```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score

```

```python
data = pd.read_csv("machine failure.csv")
data
```

	UDI	Product ID	Type	Air temperature [K]	Process temperature [K]	Rotational speed [rpm]	Torque [Nm]	Tool wear [min]	Ma fa
0	1	M14860	M	298.1	308.6	1551	42.8	0	
1	2	L47181	L	298.2	308.7	1408	46.3	3	
2	3	L47182	L	298.1	308.5	1498	49.4	5	
3	4	L47183	L	298.2	308.6	1433	39.5	7	
4	5	L47184	L	298.2	308.7	1408	40.0	9	
...	...	...	...	...	...	...	...	...	
9995	9996	M24855	M	298.8	308.4	1604	29.5	14	
9996	9997	H39410	H	298.9	308.4	1632	31.8	17	
9997	9998	M24857	M	299.0	308.6	1645	33.4	22	
9998	9999	H39412	H	299.0	308.7	1408	48.5	25	
9999	10000	M24859	M	299.0	308.7	1500	40.2	30	

Data Preprocessing

```python
data.columns
```

```
Index(['UDI', 'Product ID', 'Type', 'Air temperature [K]',
       'Process temperature [K]', 'Rotational speed [rpm]', 'Torque [Nm]',
       'Tool wear [min]', 'Machine failure', 'TWF', 'HDF', 'PWF', 'OSF',
       'RNF'],
      dtype='object')
```

```python
data.nunique()
```

```
UDI                        10000
Product ID                 10000
Type                           3
Air temperature [K]           93
Process temperature [K]       82
Rotational speed [rpm]       941
Torque [Nm]                  577
Tool wear [min]              246
Machine failure                2
TWF                            2
HDF                            2
PWF                            2
OSF                            2
RNF                            2
dtype: int64
```

```python
data.isnull().sum()
```

```
UDI                        0
Product ID                 0
Type                       0
Air temperature [K]        0
Process temperature [K]    0
Rotational speed [rpm]     0
Torque [Nm]                0
Tool wear [min]            0
Machine failure            0
TWF                        0
HDF                        0
PWF                        0
OSF                        0
RNF                        0
dtype: int64
```

```
1 data.rename(columns= {'TWF': 'Tool Wear Failure',"HDF" : 'Head Dissipation Failure', 'PWF' : 'Power Failure', 'OSF' : 'Overstrain Fail
2 data
```

	UDI	Product ID	Type	Air temperature [K]	Process temperature [K]	Rotational speed [rpm]	Torque [Nm]	Tool wear [min]	Ma fa
0	1	M14860	M	298.1	308.6	1551	42.8	0	
1	2	L47181	L	298.2	308.7	1408	46.3	3	
2	3	L47182	L	298.1	308.5	1498	49.4	5	
3	4	L47183	L	298.2	308.6	1433	39.5	7	
4	5	L47184	L	298.2	308.7	1408	40.0	9	
...	...	...	...	...	...	...	...	...	
9995	9996	M24855	M	298.8	308.4	1604	29.5	14	
9996	9997	H39410	H	298.9	308.4	1632	31.8	17	
9997	9998	M24857	M	299.0	308.6	1645	33.4	22	
9998	9999	H39412	H	299.0	308.7	1408	48.5	25	
9999	10000	M24859	M	299.0	308.7	1500	40.2	30	

```
1 data = data.drop(['UDI', 'Product ID'], axis=1)
2 data.head()
```

	Type	Air temperature [K]	Process temperature [K]	Rotational speed [rpm]	Torque [Nm]	Tool wear [min]	Machine failure	Tool Wear Failure	Dis
0	M	298.1	308.6	1551	42.8	0	0	0	
1	L	298.2	308.7	1408	46.3	3	0	0	
2	L	298.1	308.5	1498	49.4	5	0	0	
3	L	298.2	308.6	1433	39.5	7	0	0	

```
1 data.rename(columns={'Type' : 'Quality Type'}, inplace = True)
2 data
```

	Quality Type	Air temperature [K]	Process temperature [K]	Rotational speed [rpm]	Torque [Nm]	Tool wear [min]	Machine failure	Too Wea Failu
0	M	298.1	308.6	1551	42.8	0	0	
1	L	298.2	308.7	1408	46.3	3	0	
2	L	298.1	308.5	1498	49.4	5	0	
3	L	298.2	308.6	1433	39.5	7	0	
4	L	298.2	308.7	1408	40.0	9	0	
...	...	...	...	...	...	...	...	
9995	M	298.8	308.4	1604	29.5	14	0	
9996	H	298.9	308.4	1632	31.8	17	0	
9997	M	299.0	308.6	1645	33.4	22	0	
9998	H	299.0	308.7	1408	48.5	25	0	
9999	M	299.0	308.7	1500	40.2	30	0	

```
1 qual_map = {'L' : 'Low', 'M' : 'Medium', 'H' :'High'}
2 data['Quality Type'] = data['Quality Type'].map(qual_map)
3 data
```

