuous
```

Out[164…

	Continuous Columns	Unique Values
0	Latitude	[15.986902154501571, 16.73592859833289, 16.451...
1	Longitude	[80.90826588596666, 80.23956189066698, 80.1448...
2	Precipitation (mm)	[263, 92, 89, 114, 104, 195, 113, 74, 216, 276...
3	Temperature (Â°C)	[27.6, 36.6, 34.3, 24.9, 38.4, 36.8, 39.1, 35....

Dropping irrelevant attribute

In [165…
```
updated_crops = crops.drop(columns=["Latitude","Longitude"])
```

Checking for Null values

In [166…
```
updated_crops.isnull().sum()
```

Out[166…
```
Soil_Type             0
Precipitation (mm)    0
Temperature (Â°C)      0
class                 0
dtype: int64
```

In [167…
```
classes = list(crops["class"].unique())
classes
```

Out[167…
```
['Rice',
 'Chilli',
 'Maize',
 'Turmeric',
 'Sugarcane',
 'Millet',
 'Cotton',
 'Groundnut']
```

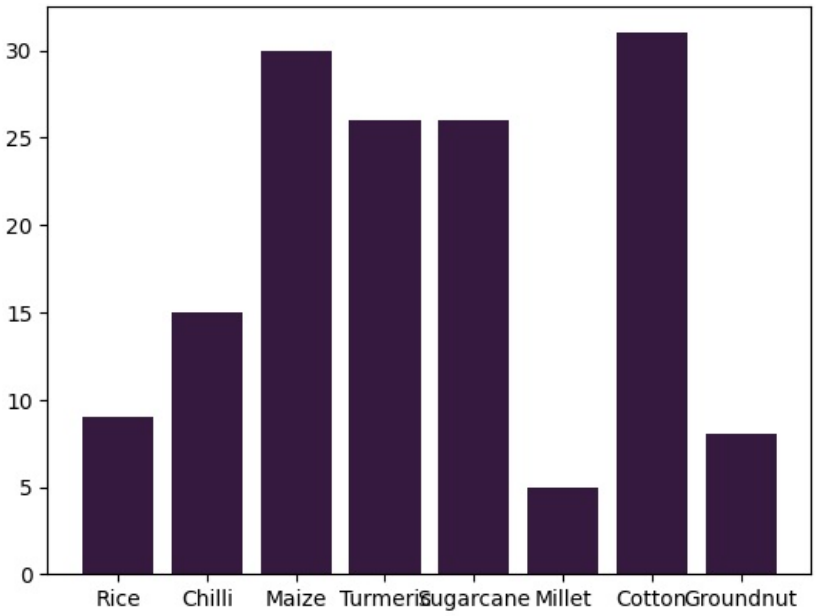
In [168…
```
updated_crops.isnull().sum()
```

Out[168…
```
Soil_Type             0
Precipitation (mm)    0
Temperature (Â°C)      0
class                 0
dtype: int64
```

Univariate Analysis

In [169…
```
Counts = []
for i in classes:
    Counts.append(len(updated_crops[updated_crops["class"]=="{}".format(i)]))
```

In [170…
```
sns.set_palette("rocket")
plt.bar(classes,Counts)
plt.show()
```



In [171…
```
column_classes = ["Soil_Type","Class"]
```

In [172…
```
updated_crops.columns
```

Out[172… `Index(['Soil_Type', 'Precipitation (mm)', 'Temperature (Â°C)', 'class'], dtype='object')`

Data Transformation

In [173…
```
label_enc=LabelEncoder()
cla={}
for i in categorical.iloc[[0,1]]['Categorical Columns']:
    updated_crops[i] = label_enc.fit_transform(updated_crops[i])
    cla[f"{i}"]=label_enc.classes_
    encoding_mapping = dict(zip(label_enc.classes_, range(len(label_enc.classes_))))
    print(encoding_mapping)
```

