```
In [ ]: import pandas as pd
         from sklearn import svm
         import matplotlib.pyplot as plt
         from sklearn import tree
         from sklearn.tree import DecisionTreeClassifier
         from sklearn.svm import SVC
In [ ]: df = pd.read_csv("nasav3.csv")
         df
Out[ ]:
                                          Est Dia
                                                     Epoch Date
                               Est Dia
                                                                       Relative
                                                                                                                              Minimum
                                                                                                                                            Jupiter
                  Absolute
                                                                                    Miles per
                                                                                                  Miss Dist.
                                                                                                                     Orbit
                                                          Close
                                                                   Velocity km
                                                                                                                                  Orbit
                                                                                                                                         Tisserand
                                   in
                                              in
                Magnitude
                                                                                        hour
                                                                                                (kilometers) Uncertainity
                             KM(min)
                                                                                                                            Intersection
                                       KM(max)
                                                                                                                                         Invariant
                                                      Approach
                                                                        per hr
             0
                     21.600
                             0.127220
                                        0.284472 7.890000e+11
                                                                  22017.00380
                                                                                13680.509940 6.275369e+07
                                                                                                                         5
                                                                                                                               0.025282
                                                                                                                                             4.634
             1
                     21.300
                             0.146068
                                        0.326618 7.890000e+11
                                                                  65210.34609 40519.173110 5.729815e+07
                                                                                                                         3
                                                                                                                               0.186935
                                                                                                                                             5.457
                                        0.517654 7.900000e+11
                                                                  27326.56018 16979.661800 7.622912e+06
                                                                                                                        0
                                                                                                                               0.043058
             2
                     20.300 0.231502
                                                                                                                                             4.557
                     27.400 0.008801
                                        0.019681 7.900000e+11
                                                                  40225.94819 24994.839860 4.268362e+07
                                                                                                                               0.005512
                                                                                                                                             5.093
                                                                  35426.99179 22012.954980 6.101082e+07
             4
                     21.600 0.127220
                                        0.284472 7.900000e+11
                                                                                                                         1
                                                                                                                               0.034798
                                                                                                                                             5.154
          4682
                     23.900 0.044112
                                        0.098637 1.470000e+12
                                                                  79755.35427 49556.875550 6.187511e+06
                                                                                                                         8
                                                                                                                               0.019777
                                                                                                                                             5.156
         4683
                                        0.013616 1.470000e+12
                                                                                7214 337772 9 677324e+05
                     28 200 0 006089
                                                                  11610 53958
                                                                                                                         6
                                                                                                                               0.006451
                                                                                                                                             5 742
          4684
                     22.700 0.076658
                                        0.171412 1.470000e+12
                                                                  25889.91063 16086.983630 9.126775e+06
                                                                                                                               0.059972
                                                                                                                         6
                                                                                                                                             4.410
                                                                                                                         5
          4685
                     21.800 0.116026
                                        0.259442 1.470000e+12
                                                                  40867.52231 25393.489070 3.900908e+07
                                                                                                                               0.177510
                                                                                                                                             4.477
          4686
                     6
                                                                                                                               0.051777
                                                                                                                                             4.108
        4687 rows × 23 columns
         - 4 | -
In [ ]: df.columns
Out[ ]: Index(['Absolute Magnitude', 'Est Dia in KM(min)', 'Est Dia in KM(max)',
                  'Epoch Date Close Approach', 'Relative Velocity km per hr',
                  'Miles per hour', 'Miss Dist.(kilometers)', 'Orbit Uncertainity', 'Minimum Orbit Intersection', 'Jupiter Tisserand Invariant',
                  'Epoch Osculation', 'Eccentricity', 'Semi Major Axis', 'Inclination', 'Asc Node Longitude', 'Orbital Period', 'Perihelion Distance',
                  'Perihelion Arg', 'Aphelion Dist', 'Perihelion Time', 'Mean Anomaly',
                  'Mean Motion', 'Hazardous'],
                dtype='object')
In [ ]: df["Hazardous"]
Out[]: 0
                  1
                  0
          2
                  1
          3
                  0
         4
                  1
          4682
                  0
          4683
                  0
         4684
                  0
          4685
                  0
         4686
          Name: Hazardous, Length: 4687, dtype: int64
In [ ]: features = ['Absolute Magnitude', 'Est Dia in KM(max)',
                  'Relative Velocity km per hr', 'Miles per hour',
                  'Miss Dist.(kilometers)', 'Orbit Uncertainity',
                  'Minimum Orbit Intersection', 'Jupiter Tisserand Invariant',
                 'Epoch Osculation', 'Eccentricity', 'Semi Major Axis', 'Inclination', 'Asc Node Longitude', 'Orbital Period', 'Perihelion Distance',
                  'Perihelion Arg', 'Aphelion Dist', 'Perihelion Time', 'Mean Anomaly',
                  'Mean Motion']
         print(features)
        ['Absolute Magnitude', 'Est Dia in KM(max)', 'Relative Velocity km per hr', 'Miles per hour', 'Miss Dist.(kilometers)', 'Or
        bit Uncertainity', 'Minimum Orbit Intersection', 'Jupiter Tisserand Invariant', 'Epoch Osculation', 'Eccentricity', 'Semi M ajor Axis', 'Inclination', 'Asc Node Longitude', 'Orbital Period', 'Perihelion Distance', 'Perihelion Arg', 'Aphelion Dis
        t', 'Perihelion Time', 'Mean Anomaly', 'Mean Motion']
In [ ]: x = df[features]
         y = df['Hazardous']
```

```
In [ ]: from sklearn.preprocessing import StandardScaler
         scaler=StandardScaler()
         scaler.fit(x)
         X=scaler.transform(x)
{\tt Out[\ ]:\ array([[-0.23104209,\ -0.20941058,\ -1.07713904,\ \ldots,\ 0.45919054,\ )}
                  0.77839321, -0.43110028],
                [-0.33482448, -0.15840557, 0.56814611, ..., 0.07081746,
                 -0.06909298, 0.31258164],
                [-0.68076581, 0.07278876, -0.8748918, ..., 0.41557982, 1.03940428, -0.52211437],
                [0.14949337, -0.34623784, -0.92961547, ..., 0.60624511,
                  0.20776991, -0.63207867],
                [-0.16185382, -0.23970271, -0.35910064, ..., 0.59330298,
                0.2079915 , -0.56766111],
[-1.09278193, 0.53049632, 3.01353553, ..., 0.6254237 ,
                  0.03397983, -0.54733945]])
In [ ]: n_components = 2
         # Importing PCA
        from sklearn.decomposition import PCA
         # Let's say, components = 2
        pca = PCA(n_components=2)
        pca.fit(X)
         x_pca = pca.transform(X)
         # Create the dataframe
        df_pca1 = pd.DataFrame(x_pca,columns=['PC{}'.format(i+1) for i in range(n_components)])
        print(df_pca1)
                  PC1
                             PC2
       0
           0.035467 -0.877898
          -0.661874 1.781214
            0.335957 -0.998262
           -1.107668 -1.784543
       4 -0.763059 -0.068245
                  . . .
       4682 -0.781252 0.627510
       4683 -2.411124 -3.223169
       4684 0.391110 -2.031184
       4685 0.565106 -0.652516
       4686 1.491336 4.106644
       [4687 rows x 2 columns]
In [ ]: from sklearn.model_selection import train_test_split
        X_{train}, X_{test}, y_{train}, y_{test} = train_{test\_split}(df_{pca1},y),
                                             random_state=104,
                                             test size=0.25,
                                             shuffle=True)
```

