```
# Topic: Implement KNN in Water Quality Dataset
# Collaborated by : Aadith Joseph Mathew and Devika S Vinod
# Roll No: 23122101, 23122113
# Date: 16th May 2024
# Submission : 17th May 2024
```

Dataset Description:

• Rows: 7,999

Columns: 21

Features: Chemical concentrations: Includes various chemicals like aluminium, ammonia, arsenic, barium, cadmium, chloramine, chromium, copper, flouride, lead, nitrates, nitrites, mercury, perchlorate, radium, selenium, silver, and uranium. Biological parameters: bacteria and viruses, indicating the presence of biological contaminants. Safety Indicator: is_safe (1 for safe, 0 for not safe), indicating whether the water quality is considered safe for consumption based on the measured parameters.

References:

- https://www.kaggle.com/code/sabrinajeannin/wine-pca-hierarchical-clustering
- https://www.kaggle.com/code/elisthefox/ultimate-guide-to-k-nearest-neighbors-k-nn#4.-Results-of-K-NN-implementation-after-preparation-of-data

Tools and Libraries:

- Pandas: For data manipulation and analysis.
- Matplotlib: For creating visualizations such as plots.
- Seaborn: For enhancing the visual aesthetics of plots.
- Scikit-learn: For building and evaluating machine learning models.

Sections:

- Importing Libraries
- Loading and Viewing the Dataset
- EDA
- Visualization
- Model Building
- Model Improvement
- Hyperparameter Tuning

Importing Libraries

```
# Importing required libraries
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
import seaborn as sns
```

```
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.model_selection import GridSearchCV
```

Loading and Viewing the dataset

```
# Loading dataset
df = pd.read_csv("waterQuality1.csv")
# Print first 5 rows of the dataframe
df.head()
   aluminium ammonia arsenic
                                 barium cadmium chloramine
                                                                chromium
copper \
        1.65
                 9.08
                           0.04
                                   2.85
                                            0.007
                                                         0.35
                                                                    0.83
0.17
1
        2.32
                21.16
                           0.01
                                   3.31
                                            0.002
                                                         5.28
                                                                    0.68
0.66
                                                         4.24
        1.01
                14.02
                           0.04
                                   0.58
                                            0.008
                                                                    0.53
0.02
        1.36
                11.33
                           0.04
                                   2.96
                                            0.001
                                                         7.23
                                                                    0.03
1.66
        0.92
                24.33
                           0.03
                                   0.20
                                            0.006
                                                         2.67
                                                                    0.69
0.57
   flouride
             bacteria ... lead nitrates
                                               nitrites
                                                         mercury
perchlorate
       0.05
                 0.20
                             0.054
                                        16.08
                                                   1.13
                                                           0.007
37.75
       0.90
                 0.65 ...
                             0.100
                                         2.01
                                                   1.93
                                                           0.003
32.26
       0.99
                 0.05 ...
                             0.078
                                        14.16
                                                           0.006
2
                                                   1.11
50.28
       1.08
                 0.71 ...
                             0.016
                                         1.41
                                                   1.29
                                                           0.004
9.12
       0.61
                 0.13 ...
                             0.117
                                         6.74
                                                   1.11
                                                           0.003
4
16.90
   radium
           selenium
                                        is safe
                      silver
                              uranium
0
     6.78
               0.08
                        0.34
                                 0.02
                                              1
1
     3.21
               0.08
                        0.27
                                 0.05
                                              1
2
     7.07
                        0.44
                                 0.01
                                              0
               0.07
3
     1.72
               0.02
                        0.45
                                 0.05
                                              1
     2.41
4
               0.02
                                              1
                        0.06
                                 0.02
[5 rows x 21 columns]
```

```
# Print last 5 rows of the dataframe
df.tail()
      aluminium ammonia arsenic barium cadmium chloramine
chromium \
           0.05
                             0.00
7991
                   7.78
                                     1.95
                                              0.04
                                                          0.10
0.03
7992
           0.05
                   24.22
                             0.02
                                     0.59
                                              0.01
                                                          0.45
0.02
7993
           0.09
                   6.85
                             0.00
                                     0.61
                                              0.03
                                                          0.05
0.05
7994
           0.01
                   10.00
                             0.01
                                     2.00
                                              0.00
                                                          2.00
0.00
7995
           0.04
                   6.85
                             0.01 0.70
                                              0.03
                                                          0.05
0.01
      copper flouride bacteria ... lead nitrates
                                                        nitrites
mercury
       0.03
                  1.37
                                      0.197
                                                 14.29
7991
                             0.0
                                                             1.0
0.005
7992
       0.02
                             0.0 ...
                                                             1.0
                  1.48
                                      0.031
                                                 10.27
0.001
7993
       0.02
                 0.91
                             0.0
                                 . . .
                                      0.182
                                                 15.92
                                                             1.0
0.000
7994
        0.09
                  0.00
                             0.0
                                     0.000
                                                  0.00
                                                             0.0
0.000
7995
        0.03
                  1.00
                             0.0 ...
                                      0.182
                                                 15.92
                                                             1.0
0.000
      perchlorate
                   radium
                           selenium
                                     silver
                                            uranium is safe
7991
             3.57
                     2.13
                               0.09
                                       0.06
                                                0.03
                                                            1
7992
                                       0.10
             1.48
                     1.11
                               0.09
                                                0.08
                                                            1
             1.35
                                                            1
7993
                     4.84
                               0.00
                                       0.04
                                                0.05
7994
             0.00
                     0.00
                               0.00
                                       0.00
                                                0.00
                                                            1
7995
             1.35
                     4.84
                               0.00
                                       0.04
                                                0.05
                                                            1
[5 rows x 21 columns]
# Getting the shape of the dataframe
df.shape
(7996, 21)
```