```
{'Alluvial Soil': 0, 'Clay Loam': 1, 'Red Soil': 2, 'Sandy Loam': 3}
{'Chilli': 0, 'Cotton': 1, 'Groundnut': 2, 'Maize': 3, 'Millet': 4, 'Rice': 5, 'Sugarcane': 6, 'Turmeric': 7}
```

In [174…
```
updated_crops.head()
```

Out[174…

	Soil_Type	Precipitation (mm)	Temperature (Â°C)	class
0	1	263	27.6	5
1	0	92	36.6	0
2	0	89	34.3	0
3	3	114	24.9	3
4	2	104	38.4	7

In [175…
```
print(cla)
```

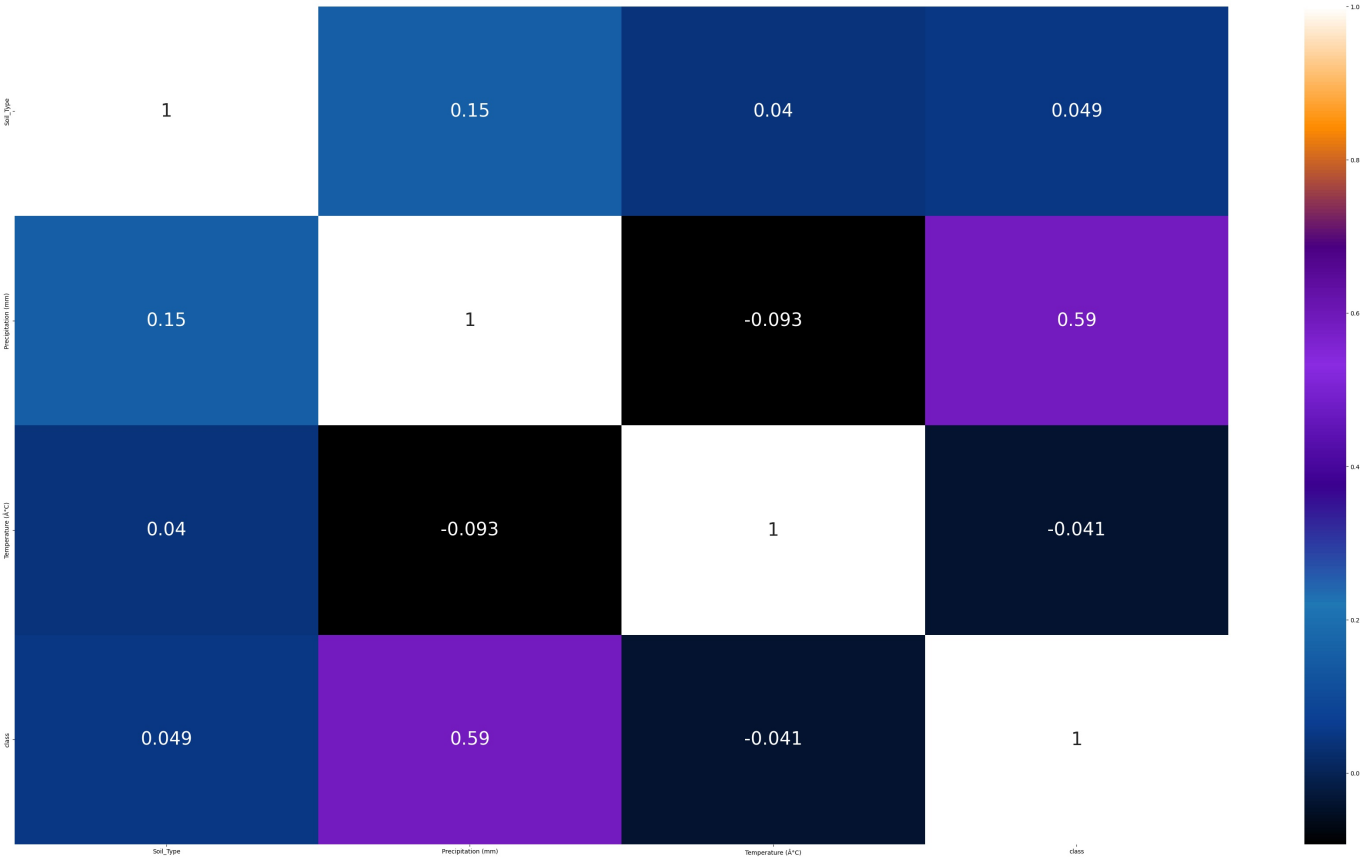
```
{'Soil_Type': array(['Alluvial Soil', 'Clay Loam', 'Red Soil', 'Sandy Loam'],
      dtype=object), 'class': array(['Chilli', 'Cotton', 'Groundnut', 'Maize', 'Millet', 'Rice',
       'Sugarcane', 'Turmeric'], dtype=object)}
```

In [176…
```
classes_encoded = list(updated_crops["class"].unique())
classes_encoded
```

Out[176… `[5, 0, 3, 7, 6, 4, 1, 2]`

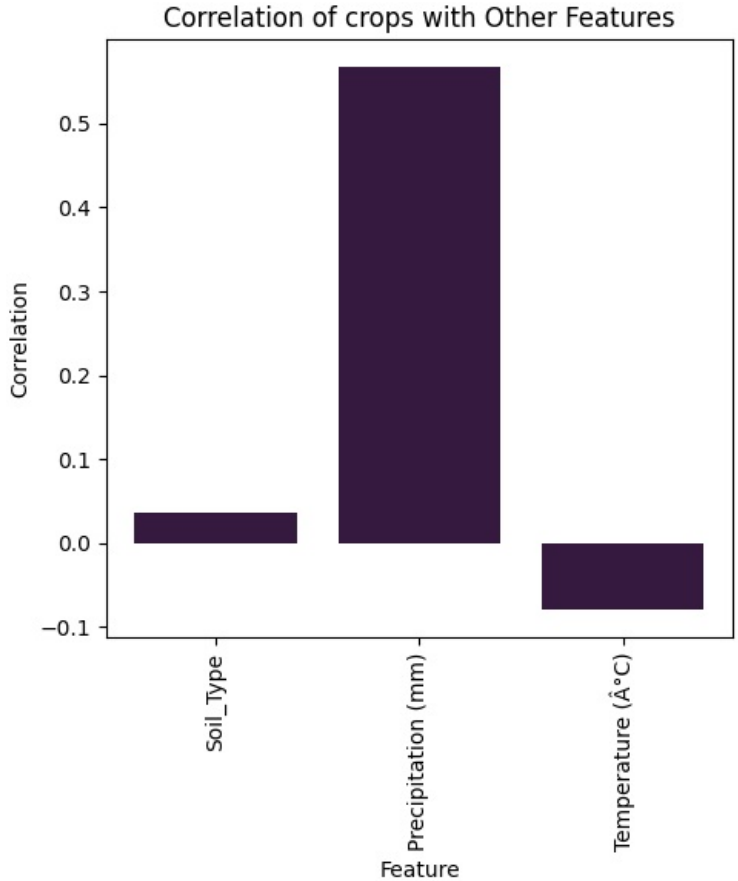
In [177…
```
analysis_columns =list(updated_crops.columns[updated_crops.dtypes!='O'])
correlation_matrix = updated_crops[analysis_columns].corr()
```

In [178…
```
plt.figure(figsize=(45,25))
space_colors = ["#000000", "#0b3d91", "#1f77b4", "#3b008f", "#8a2be2", "#4b0082", "#ff8c00", "#ffffff"]
space_cmap = LinearSegmentedColormap.from_list("space_cmap", space_colors)
sns.heatmap(correlation_matrix,annot = True,cmap=space_cmap,annot_kws={"size":30})
plt.show()
```



In [232…