	Quality Type	Air temperature [K]	Process temperature [K]	Rotational speed [rpm]	Torque [Nm]	Tool wear [min]	Machine failure	To We Failu
0	Medium	298.1	308.6	1551	42.8	0	0	
1	Low	298.2	308.7	1408	46.3	3	0	
2	Low	298.1	308.5	1498	49.4	5	0	
3	Low	298.2	308.6	1433	39.5	7	0	
4	Low	298.2	308.7	1408	40.0	9	0	

```
1 qual_map = {'Low' : -1, 'Medium' : 0, 'High' : 1}
2 data['Quality_Binary'] = data['Quality Type'].map(qual_map)
3 data
```

	Quality Type	Air temperature [K]	Process temperature [K]	Rotational speed [rpm]	Torque [Nm]	Tool wear [min]	Machine failure	To We Failu
0	Medium	298.1	308.6	1551	42.8	0	0	
1	Low	298.2	308.7	1408	46.3	3	0	
2	Low	298.1	308.5	1498	49.4	5	0	
3	Low	298.2	308.6	1433	39.5	7	0	
4	Low	298.2	308.7	1408	40.0	9	0	
...	...	...	...	...	...	...	...	
9995	Medium	298.8	308.4	1604	29.5	14	0	
9996	High	298.9	308.4	1632	31.8	17	0	
9997	Medium	299.0	308.6	1645	33.4	22	0	
9998	High	299.0	308.7	1408	48.5	25	0	
9999	Medium	299.0	308.7	1500	40.2	30	0	

```
1 data.tail()
```

	Quality Type	Air temperature [K]	Process temperature [K]	Rotational speed [rpm]	Torque [Nm]	Tool wear [min]	Machine failure	To We Failu
9995	Medium	298.8	308.4	1604	29.5	14	0	
9996	High	298.9	308.4	1632	31.8	17	0	
9997	Medium	299.0	308.6	1645	33.4	22	0	
9998	High	299.0	308.7	1408	48.5	25	0	

```
1 data.describe()
```

	Air temperature [K]	Process temperature [K]	Rotational speed [rpm]	Torque [Nm]	Tool wear [min]	Ma fa
count	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.0
mean	300.004930	310.005560	1538.776100	39.986910	107.951000	0.0
std	2.000259	1.483734	179.284096	9.968934	63.654147	0.1
min	295.300000	305.700000	1168.000000	3.800000	0.000000	0.0
25%	298.300000	308.800000	1423.000000	33.200000	53.000000	0.0
50%	300.100000	310.100000	1503.000000	40.100000	108.000000	0.0
75%	301.500000	311.100000	1612.000000	46.800000	162.000000	0.0

```
1 data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 13 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   Quality Type             10000 non-null  object
```

```
 1   Air temperature [K]       10000 non-null  float64
 2   Process temperature [K]   10000 non-null  float64
 3   Rotational speed [rpm]    10000 non-null  int64
 4   Torque [Nm]               10000 non-null  float64
 5   Tool wear [min]           10000 non-null  int64
 6   Machine failure           10000 non-null  int64
 7   Tool Wear Failure         10000 non-null  int64
 8   Head Dissipation Failure  10000 non-null  int64
 9   Power Failure             10000 non-null  int64
 10  Overstrain Failure        10000 non-null  int64
 11  Random Failures           10000 non-null  int64
 12  Quality_Binary            10000 non-null  int64
dtypes: float64(3), int64(9), object(1)
memory usage: 1015.8+ KB
```