EDA

```
'lead',
       'nitrates', 'nitrites', 'mercury', 'perchlorate', 'radium',
'selenium',
       'silver', 'uranium', 'is safe'],
      dtype='object')
# Getting column information of the dataframe
df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7996 entries, 0 to 7995
Data columns (total 21 columns):
#
                  Non-Null Count
     Column
                                   Dtype
- - -
 0
                  7996 non-null
                                   float64
     aluminium
 1
     ammonia
                  7996 non-null
                                   float64
 2
                                   float64
     arsenic
                  7996 non-null
                  7996 non-null
 3
     barium
                                   float64
 4
                  7996 non-null
                                   float64
     cadmium
 5
                  7996 non-null
                                   float64
     chloramine
 6
     chromium
                  7996 non-null
                                   float64
 7
                  7996 non-null
                                   float64
     copper
 8
                  7996 non-null
     flouride
                                   float64
 9
                  7996 non-null
                                   float64
     bacteria
 10
                  7996 non-null
                                   float64
    viruses
 11
    lead
                  7996 non-null
                                   float64
 12
    nitrates
                  7996 non-null
                                   float64
 13
    nitrites
                  7996 non-null
                                   float64
 14
                  7996 non-null
                                   float64
     mercury
     perchlorate 7996 non-null
 15
                                   float64
 16
                  7996 non-null
                                   float64
    radium
17
                  7996 non-null
                                   float64
     selenium
 18
    silver
                  7996 non-null
                                   float64
19
     uranium
                  7996 non-null
                                   float64
                  7996 non-null
                                   int64
20
     is safe
dtypes: float64(20), int64(1)
memory usage: 1.3 MB
# Unique values of each columns
df.nunique()
aluminium
                495
               2563
ammonia
arsenic
                107
                480
barium
cadmium
                 23
                812
chloramine
                 91
chromium
                201
copper
flouride
                151
```

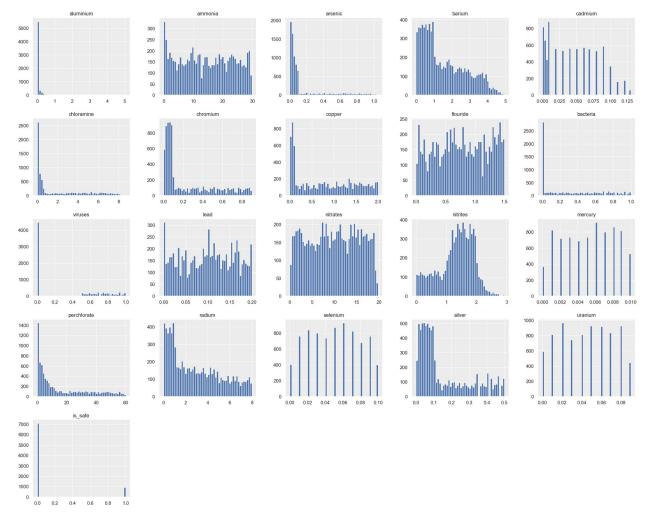
```
bacteria
                101
                 61
viruses
lead
                200
nitrates
               1803
nitrites
                280
mercury
                 11
perchlorate
               2999
radium
                735
selenium
                  11
silver
                 51
uranium
                 10
is safe
                  2
dtype: int64
# Checking for null values
df.isnull().sum()
               0
aluminium
               0
ammonia
               0
arsenic
barium
               0
cadmium
               0
chloramine
               0
               0
chromium
               0
copper
flouride
               0
bacteria
               0
viruses
               0
lead
               0
nitrates
               0
nitrites
               0
mercury
               0
perchlorate
               0
radium
               0
selenium
               0
               0
silver
               0
uranium
is safe
               0
dtype: int64
# Statistical summary of the dataframe
df.describe(include='all')
                                                                  cadmium
         aluminium
                         ammonia
                                      arsenic
                                                     barium
count 7996.000000 7996.000000 7996.000000
                                                7996.000000
                                                             7996.000000
                       14.278212
                                                   1.567928
          0.666396
                                     0.161477
                                                                 0.042803
mean
std
          1.265323
                        8.878930
                                     0.252632
                                                   1.216227
                                                                 0.036049
```

min	0.000000	-0.080000	0.000000	0.000000	0.000000
25%	0.040000	6.577500	0.030000	0.560000	0.008000
50%	0.070000	14.130000	0.050000	1.190000	0.040000
75%	0.280000	22.132500	0.100000	2.482500	0.070000
max	5.050000	29.840000	1.050000	4.940000	0.130000
\	chloramine	chromium	copper	flouride	bacteria
count	7996.000000	7996.000000	7996.000000	7996.000000	7996.000000
mean	2.177589	0.247300	0.805940	0.771646	0.319714
std	2.567210	0.270663	0.653595	0.435423	0.329497
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.100000	0.050000	0.090000	0.407500	0.000000
50%	0.530000	0.090000	0.750000	0.770000	0.220000
75%	4.240000	0.440000	1.390000	1.160000	0.610000
max	8.680000	0.900000	2.000000	1.500000	1.000000
	lead	nitrates	nitrites	mercury	perchlorate
count	7996.000000	7996.000000	7996.000000	7996.000000	7996.000000
mean	0.099431	9.819250	1.329846	0.005193	16.465266
std	0.058169	5.541977	0.573271	0.002967	17.688827
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.048000	5.000000	1.000000	0.003000	2.170000
50%	0.102000	9.930000	1.420000	0.005000	7.745000
75%	0.151000	14.610000	1.760000	0.008000	29.487500
max	0.200000	19.830000	2.930000	0.010000	60.010000
	radium	selenium	silver	uranium	is_safe

count	7996.000000	7996.000000	7996.000000	7996.000000	7996.000000			
mean	2.920106	0.049684	0.147811	0.044672	0.114057			
std	2.322805	0.028773	0.143569	0.026906	0.317900			
min	0.000000	0.000000	0.000000	0.000000	0.000000			
25%	0.820000	0.020000	0.040000	0.020000	0.000000			
50%	2.410000	0.050000	0.080000	0.050000	0.000000			
75%	4.670000	0.070000	0.240000	0.070000	0.000000			
max	7.990000	0.100000	0.500000	0.090000	1.000000			
	21 1	,						
[8 rows x 21 columns]								

Visualization

```
# Viewing the histograms for each numerical feature
df.hist(bins=50, figsize=(25,20));
```

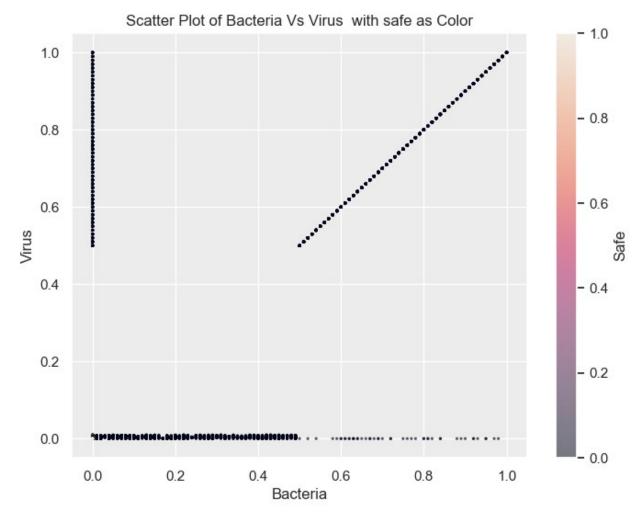


```
# Plotting Geographical data using Scatter Plot
plt.figure(figsize=(8, 6))
plt.scatter(df['bacteria'], df['viruses'], c=df['is_safe'],alpha=0.5,s=2)

# Define color using median house value
plt.colorbar(label='Safe')

# Add labels and title
plt.xlabel('Bacteria')
plt.ylabel('Virus')
plt.title('Scatter Plot of Bacteria Vs Virus with safe as Color')

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



