CROP RECOMMENDATION ON WARD REVITIZATION PROGRAM FOR BUSIA COUNTY GOVERNMENT

OBJECTIVE

The County Government of Busia County has initiated a plan to comercialise farming in the county.Over the years crop farming has been yielding very poor production.

This Project seeks to provide an insight on the better crops that the county can fund to ehnance better yields in its ward revitilization program.Ward Revitilization Program that is accelerated by need of the National Government Constructing Industrial Park in every County,will in the long run not just enhance food security in the county but also provide employment to young people.

For that and many reasons,methicks the county has to get it right on what crops need to be farmed and how climate change is affecting crop production.This project will help the County Government of Busia and other stakeholders on what crops to recommend to the farmers so that they can have increased production.

This Project will also enhance crop resilience to variations in climate change.In doing so it will mitigate losses that could occur during extreme weather events.

SCOPE

This Project seeks to cover Crop Farming in the Sub Counties of:

- Butula
- Matayos
- Nambale
- Bunyala
- Samia
- Teso South,Teso North and Teso Central

DATA COLLECTION

The Datasets used in this Project is sourced from:

County Agricultural Office,Busia

Sub County Agricultual Office,Butula

KALRO, Alupe Ofices.

This Data was combined from the above secondary sources into a dataset I have referred to as "Crop Recommendation Dataset".

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ATTRIBUTES

Categorical Atributes include:Maize,Apple,Banana,Sunflower,Cotton,Watermelon,Rice,Groundnuts,Arrowroots,Fingermillet,Sugarcane. Numerical Atributes include:

N(The ratio of Nitrogen content in the soil)

P(The ratio of Phosphorus content in the soil)

K(The ratio of Potassium content in the soil)

Temperature - temperature in degrees Celsius

Humidity - relative humidity in %

pH_Value - pH value of the soil

Rainfall - rainfall in mm

Data Exploration and Cleaning

```
#Importing The Libraries
from __future__ import print_function
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import classification_report
from sklearn import metrics
from sklearn import tree
import warnings
warnings.filterwarnings('ignore')
```

```
#Reading The File Path
busia=pd.read_csv("/content/CropRecommendation.csv")
```

```
#determining the first five rows
busia.head()
```

	N	P	K	temperature	humidity	ph	rainfall	label
0	90	42	43	21	82.002744	5.2	1000	rice
1	85	58	41	22	80.319644	5.2	1115	rice
2	60	55	44	23	82.320763	4.3	1130	rice
3	74	35	40	26	80.158363	5.2	1130	rice
4	78	42	42	20	81.604873	4.3	1138	rice

Next steps: Generate code with busia View recommended plots

```
#determining the file last five rows
busia.tail()
```

	N	P	K	temperature	humidity	ph	rainfall	label
1095	113	38	20	22	78.583201	5.1	752	cotton
1096	102	53	21	23	76.110215	5.2	752	cotton
1097	110	39	18	25	75.397527	4.3	752	cotton
1098	107	58	15	24	75.775038	4.3	752	cotton
1099	120	60	15	22	83.861300	5.2	752	cotton

```
#reading the file size
```

```
busia.size
```

```
8800
```

```
#reading the file shape
busia.shape
```

```
(1100, 8)
```

```
#reading the columns in the file
busia.columns
```

```
Index(['N', 'P', 'K', 'temperature', 'humidity', 'ph', 'rainfall', 'label'], dtype='object')
```

```
#reading the data in the label column
busia['label'].unique()
```

```
array(['rice', 'maize', 'sunflower', 'banana', 'sugarcane', 'watermelon',
       'arrowroots', 'fingermillet', 'groundnuts', 'cotton'], dtype=object)
```

```
#reading the data types
busia.dtypes
```

```
N               int64
P               int64
K               int64
temperature     int64
humidity      float64
ph            float64
rainfall        int64
label          object
dtype: object
```

```
busia['label'].value_counts()
```

```
label
sugarcane       200
rice            100
maize           100
sunflower       100
banana          100
watermelon      100
arrowroots      100
fingermillet    100
groundnuts      100
cotton          100
Name: count, dtype: int64
```

```
#Checking for missing values
busia.isnull().sum()
```

```
N              0
P              0
K              0
temperature    0
humidity       0
ph             0
rainfall       0
label          0
dtype: int64
```