SVM

```
In [ ]: Sclf = SVC(kernel='poly')
        Sclf = Sclf.fit(X_train, y_train)
In [ ]: from sklearn.metrics import accuracy_score,confusion_matrix,classification_report
        predicted = Sclf.predict(X_train)
        print(accuracy_score(y_train,predicted))
       0.8375533428165007
In [ ]: # For For support vector classifier
        # Predict labels for test set
        y_pred = Sclf.predict(X_test)
        # Calculate accuracy
        accuracy = accuracy_score(y_test, y_pred)
        print("Accuracy:", accuracy)
        cm = confusion_matrix(y_test,y_pred)
        print("Confusion matrix:")
        print(cm)
        cr = classification_report(y_test,y_pred)
        print(cr)
```

```
Accuracy: 0.8430034129692833
Confusion matrix:
[[988 0]
 [184
       0]]
              precision
                           recall f1-score
                                             support
           0
                   0.84
                             1.00
                                       0.91
                                                  988
                   0.00
                             0.00
                                       0.00
                                                  184
                                       0.84
                                                 1172
   accuracy
                   0.42
                             0.50
                                       0.46
                                                  1172
  macro avg
                                                 1172
weighted avg
                   0.71
                             0.84
                                       0.77
```

C:\Users\arunp\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.10_qbz5n2kfra8p0\LocalCache\local-packages\Python31
0\site-packages\sklearn\metrics_classification.py:1471: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.

_warn_prf(average, modifier, msg_start, len(result))

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_warn_prf(average, modifier, msg_start, len(result))

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_warn_prf(average, modifier, msg_start, len(result))

```
import matplotlib.pyplot as plt
plt.figure(figsize=(8, 6))
plt.scatter(df_pca1['PC1'], df_pca1['PC2'], c=df['Hazardous'], cmap='viridis')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.title('Scatter Plot of PCA Components')
plt.colorbar(label='Hazardous') # Adding colorbar for class labels
plt.grid(True)
plt.show()
```