```
# Identify the target variable
target = 'is_safe'

# Separate the independent variables
independent_vars = df.columns.difference([target])

palette = sns.color_palette("husl", len(independent_vars))

# Create box plots for all independent variables with different colors
for i, var in enumerate(independent_vars):
    plt.figure(figsize=(10, 6))
    sns.boxplot(x=target, y=var, data=df, palette=[palette[i]])
    plt.title(f'Box Plot of {var} vs {target}')
    plt.xlabel(target)
    plt.ylabel(var)
plt.show();

C:\Users\IDZ\AppData\Local\Temp\ipykernel_14484\4172465249.py:12:
FutureWarning:
```

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect. sns.boxplot(x=target, y=var, data=df, palette=[palette[i]]) C:\Users\IDZ\AppData\Local\Temp\ipykernel 14484\4172465249.py:12: UserWarning: The palette list has fewer values (1) than needed (2) and will cycle, which may produce an uninterpretable plot. sns.boxplot(x=target, y=var, data=df, palette=[palette[i]]) C:\Users\IDZ\AppData\Local\Temp\ipykernel 14484\4172465249.py:12: FutureWarning: Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect. sns.boxplot(x=target, y=var, data=df, palette=[palette[i]]) C:\Users\IDZ\AppData\Local\Temp\ipykernel 14484\4172465249.py:12: UserWarning: The palette list has fewer values (1) than needed (2) and will cycle, which may produce an uninterpretable plot. sns.boxplot(x=target, y=var, data=df, palette=[palette[i]]) C:\Users\IDZ\AppData\Local\Temp\ipykernel 14484\4172465249.py:12: FutureWarning: Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect. sns.boxplot(x=target, y=var, data=df, palette=[palette[i]]) C:\Users\IDZ\AppData\Local\Temp\ipykernel 14484\4172465249.py:12: UserWarning: The palette list has fewer values (1) than needed (2) and will cycle, which may produce an uninterpretable plot. sns.boxplot(x=target, y=var, data=df, palette=[palette[i]]) C:\Users\IDZ\AppData\Local\Temp\ipykernel 14484\4172465249.py:12: FutureWarning: Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect. sns.boxplot(x=target, y=var, data=df, palette=[palette[i]]) C:\Users\IDZ\AppData\Local\Temp\ipykernel 14484\4172465249.py:12: UserWarning: The palette list has fewer values (1) than needed (2) and will cycle, which may produce an uninterpretable plot. sns.boxplot(x=target, y=var, data=df, palette=[palette[i]])

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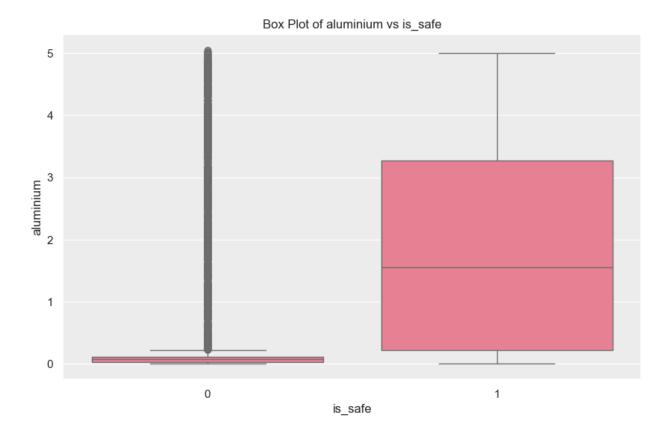
```
The palette list has fewer values (1) than needed (2) and will cycle,
which may produce an uninterpretable plot.
  sns.boxplot(x=target, y=var, data=df, palette=[palette[i]])
C:\Users\IDZ\AppData\Local\Temp\ipykernel 14484\4172465249.py:12:
FutureWarning:
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removed in v0.14.0. Assign the `x` variable to `hue` and set
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UserWarning:
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```

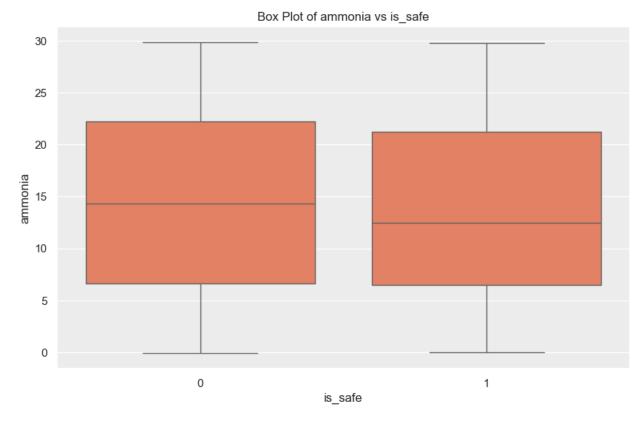
```
C:\Users\IDZ\AppData\Local\Temp\ipykernel 14484\4172465249.py:12:
UserWarning:
The palette list has fewer values (1) than needed (2) and will cycle,
which may produce an uninterpretable plot.
  sns.boxplot(x=target, y=var, data=df, palette=[palette[i]])
C:\Users\IDZ\AppData\Local\Temp\ipykernel 14484\4172465249.py:12:
FutureWarning:
Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.
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The palette list has fewer values (1) than needed (2) and will cycle,
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FutureWarning:
Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.
```