There are no null values in the dataset

```
#Checking for duplicates
busia.duplicated().sum()
```

```
0
```

There are no duplicates in the file

```
#Cchecking statistic values
```

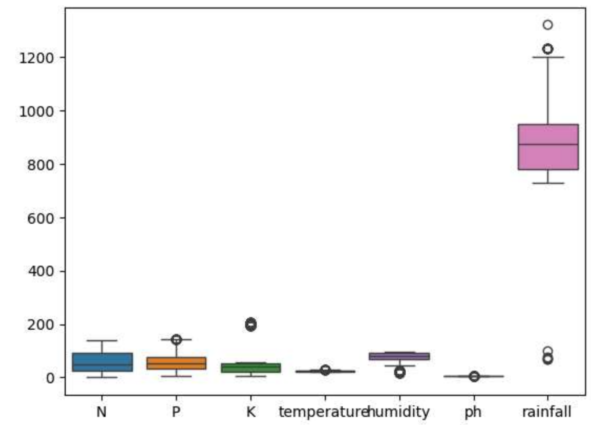


```
busia.describe()
```

	N	P	K	temperature	humidity	ph	
count	1100.000000	1100.000000	1100.000000	1100.000000	1100.000000	1100.000000	110
mean	57.211818	61.667273	62.682727	24.630909	74.842834	5.083273	89
std	38.679284	39.574123	66.211811	2.839047	20.891193	0.190618	13
min	0.000000	5.000000	5.000000	20.000000	18.092240	4.300000	6
25%	24.000000	35.000000	21.000000	23.000000	69.567073	5.100000	78
50%	49.000000	54.000000	40.000000	24.000000	81.972846	5.100000	87
75%	92.000000	78.000000	53.000000	26.000000	90.312475	5.200000	95
max	140.000000	145.000000	205.000000	31.000000	94.964199	5.200000	132

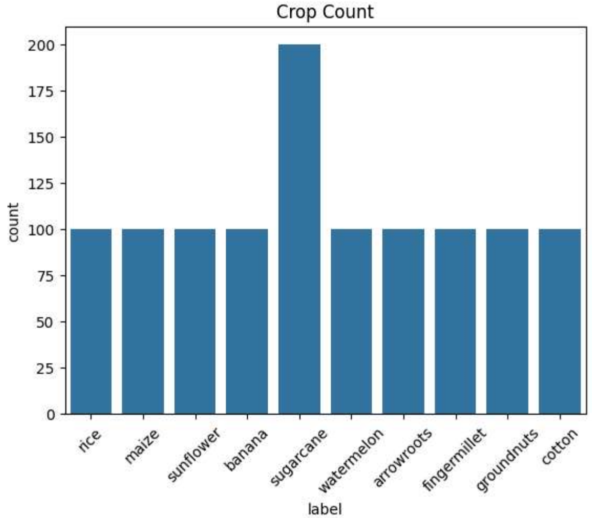
```
#Checking outliers
sns.boxplot(data=busia)
```

```
<Axes: >
```



It is evident that the rainfall distribution across the county on various crops is not consistent,therefore having such outliers.The rainfall distribution in the dataset ranges from 750mm to 1200mm. The content of Potassium in the soil also in the dataset is not evenly distributed.