```
correlation_dict = {}
for col in updated_crops.drop(columns=['class']).columns:
  correlation_dict[col] = updated_crops['class'].corr(updated_crops[col])
correlation_values = list(correlation_dict.values())
column_names = list(correlation_dict.keys())
plt.figure(figsize=(5, 6))
plt.bar(column_names, correlation_values)
plt.xlabel('Feature')
plt.ylabel('Correlation')
plt.title('Correlation of crops with Other Features')
plt.xticks(rotation=90)
plt.tight_layout()
```



Training and Testing Model

In [180…
```
test_size = int(0.3*(updated_crops.shape[0]))
test_data = updated_crops.sample(test_size,random_state=42)
updated_crops.drop(test_data.index,inplace=True)
```

In [181…
```
Xtest = test_data.drop(columns=["class"],axis=1)
ytest = test_data['class']
```

balancing imbalanced data by undersampling

In [182…
```
x = updated_crops.drop(columns=["class"],axis=1)
y = updated_crops["class"]
ros = RandomOverSampler(random_state = 42)
X_resampled,y_resampled = ros.fit_resample(x,y)
```

Balanced data

In [183…
```
print(y.value_counts())
print(y_resampled.value_counts())
```

```
class
3    22
6    20
1    19
7    17
0    13
2     7
5     5
4     2
Name: count, dtype: int64
class
5    22
0    22
3    22
7    22
6    22
1    22
2    22
4    22
Name: count, dtype: int64
```

In [184…
```
print(X_resampled.shape)
print(y_resampled.shape)
```

```
(176, 3)
(176,)
```

In [185…
```
kf=KFold(n_splits=15,random_state=42,shuffle=True)
Accuracy,All_prec,All_rec,test_recall,test_accuracy,test_precision = {},{},{},{},{},{}
```

RANDOM FOREST CLASSIFIER

In [186…
```
rfc = RandomForestClassifier()
```

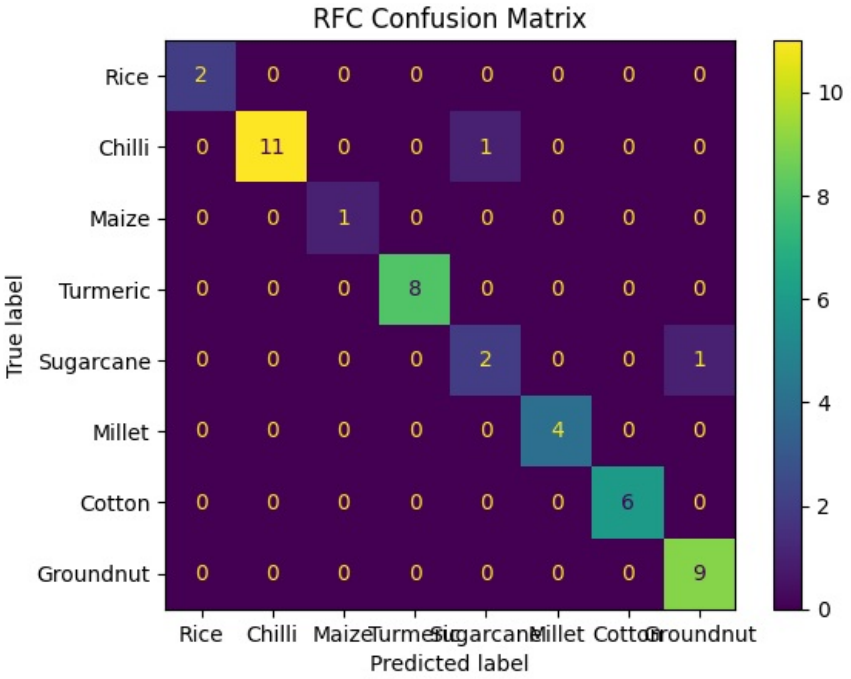
In [187…
```
X_train, X_test, y_train, y_test = train_test_split(X_resampled, y_resampled,train_size=0.7,random_state=42)
rfc.fit(X_train,y_train)
y_pred= rfc.predict(X_test)
print(f'Accuracy:{accuracy_score(y_test,y_pred)*100:.4f}%')
```

```
Accuracy:100.0000%
```

In [188…
```
y_pred = rfc.predict(Xtest)
print(f'Unseen Data Accuracy:{accuracy_score(ytest,y_pred)*100:.4f}%')
```

```
Unseen Data Accuracy:95.5556%
```

In [189…
```
confusion_mat = confusion_matrix(ytest,y_pred)
cm_display = ConfusionMatrixDisplay(confusion_matrix = confusion_mat, display_labels = classes)
cm_display.plot()
plt.title("RFC Confusion Matrix")
plt.show()
```



In [190…
```
print(classification_report(ytest,y_pred))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00         2
           1       1.00      0.92      0.96        12
           2       1.00      1.00      1.00         1
           3       1.00      1.00      1.00         8
           4       0.67      0.67      0.67         3
           5       1.00      1.00      1.00         4
           6       1.00      1.00      1.00         6
           7       0.90      1.00      0.95         9

