ELG 5255: Applied Machine Learning
Assignment:1

BY: Group 5

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Part 1: Calculations

Part 1 :- Calculations

Points → $A_1 = (3,6)$ $A_2 = (6,3)$

$A_3 = (8,6)$ $A_4 = (2,1)$

$A_5 = (5,9)$

*** 2 clusters

*** our Initial Points as required are A_2 & A_4

← $A_2 = (6,3)$

← $A_4 = (2,1)$

Points	Distance To A_2 (6, 3)	Distance To A_4 (2, 1)	cluster	New cluster
A_1 (3,6)	4.243	5.1	A_2 ①	
A_2 (6,3)	0	4.5	A_2 ①	
A_3 (8,6)	3.6	7.8	A_2 ①	
A_4 (2,1)	4.8	0	A_4 ②	
A_5 (5,9)	6.08	8.54	A_2 ①	

Euclidean Distance between Two points :-

$$d(P_1, P_2) = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

$\therefore$ $\underbrace{(3,6)}_{\text{Point } A_1}^{x_1 \; y_1}$ $\underbrace{(6,3)}_{\text{initial Point } (A_2)}^{x_2 \; y_2}$

$$d = \sqrt{(6-3)^2 + (3-6)^2} = 4.243$$

(3,6) (2,1)

$$d = \sqrt{(2-3)^2 + (1-6)^2} = 5.1$$

(6,3) (6,3)

$$d = \sqrt{(6-6)^2 + (3-3)^2} = \boxed{0}$$

(6,3) (2,1)

$$d = \sqrt{(2-6)^2 + (1-3)^2} = \boxed{4.47}$$

(8,6) (6,3)

$$d = \sqrt{(6-8)^2 + (3-6)^2} = 3.61$$

(8,6) (2,1)

$$d = \sqrt{(2-8)^2 + (1-6)^2} = 7.81$$

(2,1) (6,3)

$$d = \sqrt{(6-2)^2 + (3-1)^2} = 4.47$$

(2,1) (2,1)

$$d = \sqrt{(2-2)^2 + (1-1)^2} = 0$$

(5,9) (6,3)

$$d = \sqrt{(6-5)^2 + (3-9)^2} = 6.08$$

(5,9) (2,1)

$$d = \sqrt{(2-5)^2 + (1-9)^2} = 8.54$$

Let's Calculate New Centroids

We have 1 Point only in Cluster 2

So We will take it again as Centroid Point

But, for Cluster 1 ...

$$\left(\frac{3+6+8+5}{4} , \frac{6+3+6+9}{4} \right) =$$

(5.5 , 6) ⟹ Second Centroid

New Centroids are → (2,1)
→ (5.5, 6)

Points	Distance To (2,1)	(5.5,6)	Cluster	New Cluster
A_1 (3,6)	5.1	2.5	A_2 1	A_4 2
A_2 (6,3)	4.47	3.04	A_2 1	A_4 2
A_3 (8,6)	7.81	2.5	A_2 1	A_4 2
A_4 (2,1)	0	6.1	A_4 2	A_2 1
A_5 (5,9)	8.54	3.04	A_2 1	A_4 2

(3,6) (2,1)

$$d = \sqrt{(2-3)^2 + (1-6)^2} = 5.1$$

(3,6) (5.5, 6)

$$d = \sqrt{(5.5-3)^2 + (6-6)^2} = 2.5$$

(6,3) (2,1)

$$d = \sqrt{(2-6)^2 + (1-3)^2} = 4.5$$

(6,3) (5.5, 6)

$$d = \sqrt{(5.5-6)^2 + (6-3)^2} = 3.04$$

(8,6) (2,1)

$$d = \sqrt{(2-8)^2 + (1-6)^2} = 7.81$$

(8,6) (5.5, 6)

$$d = \sqrt{(5.5-8)^2 + (6-6)^2} = 2.5$$

(2,1) (2,1)

$d = 0$

(2,1) (5.5,6)

$$d = \sqrt{(5.5-2)^2 + (6-1)} = 6.1$$

(5,9) (2,1)

$$d = \sqrt{(2-5)^2 + (1-9)^2} = 8.54$$

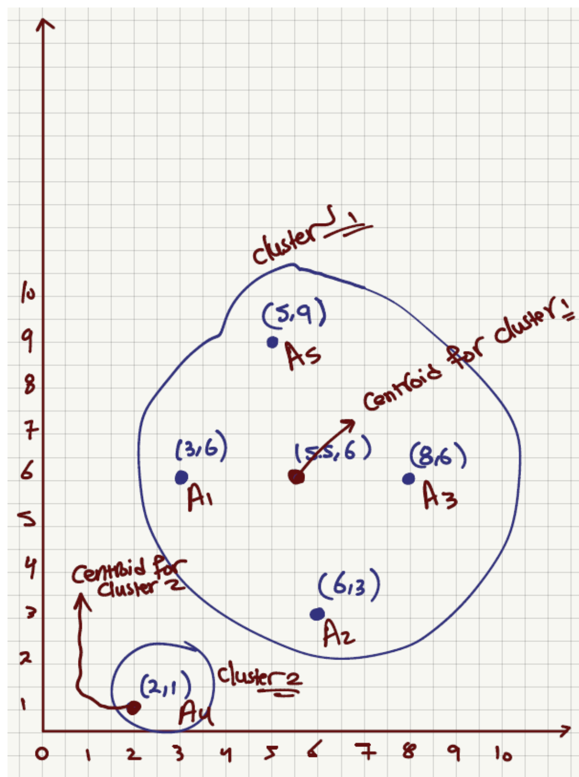
(5,9) (5.5, 6)

$$d = \sqrt{(5.5-5)^2 + (6-9)^2} = 3.04$$

Update Centroids

$$\left(\frac{3+6+8+5}{4}, \frac{6+3+6+9}{4}\right) = (5.5, 6)$$

New Centroids are → (5.5, 6)
→ (2,1)
didn't change



(c) Calculate the silhoutte score and WSS score

* the silhoutte score measures how well each point fits into its assigned cluster, ranging from −1 to 1.

* Higher silhoutte score indicates better clustering.

	A_1	A_2	A_3	A_4	A_5
A_1 (3,6)	0	4.243	5	5.1	3.6
A_2 (6,3)	4.243	0	3.61	4.47	6.08
A_3 (8,6)	5	3.61	0	7.81	4.243
A_4 (2,1)	5.1	4.47	7.81	0	8.54
A_5 (5,9)	3.6	6.08	4.243	8.54	0

$$a(A_1) = \frac{A_2 + A_3 + A_5}{3}$$

$$= \frac{(4.243) + (5) + (3.6)}{3} = 4.281$$

$$b(A_1) = 5.1$$

$$\therefore S(A_1) = \frac{5.1 - 4.281}{5.1} = 0.1605$$

$$a(A_2) = \frac{A_1 + A_3 + A_5}{3}$$

$$= \frac{(4.243) + (3.61) + (6.08)}{3} = 4.644$$

$$b(A_2) = 4.47$$

$$\therefore S(A_2) = \frac{4.47 - 4.644}{4.644} = -0.037$$

$$a(A_3) = \frac{A_1 + A_2 + A_5}{3} =$$

$$= \frac{5 + 3.61 + 4.243}{3} = 4.283$$

$$b(A_3) = 7.81$$

$$\therefore S(A_3) = \frac{(7.818) - (4.283)}{7.81}$$

$$= 0.452$$

$$a(A_4) = 0$$

$$b(A_4) = \frac{A_1 + A_2 + A_3 + A_5}{4}$$

$$= \frac{5.1 + 4.47 + 7.81 + 8.54}{4}$$

$$= 6.48$$

$$\therefore S(A_4) = \frac{6.48 - 0}{6.48} = 1$$

$$a(A_5) = \frac{A_1 + A_2 + A_3}{3}$$

$$= \frac{3.6 + 6.08 + 4.243}{3} = 4.41$$

$$b(A_5) = 8.54$$

$$\therefore S(A_5) = \frac{8.54 - 4.41}{8.54} = 0.483$$

$$\therefore \text{Silhoutte score} = \frac{S(A_1) + S(A_2) + S(A_3) + S(A_4) + S(A_5)}{5}$$

$$= \frac{0.1605 + (-0.037) + 0.452 + 1 + 0.483}{5}$$

$$= 0.4117$$

Calculating WSS:-

$$WSS = \sum_{i=1}^{m} (x_i - c_i)^2$$

We have $\underline{\underline{2}}$ centroids → (5.5 , 6) for cluster $\underline{\underline{1}}$

→ (2,1) for cluster $\underline{\underline{2}}$

* cluster $\underline{\underline{1}}$ include A_1, A_2, A_3, A_5

* cluster $\underline{\underline{2}}$ include A_4 only

∴ (A_1, C_1) Centroid cluster1

(3,6) (5.5,6)

$$(3-5.5)^2 + (6-6)^2 = \boxed{6.25}$$

(A_2, C_1) ---> (6,3) (5.5,6)

$$(6-5.5)^2 + (3-6)^2 = \boxed{9.25}$$

(A_3, C_1) ---> (8,6) (5.5,6)

$$(8-5.5)^2 + (6-6)^2 = \boxed{6.25}$$

(A_5, C_1) ---> (5,9) (5.5,6)

$$(5-5.5)^2 + (6-9)^2 = \boxed{9.25}$$

*****

(A_4, C_2) Centroid Cluster2

(2,1) (2,1)

$$(2-2)^2 + (1-1)^2 = \boxed{0}$$

∴ WSS = 6.25 +9.25 +6.25 +9.25 } $\underline{\underline{1}}$

+ zero } $\underline{\underline{2}}$

WSS = $\underline{\underline{31}}$

Part 2: Programming

★ Importig important libraries

```
import pandas as pd
import numpy as np
from sklearn.exceptions import UndefinedMetricWarning
from  sklearn.naive_bayes import GaussianNB

from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier

from sklearn.feature_selection import SequentialFeatureSelector
from sklearn.feature_selection import RFECV
from sklearn.pipeline import Pipeline
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix,classification_report
from sklearn.metrics import accuracy_score, f1_score
from sklearn.feature_selection import RFE

from yellowbrick.text import TSNEVisualizer
from sklearn.manifold import TSNE
from sklearn.utils.multiclass import unique_labels
from sklearn.feature_selection import SelectKBest, f_classif, VarianceThreshold, mutual_info_classif

from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
from keras.models import Model
from keras.layers import Input, Dense
from sklearn.inspection import permutation_importance

import warnings
warnings.filterwarnings("ignore", category=UndefinedMetricWarning)
warnings.simplefilter(action='ignore', category=FutureWarning)
```

★ Creating and displaying a confusion matrix, along with an optional classification report. That used to evaluate the performance of a classification model by showing the counts of true positives, true negatives, false positives, and false negatives.

```
[ ]  def conf_matrix(x, y, title, show_report=False):
         cm = confusion_matrix(x, y)
         plt.figure(figsize=(6, 4))

         sns.heatmap(cm, annot=True, fmt='d', cmap="Oranges", cbar=False)
         plt.title(f'Confusion Matrix - {title} Data')
         plt.xlabel('Predicted Class')
         plt.ylabel('True Class')
         plt.show()
         if not show_report:
             print("F1 scores: ", f1_score(x, y))

         if show_report:
             report = classification_report(x, y)
             print("Classification Report:")
             print(report)
             plt.show()
         return f1_score(x, y)
```

★ Reading Data from CSV file

```
[ ] MCS_data=pd.read_csv("https://raw.githubusercontent.com/ahmedbadawy11/Machine-Learning-tasks/anas/main/MCSDatasetNEXTCONLab.csv")
```

```
[ ] MCS_data.head(10)
```

	ID	Latitude	Longitude	Day	Hour	Minute	Duration	RemainingTime	Resources	Coverage	OnPeakHours	GridNumber	Ligitimacy
0	1	45.442142	-75.303369	1	4	13	40	40	9	91	0	131380	1
1	1	45.442154	-75.304366	1	4	23	40	30	9	91	0	131380	1
2	1	45.442104	-75.303963	1	4	33	40	20	9	91	0	121996	1
3	1	45.441868	-75.303577	1	4	43	40	10	9	91	0	121996	1
4	2	45.447727	-75.147722	2	15	49	30	30	5	47	0	140784	1
5	2	45.447747	-75.147951	2	15	59	30	20	5	47	0	140784	1
6	2	45.447790	-75.148303	2	16	9	30	10	5	47	0	140784	1
7	3	45.508896	-75.259807	2	12	27	30	30	4	43	0	243994	1
8	3	45.508748	-75.260652	2	12	37	30	20	4	43	0	243994	1
9	3	45.508082	-75.260380	2	12	47	30	10	4	43	0	243994	1

```
[ ] MCS_data.shape

(14484, 13)
```