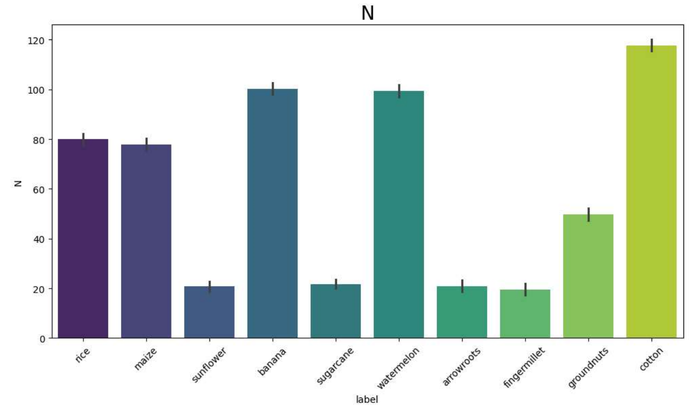
```
#creating bar plots
sns.countplot(x="label", data=busia)
plt.xticks(rotation=45)
plt.title("Crop Count")
plt.show()
```

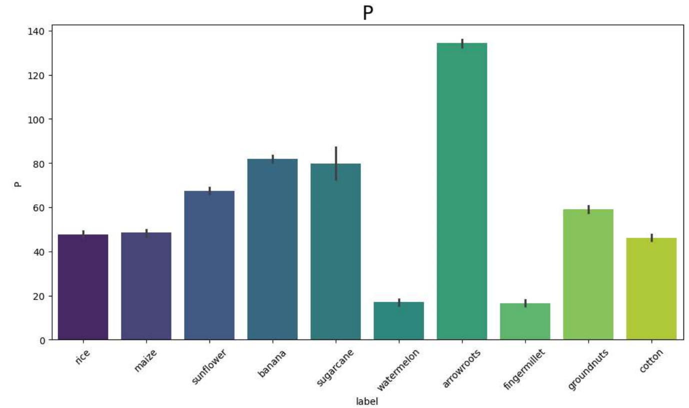


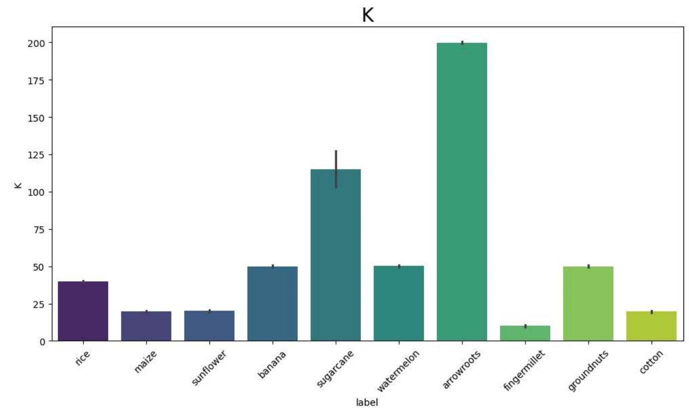
The dataset above shows the count of crops.Each crop has a count of 100 save for sugarcane.Sugarcane has a count of 200 representing the largest crop by count.

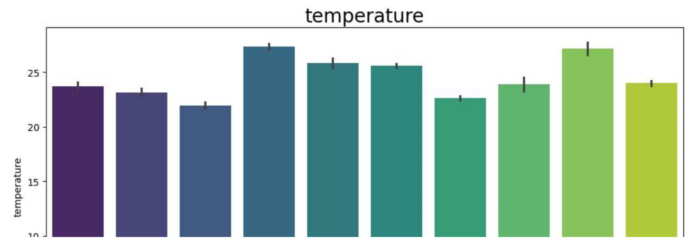
Visualization

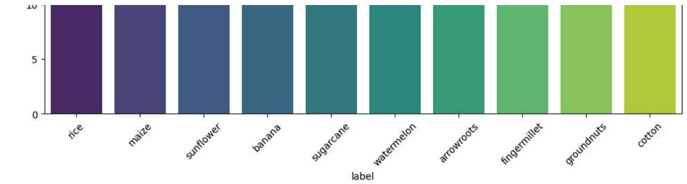
```
#Visualizing the dataset
columns = busia.select_dtypes(include = ['float64', 'int64']).columns

for col in columns:
    plt.figure(figsize = (12,6))
    plt.title(col, fontsize = 20)
    sns.barplot(x = 'label', y = col, palette = 'viridis', data = busia)
    plt.xticks(rotation = 45)
```