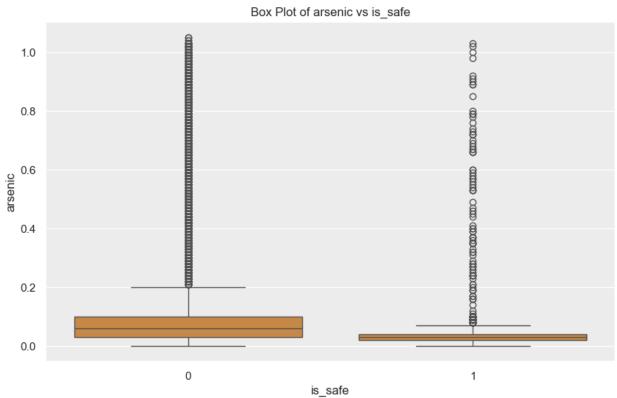
sns.boxplot(x=target, y=var, data=df, palette=[palette[i]])
C:\Users\IDZ\AppData\Local\Temp\ipykernel_14484\4172465249.py:12:
UserWarning:

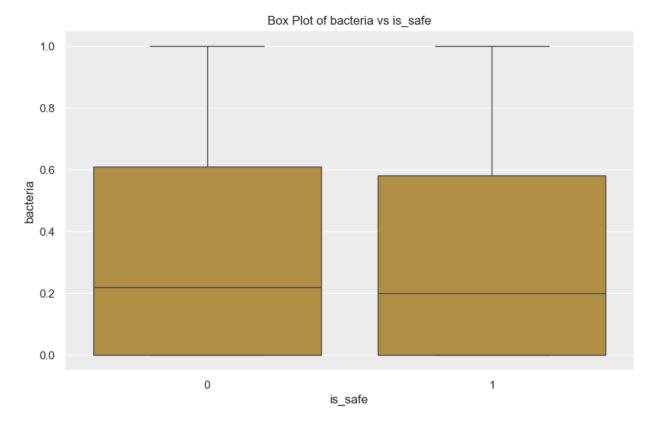
The palette list has fewer values (1) than needed (2) and will cycle, which may produce an uninterpretable plot.

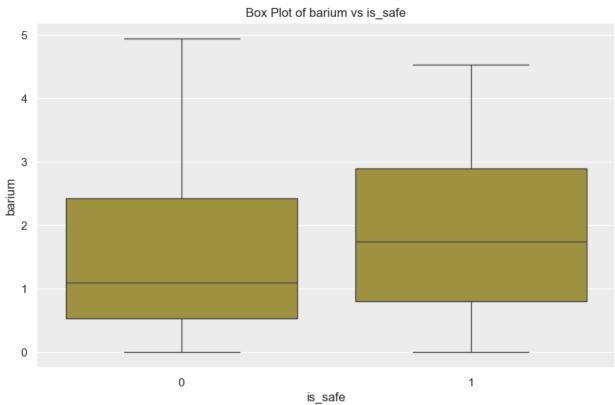
sns.boxplot(x=target, y=var, data=df, palette=[palette[i]])