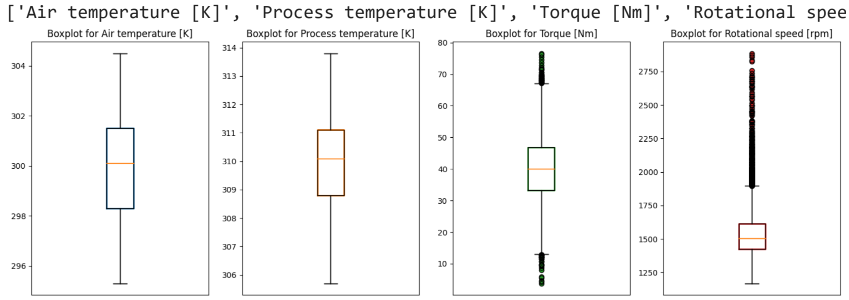
```
data.shape
```

```
(10000, 13)
```

Data Analysis

```
#Outlier Detection and removal
data = pd.DataFrame(data)
numerical_cols = data.select_dtypes(include=['float64']).columns.tolist() + ['Rotational speed [rpm]']
# numerical_cols.append('Rotational speed [rpm]')
print(numerical_cols)

# Create a custom color palette for boxplots
colors = ['#1f77b4', '#ff7f0e', '#2ca02c', '#d62728', '#9467bd', '#8c564b', '#e377c2', '#7f7f7f', '#bcbd22', '#17becf']



fig, axes = plt.subplots(nrows = 1, ncols = len(numerical_cols), figsize = (15,5))

#Loop through nnumerical_cols and create boxplots
for i, column in enumerate(numerical_cols):
    ax = axes[i]

     # Customize boxplot appearance
    boxprops = dict(linewidth=2, color=colors[i])
    flierprops = dict(marker='o', markersize=6, markerfacecolor=colors[i], markeredgecolor='none')

    ax.boxplot(data[column], boxprops=boxprops, flierprops=flierprops)


    ax.boxplot(data[column])
    ax.set_title(f'Boxplot for {column}')
    ax.set_xticks([])

plt.tight_layout()
plt.show()
```

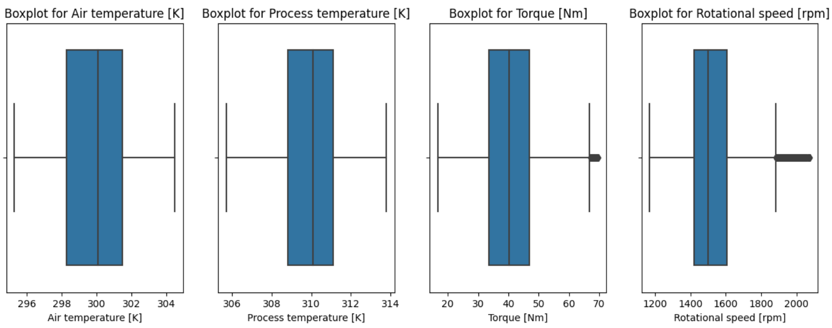
```
['Air temperature [K]', 'Process temperature [K]', 'Torque [Nm]', 'Rotational spee
```



```
#Detecting outliers
from scipy import stats
# Define the z-score threshold (e.g., 3)
z_score_threshold = 3

# Create a mask to identify outliers for each numerical column
outlier_mask = np.abs(stats.zscore(data[numerical_cols])) > z_score_threshold

# Apply the mask to remove outliers from the DataFrame
data_no_outliers = data[~outlier_mask.any(axis=1)]

# Print the shape of the DataFrame before and after removing outliers
print("Original Data Shape:", data.shape)
print("Data Shape After Removing Outliers:", data_no_outliers.shape)

# Optionally, you can reset the index if needed
data_no_outliers.reset_index(drop=True, inplace=True)
```

```
Original Data Shape: (10000, 13)
Data Shape After Removing Outliers: (9822, 13)
```

```
# Optionally, you can reset the index if needed
# data_no_outliers.reset_index(drop=True, inplace=True)

# Plot boxplots for numerical columns in data_no_outliers
fig, axes = plt.subplots(nrows=1, ncols=len(numerical_cols), figsize=(15, 5))

for i, column in enumerate(numerical_cols):
    sns.boxplot(x=data_no_outliers[column], ax=axes[i])
    axes[i].set_title(f'Boxplot for {column}')

```




```
data_no_outliers.describe()
```

	Air temperature [K]	Process temperature [K]	Rotational speed [rpm]	Torque [Nm]	Tool wear [min]	Machine failure
count	9822.000000	9822.000000	9822.000000	9822.000000	9822.000000	9822.000000
mean	300.001161	310.002861	1526.222765	40.350713	107.912441	0.029831
std	1.998035	1.482233	147.382767	9.448740	63.616929	0.170130
min	295.300000	305.700000	1168.000000	16.700000	0.000000	0.000000
25%	298.300000	308.800000	1422.000000	33.600000	53.000000	0.000000
50%	300.100000	310.100000	1500.000000	40.200000	108.000000	0.000000
75%	301.500000	311.100000	1606.000000	46.900000	162.000000	0.000000

```
data = data_no_outliers
```

```
1 data
```