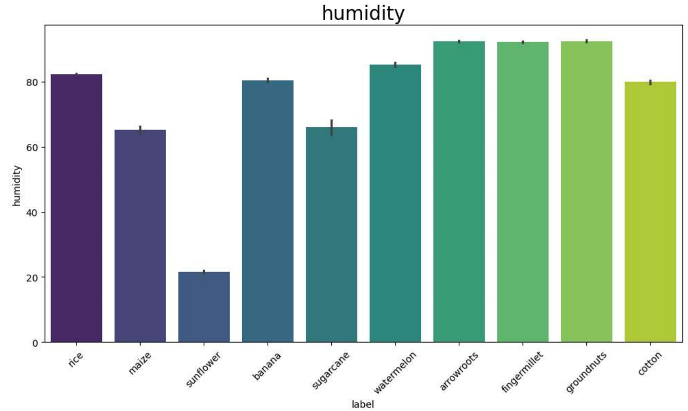



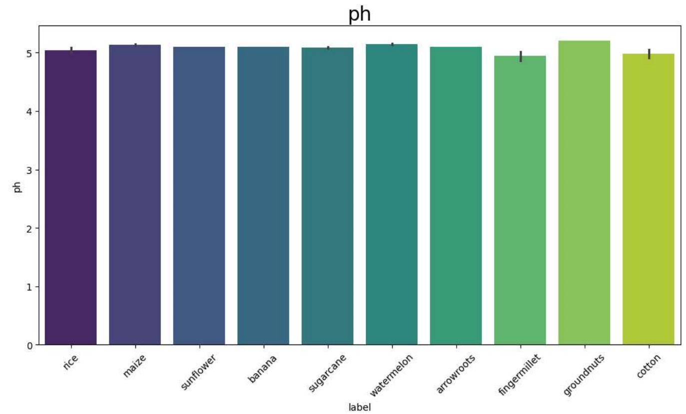


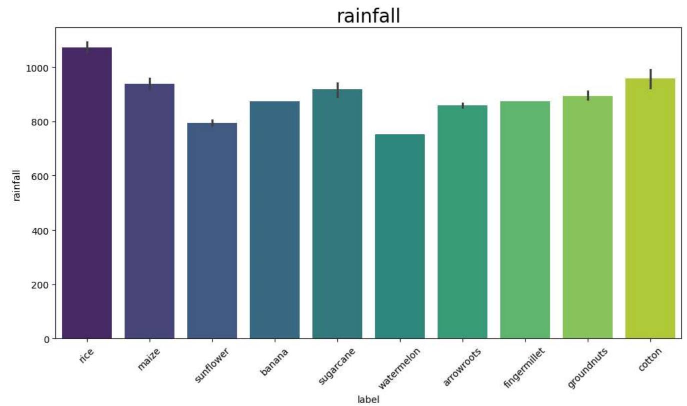





0
5
10
rice
maize
sunflower
banana
sugarcane
watermelon
arrowroots
fingermillet
groundnuts
cotton
label

