Data preprocessing & Apply Machine Learning Techniques

Data Preprocessing

1.import real dataset & dependencies

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import sklearn
```

```
df= pd.read_csv('fake_currency_data.csv')
df
```

	Country	Denomination	Counterfeit	SerialNumber	SecurityFeatures	Weight	Le
0	USA	$100	1	25973198	Hologram	1.731759	130.24
1	USA	$20	1	95903230	Security Thread	1.002179	152.59
2	EU	€10	0	82937914	Hologram	2.306713	152.85
3	USA	€20	1	23612989	Microprint	1.366965	143.13
4	EU	€20	1	56025342	Watermark	1.796075	129.66
...	...	...	...	...	...	...	
999995	EU	$100	1	24436622	Watermark	1.472511	134.88
999996	EU	£20	1	82654212	Hologram	2.355633	147.83
999997	USA	$5	0	59174754	Microprint	1.393764	150.05
999998	EU	£10	0	55268089	Watermark	2.026417	142.85
999999	EU	£10	0	59464296	Watermark	0.867139	127.64

1000000 rows × 9 columns

2.remove the missing values from datasets

- here no-null values in datasets

```
df.isnull().sum()
```

```
Country             0
Denomination        0
Counterfeit         0
SerialNumber        0
SecurityFeatures    0
Weight              0
Length              0
Width               0
Thickness           0
dtype: int64
```

3.Adding new features from existing features

- Area=length x width
- volume=length x width x thickness
- Aspect_ratio=length / width

- weight_to_Area_ratio= weight / Area
- weight_to_volume_ratio= weigth / volume

```
df['Area'] = df['Length'] * df['Width']
df['Volume'] = df['Length'] * df['Width'] * df['Thickness']
df['Aspect_Ratio'] = df['Length'] / df['Width']
df['Weight_to_Area_Ratio'] = df['Weight'] / df['Area']
df['Weight_to_Volume_Ratio'] = df['Weight'] / df['Volume']
```

4.Remove the unnecessary & not depending for results columns

- serial_number is not depending the results because it has unigue identifier

```
df = df.drop(['SerialNumber'], axis=1)
df
```

	Country	Denomination	Counterfeit	SecurityFeatures	Weight	Length	Width
0	USA	$100	1	Hologram	1.731759	130.243185	66.537999
1	USA	$20	1	Security Thread	1.002179	152.596364	76.135834
2	EU	€10	0	Hologram	2.306713	152.857126	66.772442
3	USA	€20	1	Microprint	1.366965	143.133672	78.377052
4	EU	€20	1	Watermark	1.796075	129.664777	75.916093
...	...	...	...	...	...	...	..
999995	EU	$100	1	Watermark	1.472511	134.888731	75.425943
999996	EU	£20	1	Hologram	2.355633	147.830149	65.232274
999997	USA	$5	0	Microprint	1.393764	150.050308	69.273269
999998	EU	£10	0	Watermark	2.026417	142.852137	77.878841
999999	EU	£10	0	Watermark	0.867139	127.645125	72.608513

1000000 rows × 13 columns

5.Datasets cleaning for uniformly distrubated dataset

- this datastets are uniformly distrubted.that why i remove some counterfeits notes.
- only 5% of counterfeits notes are presents in new datasets
- this 5% note are equally country,denomination and seacurity features by counterfeits.