	Quality Type	Air temperature [K]	Process temperature [K]	Rotational speed [rpm]	Torque [Nm]	Tool wear [min]	Machine failure	Tool Wear Failu
0	Medium	298.1	308.6	1551	42.8	0	0	
1	Low	298.2	308.7	1408	46.3	3	0	
2	Low	298.1	308.5	1498	49.4	5	0	
3	Low	298.2	308.6	1433	39.5	7	0	
4	Low	298.2	308.7	1408	40.0	9	0	
...	...	...	...	...	...	...	...	
9817	Medium	298.8	308.4	1604	29.5	14	0	
9818	High	298.9	308.4	1632	31.8	17	0	
9819	Medium	299.0	308.6	1645	33.4	22	0	
9820	High	299.0	308.7	1408	48.5	25	0	
9821	Medium	299.0	308.7	1500	40.2	30	0	

Feature Importance in the Dataset

```
1 data.columns
```

```
Index(['Quality Type', 'Air temperature [K]', 'Process temperature [K]',
       'Rotational speed [rpm]', 'Torque [Nm]', 'Tool wear [min]',
       'Machine failure', 'Tool Wear Failure', 'Head Dissipation Failure',
       'Power Failure', 'Overstrain Failure', 'Random Failures',
       'Quality_Binary'],
      dtype='object')
```

```
1 from sklearn.ensemble import RandomForestClassifier
2 from sklearn.preprocessing import LabelEncoder
3 X = data.drop(['Machine failure', 'Quality Type'], axis=1)
4 y = data['Machine failure']
```

```
1 X.columns
```

```
Index(['Air temperature [K]', 'Process temperature [K]',
       'Rotational speed [rpm]', 'Torque [Nm]', 'Tool wear [min]',
       'Tool Wear Failure', 'Head Dissipation Failure', 'Power Failure',
       'Overstrain Failure', 'Random Failures', 'Quality_Binary'],
      dtype='object')
```

```
1 X.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9822 entries, 0 to 9821
Data columns (total 11 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   Air temperature [K]       9822 non-null   float64
 1   Process temperature [K]   9822 non-null   float64
 2   Rotational speed [rpm]    9822 non-null   int64  
 3   Torque [Nm]               9822 non-null   float64
 4   Tool wear [min]           9822 non-null   int64  
 5   Tool Wear Failure         9822 non-null   int64  
 6   Head Dissipation Failure  9822 non-null   int64  
 7   Power Failure             9822 non-null   int64  
 8   Overstrain Failure        9822 non-null   int64  
 9   Random Failures           9822 non-null   int64  
 10  Quality_Binary            9822 non-null   int64  
dtypes: float64(3), int64(8)
memory usage: 844.2 KB
```

```
1 label_encoder = LabelEncoder()
2 y = label_encoder.fit_transform(y)
```

```
1 y
```

```
array([0, 0, 0, ..., 0, 0, 0], dtype=int64)
```

```
model = RandomForestClassifier()
model
```

```
▾ RandomForestClassifier
RandomForestClassifier()
```

```
model.fit(X, y)
```

```
▾ RandomForestClassifier
RandomForestClassifier()
```

```
#Get feature importance from the trained mmodel
feature_importance = model.feature_importances_
feature_importance
```

```
array([2.07506225e-02, 1.43808631e-02, 3.75407208e-02, 7.51327823e-02,
       4.66449261e-02, 1.29783416e-01, 3.42184822e-01, 1.01555714e-01,
       2.27190008e-01, 3.31725977e-04, 4.50439814e-03])
```

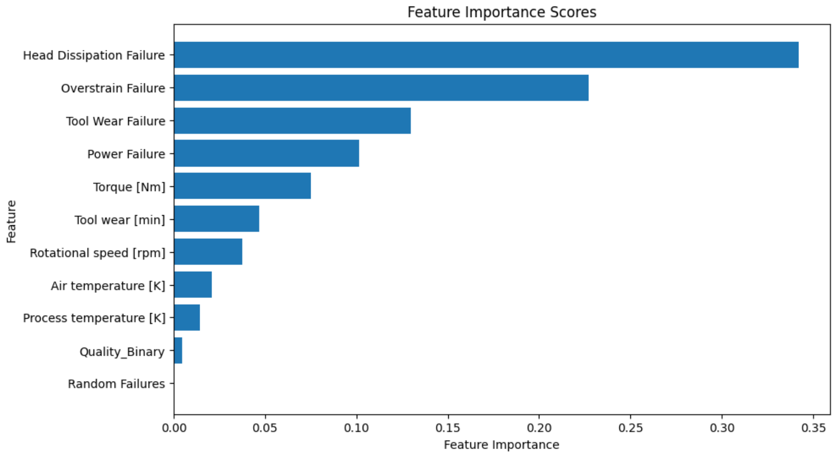
```
# Create a DataFrame to display feature importances
importance_df = pd.DataFrame({'Feature': X.columns, 'Importance': feature_importance})
importance_df
```