★ Splitting the dataset into two parts as training data and test data

- ★ the training data is the values 0, 1, and 2 in column day
- ★ test data is the value 3 in column day

```
[ ] MCS_data['Day'].value_counts()

2    2483
1    2467
3    2460
5    2457
0    2305
4    2279
6      33
Name: Day, dtype: int64
```

```
[ ] train_dataset = MCS_data[MCS_data['Day'].isin([0, 1, 2])]
    test_dataset = MCS_data[MCS_data['Day'] == 3]
```

★ Drop ID and Day Features from training and test data

```
[ ] train_dataset = train_dataset.drop(['ID', 'Day'], axis=1)
    test_dataset = test_dataset.drop(['ID', 'Day'], axis=1)
```

Output

```
[ ] train_dataset
```

	Latitude	Longitude	Hour	Minute	Duration	RemainingTime	Resources	Coverage	OnPeakHours	GridNumber	Ligitimacy
0	45.442142	-75.303369	4	13	40	40	9	91	0	131380	1
1	45.442154	-75.304366	4	23	40	30	9	91	0	131380	1
2	45.442104	-75.303963	4	33	40	20	9	91	0	121996	1
3	45.441868	-75.303577	4	43	40	10	9	91	0	121996	1
4	45.447727	-75.147722	15	49	30	30	5	47	0	140784	1
...	...	...	...	...	...	...	...	...	...	...	...
14479	45.445303	-75.165596	1	18	20	20	10	80	0	131397	1
14480	45.445574	-75.165168	1	28	20	10	10	80	0	131397	1
14481	45.436682	-75.152416	12	21	30	30	4	63	0	122015	1
14482	45.436978	-75.153278	12	31	30	20	4	63	0	122015	1
14483	45.436983	-75.153240	12	41	30	10	4	63	0	122015	1

7255 rows × 11 columns

```
[ ] test_dataset
```

	Latitude	Longitude	Hour	Minute	Duration	RemainingTime	Resources	Coverage	OnPeakHours	GridNumber	Ligitimacy
16	45.410236	-75.208755	22	25	30	30	10	32	0	75088	1
17	45.409787	-75.208022	22	35	30	20	10	32	0	75088	1
18	45.409407	-75.207825	22	45	30	10	10	32	0	65704	1
26	45.544018	-75.146364	20	39	20	20	2	82	0	300312	1
27	45.544576	-75.146364	20	49	20	10	2	82	0	300312	1
...	...	...	...	...	...	...	...	...	...	...	...
14429	45.541816	-75.177356	4	36	60	10	9	43	0	300308	1
14445	45.461207	-75.209171	3	4	40	40	4	60	0	159544	1
14446	45.461241	-75.209067	3	14	40	30	4	60	0	159544	1
14447	45.461261	-75.209205	3	24	40	20	4	60	0	159544	1
14448	45.461007	-75.208843	3	34	40	10	4	60	0	159544	1

2460 rows × 11 columns

```
[ ] MCS_data['Ligitimacy'].value_counts()

1    12587
0     1897
Name: Ligitimacy, dtype: int64
```

★ train_dataset for x_train and y_train
★ test_dataset for x_test and y_test

```
[ ] X_train = train_dataset.drop('Ligitimacy', axis=1)
    y_train = train_dataset['Ligitimacy']

    X_test = test_dataset.drop('Ligitimacy', axis=1)
    y_test = test_dataset['Ligitimacy']
```

Part 2 ---> (1) B

Function "Naive_Bayes_Models"

★ this is user-defined function which apply Naive Bayes models
★ It Takes 4 parameters Model_classifier , X__train , Y__train , X__test
★ then path X__train and Y__train to fit function then path X__test to predict functoin to calculate classifier_predictions

```
[ ] def Naive_Bayes_Models(classifier,X__train,Y__train,X__test):
        classifier.fit(X__train, Y__train)
        classifier_predictions = classifier.predict(X__test)
        return classifier_predictions
```

Function "knn_model"

★ this is user-defined function which apply KNN model
★ It Takes 4 parameters number of K , X__train , Y__train , X__test
★ then path X__train and Y__train to fit function then path X__test to predict function to calculate y_test_pred

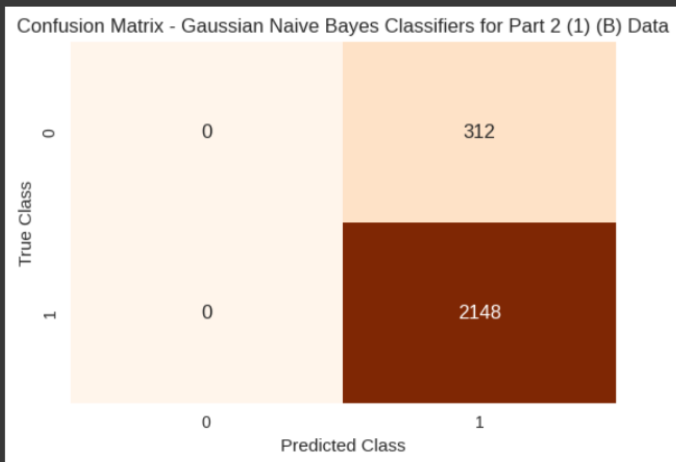
```
def knn_model(x_train, y_train, X_test, k):
    knn = KNeighborsClassifier(n_neighbors=k, metric="euclidean")
    knn.fit(x_train, y_train)

    y_test_pred = knn.predict(X_test)
    return y_test_pred
```

★ **Run "Classifier_Models" Function using GaussianNB classifier**

```
[ ] Gaussian_predictions=Naive_Bayes_Models(GaussianNB(),X_train,y_train,X_test)
```

★ **Display the confusion matrix for the GaussianNB classifier and F1 scores**

```
[ ] nb_baseline_f1= conf_matrix(y_test,Gaussian_predictions,"Gaussian Naive Bayes Classifiers for Part 2 (1) (B)")
```



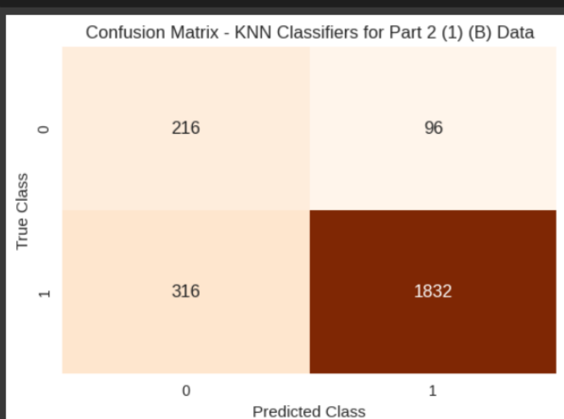

```
F1 scores:  0.9322916666666667
```

★ **Run "knn_model" Function using k=2**

```
[ ] y_test_pred_knn = knn_model(X_train, y_train, X_test, k=2)
```

★ **Display the confusion matrix for the KNN classifier and F1 scores**

```
knn_baseline_f1=conf_matrix(y_test,y_test_pred_knn,"KNN Classifiers for Part 2 (1) (B)")
```




```
F1 scores:  0.8989205103042198
```

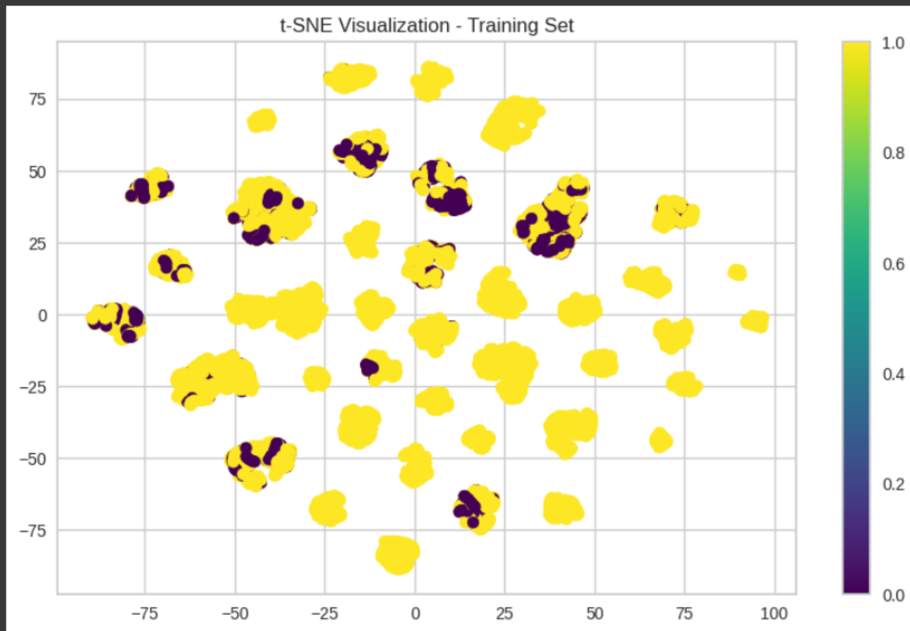
Part 2----> (1) C

Function (draw_TSNE) takes high-dimensional data and their corresponding labels, applies t-SNE to reduce the dimensionality to 2, and visualizes the data points in a scatter plot using different colors and labels.

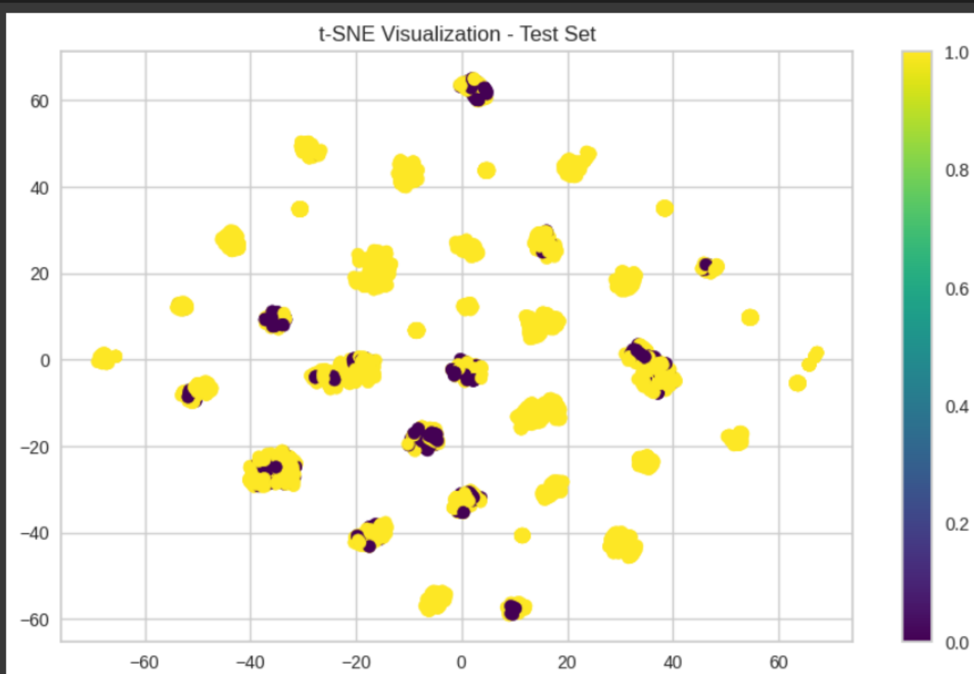
```
def draw_TSNE(data, data_labels, title=None, labels=None, colors=None):
    # method-1
#     data = X  # change this for different plotting
#     data_labels = y  # change this for different plotting
    tsne = TSNE(n_components=2, random_state=0)
    X_2d = tsne.fit_transform(data)

    # plot tsne for x_test and x_train
    classes = unique_labels(data_labels)
    target_ids = range(len(classes))
    plt.figure(figsize=(6, 5))
    colors = 'blue','r', 'g', 'b', 'c', 'm', 'k','y', 'orange', 'tomato', 'lime'
    for i, c, label in zip(target_ids, colors, classes):
        plt.scatter(X_2d[data_labels == i, 1], X_2d[data_labels == i, 0], c=c, label=label)
        # print(i)
        # print(data_labels)
        # print(X_2d[data_labels == i, 0])
    plt.legend()
    plt.title(f't-SNE Plot -{title}')
    plt.show()
```

```
# draw_TSNE(X_train,y_train,"Training Set")
# draw_TSNE(X_test,y_test,"Test Set")
def Perform_TSNE(X_Data_pca,Lable,Title=None):
    tsne = TSNE(n_components=2, random_state=0)
    X_train_tsne = tsne.fit_transform(X_Data_pca)
#     X_test_tsne = tsne.fit_transform(X_test_pca)


    plt.figure(figsize=(10, 6))
    plt.scatter(X_train_tsne[:, 0], X_train_tsne[:, 1], c=Lable, cmap="viridis")
    plt.title(f"t-SNE Visualization - {Title}")
    plt.colorbar()
    plt.show()
```

```
Perform_TSNE(X_train,y_train,"Training Set")
```




```
Perform_TSNE(X_test,y_test,"Test Set")
```



+ Code + Text

Conclusion

After we plot TSNE we notice that there is many overlapping in the train and test data and this need more effort to clustering and classify the data.