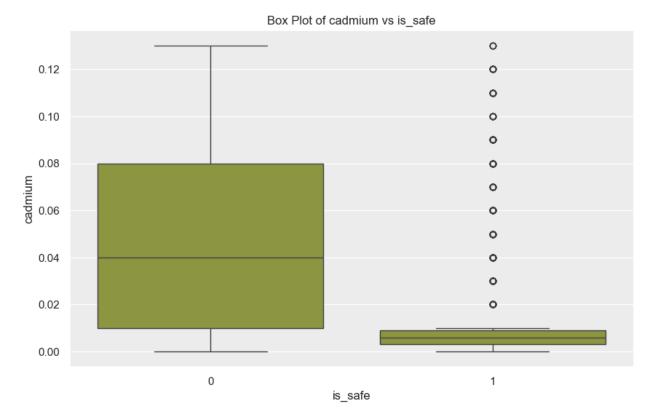


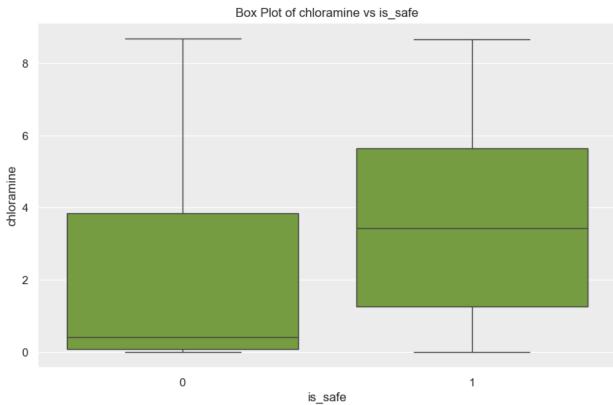


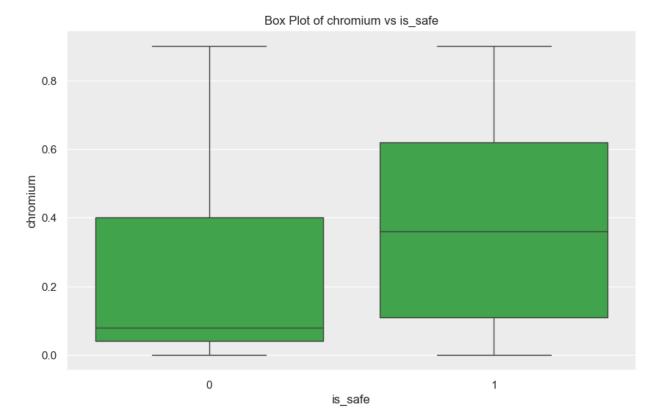


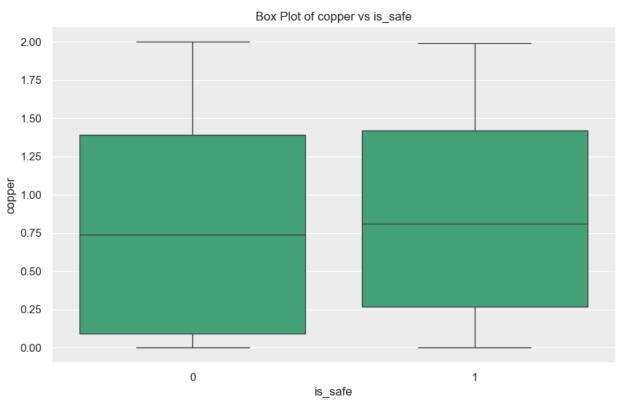


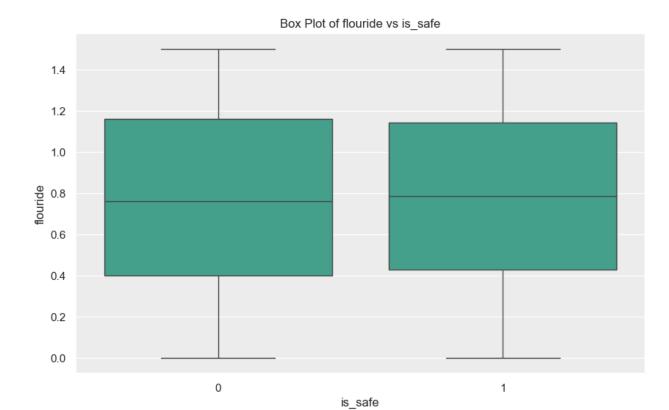


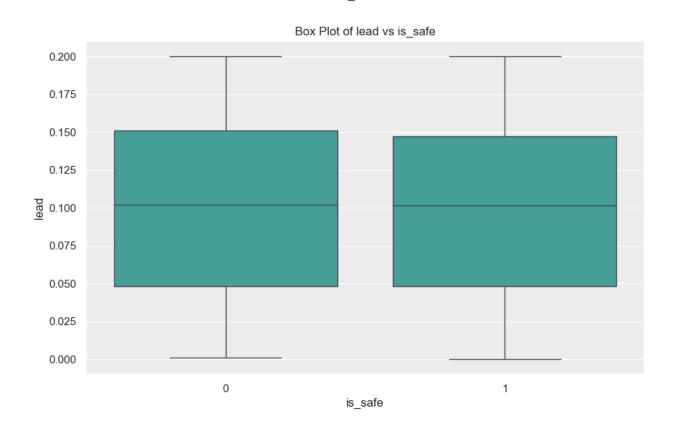


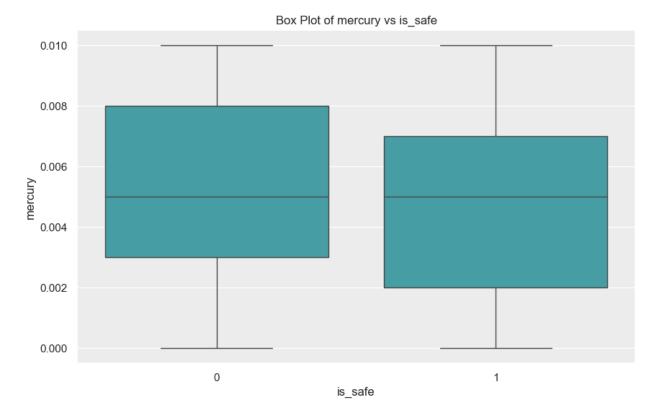


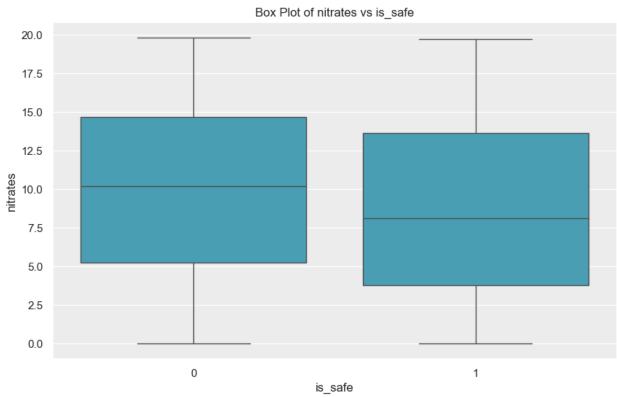


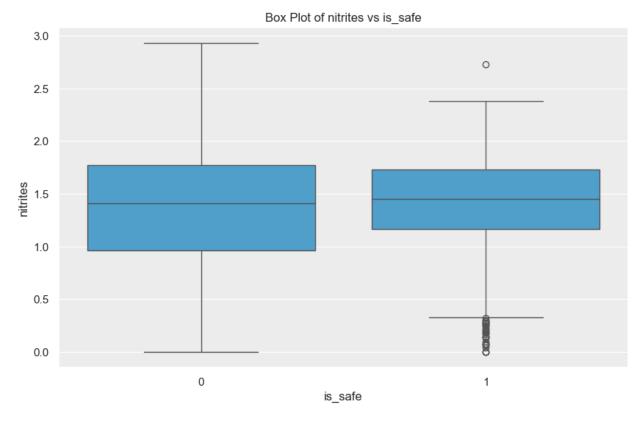


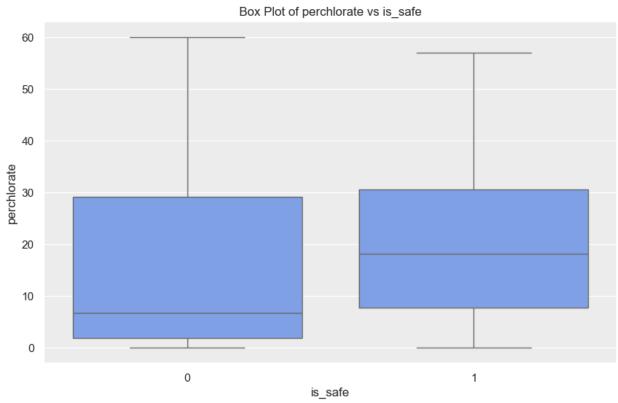


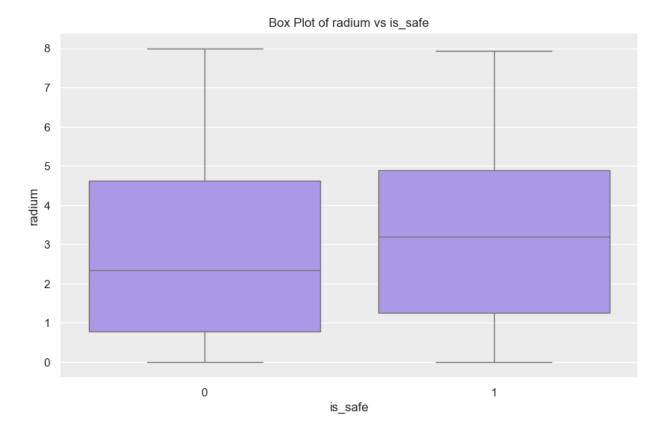


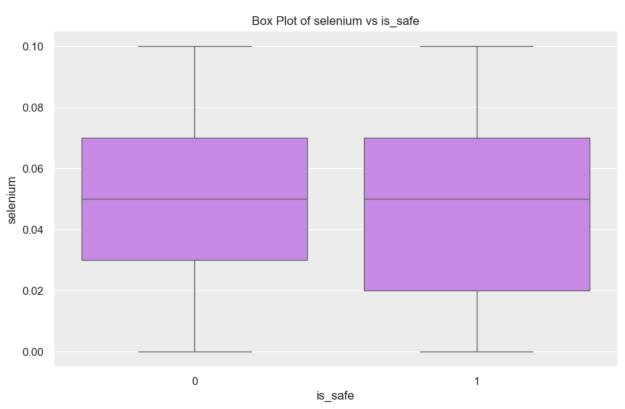


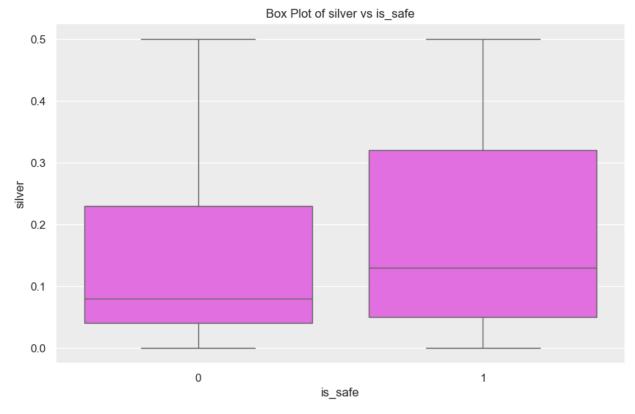


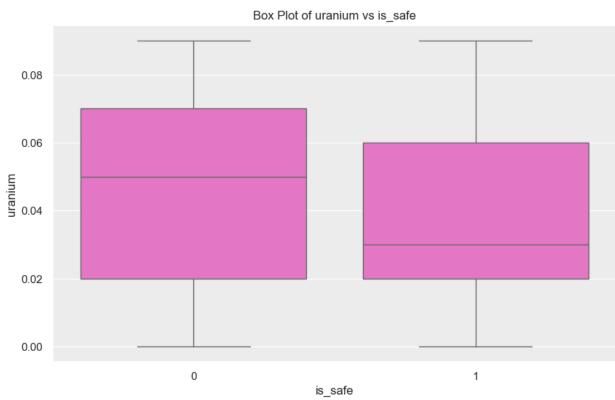


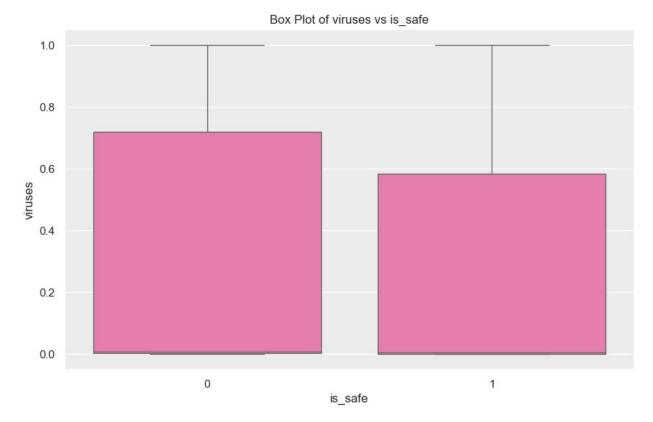




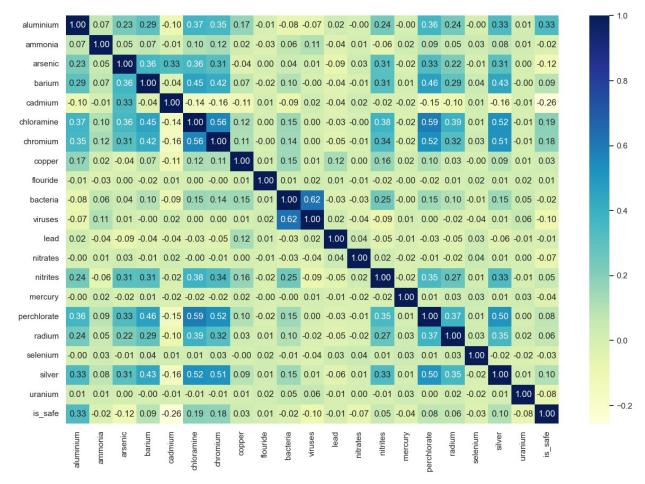






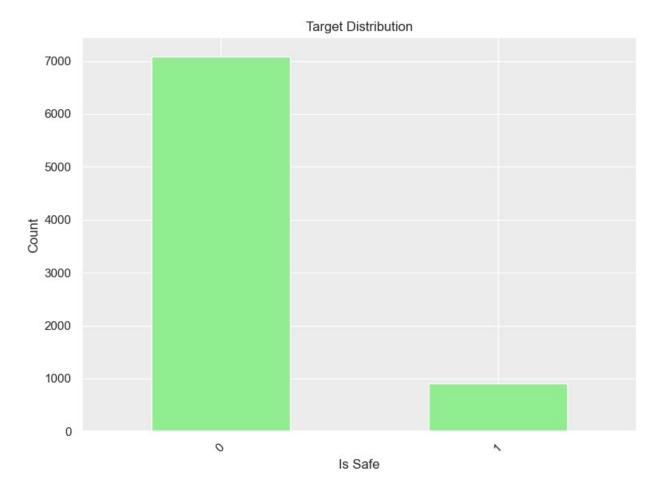


```
# Plotting heatmap
plt.figure(figsize = (15, 10))
df_corr = df.corr()
sns.heatmap(df_corr, fmt = ".2f", annot = True, cmap = "YlGnBu")
plt.show()
```



```
is_safe = df['is_safe'].value_counts()

# Plotting the bar plot
plt.figure(figsize=(8, 6))
is_safe.plot(kind='bar', color='lightgreen')
plt.title('Target Distribution')
plt.xlabel('Is Safe')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



Model Building

```
X = np.array(df)
features = X[:,0:19]
target = X[:,-1]

# Splitting data for Model Building
X_train, X_test, y_train, y_test = train_test_split(features, target, test_size=0.2, random_state=42)

# Fitting the model

model = KNeighborsClassifier()
model.fit(X_train,y_train)