	Feature	Importance
0	Air temperature [K]	0.020751
1	Process temperature [K]	0.014381
2	Rotational speed [rpm]	0.037541
3	Torque [Nm]	0.075133
4	Tool wear [min]	0.046645
5	Tool Wear Failure	0.129783
6	Head Dissipation Failure	0.342185
7	Power Failure	0.101556
8	Overstrain Failure	0.227190
9	Random Failures	0.000332
10	Quality_Binary	0.004504

```
# Sort the DataFrame by importance values in descending order
importance_df = importance_df.sort_values(by='Importance', ascending=False)
importance_df
```

	Feature	Importance
6	Head Dissipation Failure	0.342185
8	Overstrain Failure	0.227190
5	Tool Wear Failure	0.129783
7	Power Failure	0.101556
3	Torque [Nm]	0.075133
4	Tool wear [min]	0.046645
2	Rotational speed [rpm]	0.037541
0	Air temperature [K]	0.020751
1	Process temperature [K]	0.014381
10	Quality_Binary	0.004504
9	Random Failures	0.000332

```
# Create a bar plot to visualize feature importances
plt.figure(figsize=(10, 6))
plt.barh(importance_df['Feature'], importance_df['Importance'])
plt.xlabel('Feature Importance')
plt.ylabel('Feature')
plt.title('Feature Importance Scores')
plt.gca().invert_yaxis()  # Invert the y-axis to display the most important features at the top
plt.show()
```




```
data.columns
```

```
Index(['Quality Type', 'Air temperature [K]', 'Process temperature [K]',
       'Rotational speed [rpm]', 'Torque [Nm]', 'Tool wear [min]',
       'Machine failure', 'Tool Wear Failure', 'Head Dissipation Failure',
       'Power Failure', 'Overstrain Failure', 'Random Failures',
       'Quality_Binary'],
      dtype='object')
```

```
# Sort importance_df to get the top 8 important features
top_features = importance_df.nlargest(8, 'Importance')['Feature']

# Create a new DataFrame with the top 8 features and the target variable 'Machine Failures'
new_data = data[list(top_features) + ['Machine failure'] + ['Quality_Binary']]
new_data
```

	Head Dissipation Failure	Overstrain Failure	Tool Wear Failure	Power Failure	Torque [Nm]	Tool wear [min]	Rotational speed [rpm]	temper
0	0	0	0	0	42.8	0	1551	
1	0	0	0	0	46.3	3	1408	
2	0	0	0	0	49.4	5	1498	
3	0	0	0	0	39.5	7	1433	
4	0	0	0	0	40.0	9	1408	
...	...	...	...	...	...	...	...	
9817	0	0	0	0	29.5	14	1604	
9818	0	0	0	0	31.8	17	1632	
9819	0	0	0	0	33.4	22	1645	
9820	0	0	0	0	48.5	25	1408	
9821	0	0	0	0	40.2	30	1500	

```
len(data.columns)
```

```
13
```

```
len(new_data.columns)
```

```
10
```

```
# Get the set of columns in the original data DataFrame
data_columns = set(data.columns)

```

```
# Get the set of columns in the new_data DataFrame
new_data_columns = set(new_data.columns)
```

```
# Find the columns that are in 'data' but not in 'new_data'
columns_not_in_new_data = data_columns - new_data_columns

# Now, 'columns_not_in_new_data' contains the columns that are in 'data' but not in 'new_data'
print("Columns not in new_data:", columns_not_in_new_data)
```

```
Columns not in new_data: {'Random Failures', 'Quality Type', 'Process temperature [K]'}
```