Part 2 ---> (2) A

★ Applying feature scaling to ensure that the training and test data are standardized to have zero mean and unit variance.

```
[ ] scaler = StandardScaler()
    X_train_scaled = scaler.fit_transform(X_train)
    X_test_scaled = scaler.transform(X_test)
```

```
[ ] pca = PCA(n_components=2, random_state=0)
    X_train_pca = pca.fit_transform(X_train_scaled)
    X_test_pca = pca.transform(X_test_scaled)
```

```
[ ] input_dim = X_train_scaled.shape[1]
    encoding_dim = int(input_dim / 2)
```

```python
def create_autoencoder_model(data,outputs):
    """
    :param data:
    :param outputs:
    :return:
    Create an autoencoder model
    """
    input_layer = Input(shape=(data.shape[1],))
    encoder = Dense(10, activation="relu")(input_layer)
    encoder = Dense(7, activation="relu")(encoder)
    encoder = Dense(5, activation="relu")(encoder)
    encoder = Dense(3, activation="relu")(encoder)
    encoder = Dense(outputs, activation="relu")(encoder)
    decoder = Dense(3, activation="relu")(encoder)
    decoder = Dense(5, activation="relu")(decoder)
    decoder = Dense(7, activation="relu")(decoder)
    decoder = Dense(10, activation="relu")(decoder)
    decoder = Dense(data.shape[1], activation="sigmoid")(decoder)
    autoencoder = Model(inputs=input_layer, outputs=decoder)
    autoencoder.compile(optimizer="adam", loss="mse")
    autoencoder.fit(data, data, epochs=10, batch_size=32, verbose=0)
    encoder = Model(inputs=input_layer, outputs=encoder)
    return encoder.predict(data)
```

```python
[ ]  X_train_ae = create_autoencoder_model(X_train_scaled, encoding_dim)

     X_test_ae = create_autoencoder_model(X_test_scaled, encoding_dim)
```

★ Train and predict using KNN with PCA

```python
[ ]  pca_components = [2, 3, 4, 5, 6, 7, 8, 9, 10]
     pca_f1_scores = np.zeros((len(pca_components), 2))
     for i, component in enumerate(pca_components):
         pca = PCA(n_components=component, random_state=0)
         X_train_pca = pca.fit_transform(X_train_scaled)
         X_test_pca = pca.transform(X_test_scaled)
         knn_classifier = KNeighborsClassifier(n_neighbors=5)
         knn_classifier.fit(X_train_pca, y_train)
         y_pred = knn_classifier.predict(X_test_pca)
         pca_f1_scores[i, 0] = component
         pca_f1_scores[i, 1] = f1_score(y_test, y_pred)
         print("KNN with PCA (n_components = {}): {}".format(component, pca_f1_scores[i, 1]))
         print(classification_report(y_test, y_pred))
```

```
KNN with PCA (n_components = 2): 0.9222727272727272
              precision    recall  f1-score   support

           0       0.43      0.29      0.34       312
           1       0.90      0.94      0.92      2148

    accuracy                           0.86      2460
   macro avg       0.66      0.61      0.63      2460
weighted avg       0.84      0.86      0.85      2460

KNN with PCA (n_components = 3): 0.9366736256089075
              precision    recall  f1-score   support

           0       0.57      0.54      0.55       312
           1       0.93      0.94      0.94      2148

    accuracy                           0.89      2460
   macro avg       0.75      0.74      0.74      2460
weighted avg       0.89      0.89      0.89      2460

KNN with PCA (n_components = 4): 0.9225850650833523
              precision    recall  f1-score   support

           0       0.44      0.32      0.37       312
           1       0.91      0.94      0.92      2148

    accuracy                           0.86      2460
   macro avg       0.67      0.63      0.65      2460
weighted avg       0.85      0.86      0.85      2460

KNN with PCA (n_components = 5): 0.9128555176336747
              precision    recall  f1-score   support

           0       0.33      0.23      0.27       312
           1       0.89      0.93      0.91      2148

    accuracy                           0.84      2460
   macro avg       0.61      0.58      0.59      2460
weighted avg       0.82      0.84      0.83      2460

KNN with PCA (n_components = 6): 0.9236763694705478
```

```
              precision    recall  f1-score   support

           0       0.46      0.36      0.40       312
           1       0.91      0.94      0.92      2148

    accuracy                           0.86      2460
   macro avg       0.68      0.65      0.66      2460
weighted avg       0.85      0.86      0.86      2460

KNN with PCA (n_components = 7): 0.9219038817005545
              precision    recall  f1-score   support

           0       0.45      0.41      0.43       312
           1       0.92      0.93      0.92      2148

    accuracy                           0.86      2460
   macro avg       0.68      0.67      0.68      2460
weighted avg       0.86      0.86      0.86      2460

KNN with PCA (n_components = 8): 0.9209065679925994
              precision    recall  f1-score   support

           0       0.45      0.41      0.43       312
           1       0.91      0.93      0.92      2148

    accuracy                           0.86      2460
   macro avg       0.68      0.67      0.67      2460
weighted avg       0.86      0.86      0.86      2460

KNN with PCA (n_components = 9): 0.9231481481481482
              precision    recall  f1-score   support

           0       0.47      0.43      0.45       312
           1       0.92      0.93      0.92      2148

    accuracy                           0.87      2460
   macro avg       0.69      0.68      0.68      2460
weighted avg       0.86      0.87      0.86      2460

KNN with PCA (n_components = 10): 0.9231481481481482
```

```
              precision    recall  f1-score   support

           0       0.47      0.43      0.45       312
           1       0.92      0.93      0.92      2148

    accuracy                           0.87      2460
   macro avg       0.69      0.68      0.68      2460
weighted avg       0.86      0.87      0.86      2460
```

★ Train and predict using KNN with AE

```
[ ] ae_components = [2, 3, 4, 5, 6, 7, 8, 9, 10]
    ae_f1_scores = np.zeros((len(ae_components), 2))
    for i, component in enumerate(ae_components):
        X_train_ae = create_autoencoder_model(X_train_scaled, component)
        X_test_ae = create_autoencoder_model(X_test_scaled, component)
        knn_classifier = KNeighborsClassifier(n_neighbors=5)
        knn_classifier.fit(X_train_ae, y_train)
        y_pred = knn_classifier.predict(X_test_ae)
        ae_f1_scores[i, 0] = component
        ae_f1_scores[i, 1] = f1_score(y_test, y_pred)
        print("KNN with AE (n_components = {}): {}".format(component, ae_f1_scores[i, 1]))
        print(classification_report(y_test, y_pred))
```

```
227/227 [==============================] - 0s 1ms/step
77/77 [==============================] - 1s 5ms/step
KNN with AE (n_components = 2): 0.9260393873085339
              precision    recall  f1-score   support

           0       0.16      0.02      0.03       312
           1       0.87      0.99      0.93      2148

    accuracy                           0.86      2460
   macro avg       0.52      0.50      0.48      2460
weighted avg       0.78      0.86      0.81      2460

227/227 [==============================] - 0s 1ms/step
77/77 [==============================] - 0s 1ms/step
KNN with AE (n_components = 3): 0.9254058797718298
              precision    recall  f1-score   support

           0       0.22      0.04      0.06       312
           1       0.88      0.98      0.93      2148

    accuracy                           0.86      2460
   macro avg       0.55      0.51      0.49      2460
weighted avg       0.79      0.86      0.82      2460

227/227 [==============================] - 0s 1ms/step
77/77 [==============================] - 0s 1ms/step
KNN with AE (n_components = 4): 0.6603212373587152
              precision    recall  f1-score   support

           0       0.17      0.67      0.27       312
           1       0.91      0.52      0.66      2148

    accuracy                           0.54      2460
   macro avg       0.54      0.59      0.46      2460
weighted avg       0.82      0.54      0.61      2460

227/227 [==============================] - 0s 1ms/step
77/77 [==============================] - 0s 1ms/step
KNN with AE (n_components = 5): 0.8472121650977552
```

```
              precision    recall  f1-score   support

           0       0.15      0.23      0.19       312
           1       0.88      0.82      0.85      2148

    accuracy                           0.74      2460
   macro avg       0.52      0.52      0.52      2460
weighted avg       0.79      0.74      0.76      2460

227/227 [==============================] - 0s 1ms/step
77/77 [==============================] - 0s 1ms/step
KNN with AE (n_components = 6): 0.9148418491484186
              precision    recall  f1-score   support

           0       0.08      0.02      0.04       312
           1       0.87      0.96      0.91      2148

    accuracy                           0.84      2460
   macro avg       0.48      0.49      0.47      2460
weighted avg       0.77      0.84      0.80      2460

227/227 [==============================] - 0s 1ms/step
77/77 [==============================] - 0s 2ms/step
KNN with AE (n_components = 7): 0.9271696467509812
              precision    recall  f1-score   support

           0       0.00      0.00      0.00       312
           1       0.87      0.99      0.93      2148

    accuracy                           0.86      2460
   macro avg       0.44      0.49      0.46      2460
weighted avg       0.76      0.86      0.81      2460

227/227 [==============================] - 0s 1ms/step
77/77 [==============================] - 0s 1ms/step
KNN with AE (n_components = 8): 0.8741905642923219
```

```
              precision    recall  f1-score   support

           0       0.09      0.08      0.09       312
           1       0.87      0.88      0.87      2148

    accuracy                           0.78      2460
   macro avg       0.48      0.48      0.48      2460
weighted avg       0.77      0.78      0.77      2460

227/227 [==============================] - 0s 1ms/step
77/77 [==============================] - 0s 2ms/step
KNN with AE (n_components = 9): 0.869134638057062
              precision    recall  f1-score   support

           0       0.17      0.20      0.18       312
           1       0.88      0.86      0.87      2148

    accuracy                           0.77      2460
   macro avg       0.52      0.53      0.53      2460
weighted avg       0.79      0.77      0.78      2460

227/227 [==============================] - 1s 2ms/step
77/77 [==============================] - 0s 2ms/step
KNN with AE (n_components = 10): 0.6023444544634806
              precision    recall  f1-score   support

           0       0.11      0.43      0.17       312
           1       0.85      0.47      0.60      2148

    accuracy                           0.46      2460
   macro avg       0.48      0.45      0.39      2460
weighted avg       0.76      0.46      0.55      2460
```

★ Train and predict using Naive Bayes with PCA

```
[ ] pca_nb_components = [2, 3, 4, 5, 6, 7, 8, 9, 10]
    pca_nb_f1_scores = np.zeros((len(pca_nb_components), 2))
    for i, component in enumerate(pca_nb_components):
        pca = PCA(n_components=component, random_state=0)
        X_train_pca = pca.fit_transform(X_train_scaled)
        X_test_pca = pca.transform(X_test_scaled)
        nb_classifier = GaussianNB()
        nb_classifier.fit(X_train_pca, y_train)
        y_pred = nb_classifier.predict(X_test_pca)
        pca_nb_f1_scores[i, 0] = component
        pca_nb_f1_scores[i, 1] = f1_score(y_test, y_pred)
        print("Naive Bayes with PCA (n_components = {}): {}".format(component, pca_nb_f1_scores[i, 1]))
        print(classification_report(y_test, y_pred))
```

```
Naive Bayes with PCA (n_components = 2): 0.9322916666666667
              precision    recall  f1-score   support

           0       0.00      0.00      0.00       312
           1       0.87      1.00      0.93      2148

    accuracy                           0.87      2460
   macro avg       0.44      0.50      0.47      2460
weighted avg       0.76      0.87      0.81      2460

Naive Bayes with PCA (n_components = 3): 0.9344919786096257
              precision    recall  f1-score   support

           0       0.57      0.22      0.32       312
           1       0.90      0.98      0.93      2148

    accuracy                           0.88      2460
   macro avg       0.74      0.60      0.63      2460
weighted avg       0.86      0.88      0.86      2460

Naive Bayes with PCA (n_components = 4): 0.9329472042771219
              precision    recall  f1-score   support

           0       0.55      0.21      0.30       312
           1       0.89      0.97      0.93      2148

    accuracy                           0.88      2460
   macro avg       0.72      0.59      0.62      2460
weighted avg       0.85      0.88      0.85      2460

Naive Bayes with PCA (n_components = 5): 0.9342545130376644
              precision    recall  f1-score   support

           0       0.57      0.22      0.32       312
           1       0.90      0.98      0.93      2148

    accuracy                           0.88      2460
   macro avg       0.73      0.60      0.63      2460
weighted avg       0.85      0.88      0.86      2460
```

```
Naive Bayes with PCA (n_components = 6): 0.9349720670391062
              precision    recall  f1-score   support

           0       0.58      0.25      0.35       312
           1       0.90      0.97      0.93      2148

    accuracy                           0.88      2460
   macro avg       0.74      0.61      0.64      2460
weighted avg       0.86      0.88      0.86      2460

Naive Bayes with PCA (n_components = 7): 0.9355992844364939
              precision    recall  f1-score   support

           0       0.59      0.26      0.36       312
           1       0.90      0.97      0.94      2148

    accuracy                           0.88      2460
   macro avg       0.74      0.62      0.65      2460
weighted avg       0.86      0.88      0.86      2460

Naive Bayes with PCA (n_components = 8): 0.9249771271729186
              precision    recall  f1-score   support

           0       0.47      0.35      0.40       312
           1       0.91      0.94      0.92      2148

    accuracy                           0.87      2460
   macro avg       0.69      0.65      0.66      2460
weighted avg       0.85      0.87      0.86      2460

Naive Bayes with PCA (n_components = 9): 0.9239578561612459
              precision    recall  f1-score   support

           0       0.46      0.36      0.40       312
           1       0.91      0.94      0.92      2148

    accuracy                           0.87      2460
   macro avg       0.68      0.65      0.66      2460
weighted avg       0.85      0.87      0.86      2460
```

```
Naive Bayes with PCA (n_components = 10): 0.9244159413650939
              precision    recall  f1-score   support

           0       0.46      0.36      0.40       312
           1       0.91      0.94      0.92      2148

    accuracy                           0.87      2460
   macro avg       0.69      0.65      0.66      2460
weighted avg       0.85      0.87      0.86      2460
```