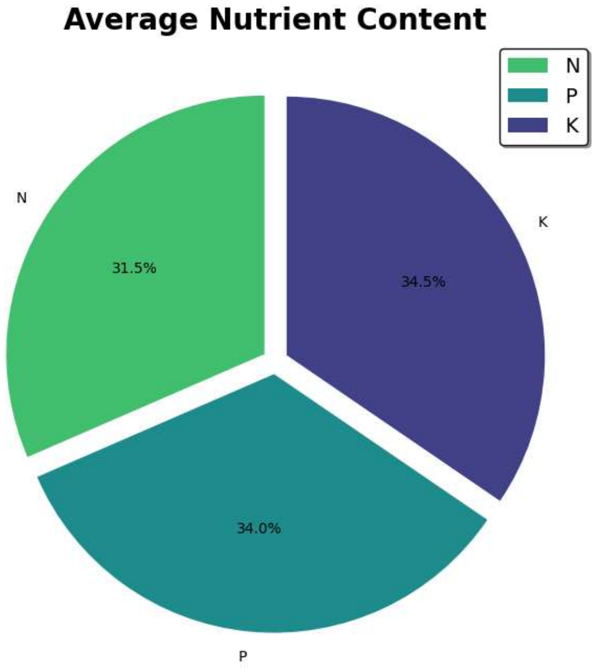

humidity
humidity
0
20
40
60
80
rice
maize
sunflower
banana
sugarcane
watermelon
arrowroots
fingermillet
groundnuts
cotton
label


ph
ph
0
1
2
3
4
5
rice
maize
sunflower
banana
sugarcane
watermelon
arrowroots
fingermillet
groundnuts
cotton
label


rainfall
rainfall
0
200
400
600
800
1000
rice
maize
sunflower
banana
sugarcane
watermelon
arrowroots
fingermillet
groundnuts
cotton
label

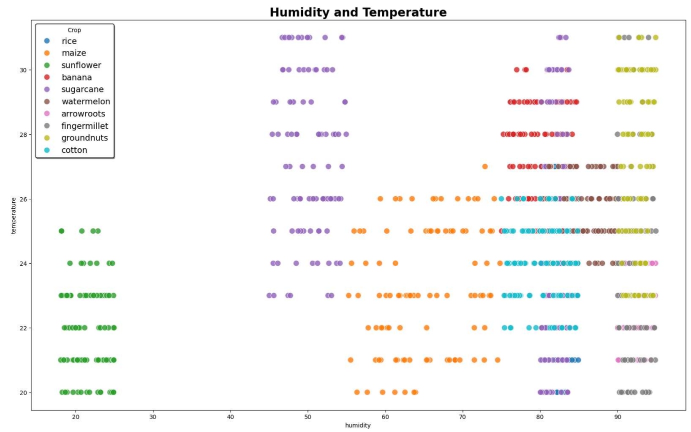
```
!pip install matplotlib
import matplotlib.pyplot as plt
import matplotlib.cm as cm # Import the cm module for colormaps

colors = cm.viridis_r([0.3, 0.5, 0.8])

fig, ax = plt.subplots(figsize = (8, 8))
nutrients = ['N', 'P', 'K']
sizes = [busia['N'].mean(), busia['P'].mean(), busia['K'].mean()]

explode = [0.05, 0.05, 0.05]
ax.pie(sizes, labels = nutrients, colors = colors, autopct = '%1.1f%%', startangle = 90, explode = explode)
ax.set_title('Average Nutrient Content', fontsize = 20, fontweight = 'bold')
ax.legend(fontsize = 14, loc = 'best', frameon = True, edgecolor = 'black', shadow = True)

plt.show()
```

```
Requirement already satisfied: matplotlib in /usr/local/lib/python3.10/dist-packages
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.10/dist-pac
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-package
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-pa
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/dist-pa
Requirement already satisfied: numpy>=1.20 in /usr/local/lib/python3.10/dist-packages
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-pack
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/dist-packag
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.10/dist-pac
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.10/dist
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (f
```