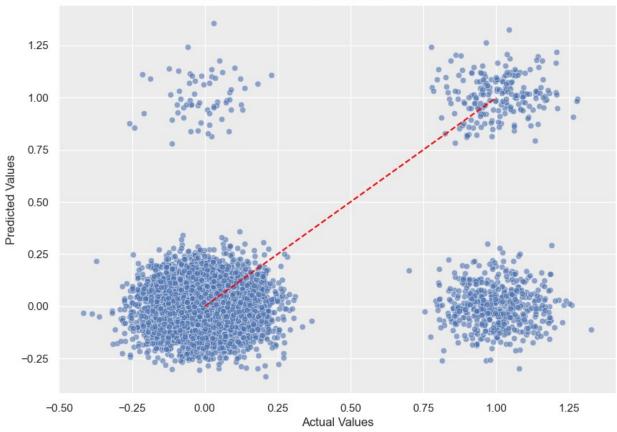
# Predicting for training set
train_pred = model.predict(X_train)

# Calculating training accuracy
train_accuracy = accuracy_score(y_train,train_pred)
print("Training accuracy is : " + str(train_accuracy))

# Getting confusion matrix and classification report
```

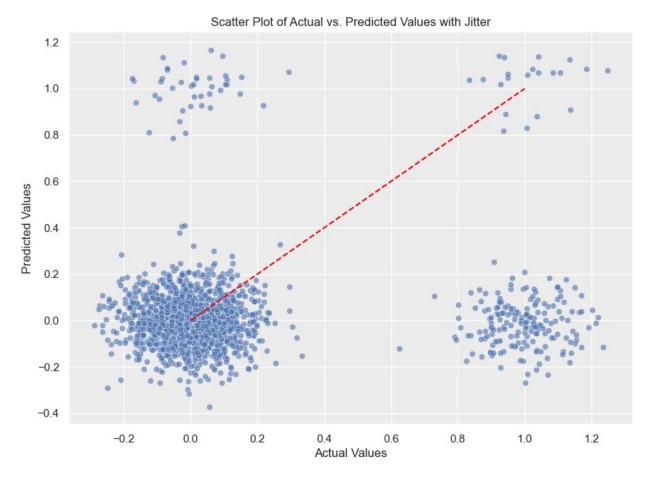
```
print("Confusion Matrix:")
print(confusion matrix(y train, train pred))
print("Classification Report:")
print(classification report(y train, train pred))
Training accuracy is : 0.9111944965603502
Confusion Matrix:
        641
[[5620
        20811
 [ 504
Classification Report:
              precision
                           recall f1-score
                                              support
         0.0
                   0.92
                             0.99
                                       0.95
                                                 5684
                   0.76
         1.0
                             0.29
                                       0.42
                                                  712
                                       0.91
                                                 6396
    accuracy
                   0.84
                             0.64
                                       0.69
                                                 6396
   macro avq
weighted avg
                   0.90
                             0.91
                                       0.89
                                                 6396
# Adding jitter to avoid overlap in scatter plot
def add_jitter(arr, jitter_strength=0.1):
    stdev = jitter strength * (max(arr) - min(arr))
    return arr + np.random.randn(len(arr)) * stdev
# Plotting the scatter plot for actual vs predicted values
plt.figure(figsize=(10, 7))
sns.scatterplot(x=add jitter(y train), y=add jitter(train pred),
marker='o', alpha=0.6)
# Adding a diagonal line to show perfect prediction
plt.plot([min(y train), max(y train)], [min(y train), max(y train)],
color='red', linestyle='--')
plt.xlabel('Actual Values')
plt.vlabel('Predicted Values')
plt.title('Scatter Plot of Actual vs. Predicted Values with Jitter')
plt.show()
```





```
# Predicting for testing set
test pred = model.predict(X test)
# Calculating testing accuracy
test_accuracy = accuracy_score(y_test,test_pred)
print("Training accuracy is : " + str(test_accuracy))
# Getting confusion matrix and classification report
print("Confusion Matrix:")
print(confusion_matrix(y_test,test_pred))
print("Classification Report:")
print(classification report(y test, test pred))
Training accuracy is: 0.8625
Confusion Matrix:
[[1359]
         411
[ 179
         21]]
Classification Report:
              precision
                            recall f1-score
                                               support
                                                  1400
         0.0
                   0.88
                             0.97
                                        0.93
         1.0
                   0.34
                             0.10
                                                   200
                                        0.16
```

```
0.86
                                                 1600
    accuracy
                                                 1600
                   0.61
                             0.54
                                       0.54
   macro avg
weighted avg
                   0.82
                             0.86
                                       0.83
                                                 1600
# Plotting the scatter plot for actual vs predicted values
plt.figure(figsize=(10, 7))
sns.scatterplot(x=add_jitter(y_test), y=add_jitter(test_pred),
marker='o', alpha=0.6
# Adding a diagonal line to show perfect prediction
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)],
color='red', linestyle='--')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.title('Scatter Plot of Actual vs. Predicted Values with Jitter')
plt.show()
```

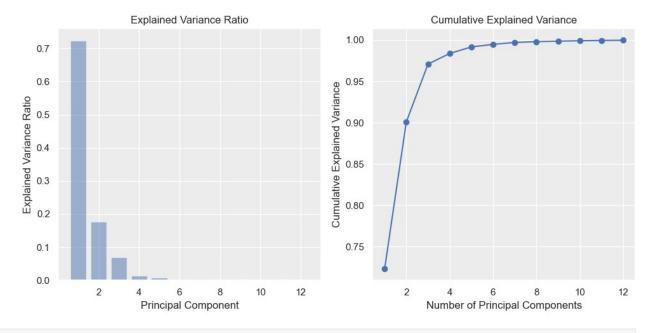


Model Improvement