```
# create a new dataset only 5% counterfeit present and all non counterfeit present in df.in sample country,denomir

# Separate counterfeit and non-counterfeit data
counterfeit = df[df['Counterfeit'] == 1]
non_counterfeit = df[df['Counterfeit'] == 0]

# Sample 5% of counterfeit data
counterfeit_sample = counterfeit.sample(frac=0.05)

# Combine sampled counterfeit data with all non-counterfeit data
new_df = pd.concat([counterfeit_sample, non_counterfeit])

# Shuffle the new dataset
new_df = new_df.sample(frac=1).reset_index(drop=True)

# Update the country, denomination, and security features by 5%
new_df['Country'] = new_df['Country'].apply(lambda x: 'other' if np.random.random() < 0.05 else x)
new_df['Denomination'] = new_df['Denomination'].apply(lambda x: 100 if np.random.random() < 0.05 else x)
new_df['SecurityFeatures'] = new_df['SecurityFeatures'].apply(lambda x: 'high' if np.random.random() < 0.05 else >

# Print the new dataset
new_df
```

	Country	Denomination	Counterfeit	SecurityFeatures	Weight	Length	Width
0	USA	£5	0	Microprint	1.951739	120.342934	76.34252C
1	EU	€10	0	Security Thread	1.973224	143.249467	78.939662
2	EU	$100	0	Hologram	1.375517	127.144896	63.188832
3	UK	$5	0	Watermark	1.576948	124.839820	68.335544
4	UK	100	0	Hologram	0.987226	136.402692	77.702892
...	...	...	...	...	...	...	..
525574	USA	100	0	Microprint	2.464214	159.134403	66.011519
525575	EU	$20	0	Security Thread	1.223090	137.254132	78.175685
525576	USA	$100	0	Security Thread	1.220706	145.120703	68.195325
525577	other	$5	0	Security Thread	1.814900	126.424226	76.442372
525578	EU	$20	0	Hologram	1.641367	147.055068	74.235277

525579 rows × 13 columns

6.Encoding for the categorical featurs

- here used **one hot encoding** for country,denomination and seacurity features

```
# one hot encoding for Country  Denomination and SecurityFeatures

new_df = pd.get_dummies(new_df, columns=['Country', 'Denomination', 'SecurityFeatures'], dtype=int)
new_df
```

	Counterfeit	Weight	Length	Width	Thickness	Area	Volume	Asp
0	0	1.951739	120.342934	76.342520	0.099082	9187.282800	910.292480	
1	0	1.973224	143.249467	78.939662	0.067950	11308.064435	768.384908	
2	0	1.375517	127.144896	63.188832	0.083753	8034.137481	672.882234	
3	0	1.576948	124.839820	68.335544	0.056304	8530.996979	480.332534	
4	0	0.987226	136.402692	77.702892	0.090591	10598.883658	960.161630	
...	...	...	...	...	...	...	...	
525574	0	2.464214	159.134403	66.011519	0.089326	10504.703588	938.340540	
525575	0	1.223090	137.254132	78.175685	0.053399	10729.935732	572.964435	
525576	0	1.220706	145.120703	68.195325	0.058913	9896.553425	583.031356	
525577	0	1.814900	126.424226	76.442372	0.072203	9664.167667	697.781986	
525578	0	1.641367	147.055068	74.235277	0.075097	10916.673755	819.809470	

525579 rows × 32 columns