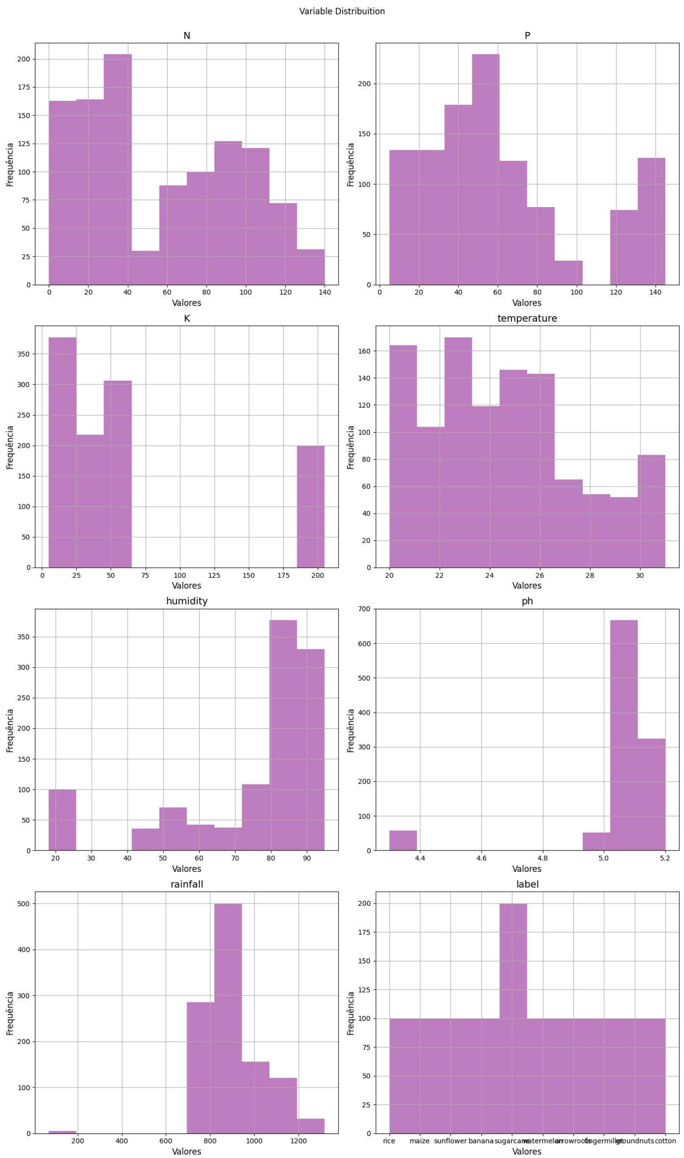
This shows the average nutrient content in the soil for the above dataset


```
#checking how temperature and humidity affect crop
fig, ax = plt.subplots(figsize=(20, 12))

sns.scatterplot(x = "humidity", y = "temperature", hue = "label", data = busia, s = 100, alpha = 0.8)
ax.set_title("Humidity and Temperature", fontsize=20, fontweight = 'bold')
ax.legend(title = "Crop", fontsize = 14, loc = 'upper left', frameon = True, edgecolor = 'black', shadow = True)

plt.show()
```