    accuracy                           0.96        45
   macro avg       0.95      0.95      0.95        45
weighted avg       0.96      0.96      0.96        45
```

In [191…
```
param_dist = {
    'n_estimators': [10, 50],
    'max_depth':[3, 5, 10, 15],
    'min_samples_split': [2, 4],
    'min_samples_leaf': [1, 2],
    'max_features': ['auto', 'sqrt']
}
```

In [192…
```
random_search = RandomizedSearchCV(estimator=rfc,param_distributions=param_dist,scoring="accuracy",cv=10)
random_search.fit(X_train, y_train)
```

Out[192…
```
▸ RandomizedSearchCV
▸ best_estimator_: RandomForestClassifier
    ▸ RandomForestClassifier
```

In [193…
```
best_params = random_search.best_params_
max_depth = best_params['max_depth']
n_estimators = best_params['n_estimators']
min_sample_split = best_params['min_samples_split']
min_sample_leaf = best_params['min_samples_leaf']
best_params
```

Out[193…
```
{'n_estimators': 50,
 'min_samples_split': 4,
 'min_samples_leaf': 1,
 'max_features': 'sqrt',
 'max_depth': 3}
```

In [194…
```
best_rfc=RandomForestClassifier(n_estimators=n_estimators,min_samples_split=min_sample_split, min_samples_leaf=
```

In [195…
```
scores=[]
precision= []
recall=[]
```

```
for train_index, test_index in kf.split(X_resampled,y_resampled):
  X_train, X_test = X_resampled.iloc[train_index], X_resampled.iloc[test_index]
  y_train, y_test = y_resampled.iloc[train_index], y_resampled.iloc[test_index]
  best_rfc.fit(X_train, y_train)
  y_pred=best_rfc.predict(X_test)
  prec = precision_score(y_test,y_pred,average = 'macro')
  rec = recall_score(y_test,y_pred,average = 'macro')
  score = accuracy_score(y_test,y_pred)
  precision.append(prec)
  scores.append(score)
  recall.append(rec)
  print(f'Fold Score: {score}')
```

```
Fold Score: 1.0
Fold Score: 1.0
Fold Score: 1.0
Fold Score: 0.9166666666666666
Fold Score: 0.9166666666666666
Fold Score: 1.0
Fold Score: 0.9166666666666666
Fold Score: 0.8333333333333334
Fold Score: 1.0
Fold Score: 0.9166666666666666
Fold Score: 1.0
Fold Score: 0.9090909090909091
Fold Score: 0.9090909090909091
Fold Score: 1.0
Fold Score: 0.7272727272727273
```

In [196…

```
average_score = sum(scores) / len(scores)
average_precision = sum(precision)/len(precision)
average_recall = sum(recall)/len(recall)
Accuracy['Random Forest'] = average_score
All_prec['Random Forest'] = average_precision
All_rec['Random Forest'] = average_recall
print(f'Average Cross-Validation Score: {average_score*100:.4f}')
print(f'Average Precision score: {average_precision*100:.4f}')
print(f'Average Recall score: {average_recall*100:.4f}')
```

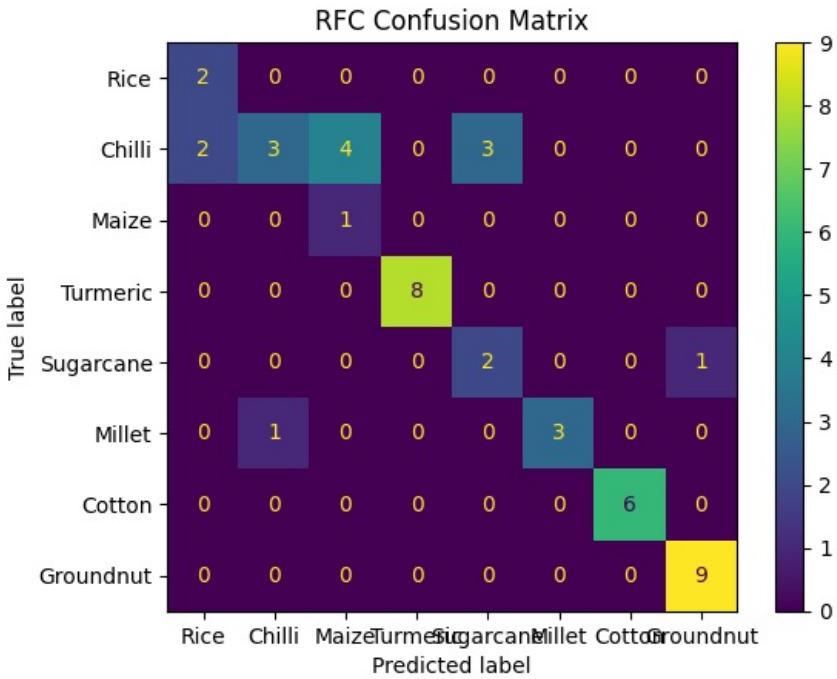
```
Average Cross-Validation Score: 93.6364
Average Precision score: 93.4101
Average Recall score: 92.9074
```

In [197…

```
y_pred=best_rfc.predict(Xtest)
test_accuracy['Random Forest'] = accuracy_score(ytest,y_pred)
test_precision['Random Forest'] = precision_score(ytest,y_pred,average="macro")
test_recall['Random Forest'] = recall_score(ytest,y_pred,average="macro")
```

In [198…

```
confusion_mat=confusion_matrix(ytest,y_pred)
cm_display = ConfusionMatrixDisplay(confusion_matrix = confusion_mat, display_labels = classes)
cm_display.plot()
plt.title('RFC Confusion Matrix')
plt.show()
```



In [199…