★ Train and predict using Naive Bayes with AE

```
[ ]
    ae_nb_components = [2, 3, 4, 5, 6, 7, 8, 9, 10]
    ae_nb_f1_scores = np.zeros((len(ae_nb_components), 2))
    for i, component in enumerate(ae_nb_components):
        X_train_ae = create_autoencoder_model(X_train_scaled, component)
        X_test_ae = create_autoencoder_model(X_test_scaled, component)
        nb_classifier = GaussianNB()
        nb_classifier.fit(X_train_ae, y_train)
        y_pred = nb_classifier.predict(X_test_ae)
        ae_nb_f1_scores[i, 0] = component
        ae_nb_f1_scores[i, 1] = f1_score(y_test, y_pred)
        print("Naive Bayes with AE (n_components = {}): {}".format(component, ae_nb_f1_scores[i, 1]))
        print(classification_report(y_test, y_pred))
```

```
227/227 [==============================] - 1s 3ms/step
77/77 [==============================] - 0s 1ms/step
Naive Bayes with AE (n_components = 2): 0.9322916666666667
              precision    recall  f1-score   support

           0       0.00      0.00      0.00       312
           1       0.87      1.00      0.93      2148

    accuracy                           0.87      2460
   macro avg       0.44      0.50      0.47      2460
weighted avg       0.76      0.87      0.81      2460

227/227 [==============================] - 1s 4ms/step
77/77 [==============================] - 0s 1ms/step
Naive Bayes with AE (n_components = 3): 0.09804772234273319
              precision    recall  f1-score   support

           0       0.12      0.86      0.20       312
           1       0.72      0.05      0.10      2148

    accuracy                           0.15      2460
   macro avg       0.42      0.46      0.15      2460
weighted avg       0.64      0.15      0.11      2460

227/227 [==============================] - 0s 1ms/step
77/77 [==============================] - 0s 1ms/step
Naive Bayes with AE (n_components = 4): 0.8455125061304561
              precision    recall  f1-score   support

           0       0.20      0.34      0.25       312
           1       0.89      0.80      0.85      2148

    accuracy                           0.74      2460
   macro avg       0.55      0.57      0.55      2460
weighted avg       0.81      0.74      0.77      2460
```

```
227/227 [==============================] - 0s 1ms/step
77/77 [==============================] - 0s 1ms/step
Naive Bayes with AE (n_components = 5): 0.6723832052040213
              precision    recall  f1-score   support

           0       0.18      0.69      0.28       312
           1       0.92      0.53      0.67      2148

    accuracy                           0.55      2460
   macro avg       0.55      0.61      0.48      2460
weighted avg       0.83      0.55      0.62      2460

227/227 [==============================] - 1s 1ms/step
77/77 [==============================] - 0s 1ms/step
Naive Bayes with AE (n_components = 6): 0.7305548181576852
              precision    recall  f1-score   support

           0       0.08      0.22      0.12       312
           1       0.85      0.64      0.73      2148

    accuracy                           0.59      2460
   macro avg       0.47      0.43      0.43      2460
weighted avg       0.75      0.59      0.65      2460

227/227 [==============================] - 0s 2ms/step
77/77 [==============================] - 0s 2ms/step
Naive Bayes with AE (n_components = 7): 0.5170699370235333
              precision    recall  f1-score   support

           0       0.14      0.71      0.23       312
           1       0.90      0.36      0.52      2148

    accuracy                           0.41      2460
   macro avg       0.52      0.54      0.38      2460
weighted avg       0.80      0.41      0.48      2460
```

```
227/227 [==============================] - 0s 1ms/step
77/77 [==============================] - 0s 2ms/step
Naive Bayes with AE (n_components = 8): 0.9322916666666667
              precision    recall  f1-score   support

           0       0.00      0.00      0.00       312
           1       0.87      1.00      0.93      2148

    accuracy                           0.87      2460
   macro avg       0.44      0.50      0.47      2460
weighted avg       0.76      0.87      0.81      2460

227/227 [==============================] - 0s 1ms/step
77/77 [==============================] - 0s 1ms/step
Naive Bayes with AE (n_components = 9): 0.5550769230769231
              precision    recall  f1-score   support

           0       0.08      0.36      0.13       312
           1       0.82      0.42      0.56      2148

    accuracy                           0.41      2460
   macro avg       0.45      0.39      0.34      2460
weighted avg       0.73      0.41      0.50      2460

227/227 [==============================] - 1s 3ms/step
77/77 [==============================] - 0s 2ms/step
Naive Bayes with AE (n_components = 10): 0.2751159196290572
              precision    recall  f1-score   support

           0       0.11      0.73      0.20       312
           1       0.81      0.17      0.28      2148

    accuracy                           0.24      2460
   macro avg       0.46      0.45      0.24      2460
weighted avg       0.72      0.24      0.27      2460
```

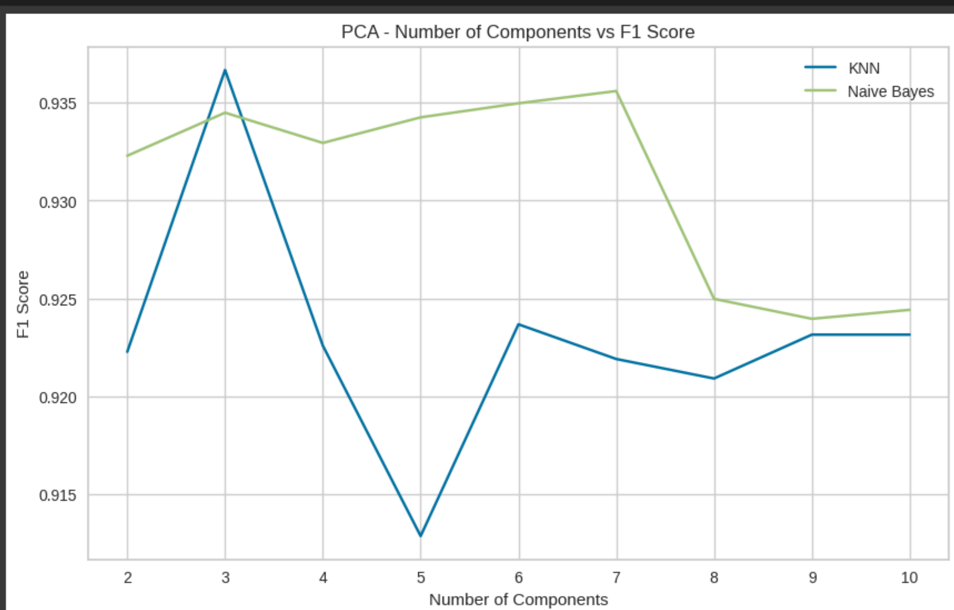
Function "Draw_POlt_No_of_components"

- this is user defined function whice apply plot
- It Takes 3 parameters KNN_f1_scores ,nb_f1_scores, Title
- then Draw plot "Number of Components" as xlabel ,"F1 Score" as ylabel

```
[ ] def Draw_POlt_No_of_components(KNN_f1_scores,nb_f1_scores,Title=None):
        plt.figure(figsize=(10, 6))
        plt.plot(KNN_f1_scores[:, 0], KNN_f1_scores[:, 1], label="KNN")
        plt.plot(nb_f1_scores[:, 0], nb_f1_scores[:, 1], label="Naive Bayes")
        plt.xlabel("Number of Components")
        plt.ylabel("F1 Score")
        plt.title(f"{Title} - Number of Components vs F1 Score")
        plt.legend()
        plt.show()
```

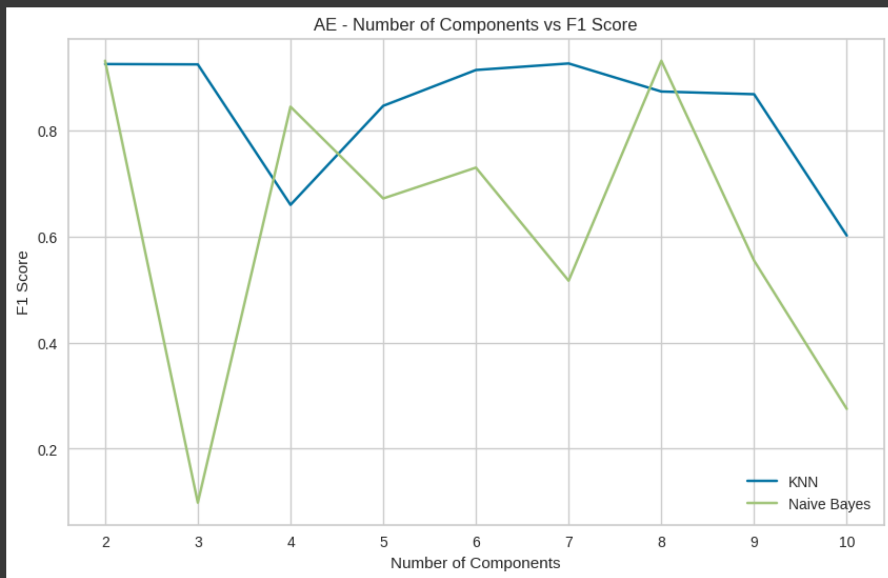
- **Plot the number of components vs F1 score for PCA for both knn and nb**

```
[ ] Draw_POlt_No_of_components(pca_f1_scores,pca_nb_f1_scores,"PCA")
```



- ★ **Plot the number of components vs F1 score for AE for both knn and nb**

```
[ ] Draw_POlt_No_of_components(ae_f1_scores,ae_nb_f1_scores,"AE")
```

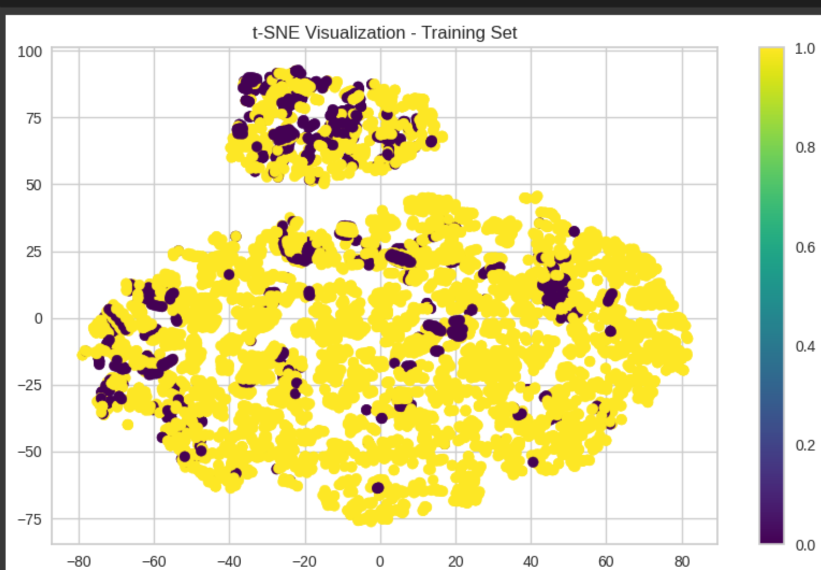


Part 2 ----> (2)B

Perform t-SNE on the best PCA-reduced data

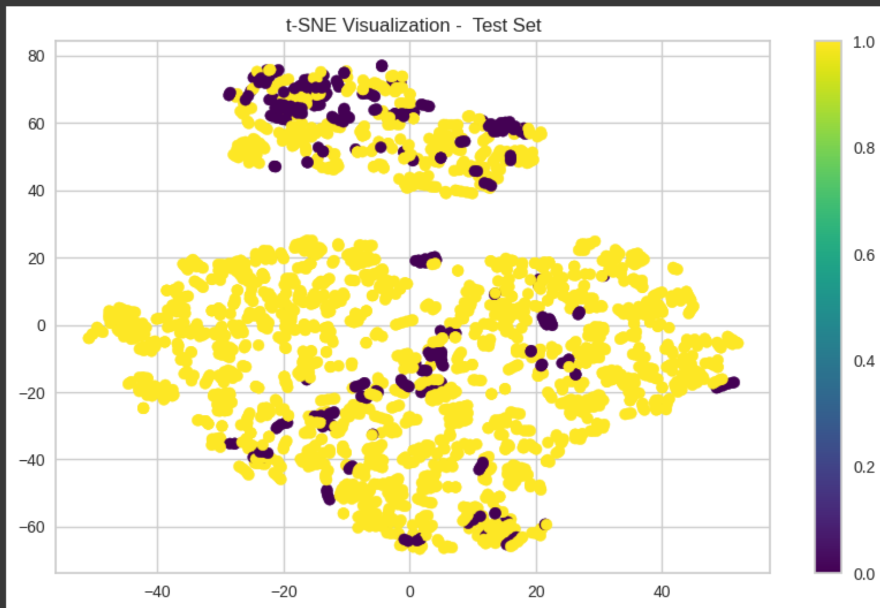
- ★ **Plot t-SNE visualization for the training set**

```
Perform_TSNE(X_train_pca,y_train,"Training Set")
```