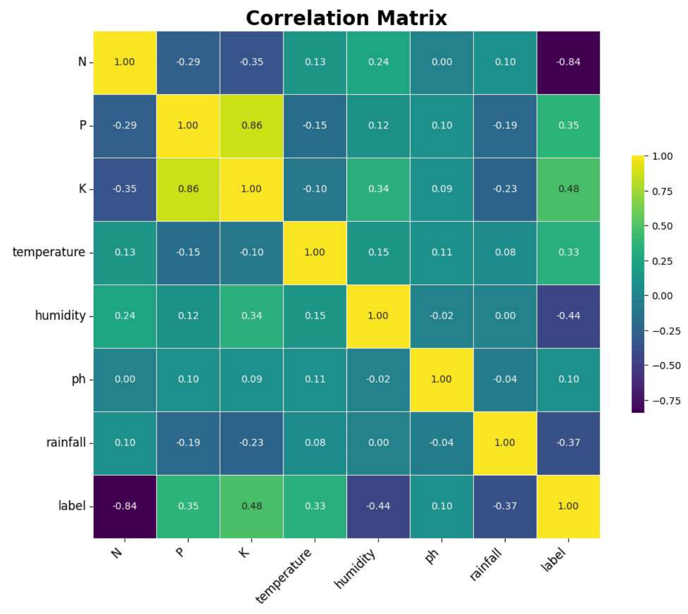


The above visualization shows how crops do in diferent range of temperature and humidity.For example we see sunflower does well at a temperature of about 25 to 26 degrees celcius. Rice will need a temperature of as low as 22 and as high as over 31 degrees celcius. Banana and Maize can do well in the same range of temperature and humidity.

```
#Checking distribution of variables
list_columns = list(busia.columns)

fig, axs = plt.subplots(4, 2, figsize = (14, 24))
fig.suptitle('Variable Distribuition')

for i, column in enumerate(list_columns):
    ax = axs.flat[i]
    ax.hist(busia[column], color = 'purple', alpha = 0.5)
    ax.set_title(column, fontsize = 14)
    ax.set_xlabel('Valores', fontsize = 12)
    ax.set_ylabel('Frequência', fontsize = 12)
    ax.grid(True)

plt.tight_layout()
plt.subplots_adjust(top = 0.95)
```

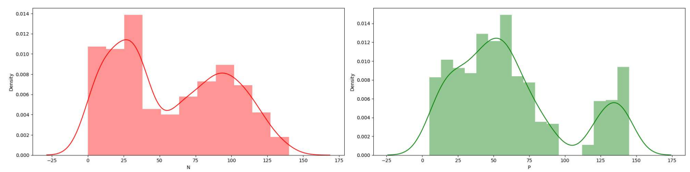



```
# Convert 'label' column to numerical data if it is meant to be included in correlation
label_mapping = {'rice': 0, 'maize': 1, 'sugarcane': 2}  # Example mapping, adjust as needed
busia['label'] = busia['label'].map(label_mapping)

corr_matrix = busia.corr()
fig, ax = plt.subplots(figsize = (12, 10))
heatmap = sns.heatmap(corr_matrix, cmap = "viridis", annot = True,
                      fmt = ".2f", square = True, linewidths = .5, cbar_kws = {"shrink": .5}, ax = ax)

heatmap.set_title("Correlation Matrix", fontsize = 20, fontweight = 'bold')
plt.subplots_adjust(left = 0.15, bottom = 0.15)
ax.tick_params(labelsize = 12)

heatmap.set_xticklabels(heatmap.get_xticklabels(), rotation = 45, ha = 'right')
heatmap.set_yticklabels(heatmap.get_yticklabels(), rotation = 0, ha = 'right')
plt.show()
```

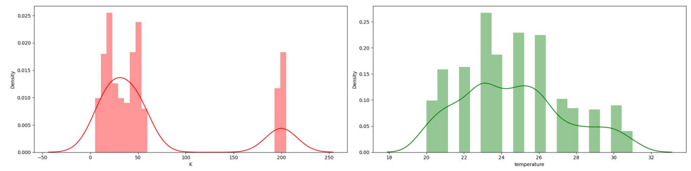


The above shows correlation between variables.

```
f= plt.figure(figsize=(20,5))
ax=f.add_subplot(121)
sns.distplot(busia['N'] , color ='red',ax=ax)

ax=f.add_subplot(122)
sns.distplot(busia['P'] , color ='green' , ax = ax)
plt.tight_layout()
```




```
f= plt.figure(figsize=(20,5))
ax=f.add_subplot(121)
sns.distplot(busia['K'] , color ='red',ax=ax)

ax=f.add_subplot(122)
sns.distplot(busia['temperature'] , color ='green' , ax = ax)
plt.tight_layout()
```



Start coding or generate with AI.