```
print(classification_report(ytest,y_pred))
```

	precision	recall	f1-score	support
0	0.50	1.00	0.67	2
1	0.75	0.25	0.38	12
2	0.20	1.00	0.33	1
3	1.00	1.00	1.00	8
4	0.40	0.67	0.50	3
5	1.00	0.75	0.86	4
6	1.00	1.00	1.00	6
7	0.90	1.00	0.95	9
accuracy			0.76	45
macro avg	0.72	0.83	0.71	45
weighted avg	0.83	0.76	0.75	45

XGB CLASSIFIER

In [200…
```
xgb_model = XGBClassifier()
```

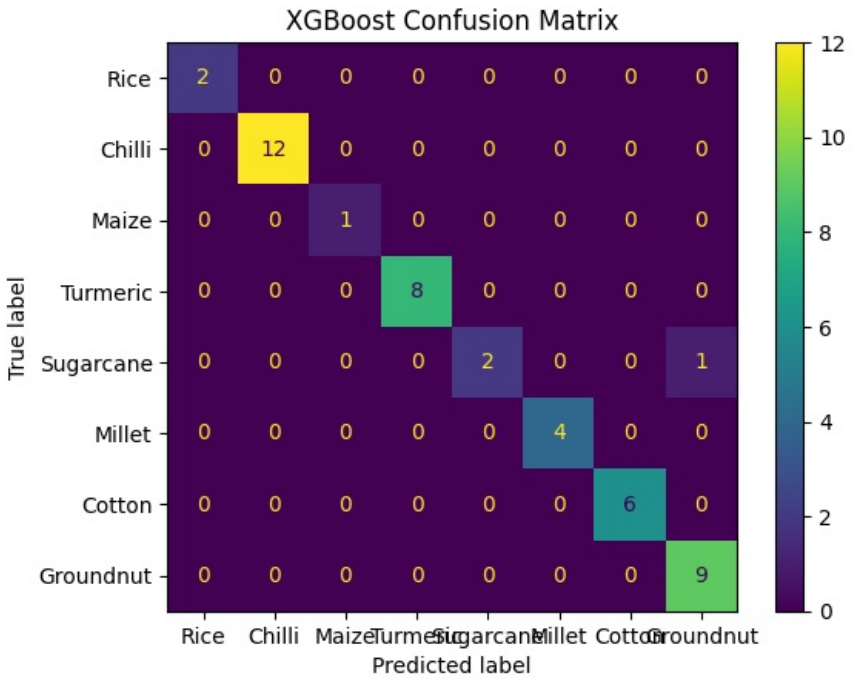
In [201…
```
X_train, X_test, y_train, y_test = train_test_split(X_resampled, y_resampled,test_size=0.3,random_state=42)
xgb_model.fit(X_train,y_train)
y_pred= xgb_model.predict(X_test)
print(f'Accuracy:{accuracy_score(y_test,y_pred)*100:.4f}%')
```

```
Accuracy:100.0000%
```

In [202…
```
y_pred = xgb_model.predict(Xtest)
print(f'Unseen Data Accuracy:{accuracy_score(ytest,y_pred)*100:.4f}%')
```

```
Unseen Data Accuracy:97.7778%
```

In [203…
```
confusion_mat = confusion_matrix(ytest,y_pred)
cm_display = ConfusionMatrixDisplay(confusion_matrix = confusion_mat, display_labels = classes)
cm_display.plot()
plt.title("XGBoost Confusion Matrix")
plt.show()
```



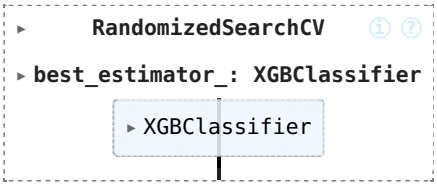
In [204…
```
print(classification_report(ytest,y_pred))
```

	precision	recall	f1-score	support
0	1.00	1.00	1.00	2
1	1.00	1.00	1.00	12
2	1.00	1.00	1.00	1
3	1.00	1.00	1.00	8
4	1.00	0.67	0.80	3
5	1.00	1.00	1.00	4
6	1.00	1.00	1.00	6
7	0.90	1.00	0.95	9
accuracy			0.98	45
macro avg	0.99	0.96	0.97	45
weighted avg	0.98	0.98	0.98	45

In [205…
```
param_dist = {
    'learning_rate': [0.001,0.01],
    'n_estimators': [10, 100],
    'min_child_weight': [1, 3, 5],
    'gamma': [0, 0.1],
    'reg_lambda':[1,10],
    'reg_alpha':[0.01,0.05]
}
```

In [206…
```
random_search = RandomizedSearchCV(estimator=xgb_model,param_distributions=param_dist,scoring="accuracy",cv=5)
random_search.fit(X_train,y_train)
```

Out[206…



In [207…
```
best_params = random_search.best_params_
learning_rate = best_params['learning_rate']
n_estimators = best_params['n_estimators']
min_child_weight = best_params['min_child_weight']
gamma = best_params['gamma']
reg_lambda = best_params['reg_lambda']
reg_alpha = best_params['reg_alpha']
```

In [208…
```
best_xgb=XGBClassifier(learning_rate=learning_rate, n_estimators=n_estimators,min_child_weight=min_child_weight
```

In [209…
```
scores=[]
precision = []
recall = []
for train_index, test_index in kf.split(X_resampled,y_resampled):
  X_train, X_test = X_resampled.iloc[train_index], X_resampled.iloc[test_index]
  y_train, y_test = y_resampled.iloc[train_index], y_resampled.iloc[test_index]
  best_xgb.fit(X_train, y_train)
  y_pred = best_xgb.predict(X_test)
  score = accuracy_score(y_test,y_pred)
  prec = precision_score(y_test,y_pred,average="macro")
  rec = recall_score(y_test,y_pred,average="macro")
  scores.append(score)
  precision.append(prec)
  recall.append(rec)
  print(f'Fold Score: {score}')
```