```
n_{components} = 12
```

```
# Importing PCA
from sklearn.decomposition import PCA
# Let's say, components = 2
pca = PCA(n components=12)
pca.fit(X)
x pca = pca.transform(X)
# Create the dataframe
df pcal = pd.DataFrame(x pca,columns=['PC{}'.format(i+1) for i in
range(n components)])
print(df pcal)
          PC1 PC2 PC3 PC4 PC5
                                                         PC6
PC7 \
    20.875094 6.460591 6.377741 -0.075213 -4.468788 1.176144
0.683676
     16.518599 -5.860612 -7.776526 1.008795 1.832076 1.220882
0.589493
     33.872073 2.291372 4.502261 0.868194 -2.580851 -1.195053 -
1.749896
    -6.982723 2.501815 -8.403896 3.420961 5.031750 0.321890
0.619224
      1.035591 -9.979904 -3.154869 -0.397186 0.542414 -0.216626 -
1.444306
           ... ... ... ... ... ...
7991 -13.441977    5.673185    4.448488    -0.555633    -0.545002    0.212029
0.908805
7992 -14.563406 -10.827515 0.293340 -1.299944 0.241330 -0.217025 -
0.346170
7993 -15.619716   6.448067   6.054763   1.461705 -2.448939 -0.271492 -
0.401118
7994 -16.733170 3.333144 -9.856313 -0.688998 2.457217 -0.059811
0.824874
7995 -15.618424 6.448248 6.054627 1.466486 -2.445993 -0.290451 -
0.302166
          PC8
                                    PC11
                   PC9 PC10
                                             PC12
    -0.786923 -0.261715 -0.484511 0.542568 0.956504
    -0.233650 0.323953 0.420361 0.016980 0.811942
1
2
    -0.955396 -0.284386 -0.207000 -0.329719 -0.045636
    0.624846 -0.557999 0.482380 -0.032048 0.675337
3
    7991 -0.772219 -0.173152 -0.049259 -0.699844 0.889071
7992 -0.757892 0.083607 -0.073058 -0.863743 0.860983
7993 -0.756346 -0.107219 -0.241161 -0.262259
                                         0.881928
7994 -1.028636 -0.996383 -0.697608 0.583452
                                         0.748330
7995 -0.742315 -0.124202 -0.206084 -0.344706 0.879444
```

```
[7996 rows x 12 columns]
explained variance = pca.explained variance
explained variance ratio = pca.explained variance ratio
cumulative explained variance = np.cumsum(explained variance ratio)
# Plot the explained variance ratio and cumulative explained variance
plt.figure(figsize=(10, 5))
# Plot explained variance ratio
plt.subplot(1, 2, 1)
plt.bar(range(1, len(explained variance ratio) + 1),
explained variance ratio, alpha=0.5, align='center')
plt.xlabel('Principal Component')
plt.ylabel('Explained Variance Ratio')
plt.title('Explained Variance Ratio')
# Plot cumulative explained variance
plt.subplot(1, 2, 2)
plt.plot(range(1, len(cumulative explained variance) + 1),
cumulative explained variance, marker='o', linestyle='-')
plt.xlabel('Number of Principal Components')
plt.ylabel('Cumulative Explained Variance')
plt.title('Cumulative Explained Variance')
plt.tight layout()
plt.show()
```



target=X[:,-1]

```
# Splitting data for model building
im X train, im X test, im y train, im y test =
train_test_split(df_pcal, target, test_size=0.2, random_state=42)
# Fitting the model
model = KNeighborsClassifier()
model.fit(im_X_train,im_y_train)
# Predicting for training set
im train pred = model.predict(im X train)
# Calculating training accuracy
im_train_accuracy = accuracy_score(im_y train,im train pred)
print("Training accuracy is: " + str(im train accuracy))
# Getting confusion matrix and Classification report
print("Confusion Matrix: ")
print(confusion_matrix(im_y_train,im_train_pred))
print("Classification Report: ")
print(classification_report(im_y_train,im_train_pred))
Training accuracy is: 0.9177611006879299
Confusion Matrix:
        52]
[[5632
 [ 474 23811
Classification Report:
              precision
                           recall f1-score
                                              support
         0.0
                   0.92
                             0.99
                                       0.96
                                                 5684
         1.0
                   0.82
                             0.33
                                       0.48
                                                  712
                                       0.92
                                                 6396
    accuracy
                   0.87
                             0.66
                                       0.72
                                                 6396
   macro avg
weighted avg
                   0.91
                             0.92
                                       0.90
                                                 6396
# Predicting for testing set
im_test_pred = model.predict(im X test)
# Calculating testing accuracy
im test accuracy = accuracy score(im y test,im test pred)
print("Training accuracy is: " + str(im test accuracy))
# Getting confusion matrix and Classification report
print("Confusion Matrix: ")
print(confusion matrix(im y test,im test pred))
print("Classification Report: ")
print(classification_report(im_y_test,im_test_pred))
```

```
Training accuracy is: 0.8725
Confusion Matrix:
[[1369]
         31]
[ 173
         27]]
Classification Report:
                           recall f1-score
              precision
                                               support
         0.0
                   0.89
                             0.98
                                        0.93
                                                  1400
         1.0
                   0.47
                             0.14
                                        0.21
                                                   200
    accuracy
                                        0.87
                                                  1600
                             0.56
                                        0.57
                                                  1600
   macro avg
                   0.68
weighted avg
                   0.84
                             0.87
                                        0.84
                                                  1600
comparisions = ['Without PCA' , 'With PCA']
accuracies = [test_accuracy, im_test_accuracy]
plt.figure(figsize=(10, 6))
plt.plot(comparisions, accuracies, marker='o', linestyle='-',
color='b', label='Testing Accuracy')
plt.ylim(0, 1)
plt.xlabel('Comparisons')
plt.ylabel('Accuracy')
plt.title('Comparison of Accuracy Scores for Testing Sets')
plt.legend()
for i, acc in enumerate(accuracies):
    plt.text(i, acc + 0.02, round(acc, 4), ha='center')
plt.show()
```



Hyperparameter Tuning

```
# create numpy array for future K value
neighbors = np.arange(1, 40)
train_accuracy = np.empty(len(neighbors))
test accuracy = np.empty(len(neighbors))
# Code Help taken from :
https://www.kaggle.com/code/elisthefox/ultimate-guide-to-k-nearest-
neighbors-k-nn#4.-Results-of-K-NN-implementation-after-preparation-of-
data
# Loop over different values of k
for i, k in enumerate(neighbors):
    # Setup a k-NN Classifier with k neighbors: knn
    knn = KNeighborsClassifier(n_neighbors=k)
    # Fit the classifier to the training data
    knn.fit(im_X_train, im_y_train)
    #Compute accuracy on the training set
    train accuracy[i] = knn.score(im X train, im y train)
    #Compute accuracy on the testing set
    test accuracy[i] = knn.score(im X test,im y test)
```

```
# Generate plot
sns.set(rc={'axes.facecolor':'#ECECEC'}) #background color of all
plots
plt.figure(figsize=(12,6.5))
plt.title(label='K-NN: Varying Number of Neighbors', fontsize=15,
fontweight='bold', fontname='Verdana', ha='center')
plt.plot(neighbors, test_accuracy, label = 'Testing Accuracy',
color='#E68753')
plt.plot(neighbors, train_accuracy, label = 'Training Accuracy', color
= '#409996')
plt.legend()
plt.xlabel('Number of Neighbors')
plt.ylabel('Accuracy')
plt.show();
```