DATA MODELLING

K NEIGHBOURS

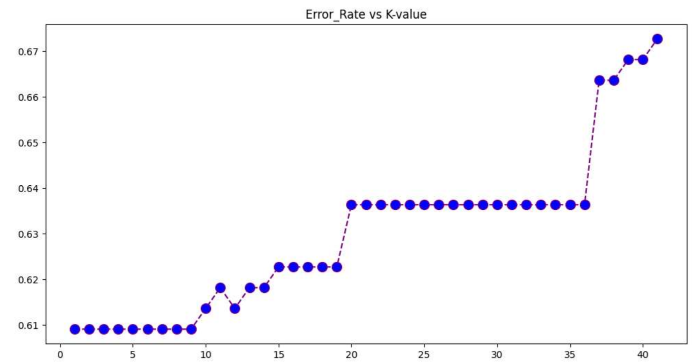
```
from sklearn.neighbors import KNeighborsClassifier
```

```
from sklearn.model_selection import train_test_split
```

```
#splitting data
# Check if 'diagnosis' is in the columns
print(busia.columns)

# If 'diagnosis is present, proceed
X_train, X_test, y_train, y_test = train_test_split(
                busia.drop('label', axis=1),
                busia['label'],
                test_size=0.2,
                random_state=42)

print("Shape of training set:", X_train.shape)
print("Shape of test set:", X_test.shape)
```

```
Index(['N', 'P', 'K', 'temperature', 'humidity', 'ph', 'rainfall', 'label'], dtype='object')
Shape of training set: (880, 7)
Shape of test set: (220, 7)
```

```
#to find which value shows the lowest mean error
error_rate = []

# Handle missing values in y_train (e.g., by dropping rows with NaNs)
y_train_clean = y_train.dropna()
X_train_clean = X_train.loc[y_train_clean.index]  # Keep corresponding rows in X_train

for i in range(1,42):
    knn = KNeighborsClassifier(n_neighbors=i)

    # Fit the model using the cleaned data
    knn.fit(X_train_clean, y_train_clean)

    pred_i = knn.predict(X_test)
    error_rate.append(np.mean(pred_i != y_test))


plt.figure(figsize=(12,6))
plt.plot(range(1,42), error_rate, color='purple', linestyle="--",
         marker='o', markersize=10, markerfacecolor='b')
plt.title('Error_Rate vs K-value')
plt.show()
```




```
knn = KNeighborsClassifier(n_neighbors=9)
# Use the cleaned training data without NaNs
knn.fit(X_train_clean, y_train_clean)
predictions2 = knn.predict(X_test)


# Handle NaNs in y_test
import numpy as np
from sklearn.metrics import confusion_matrix, classification_report

# Replace NaNs with a suitable value (e.g., -1) or remove rows with NaNs
y_test_clean = np.nan_to_num(y_test, nan=-1)  # Replace NaNs with -1

print("Confusion Matrix: \n", confusion_matrix(y_test_clean, predictions2))
print('\n')
print(classification_report(y_test_clean, predictions2))
```

```
Confusion Matrix:
 [[ 0 12 64 58]
 [ 0 24  0  0]
 [ 0  0 19  0]
 [ 0  0  0 43]]
```



```
              precision    recall  f1-score   support

        -1.0       0.00      0.00      0.00       134
         0.0       0.67      1.00      0.80        24
         1.0       0.23      1.00      0.37        19
         2.0       0.43      1.00      0.60        43

    accuracy                           0.39       220
   macro avg       0.33      0.75      0.44       220
weighted avg       0.18      0.39      0.24       220
```

To interpret this matrix:

Rows represent the actual classes. Columns represent the predicted classes. Each cell in the matrix indicates how many instances of a particular class were predicted to belong to each actual class. For example:

The cell at (0,1) (first row, second column) has a value of 12. This means that 12 instances of class 1 (assuming classes are labeled as 0, 1, 2, 3) were predicted as belonging to class 2. The cell at (2,2) (third row, third column) has a value of 19. This means that 19 instances of class 2 were correctly predicted as belonging to class 2. Classification Report: The classification report provides several metrics to evaluate the performance of a classification model. It includes metrics such as precision, recall, f1-score, and support for each class.

Here's the classification report I have provided:

markdown Copy code precision recall f1-score support

```
-1.0    0.00    0.00    0.00    134
 0.0    0.67    1.00    0.80     24
 1.0    0.23    1.00    0.37     19
 2.0    0.43    1.00    0.60     43
```