```
new_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 525579 entries, 0 to 525578
Data columns (total 32 columns):
 #   Column                           Non-Null Count   Dtype  
---  ------                           --------------   -----  
 0   Counterfeit                      525579 non-null  int64  
 1   Weight                           525579 non-null  float64
 2   Length                           525579 non-null  float64
 3   Width                            525579 non-null  float64
 4   Thickness                        525579 non-null  float64
 5   Area                             525579 non-null  float64
 6   Volume                           525579 non-null  float64
 7   Aspect_Ratio                     525579 non-null  float64
 8   Weight_to_Area_Ratio             525579 non-null  float64
 9   Weight_to_Volume_Ratio           525579 non-null  float64
 10  Country_EU                       525579 non-null  int64  
 11  Country_UK                       525579 non-null  int64  
 12  Country_USA                      525579 non-null  int64  
 13  Country_other                    525579 non-null  int64  
 14  Denomination_100                 525579 non-null  int64  
 15  Denomination_$1                  525579 non-null  int64  
 16  Denomination_$10                 525579 non-null  int64  
 17  Denomination_$100                525579 non-null  int64  
 18  Denomination_$20                 525579 non-null  int64  
 19  Denomination_$5                  525579 non-null  int64  
 20  Denomination_$50                 525579 non-null  int64  
 21  Denomination_£10                 525579 non-null  int64  
 22  Denomination_£20                 525579 non-null  int64  
 23  Denomination_£5                  525579 non-null  int64  
 24  Denomination_€10                 525579 non-null  int64  
 25  Denomination_€20                 525579 non-null  int64  
 26  Denomination_€5                  525579 non-null  int64  
 27  SecurityFeatures_Hologram        525579 non-null  int64  
 28  SecurityFeatures_Microprint      525579 non-null  int64  
 29  SecurityFeatures_Security Thread  525579 non-null  int64  
 30  SecurityFeatures_Watermark       525579 non-null  int64  
 31  SecurityFeatures_high            525579 non-null  int64  
dtypes: float64(9), int64(23)
memory usage: 128.3 MB
```

7.Normalization techniques for the numerical features as well as encoding catogirical

- here **standarscaler** use for all columns

```
# all colums transforms to standard scaler except counterfeit

from sklearn.preprocessing import StandardScaler

# Create a StandardScaler object
scaler = StandardScaler()

# Fit the scaler to the numerical columns except for 'Counterfeit'
scaler.fit(new_df.drop('Counterfeit', axis=1))

# Transform the numerical columns except for 'Counterfeit'
new_df[new_df.columns.difference(['Counterfeit'])] = scaler.transform(new_df.drop('Counterfeit', axis=1))

# Print the transformed dataset
new_df
```

	Counterfeit	Weight	Length	Width	Thickness	Area	Volume	Aspect_Ra
0	0	1.795804	-0.293699	-0.231928	-0.29399	0.615146	-0.559029	-1.705
1	0	-0.556854	-0.293699	-0.231928	-0.29399	0.658942	-0.559029	0.278
2	0	-0.556854	-0.293699	-0.231928	-0.29399	-0.559471	1.788816	-1.116
3	0	-0.556854	-0.293699	-0.231928	-0.29399	-0.148857	-0.559029	-1.316
4	0	-0.556854	-0.293699	-0.231928	-0.29399	-1.350992	1.788816	-0.314
...	...	...	...	...	...	...	...	
525574	0	1.795804	-0.293699	-0.231928	-0.29399	1.659815	-0.559029	1.654
525575	0	-0.556854	-0.293699	-0.231928	-0.29399	-0.870189	-0.559029	-0.241
525576	0	-0.556854	-0.293699	-0.231928	-0.29399	-0.875048	-0.559029	0.440
525577	0	-0.556854	-0.293699	-0.231928	-0.29399	0.336202	-0.559029	-1.179
525578	0	-0.556854	-0.293699	-0.231928	-0.29399	-0.017542	1.788816	0.607

525579 rows × 32 columns