Plot t-SNE visualization for test set

```
[ ]  Perform_TSNE(X_test_pca,y_test," Test Set")
```



Conclusion

- ★ We performed dimensionality reduction using PCA and AE, and then applies KNN and Naive Bayes classifiers to the transformed data. It also includes visualizations using t-SNE to visualize the reduced-dimensional data. The F1 scores and classification reports were printed to evaluate the models' performance.
- ★ K-nn with PCA ---→ GIVES BETTER PERFORANCE

Part 2 ----> (3) A

```python
def select_feature(X_train, y_train, X_test, y_test, FSM, model):
    fs = FSM
    fs.fit(X_train, y_train)
    X_train_new = fs.transform(X_train)
    X_test_new = fs.transform(X_test)
    model.fit(X_train_new, y_train)
    y_pred = model.predict(X_test_new)
    # acc = accuracy_score(y_test, y_pred) * 100
    f1_knn = f1_score(y_test, y_pred)* 100

    return f1_knn
```

```python
[ ] def apply_wrapper_RFECV_methods(X, y, estimator, k):
        # Recursive Feature Elimination with Cross-Validation
        rfecv = RFECV(estimator=estimator, step=1, cv=5)
        X_rfecv = rfecv.fit_transform(X, y)

        return X_rfecv
```

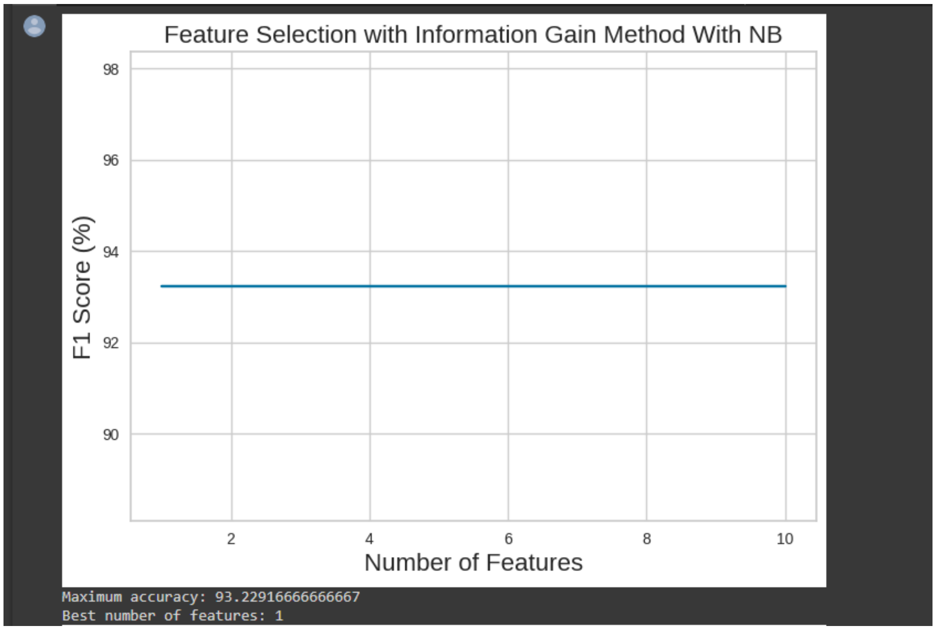
```python
[ ] def apply_wrapper_feature_elimination_methods(X, y, estimator, k, forward=True):
        # Sequential Feature Selector
        sfs = SequentialFeatureSelector(estimator, n_features_to_select=k, direction='forward' if forward else 'backward')
        X_selected = sfs.fit_transform(X, y)

        return X_selected
```

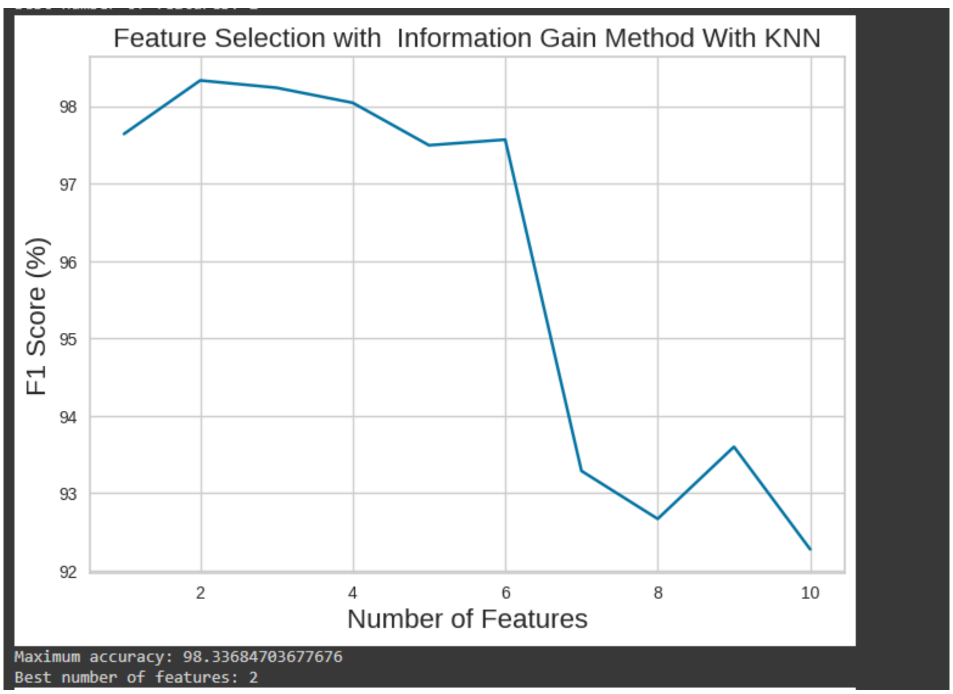
```python
acc_dict_INFOGAin_NB = {}
acc_dict_VAR_NB = {}

acc_dict_INFOGAin_KNN = {}
acc_dict_VAR_KNN = {}
```

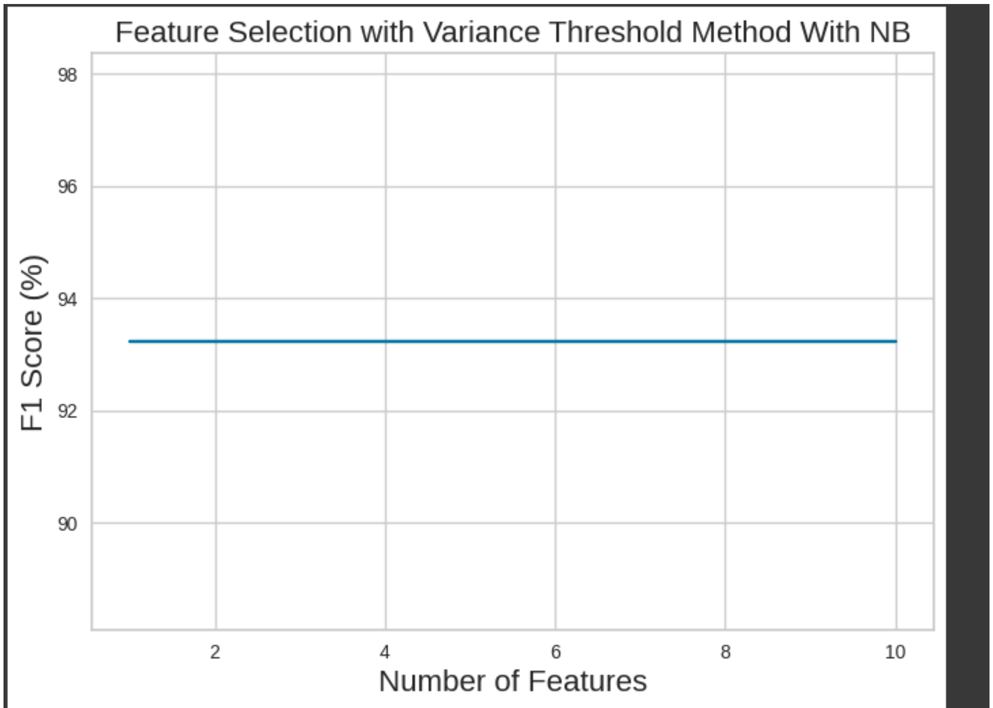
```
[ ] for k in range(1, len(X_train.columns) + 1):

        # Filter method: Information Gain
        fsm = SelectKBest(score_func=mutual_info_classif, k=k)
        # Variance Threshold
        var_threshold = VarianceThreshold(threshold=0.01)
        # X_var_threshold = var_threshold.fit_transform(X)

        # Naive Bayes classifier
        nb_classifier = GaussianNB()

        acc_InfoGainNB = select_feature(X_train, y_train, X_test, y_test, fsm, nb_classifier)
        acc_VAR_NB = select_feature(X_train, y_train, X_test, y_test, var_threshold, nb_classifier)

        acc_dict_INFOGAin_NB[k] = acc_InfoGainNB
        acc_dict_VAR_NB[k] = acc_VAR_NB


        # K-Nearest Neighbors classifier
        knn_classifier = KNeighborsClassifier()

        acc_InfoGainKNN = select_feature(X_train, y_train, X_test, y_test, fsm, knn_classifier)
        acc_VAR_KNN = select_feature(X_train, y_train, X_test, y_test, var_threshold, knn_classifier)

        acc_dict_INFOGAin_KNN[k] = acc_InfoGainKNN
        acc_dict_VAR_KNN[k] = acc_VAR_KNN
```

```
[ ] def Draw_plots(acc_list, Title=None):
        fig = plt.figure()  # Create a new figure
        plt.plot(*zip(*sorted(acc_list.items())))
        # Title = "Feature Selection with Information Gain Method"
        plt.title(Title, fontsize=16)
        plt.xlabel("Number of Features", fontsize=16)
        plt.ylabel("F1 Score (%)", fontsize=16)
        plt.show()
        print("Maximum accuracy:", max(acc_list.values()))
        print("Best number of features:", max(acc_list, key=acc_list.get))
        plt.show()
        # plt.close(fig)
```

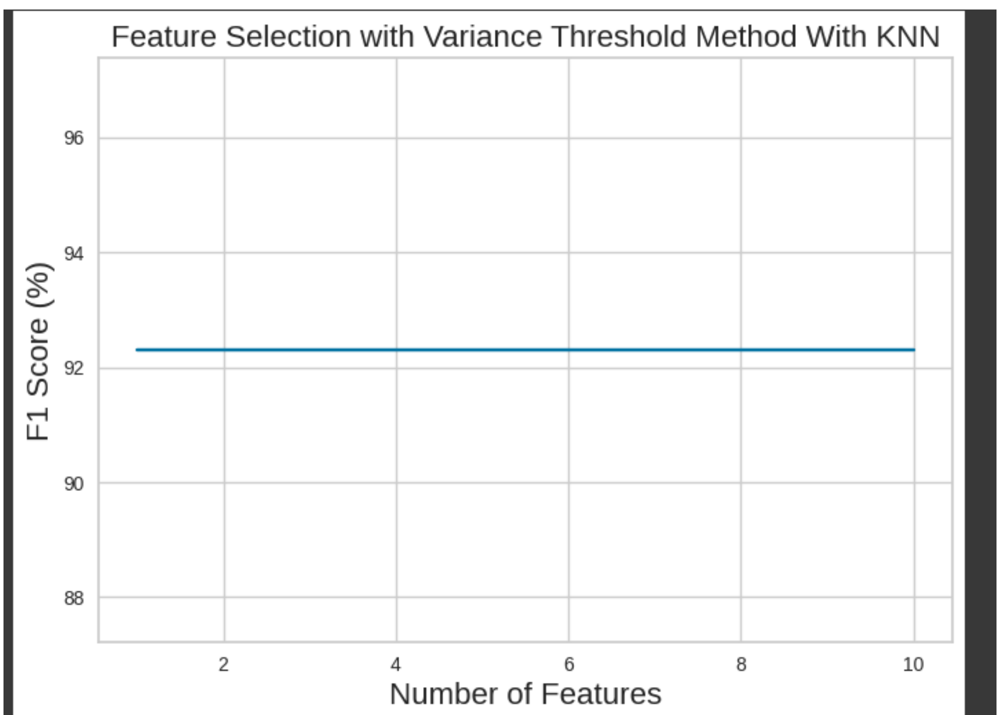
```
Draw_plots(acc_dict_INFOGAin_NB,"Feature Selection with Information Gain Method With NB")
Draw_plots(acc_dict_INFOGAin_KNN,"Feature Selection with  Information Gain Method With KNN")

Draw_plots(acc_dict_VAR_NB,"Feature Selection with Variance Threshold Method With NB")
Draw_plots(acc_dict_VAR_KNN,"Feature Selection with Variance Threshold Method With KNN")
```