```
Fold Score: 1.0
Fold Score: 1.0
Fold Score: 1.0
Fold Score: 1.0
Fold Score: 1.0
Fold Score: 1.0
Fold Score: 1.0
Fold Score: 1.0
Fold Score: 1.0
Fold Score: 1.0
Fold Score: 1.0
Fold Score: 1.0
Fold Score: 1.0
Fold Score: 1.0
Fold Score: 1.0
```

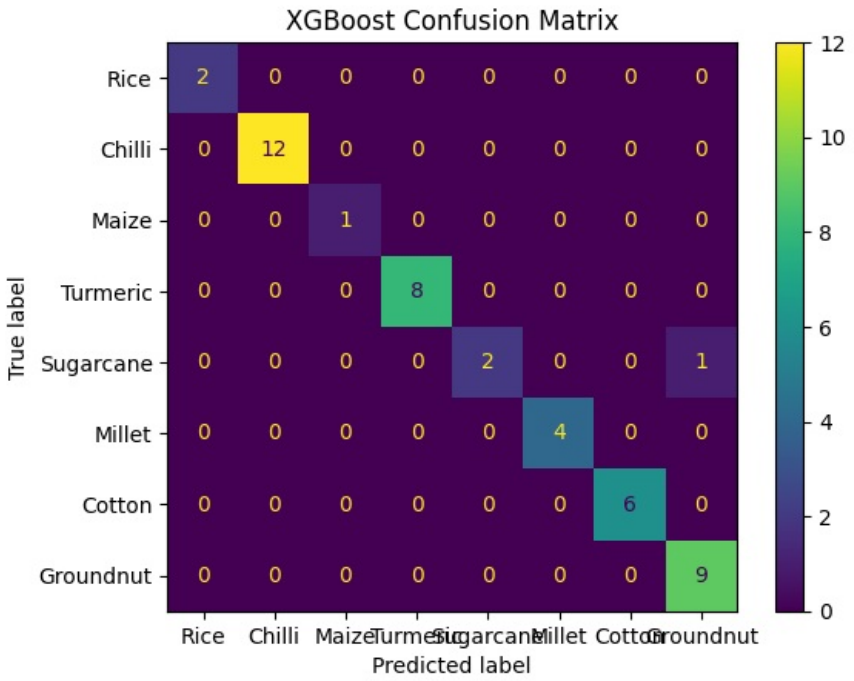
In [210…
```
average_score = sum(scores) / len(scores)
average_precision = sum(precision)/len(precision)
average_recall = sum(recall)/len(recall)
Accuracy['XGBoost'] = average_score
All_prec['XGBoost'] = average_precision
All_rec['XGBoost'] = average_recall
print(f'Average Cross-Validation Score: {average_score*100:.4f}')
print(f'Average Precision score: {average_precision*100:.4f}')
print(f'Average Recall score: {average_recall*100:.4f}')
```

```
Average Cross-Validation Score: 100.0000
Average Precision score: 100.0000
Average Recall score: 100.0000
```

In [211…
```
y_pred = best_xgb.predict(Xtest)
test_accuracy['XGBoost'] = accuracy_score(ytest,y_pred)
test_precision['XGBoost'] = precision_score(ytest,y_pred,average="macro")
test_recall['XGBoost'] = recall_score(ytest,y_pred,average="macro")
```

In [212…
```
confusion_mat=confusion_matrix(y_pred=y_pred,y_true=ytest)
cm_display = ConfusionMatrixDisplay(confusion_matrix = confusion_mat, display_labels = classes)
```

```
cm_display.plot()
plt.title('XGBoost Confusion Matrix')
plt.show()
```



In [213…
```
print(classification_report(ytest,y_pred))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00         2
           1       1.00      1.00      1.00        12
           2       1.00      1.00      1.00         1
           3       1.00      1.00      1.00         8
           4       1.00      0.67      0.80         3
           5       1.00      1.00      1.00         4
           6       1.00      1.00      1.00         6
           7       0.90      1.00      0.95         9

    accuracy                           0.98        45
   macro avg       0.99      0.96      0.97        45
weighted avg       0.98      0.98      0.98        45
```

LOGISTIC REGRESSION

In [214…
```
lr = LogisticRegression()
```

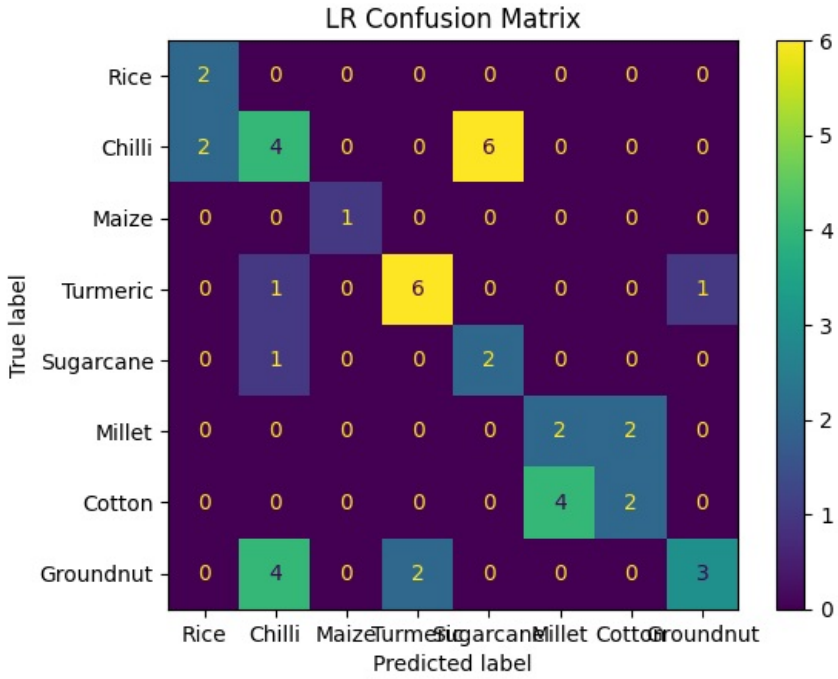
In [215…
```
X_train, X_test, y_train, y_test = train_test_split(X_resampled, y_resampled,test_size=0.3,random_state=42)
lr.fit(X_train,y_train)
y_pred= lr.predict(X_test)
print(f'Accuracy:{accuracy_score(y_test,y_pred)*100:.4f}%')
```