```
new_df['Country_EU']
```

```
0          1.098806
1          1.548682
2         -1.179670
3         -0.288159
4          1.334449
             ...
525574   -0.690726
525575    1.416346
525576   -0.312448
525577    1.116102
525578    0.733790
Name: Country_EU, Length: 525579, dtype: float64
```

8.Dimensions reduction for scaled data

- here 31 colums used are in training which lots of time taken to traing that why used in dimension reduction techniques

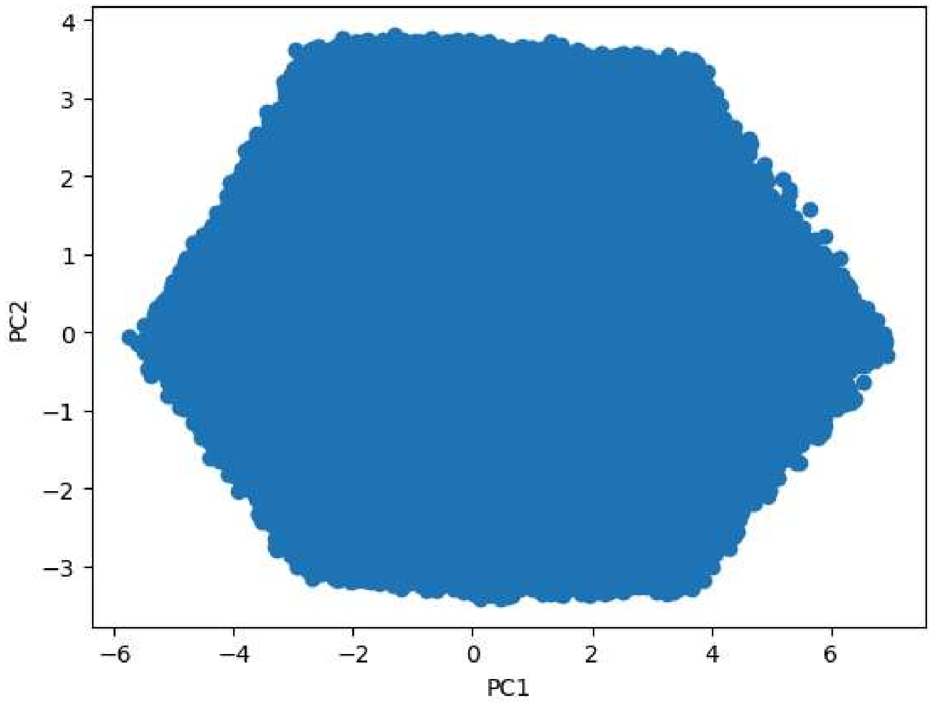
```
# dimension reduction for all colums except counterfeit colums

from sklearn.decomposition import PCA

# Create a PCA instance with 20 components
pca = PCA(n_components=20)

# Fit the PCA instance to the scaled data
new_df_reduced = pca.fit_transform(new_df.drop('Counterfeit', axis=1))

# Convert the reduced data back to a DataFrame
new_df_reduced = pd.DataFrame(new_df_reduced, columns=[f"PC{i+1}" for i in range(20)])

# Print the reduced data
new_df_reduced
```

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	
0	-0.071473	-2.779175	0.810168	-2.147168	-0.624003	1.607269	-0.207548	1.442548	-1.3
1	-0.551810	-1.322070	1.295156	1.437781	-1.208118	-1.209345	-1.510702	-1.379438	-0.2
2	0.777361	0.108055	-1.571103	-1.681333	-1.125946	-1.346702	1.772576	-0.948061	-0.1
3	2.279677	-0.976669	-1.509885	0.604846	1.742494	-0.374048	-0.182807	0.884069	1.8
4	-3.058643	-1.575388	-0.495288	-0.604619	1.743375	-0.383214	1.771362	-0.916322	-0.2
...	...	...	...	...	...	...	...	...	
525574	0.012879	2.170762	2.780677	-0.770017	-0.616550	1.616295	-0.151643	1.450816	-1.4
525575	-0.708596	-1.533118	-1.161928	2.211188	-1.131349	-1.185890	-1.472503	-1.409947	-0.1
525576	-0.240707	0.805940	-1.394542	1.223429	-0.543476	1.757775	-1.438491	-1.323689	-0.1
525577	0.558330	-2.217285	0.036853	0.097417	-0.024370	0.061467	-1.526770	-1.388498	-0.2
525578	-1.265175	-0.222027	0.654549	0.608182	-1.114148	-1.282989	1.792487	-0.963647	-0.1

525579 rows × 20 columns

9.scatter plot between components

```
# create scatter plot pc1 vs pc2

import matplotlib.pyplot as plt

# Create a scatter plot of PC1 vs PC2
plt.scatter(new_df_reduced['PC1'], new_df_reduced['PC2'])

# Label the axes
plt.xlabel('PC1')
plt.ylabel('PC2')

# Show the plot
plt.show()
```



Apply Machine Learning Techniques

A.supervised learning

1.Logistics regression

- accuracy:95.25%