Feature Selection with Information Gain Method With NB
F1 Score (%)
98
96
94
92
90
2
4
6
8
10
Number of Features
Maximum accuracy: 93.22916666666667
Best number of features: 1


Feature Selection with Information Gain Method With KNN
F1 Score (%)
98
97
96
95
94
93
92
2
4
6
8
10
Number of Features
Maximum accuracy: 98.33684703677676
Best number of features: 2




```
Maximum accuracy: 93.22916666666667
Best number of features: 1
```




```
Maximum accuracy: 92.30055658627087
Best number of features: 1
```

Part 2----> (3) B

- Function forward_backward_feature()
- This function applies wrapper methods to different models

```
[ ]  num_features = np.arange(1, 10)
     def forward_backward_feature(estimator, X_train, y_train, X_test, y_test,dr ="forward"):

         accuracies = []

         for k in num_features:
             # Sequential Feature Selector
             sfs = SequentialFeatureSelector(estimator, n_features_to_select=k,direction=dr)
             X_selected = sfs.fit_transform(X_train, y_train)

             # Train a model using the selected features
             estimator.fit(X_selected, y_train)
             X_test_selected = sfs.transform(X_test)
             predictions = estimator.predict(X_test_selected)

             # Calculate the accuracy
             accuracy = f1_score(y_test, predictions)
             accuracies.append(accuracy)

         return accuracies
```

- Function rfe_feature()
- This function applies recursion feature elemination to different models

```
def compute_permutation_importances(classifier, X, y, scoring='f1', n_repeats=10, random_state=0):
    result = permutation_importance(classifier, X, y, scoring=scoring, n_repeats=n_repeats, random_state=random_state)
    return np.array(result.importances_mean)
min_features = 2
max_features = X_train.shape[1]

def rfe_feature(estimator, X_train, y_train, X_test, y_test):
  rfe_f1_scores = []
  for num_features in range(min_features, max_features+1):
    classifier_rfe = estimator
    classifier_rfe.fit(X_train.iloc[:, :num_features], y_train)
    permutation_importances = compute_permutation_importances(classifier_rfe, X_test.iloc[:, :num_features], y_test)
    classifier = estimator
    rfe = RFE(estimator=classifier, n_features_to_select=num_features, importance_getter=lambda _: permutation_importances)
    X_train_rfe = rfe.fit_transform(X_train, y_train)
    X_test_rfe = rfe.transform(X_test)
    classifier.fit(X_train_rfe, y_train)
    predictions = classifier.predict(X_test_rfe)
    score = f1_score(y_test, predictions)
    rfe_f1_scores.append(score)
  return rfe_f1_scores
```

★ Applying wrapper method (Forward Feature Elimination) with KNN

```
accuracies_knn_fs = forward_backward_feature(KNeighborsClassifier(), X_train, y_train, X_test, y_test)
print(f'max score knn_fs {max(accuracies_knn_fs)}')
```

```
max score knn_fs 0.9837990138530172
```

★ Applying wrapper method (Recursoin Feature Elimination) with KNN

```
[ ] accuracies_nb_rfe = rfe_feature(GaussianNB(), X_train, y_train, X_test, y_test)
    print(f'max score nb_rfe {max(accuracies_nb_rfe)}')
```

```
max score nb_rfe 0.9322916666666667
```

```
[ ] accuracies_knn_rfe = rfe_feature(KNeighborsClassifier(), X_train, y_train, X_test, y_test)
    print(f'max score knn_rfe {max(accuracies_knn_rfe)}')
```

```
max score knn_rfe 0.9833684703677676
```

```
[ ] # accuracies_knn_bs = forward_backward_feature(KNeighborsClassifier(), X_train, y_train, X_test, y_test,dr="backward")
```

Apply wrapper method (Recursoin Feature Elimination) with Naive bayse

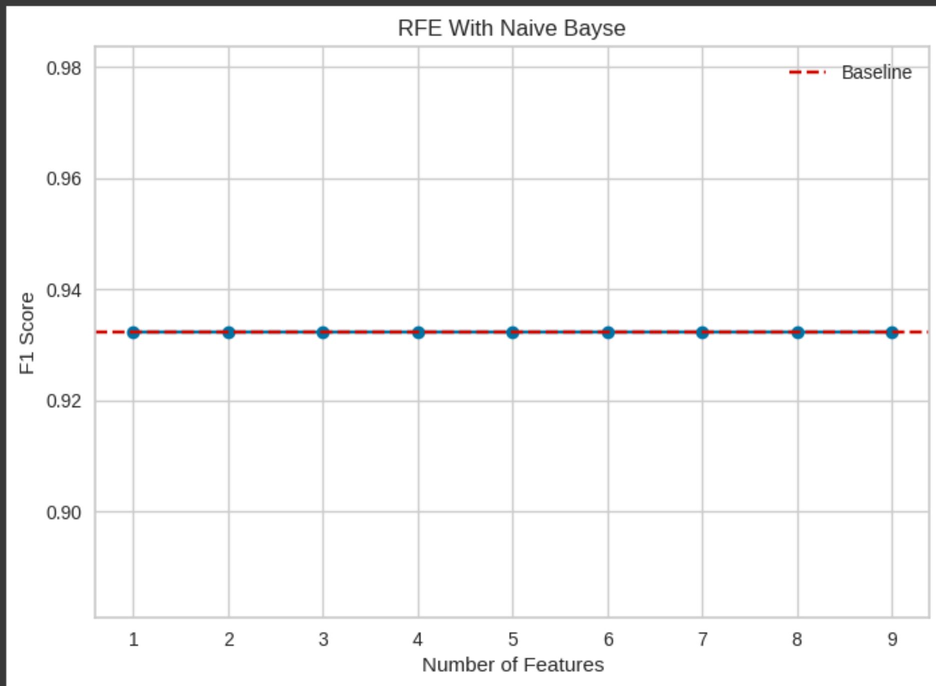
```
[ ] # accuracies_nb_bs = forward_backward_feature(GaussianNB(), X_train, y_train, X_test, y_test,dr="backward")
```

★ **Function plot_num_features_vs_accuracy()**

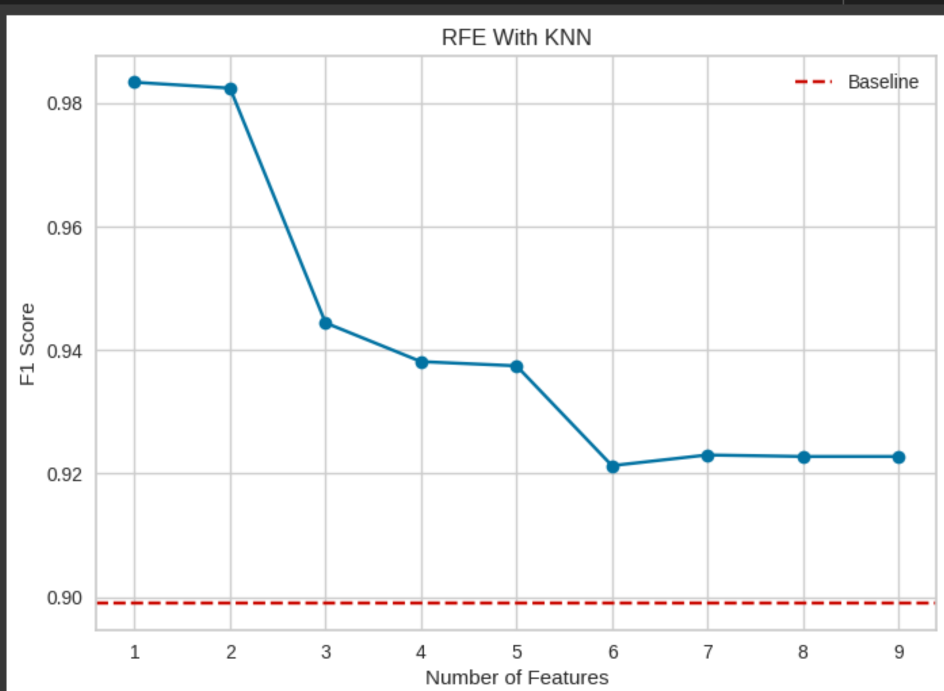
★ **To plot the accuarcy with each number of feature**

```
[ ] def plot_num_features_vs_accuracy(accuracies, baseline_accuracy,name_estimator ):
        plt.plot(num_features, accuracies, marker='o')
        plt.axhline(y=baseline_accuracy, color='r', linestyle='--', label='Baseline')
        plt.xlabel('Number of Features')
        plt.ylabel("F1 Score")
        plt.title(f'{name_estimator}')
        plt.legend()
        plt.show()
```

```
plot_num_features_vs_accuracy(accuracies_nb_rfe,nb_baseline_f1,"RFE With Naive Bayse")
```

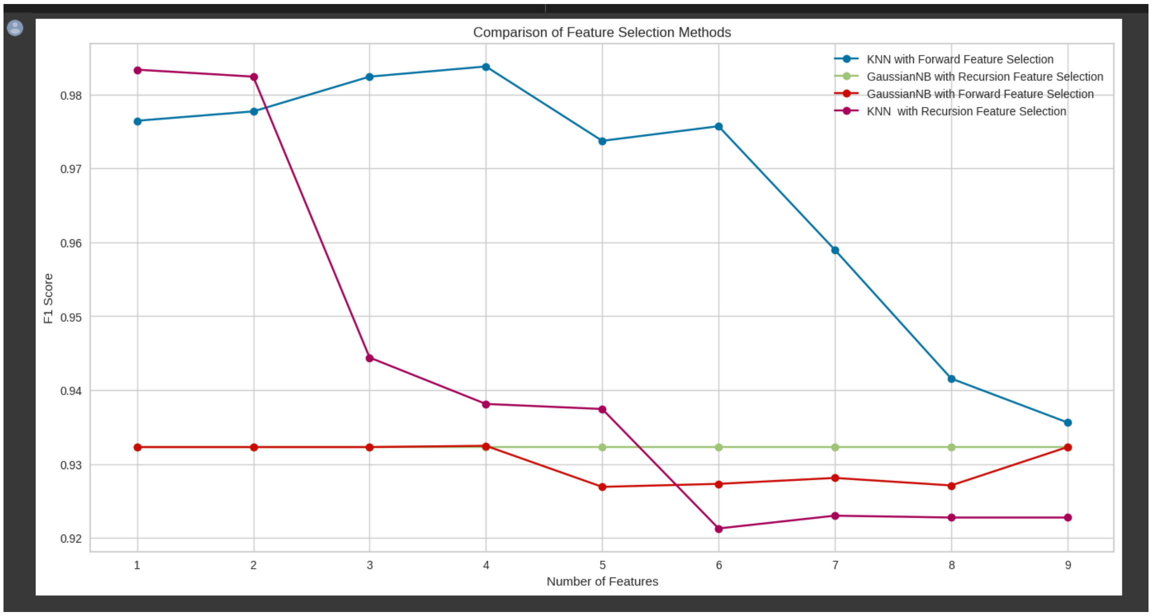



```
plot_num_features_vs_accuracy(accuracies_knn_rfe,knn_baseline_f1,"RFE With KNN")
```