```
Accuracy:79.2453%
```

In [216…
```
y_pred = lr.predict(Xtest)
print(f'Unseen Data Accuracy:{accuracy_score(ytest,y_pred)*100:.4f}%')
```

```
Unseen Data Accuracy:48.8889%
```

In [217…
```
confusion_mat = confusion_matrix(ytest,y_pred)
cm_display = ConfusionMatrixDisplay(confusion_matrix = confusion_mat, display_labels = classes)
cm_display.plot()
plt.title("LR Confusion Matrix")
plt.show()
```



In [218…
```
print(classification_report(ytest,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.50      1.00      0.67         2
           1       0.40      0.33      0.36        12
           2       1.00      1.00      1.00         1
           3       0.75      0.75      0.75         8
           4       0.25      0.67      0.36         3
           5       0.33      0.50      0.40         4
           6       0.50      0.33      0.40         6
           7       0.75      0.33      0.46         9

    accuracy                           0.49        45
   macro avg       0.56      0.61      0.55        45
weighted avg       0.55      0.49      0.49        45
```

In [219…
```
param_dist = {
    'C': [0.001, 0.01, 0.1, 1, 10, 100],
    'solver': ['liblinear', 'lbfgs']
}
```

In [220…
```
grid_search = RandomizedSearchCV(estimator=lr,param_distributions=param_dist,scoring='accuracy',cv=10)
grid_search.fit(X_train,y_train)
```

Out[220…

▸ RandomizedSearchCV

▸ best_estimator_: LogisticRegression

▸ LogisticRegression

In [221…
```
best_params = grid_search.best_params_
C = best_params['C']
Solver = best_params['solver']
best_lr = LogisticRegression(C=C,solver=Solver)
```

In [222…
```
scores=[]
precision =[]
recall = []
for train_index, test_index in kf.split(X_resampled,y_resampled):
  X_train, X_test = X_resampled.iloc[train_index], X_resampled.iloc[test_index]
  y_train, y_test = y_resampled.iloc[train_index], y_resampled.iloc[test_index]
  best_lr.fit(X_train, y_train)
  y_pred=best_lr.predict(X_test)
  prec = precision_score(y_test,y_pred,average="macro")
  rec = recall_score(y_test,y_pred,average='macro')
  score = best_lr.score(X_test, y_test)
  scores.append(score)
  precision.append(prec)
  recall.append(rec)
  print(f'Fold Score: {score}')
```

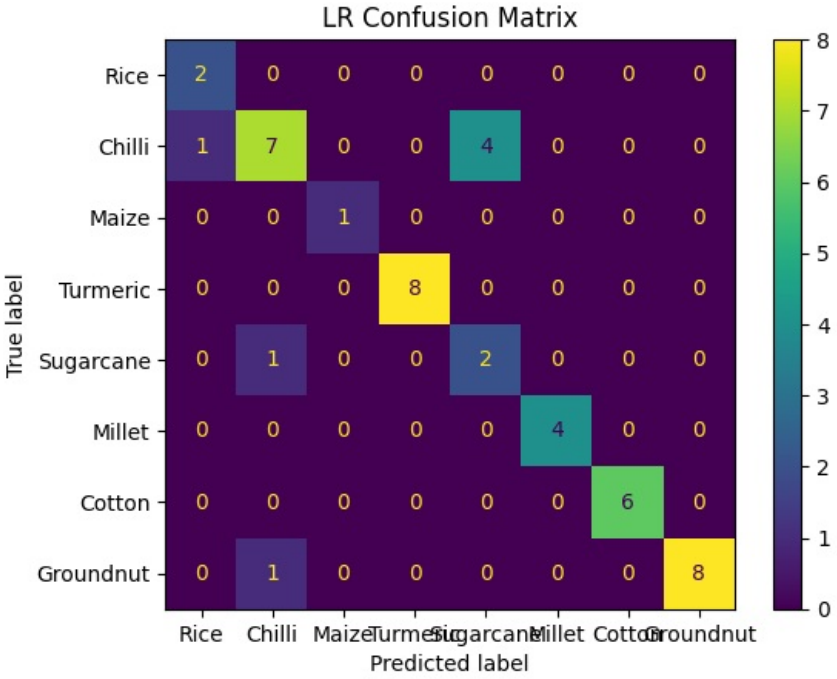
```
Fold Score: 0.8333333333333334
Fold Score: 1.0
Fold Score: 0.9166666666666666
Fold Score: 0.9166666666666666
Fold Score: 0.9166666666666666
Fold Score: 1.0
Fold Score: 0.8333333333333334
Fold Score: 0.75
Fold Score: 1.0
Fold Score: 0.9166666666666666
Fold Score: 0.9166666666666666
Fold Score: 0.9090909090909091
Fold Score: 0.8181818181818182
Fold Score: 1.0
Fold Score: 0.5454545454545454
```

In [223…
```
average_score = sum(scores) / len(scores)
average_precision = sum(precision)/len(precision)
average_recall = sum(recall)/len(recall)
Accuracy['Logistic Regression'] = average_score
All_prec['Logistic Regression'] = average_precision
All_rec['Logistic Regression '] = average_recall
print(f'Average Cross-Validation Score: {average_score*100:.4f}')
print(f'Average Precision score: {average_precision*100:.4f}')
print(f'Average Recall score: {average_recall*100:.4f}')
```