```
#logistic regression

# from sklearn.model_selection import train_test_split
# from sklearn.linear_model import LogisticRegression
# from sklearn.metrics import accuracy_score

# # Split the data into train and test sets
# X_train, X_test, y_train, y_test = train_test_split(new_df_reduced, new_df['Counterfeit'], test_size=0.2, random

# # Train a Logistic Regression model
# model_logistic = LogisticRegression()
# model_logistic.fit(X_train, y_train)

# # Evaluate the model on the test set
# y_pred = model_logistic.predict(X_test)
# accuracy = accuracy_score(y_test, y_pred)
# print(f"Accuracy: {accuracy}")
```

2.DecisionTreeClassifier

- accuracy:90.04%

```
# from sklearn.tree import DecisionTreeClassifier
# from sklearn.model_selection import train_test_split
# from sklearn.metrics import accuracy_score
# # Split the data into training and testing sets
# X_train, X_test, y_train, y_test = train_test_split(new_df_reduced, new_df['Counterfeit'], test_size=0.2, random

# # Train a decision tree classifier
# clf = DecisionTreeClassifier()
# clf.fit(X_train, y_train)

# # Evaluate the classifier on the test set
# score = clf.score(X_test, y_test)

# # Print the accuracy score
# print("Accuracy:", score)
```

3.Random forest

- acurracy:95.19%

```
# from sklearn.ensemble import RandomForestClassifier
# from sklearn.model_selection import train_test_split
# from sklearn.metrics import accuracy_score
# # Separate features and target
# X = new_df_reduced
# y = new_df['Counterfeit']

# # Split data into training and test sets
# X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# # Train a classifier
# classifier = RandomForestClassifier()
# classifier.fit(X_train, y_train)

# # Evaluate the classifier on the test set
# y_pred = classifier.predict(X_test)
# accuracy = accuracy_score(y_test, y_pred)
# print(f"Accuracy: {accuracy}")
```

4.Support vector machine

- accuracy:

```
# from sklearn.svm import SVC
# from sklearn.model_selection import train_test_split
# from sklearn.metrics import accuracy_score
# # Split the data into training and test sets
# X_train, X_test, y_train, y_test = train_test_split(new_df_reduced, new_df['Counterfeit'], test_size=0.2, random