★ Comparing with each accuracy to get the best number of features

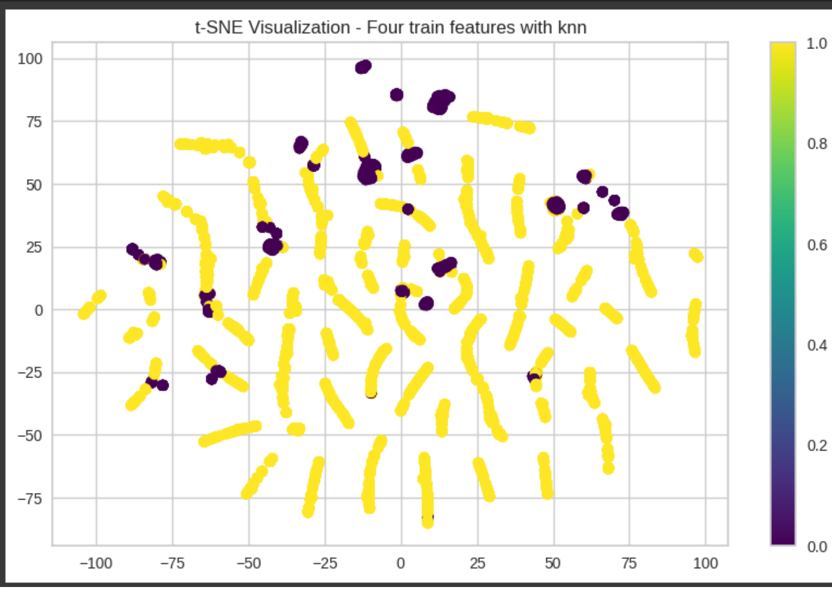
```python
plt.figure(figsize=(16, 8))
plt.plot(num_features, accuracies_knn_fs, marker='o', label='KNN with Forward Feature Selection')
plt.plot(num_features, accuracies_nb_rfe, marker='o', label='GaussianNB with Recursion Feature Selection')
plt.plot(num_features, accuracies_nb_fs, marker='o', label='GaussianNB with Forward Feature Selection')
plt.plot(num_features, accuracies_knn_rfe, marker='o', label='KNN  with Recursion Feature Selection')

# plt.plot(num_features, list(acc_dict_INFOGAin_KNN.values())[:9], marker='*', label='KNN with Information Gain ')
# plt.plot(num_features, list(acc_dict_INFOGAin_NB.values())[:9], marker='*', label='GaussianNB with Information Gain')
# plt.plot(num_features, list(acc_dict_VAR_NB.values())[:9], marker='*', label='GaussianNB with Variance Threshold')
# plt.plot(num_features, list(acc_dict_VAR_KNN.values())[:9], marker='*', label='KNN  with Variance Threshold')

plt.xlabel('Number of Features')
plt.ylabel('F1 Score')
plt.title('Comparison of Feature Selection Methods')
plt.legend()
plt.grid(True)
plt.show()
```



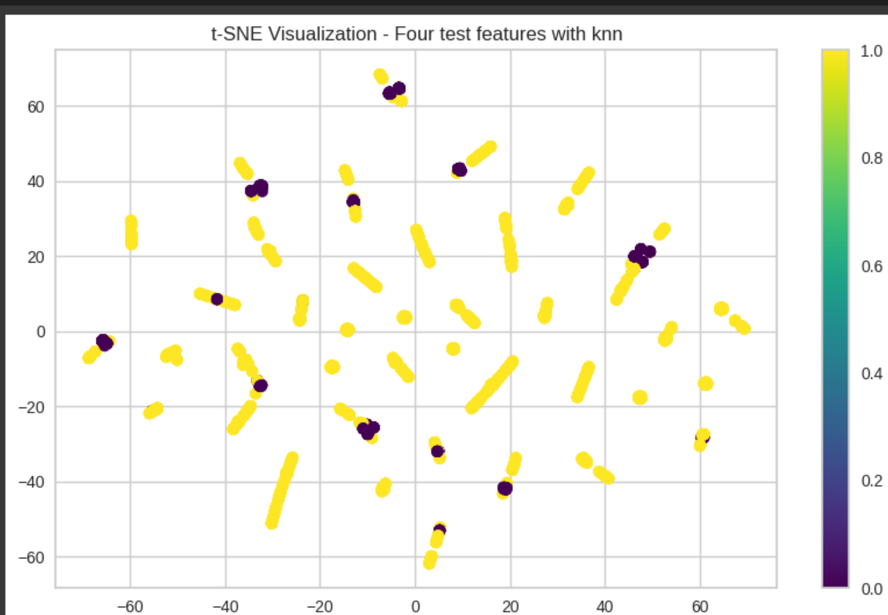
- ★ **Best method is Wrapper (Forward feature Elimination)**
- ★ **Draw Tsne when number of features is four with forward selection**

```
sfs = SequentialFeatureSelector(KNeighborsClassifier(), n_features_to_select=4)
X_selected = sfs.fit_transform(X_train, y_train)

KNeighborsClassifier().fit(X_selected, y_train)
X_test_selected = sfs.transform(X_test)
```

```
[ ] Perform_TSNE(X_selected,y_train,"Four train features with knn")
```




```
[ ] Perform_TSNE(X_test_selected,y_test,"Four test features with knn")
```



Conclusion

We performed feature selection using both filter and wrapper methods on KNN and Naive Bayes (NB) models to determine the optimal number of features. In the filter approach, we employed gain and variance threshold techniques. As for the wrapper method, we encountered difficulties when implementing Recursive Feature Elimination (RFE) because it requires models with coefficients. To overcome this, we calculated the feature importance for both KNN and Naive Bayes, enabling us to utilize RFE. The results showed that forward selection with the KNN model provided the best number of features.

Part 2 (4) A

Function "plot_No_cluster_Vs_Total_Legitimate"

- ★ this is user defined function whice apply plot number of clusters Vs Total Legitimate-only Members
- ★ It Takes 3 parameters keys , values , Title
- ★ Then plot Number of Clusters vs. Total Legitimate-only Members for each clustering model

```
[ ]  def plot_No_cluster_Vs_Total_Legitimate(keys,values,Title=None):
         for i in range(len(keys)):
             plt.scatter(keys[i], values[i], color='blue', marker='o')
         plt.plot(keys, values)
         plt.xlabel("number of clusters")
         plt.ylabel("Total Legitimate-only Members")
         plt.title(f"Number of Clusters vs. Total Legitimate-only Members {Title}")
         plt.show()
```

Function "clustering_Kmeans"

- ★ this is user defined function whice apply KMeans Model
- ★ It Takes 2 parameters dataset ,Cluster_NUM_list
- ★ then path X to fit function then get labels
- ★ then get the true lable for each cluster [0,1]
- ★ then get only legitimate member and count them for each number of K in list Cluster_NUM_list = [8, 12, 16, 20, 32]

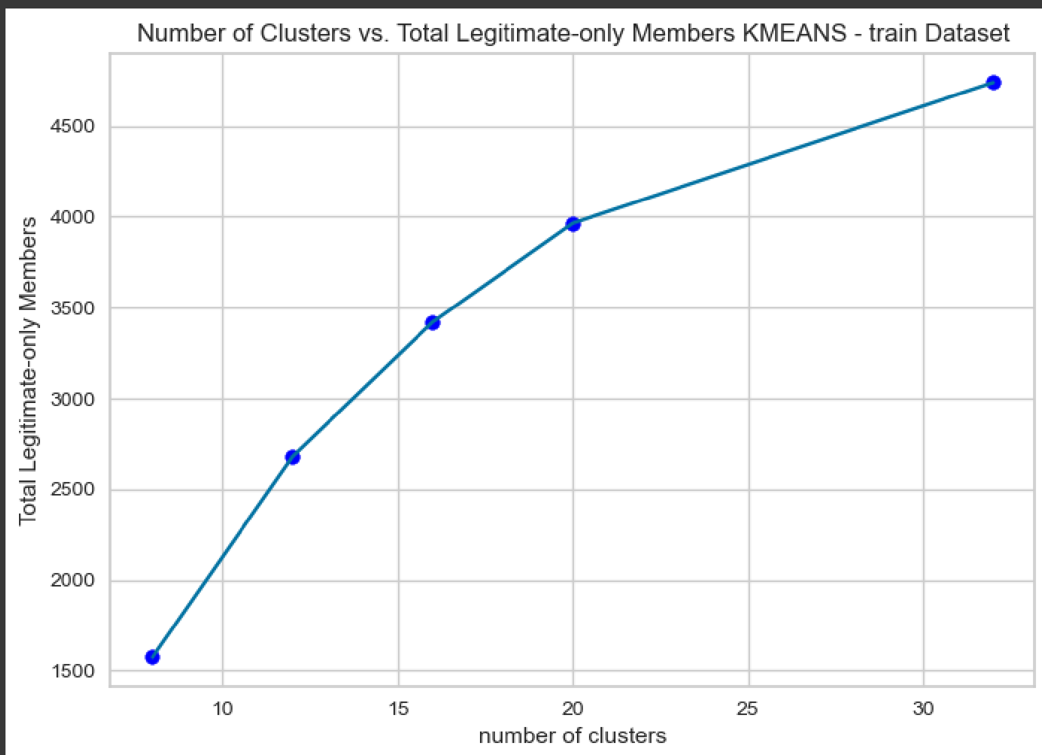
```python
def clustering_Kmeans(dataset, Cluster_NUM_list):
    Our_data = dataset[['Latitude', 'Longitude','Ligitimacy']]
    X=Our_data.iloc[:, :-1].values
    y_true = Our_data.iloc[:, -1].astype(int).values

    cluster_labels = {}
    cluster_labels_legitimate_only  = {}


    for k in Cluster_NUM_list:
        kmeans = KMeans(n_clusters=k, random_state=0)
        kmeans.fit(X)

        y_pred = kmeans.labels_

        for cluster in range(k):
            cluster_indices = np.where(y_pred == cluster)[0]
            if cluster_indices.size > 0:
                labels_in_cluster = y_true[cluster_indices]
                label_counts = np.bincount(labels_in_cluster)
                most_Repeat_label = label_counts.argmax()
                cluster_labels[(k, cluster)] = {
                    'True Label': most_Repeat_label,
                    'Counts for pair of lable': label_counts
                }

                if(label_counts[0]==0):
                    cluster_labels_legitimate_only[(k, cluster)] = {
                    'legitimate_only': label_counts[1]

                }
    sum_dict_temp = {}
    for (k, cluster), info in cluster_labels_legitimate_only.items():
        if k in sum_dict_temp:
            sum_dict_temp[k] += info['legitimate_only']
        else:
            sum_dict_temp[k] = info['legitimate_only']

    print("Pair of Num Of cluster and Count",sum_dict_temp)
    keys = list(sum_dict_temp.keys())
    values = list(sum_dict_temp.values())

    return keys,values
```

```
[ ] Cluster_NUM_list = [8, 12, 16, 20, 32]
```

```
[ ] keys,values = clustering_Kmeans(train_dataset, Cluster_NUM_list)
```

```
Pair of Num Of cluster and Count {8: 1573, 12: 2679, 16: 3420, 20: 3965, 32: 4740}
```

```
[ ] plot_No_cluster_Vs_Total_Legitimate(keys,values,"KMEANS - train Dataset")
```




```
[ ] keys,values = clustering_Kmeans(test_dataset, Cluster_NUM_list)
```

```
Pair of Num Of cluster and Count {8: 497, 12: 978, 16: 1179, 20: 1376, 32: 1713}
```

Part 2 ---> (4) B

Function "clustering_SOFM"

- ★ this is user defined function whice apply MiniSom Model
- ★ It Takes 2 parameters dataset ,Cluster_NUM_list
- ★ then path X to winner function to Get the closest cluster for each sample
- ★ then get the true lable for each cluster [0,1]
- ★ then get only legitimate member and count them for each number of K in list Cluster_NUM_list = [8, 12, 16, 20, 32]