```
Average Cross-Validation Score: 88.4848
Average Precision score: 83.7831
Average Recall score: 83.4788
```

In [224…
```
y_pred= best_lr.predict(Xtest)
test_accuracy['Logistic Regression'] = accuracy_score(ytest,y_pred)
test_recall['Logistic Regression'] = recall_score(ytest,y_pred,average="macro")
test_precision['Logistic Regression'] = precision_score(ytest,y_pred,average="macro")
```

In [225…
```
confusion_mat=confusion_matrix(y_pred=y_pred,y_true=ytest)
cm_display = ConfusionMatrixDisplay(confusion_matrix = confusion_mat, display_labels = classes)
cm_display.plot()
plt.title('LR Confusion Matrix')
plt.show()
```



In [226…
```
print(classification_report(y_pred=y_pred,y_true=ytest))
```

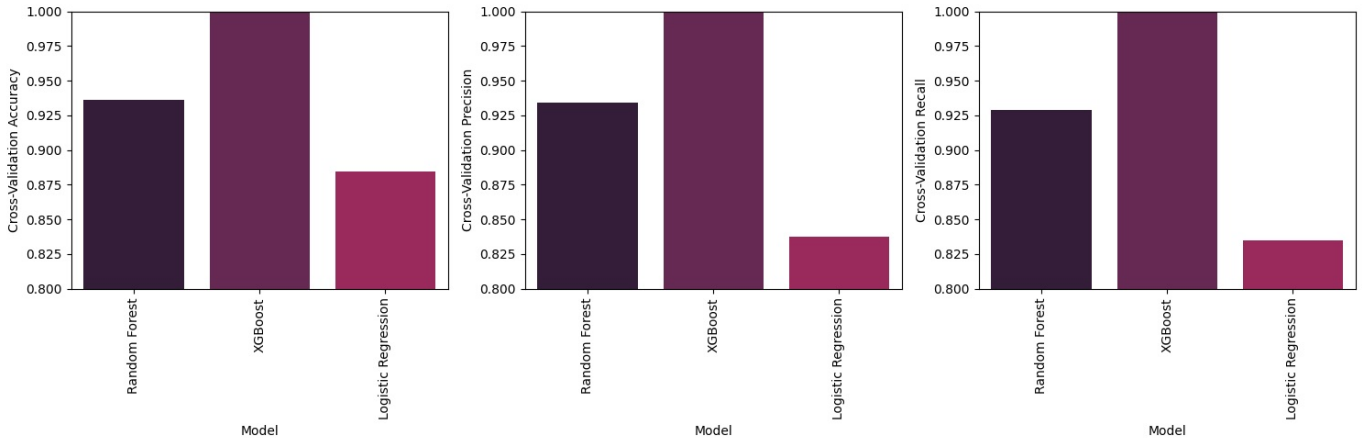
	precision	recall	f1-score	support
0	0.67	1.00	0.80	2
1	0.78	0.58	0.67	12
2	1.00	1.00	1.00	1
3	1.00	1.00	1.00	8
4	0.33	0.67	0.44	3
5	1.00	1.00	1.00	4
6	1.00	1.00	1.00	6
7	1.00	0.89	0.94	9
accuracy			0.84	45
macro avg	0.85	0.89	0.86	45
weighted avg	0.88	0.84	0.85	45

In [227…
```
model_name = [key for key in Accuracy.keys()]
model_accuracy = [acc for acc in Accuracy.values()]
model_precision = [prec for prec in All_prec.values()]
model_recall = [rec for rec in All_rec.values()]
model_data = pd.DataFrame([model_accuracy,model_precision,model_recall],index=['Accuracy','Precision','Recall']
model_data
```

Out[227…

	Random Forest	XGBoost	Logistic Regression
Accuracy	0.936364	1.0	0.884848
Precision	0.934101	1.0	0.837831
Recall	0.929074	1.0	0.834788

In [228…
```
plt.figure(figsize=(15,5))
plt.subplot(1,3,1)
sns.barplot(x=model_name,y=model_accuracy,hue=model_name)
plt.ylim(0.8,1)
plt.xlabel('Model')
plt.ylabel('Cross-Validation Accuracy')
plt.xticks(rotation=90)
plt.subplot(1,3,2)
sns.barplot(x=model_name,y=model_precision,hue=model_name)
plt.ylim(0.8,1)
plt.xticks(rotation=90)
plt.xlabel('Model')
plt.ylabel('Cross-Validation Precision')
plt.subplot(1,3,3)
sns.barplot(x=model_name,y=model_recall,hue=model_name)
plt.ylim(0.8,1)
plt.xticks(rotation=90)
plt.xlabel('Model')
plt.ylabel('Cross-Validation Recall')
plt.tight_layout()
plt.show()
```



XGBoost Overall Provides better Accuracy and Precision. Hence, will be the selected model for the time-being to classify the crops.