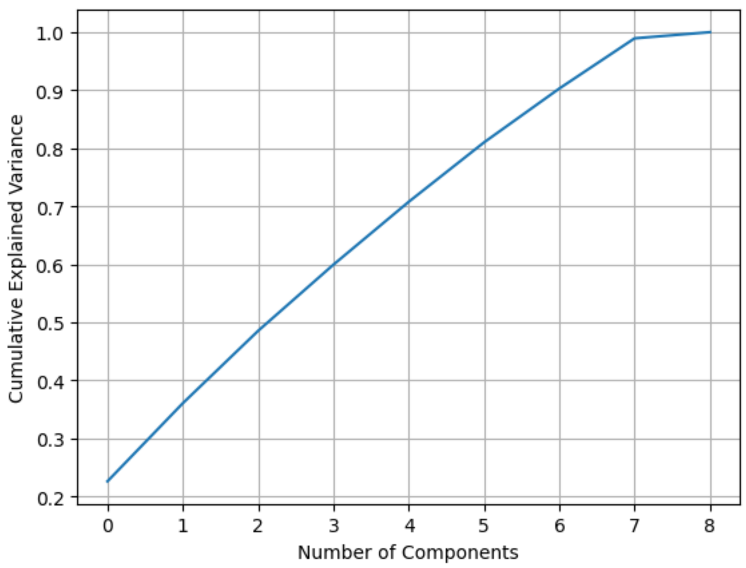
Multivariate Analysis

- Multivariate Analysis involves exploring relationships between multiple variables simultaneously. Steps -
- Standardize the data
- Apply PCA
- Select number of Components
- Transform Data
- Visualization

```
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
```

```
# Standardize the data
scaler = StandardScaler()
scaled_data = scaler.fit_transform(new_data.drop('Machine failure', axis=1))
```

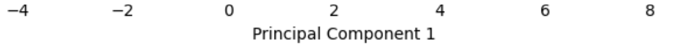
```
pca = PCA()
pca.fit(scaled_data)
explained_variance = pca.explained_variance_ratio_
cumulative_variance = np.cumsum(explained_variance)
# Plot explained variance to decide the number of components
plt.plot(cumulative_variance)
plt.xlabel('Number of Components')
plt.ylabel('Cumulative Explained Variance')
plt.grid()
plt.show()
```