# # Train a support vector machine model
# model = SVC()
# model.fit(X_train, y_train)

# # Evaluate the model on the test set
# y_pred = model.predict(X_test)
# accuracy = accuracy_score(y_test, y_pred)
# print("Accuracy:", accuracy)
```

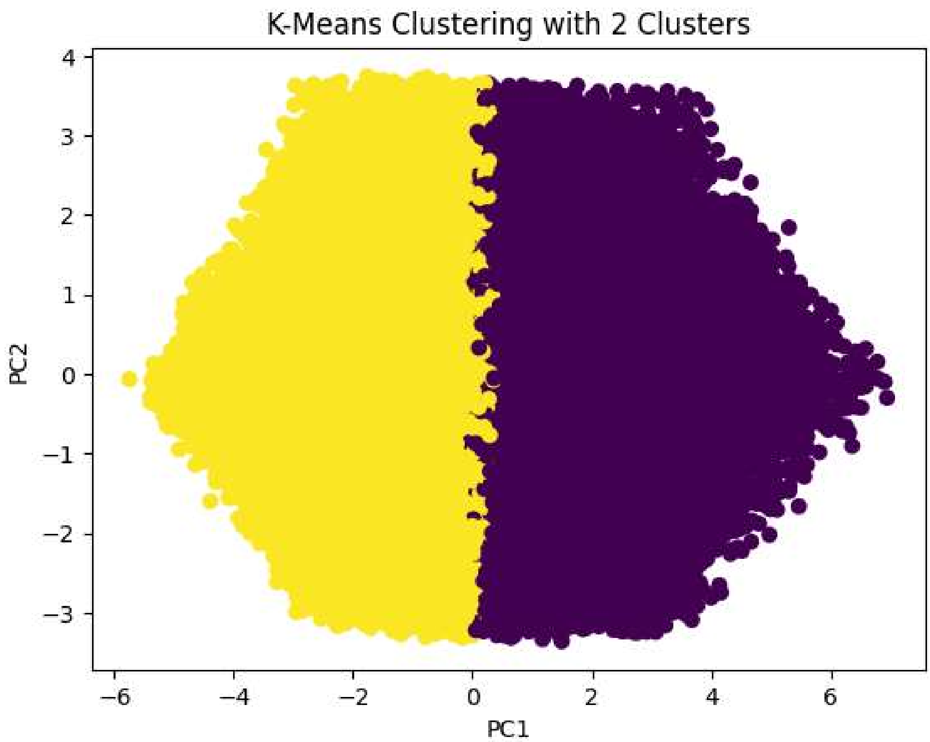
B.unsupervised learning

1.k-means culstering

- visulize the how cluster look like
- increse the value of k cluster not differences
- in elbow plot k=2 and k=3 are points which effectively work this techniques
- highest at k=2 accuracy is 54.05% (note:in unsupervised learning it doesnt means label)

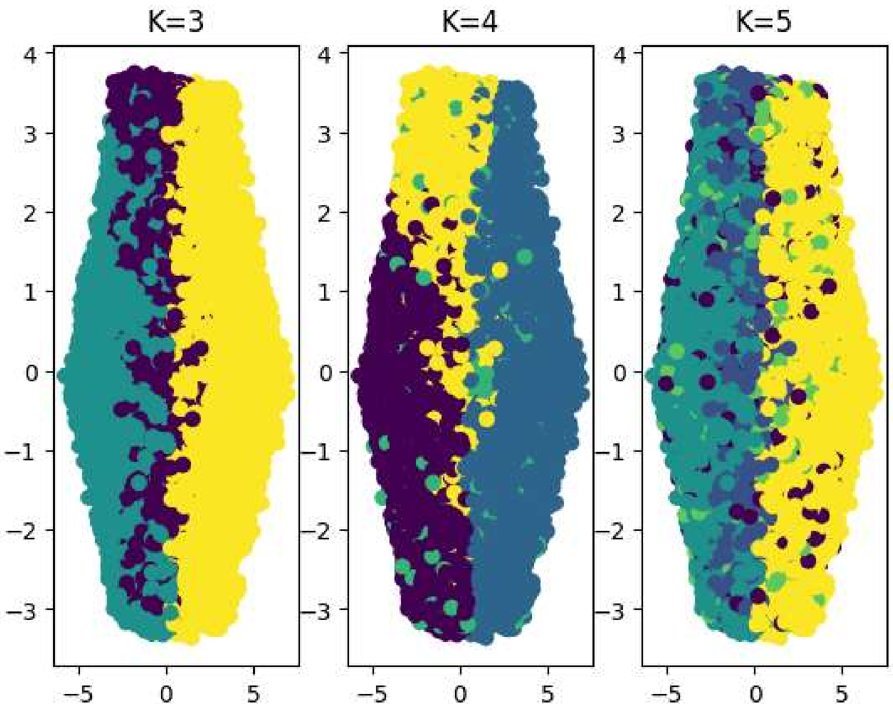
```
# Apply k-means clustering  algorithms
from sklearn.model_selection import train_test_split
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt

# Split the data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(new_df_reduced, new_df['Counterfeit'], test_size=0.2, random_st