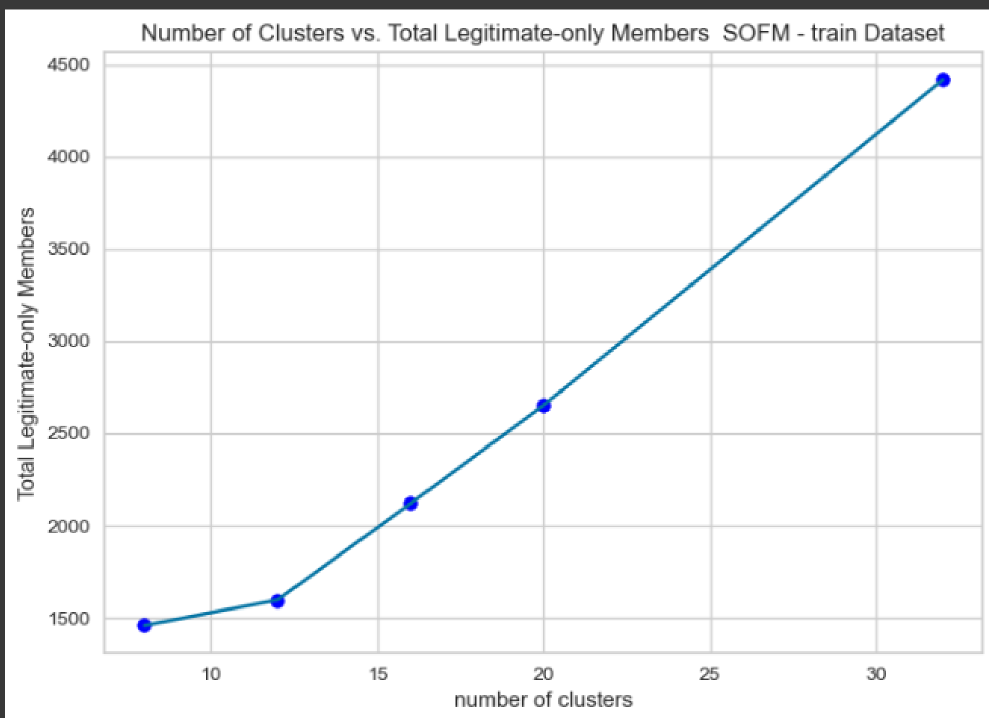
```
def clustering_SOFM(dataset, Cluster_NUM_list):
    Our_data = dataset[['Latitude', 'Longitude','Ligitimacy']]
    X = Our_data.iloc[:, :-1].values
    y_true = Our_data.iloc[:, -1].astype(int).values

    cluster_labels = {}
    cluster_labels_legitimate_only = {}

    for k in Cluster_NUM_list:
        som = MiniSom(k, 1, X.shape[1], sigma=0.5, learning_rate=0.5,random_seed=42)
        # Initialize the weights using random samples
        som.random_weights_init(X)
        # Train the model
        som.train_random(X, num_iteration=100)
        # Get the closest cluster for each sample
        y_pred = np.array([som.winner(x) for x in X])

        for cluster in range(k):
            cluster_indices = np.where(y_pred == cluster)[0]
            if cluster_indices.size > 0:
                labels_in_cluster = y_true[cluster_indices]
                label_counts = np.bincount(labels_in_cluster)
                most_Repeat_label = label_counts.argmax()
                cluster_labels[(k, cluster)] = {
                    'True Label': most_Repeat_label,
                    'Counts for pair of lable': label_counts
                }
                if label_counts[0] == 0:
                    cluster_labels_legitimate_only[(k, cluster)] = {
                        'legitimate_only': label_counts[1]
                    }

    sum_dict_temp = {}
    for (k, cluster), info in cluster_labels_legitimate_only.items():
        if k in sum_dict_temp:
            sum_dict_temp[k] += info['legitimate_only']
        else:
            sum_dict_temp[k] = info['legitimate_only']

    print("Pair of Num Of cluster and Count",sum_dict_temp)
    keys = list(sum_dict_temp.keys())
    values = list(sum_dict_temp.values())

    return keys,values
```

★ **Run clustering_SOFM using the train Dataset**

```
[ ] keys_SOFM,values_SOFM= clustering_SOFM(train_dataset, Cluster_NUM_list)

    Pair of Num Of cluster and Count {8: 1457, 12: 1595, 16: 2118, 20: 2651, 32: 4416}
```

★ **Display the Number of Clusters vs. Total Legitimate-only Members SOFM (train Dataset)**

```
[ ] plot_No_cluster_Vs_Total_Legitimate(keys_SOFM,values_SOFM," SOFM - train Dataset")
```

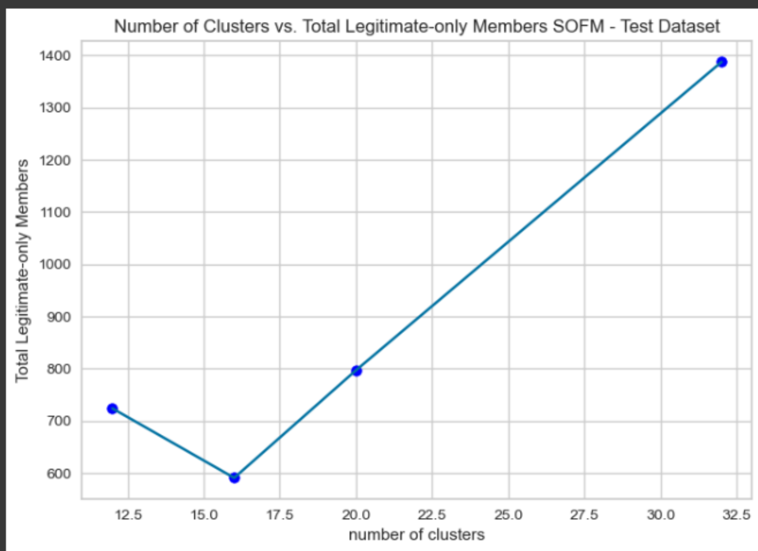


★ Run clustering_SOFM using Test Dataset

```
[ ] keys_SOFM,values_SOFM= clustering_SOFM(test_dataset, Cluster_NUM_list)

    Pair of Num Of cluster and Count {12: 724, 16: 591, 20: 797, 32: 1387}
```

★ **Display the Number of Clusters vs. Total Legitimate-only Members SOFM (Test Dataset)**

```
[ ] plot_No_cluster_Vs_Total_Legitimate(keys_SOFM,values_SOFM,"SOFM - Test Dataset")
```



Part 2 ----> (4) B

★ Try to find the eps and min_samples that obtain this Number of Clusters
★ [8, 12, 16, 20, 32]

```
[ ] Our_data = train_dataset[['Latitude', 'Longitude', 'Ligitimacy']]
    X = Our_data.iloc[:, :-1].values
    y_true = Our_data.iloc[:, -1].astype(int).values
    num_clusters = [8, 12, 16, 20, 32]
    epsList, msList,clusterList = [], [], []
    # tqdm [0.002,0.003,0.001,0.01]

    # [0.002,0.002,0.002,0.002,0.01]
    # [16,19,20,22,2]
    for eps in [0.002,0.003,0.001,0.01]:
        for ms in range(2,32):
            model = DBSCAN(eps=eps, min_samples=ms)
            model.fit(X)
            predLabels = model.fit_predict(X)
            labels = model.labels_
            n_clusters = len(set(labels)) - (1 if -1 in labels else 0)
            if n_clusters > 1 and n_clusters in num_clusters:
                epsList.append(eps)
                msList.append(ms)
                clusterList.append(n_clusters)


    print("epsList",epsList)
    print("msList",msList)
    print("clusterList",clusterList)

    epsList [0.002, 0.002, 0.002, 0.003, 0.001, 0.01]
    msList [19, 20, 22, 28, 28, 2]
    clusterList [20, 16, 12, 20, 8, 8]
```

Function "clustering_DBSCAN"

- ★ This is user defined function which apply DBSCAN Model
- ★ It Takes 1 parameters dataset
- ★ then path X to fit function to fit the model
- ★ Then get the true label for each cluster [0,1]
- ★ then get only legitimate member and count them for each number of K in list Cluster_NUM_list = [8, 12, 16, 20, 32]

```python
def clustering_DBSCAN(dataset):
    Our_data = dataset[['Latitude', 'Longitude','Ligitimacy']]
    X = Our_data.iloc[:, :-1].values
    y_true = Our_data.iloc[:, -1].astype(int).values

    cluster_labels = {}
    cluster_labels_legitimate_only = {}

    for midpoint, epsilon in [(16, 0.002), (19, 0.002), (20, 0.002), (22,0.002), (2, 0.01)]:
        dbscan = DBSCAN(eps=epsilon, min_samples=midpoint, metric='euclidean')

        # Fit the model to the data
        dbscan.fit(X)

        # Get the predicted cluster labels
        y_pred = dbscan.labels_
        n_clusters = len(set(y_pred)) - (1 if -1 in y_pred else 0)


        for cluster in range(n_clusters):
            cluster_indices = np.where(y_pred == cluster)[0]
            if cluster_indices.size > 0:
                labels_in_cluster = y_true[cluster_indices]
                label_counts = np.bincount(labels_in_cluster)
                most_Repeat_label = label_counts.argmax()
                cluster_labels[(n_clusters, cluster)] = {
                    'True Label': most_Repeat_label,
                    'Counts for pair of lable': label_counts
                }

                if(label_counts[0]==0):
                    cluster_labels_legitimate_only[(n_clusters, cluster)] = {
                    'legitimate_only': label_counts[1]

                }
    sum_dict_temp = {}
    for (k, cluster), info in cluster_labels_legitimate_only.items():
        if k in sum_dict_temp:
            sum_dict_temp[k] += info['legitimate_only']
        else:
            sum_dict_temp[k] = info['legitimate_only']

    print("Pair of Num Of cluster and Count",sum_dict_temp)
    keys = list(sum_dict_temp.keys())
    values = list(sum_dict_temp.values())

    return keys,values
```

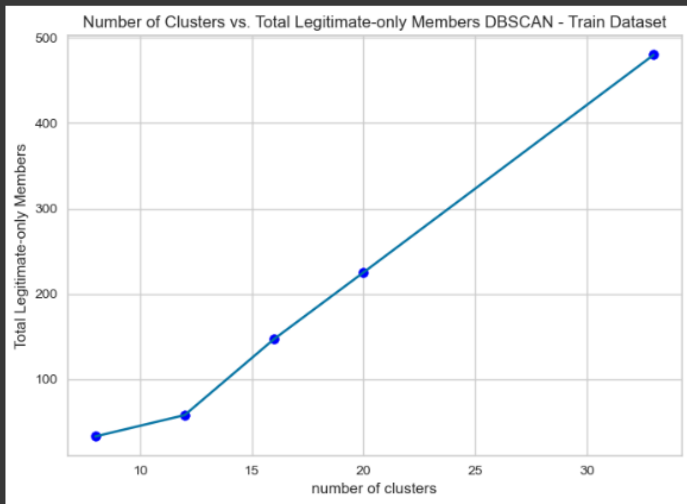
- ★ **Run clustering_DBSCAN using train Dataset**

```python
keys_DBSCAN,values_DBSCAN= clustering_DBSCAN(train_dataset)
```

```
Pair of Num Of cluster and Count {33: 480, 20: 225, 16: 147, 12: 58, 8: 33}
```

- ★ **Display the Number of Clusters vs. Total Legitimate-only Members DBSCAN (train Dataset)**

```
plot_No_cluster_Vs_Total_Legitimate(keys_DBSCAN,values_DBSCAN,"DBSCAN - Train Dataset")
```

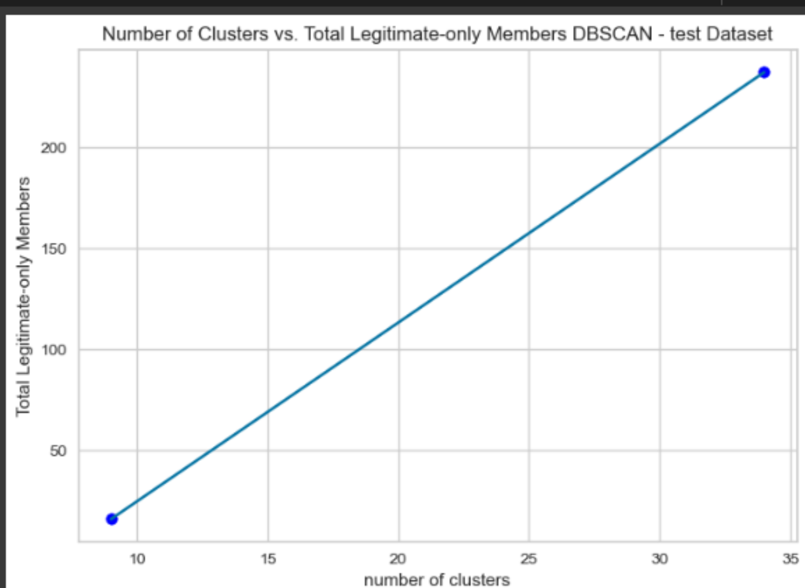


★ Run clustering_DBSCAN using Test Dataset

```
[ ] keys_DBSCAN,values_DBSCAN= clustering_DBSCAN(test_dataset)

    Pair of Num Of cluster and Count {9: 16, 34: 237}
```

★ **Display the Number of Clusters vs. Total Legitimate-only Members DBSCAN (Test Dataset)**

```
[ ] plot_No_cluster_Vs_Total_Legitimate(keys_DBSCAN,values_DBSCAN,"DBSCAN - test Dataset")
```



Conclusion

1- In K-means, we select a range of cluster numbers (8, 12, 16, 20, and 32) to obtain the most legitimate members only, and here when we go up the list the number of legitimate-only members clearly increases not only in the training data but also in the testing data.

2- In the case of Self-Organizing Feature Maps (SOFM) using the same list of cluster numbers, there is no consistent pattern of increasing or decreasing the number of legitimate members only one time it increases then the second it decreases not only in training data but also in testing data.

3- In the DBSCAN there is no clusters number to pass to the model So we have Epsilon and Min Samples we try to changed the number of min samples and we also changed the number of Epsilon to get different numbers of clusters for each number, we picked 5 numbers (0.002, 0.002, 0.002, 0.002, 0.01) for epsilon and (16, 19, 20, 22, 2) for min samples ,this 5 Numbers for epsilon and min samples gave us number of clusters (16,20,12,8 and 33) . we noticed a pattern in increasing the number of legitimate members only when we go up with the number of clusters in the both Training and Testing Data.