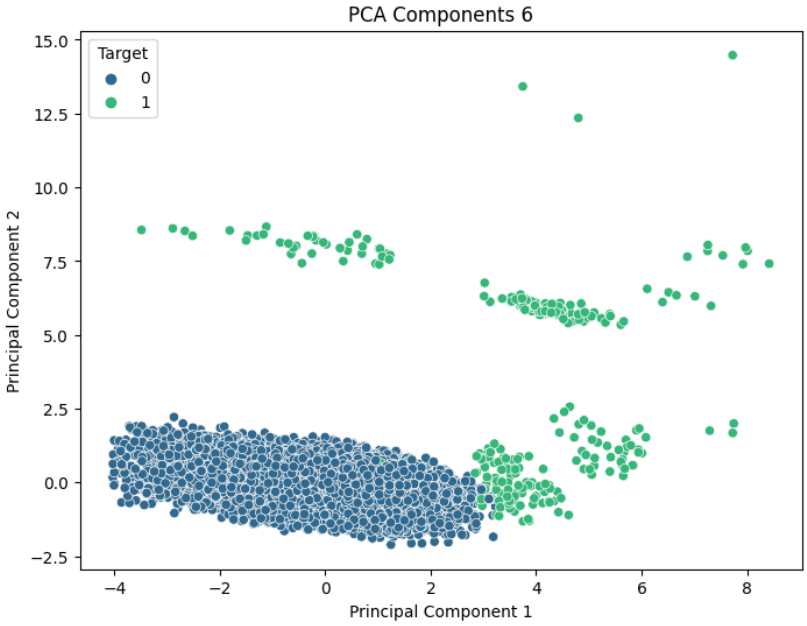


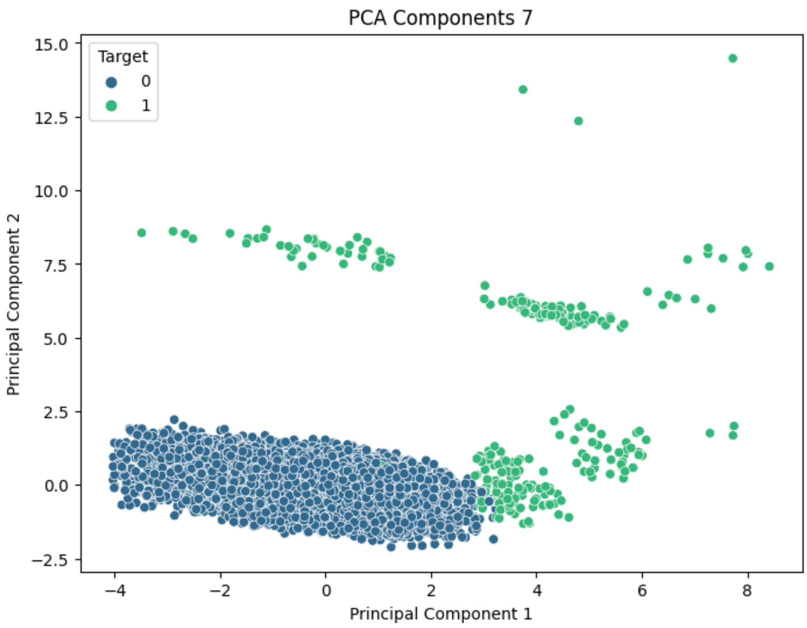

```
from sklearn.decomposition import PCA

# Assuming you have a dataset named 'scaled_data' and 'y' as your target variable

# Create a function to visualize reduced dimensions
def visualize_pca_components(components, labels):
    pca = PCA(n_components=components)
    pca_result = pca.fit_transform(scaled_data)

    # Create a scatter plot of the first two principal components
    plt.figure(figsize=(8, 6))
    sns.scatterplot(x=pca_result[:, 0], y=pca_result[:, 1], hue=labels, palette="viridis")
    plt.title(f'PCA Components {components}')
    plt.xlabel('Principal Component 1')
    plt.ylabel('Principal Component 2')
```

```
    plt.legend(title='Target', loc='best')
    plt.show()


```

```
# Call the function with different numbers of components
visualize_pca_components(2, y)  # Visualize with 2 components
visualize_pca_components(3, y)  # Visualize with 3 components
visualize_pca_components(4, y)  # Visualize with 4 components
visualize_pca_components(5, y)
visualize_pca_components(6, y)
visualize_pca_components(7, y)
```


−4 −2 0 2 4 6 8
Principal Component 1


PCA Components 6
Target
0
1
Principal Component 2
Principal Component 1


PCA Components 7
Target
0
1
Principal Component 2
Principal Component 1

```
# Apply PCA
pca = PCA(n_components=7)  # Choose the number of components you want to retain
pca_result = pca.fit_transform(scaled_data)
pca_result
```

```
array([[-0.06960303, -1.43007683, -0.70784679, ...,  0.58585201,
         0.31328833,  0.64121409],
       [ 0.83414652, -1.36355164, -0.58063326, ..., -0.38344926,
         0.91343419,  0.4224668 ],
       [ 0.65875132, -1.2900605 , -0.60034887, ..., -0.30771422,
         0.88917705,  0.48714783],
       ...,
       [-1.13026506, -0.93171705, -0.28549213, ...,  0.76713283,
         0.13257012,  0.51598165],
       [ 0.94764774, -1.57035252, -0.71710542, ...,  1.0566524 ,
        -0.33378582,  0.16785075],
       [-0.01100348, -1.09099993, -0.42095047, ...,  0.48830018,
         0.1484816 ,  0.30929213]])
```

Applying KNN

```
from sklearn.neighbors import KNeighborsClassifier
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(pca_result, y, test_size=0.2, random_state=42)
```

```
# Feature scaling (standardization)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

```
X_train_scaled.shape
```

```
(7857, 7)
```

Search for optimal number of Neighbors

```
from sklearn.model_selection import GridSearchCV
# Initialize the KNN classifier
knn_classifier = KNeighborsClassifier()
# Define a range of 'k' values to search
param_grid = {'n_neighbors': [1, 3, 5, 7, 9]}
# Perform grid search with cross-validation
grid_search = GridSearchCV(knn_classifier, param_grid, cv=5)
grid_search.fit(X_train_scaled, y_train)
```

```
▸ GridSearchCV
▸ estimator: KNeighborsClassifier
  ▸ KNeighborsClassifier
```

```
# Get the best 'k' value from the grid search
best_k = grid_search.best_params_['n_neighbors']
best_k
```

```
3
```

```
# Initialize and train the KNN classifier (you can choose the number of neighbors 'n_neighbors')
knn_classifier = KNeighborsClassifier(n_neighbors=3)
knn_classifier
```

```
▾ KNeighborsClassifier
KNeighborsClassifier(n_neighbors=3)
```

```
# Train the classifier on your data
knn_classifier.fit(X_train_scaled, y_train)
```

```
▾ KNeighborsClassifier
KNeighborsClassifier(n_neighbors=3)
```

```
# Make predictions on test data
y_pred = knn_classifier.predict(X_test_scaled)
```

```
# Evaluate the classifier's performance
accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy with k=3: {accuracy}')
```