# Create a KMeans object with 2 clusters
kmeans = KMeans(n_clusters=2)

# Fit the KMeans object to the data
kmeans.fit(X_train)

# Predict the cluster labels for the test data
cluster_labels = kmeans.predict(X_test)

# Plot the clusters
plt.scatter(X_test['PC1'], X_test['PC2'], c=cluster_labels)
plt.xlabel('PC1')
plt.ylabel('PC2')
plt.title('K-Means Clustering with 2 Clusters')
plt.show()
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The
  warnings.warn(
```



```
#k=3,4,5 cluster visulization
import matplotlib.pyplot as plt

# Create a figure with 2 subplots
fig, (ax1, ax2, ax3) = plt.subplots(1, 3)

# Plot the clusters for K=3
kmeans = KMeans(n_clusters=3)
kmeans.fit(X_train)
cluster_labels = kmeans.predict(X_test)
ax1.scatter(X_test['PC1'], X_test['PC2'], c=cluster_labels)
ax1.set_title('K=3')

# Plot the clusters for K=4
kmeans = KMeans(n_clusters=4)
kmeans.fit(X_train)
cluster_labels = kmeans.predict(X_test)
ax2.scatter(X_test['PC1'], X_test['PC2'], c=cluster_labels)
ax2.set_title('K=4')

# Plot the clusters for K=5
kmeans = KMeans(n_clusters=5)
kmeans.fit(X_train)
cluster_labels = kmeans.predict(X_test)
ax3.scatter(X_test['PC1'], X_test['PC2'], c=cluster_labels)
ax3.set_title('K=5')

# Show the plot
plt.show()
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The
  warnings.warn(
```



```
# Optimal K Value is determined using either trial and error ranging from (1 to 5) or techniques like elbow plot.


# Elbow method to determine optimal k value

import matplotlib.pyplot as plt
from sklearn.metrics import accuracy_score

# Calculate inertia for different k values
inertia = []
for k in range(1, 6):
    kmeans = KMeans(n_clusters=k)
    kmeans.fit(X_train)
    inertia.append(kmeans.inertia_)

# Plot the inertia for each k value
plt.plot(range(1, 6), inertia)
plt.xlabel('Number of clusters (k)')
plt.ylabel('WCSS')
plt.title('Elbow Method')
plt.show()

# Choose the k value with the lowest inertia
optimal_k = 2

# Create a KMeans object with the optimal k value
kmeans = KMeans(n_clusters=optimal_k)

# Fit the KMeans object to the data
kmeans.fit(X_train)

# Predict the cluster labels for the test data
cluster_labels = kmeans.predict(X_test)

# Calculate the accuracy score
accuracy = accuracy_score(y_test, cluster_labels)

# Print the accuracy score
print(f"Accuracy: {accuracy}")
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The
  warnings.warn(
```

2.DBSCAN technique

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The
```

```
from sklearn.cluster import DBSCAN

# Apply DBSCAN clustering algorithm

# Create a DBSCAN object with eps=2 and min_samples=500
dbscan = DBSCAN(eps=2, min_samples=500)

# Fit the DBSCAN object to the data
dbscan.fit(X_train)

# Predict the cluster labels for the test data
cluster_labels = dbscan.predict(X_test)

# Plot the clusters
plt.scatter(X_test['PC1'], X_test['PC2'], c=cluster_labels)
plt.xlabel('PC1')
plt.ylabel('PC2')
plt.title('DBSCAN Clustering')
plt.show()

# Calculate the accuracy score
accuracy = accuracy_score(y_test, cluster_labels)

# Print the accuracy score
print(f"Accuracy: {accuracy}")

# Choose the optimal eps and min_samples values using techniques like grid search or silhouette analysis.


# Grid search to determine optimal eps and min_samples values

from sklearn.model_selection import GridSearchCV

# Define a grid of values for eps and min_samples
param_grid = {'eps': [0.1, 0.2, 0.3, 0.4, 0.5], 'min_samples': [50, 100, 150, 200]}

# Create a DBSCAN object
dbscan = DBSCAN()
```