```
Accuracy with k=3: 0.9994910941475827
```

Checking other Accuracy measures and Scores

```
from sklearn.metrics import confusion_matrix, precision_score, recall_score, f1_score, roc_curve, roc_auc_score
from sklearn.model_selection import cross_val_score
```

```
# Calculate the confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)
print('Confusion Matrix:')
print(conf_matrix)
```

```
Confusion Matrix:
[[1905    0]
 [   1   59]]
```

```
# Calculate precision, recall, and F1-score
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)
print(f'Precision: {precision:.4f}')
print(f'Recall: {recall:.4f}')
print(f'F1-Score: {f1:.4f}')
```

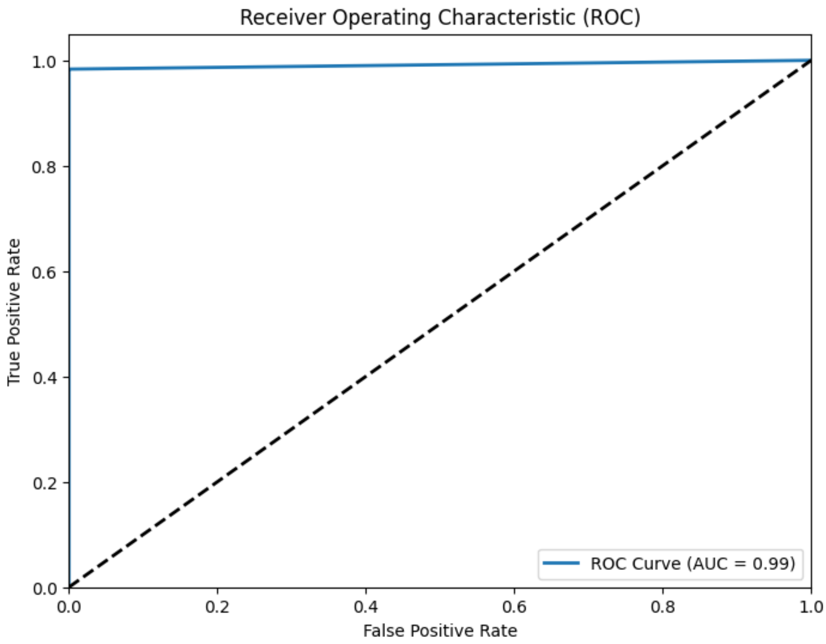
```
Precision: 1.0000
Recall: 0.9833
F1-Score: 0.9916
```

```
# Calculate ROC curve and AUC
y_prob = knn_classifier.predict_proba(X_test_scaled)[:, 1]
fpr, tpr, thresholds = roc_curve(y_test, y_prob)
roc_auc = roc_auc_score(y_test, y_prob)
print(f'ROC AUC: {roc_auc:.4f}')

```

```
ROC AUC: 0.9916
```

```
# Plot ROC curve
import matplotlib.pyplot as plt
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, linewidth=2, label=f'ROC Curve (AUC = {roc_auc:.2f})')
plt.plot([0, 1], [0, 1], 'k--', linewidth=2)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC)')
```

```
plt.legend(loc='lower right')
plt.show()
```




```
# Perform cross-validation (5-fold in this example)
cv_scores = cross_val_score(knn_classifier, X_train_scaled, y_train, cv=5)
print(f'Cross-Validation Scores: {cv_scores}')
print(f'Average Cross-Validation Score: {cv_scores.mean():.4f}')
```

```
Cross-Validation Scores: [0.99936387 0.99745547 0.99936346 0.99936346 0.99936346]
Average Cross-Validation Score: 0.9990
```

Applyin Support-Vector Machines in this Dataset

```
from sklearn.svm import SVC

# Initialize the SVM classifier with the RBF kernel
svm_classifier = SVC(kernel='rbf', random_state=42)
svm_classifier
```

```
▾ SVC
SVC(random_state=42)
```

```
# Fit the SVM model to the training data
svm_classifier.fit(X_train_scaled, y_train)
```

```
▾ SVC
SVC(random_state=42)
```

```
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix

# Make predictions on the testing data
y_pred = svm_classifier.predict(X_test_scaled)

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
classification_rep = classification_report(y_test, y_pred)

# Print the results
print("Accuracy:", accuracy)
print("Confusion Matrix:\n", conf_matrix)
print("Classification Report:\n", classification_rep)
```

```
Accuracy: 0.9994910941475827
Confusion Matrix:
 [[1905    0]
 [   1   59]]
```