Importing Libraries

In [ ]:
```
import numpy as np
import pandas as pd

import matplotlib.pyplot as plt
```

Reading Dataset

In [ ]:
```
df = pd.read_csv('magic04.data', sep=',', header=None)
df.head()
```

Out[ ]:

	0	1	2	3	4	5	6	7	8	
0	28.7967	16.0021	2.6449	0.3918	0.1982	27.7004	22.0110	-8.2027	40.0920	81.88
1	31.6036	11.7235	2.5185	0.5303	0.3773	26.2722	23.8238	-9.9574	6.3609	205.26
2	162.0520	136.0310	4.0612	0.0374	0.0187	116.7410	-64.8580	-45.2160	76.9600	256.78
3	23.8172	9.5728	2.3385	0.6147	0.3922	27.2107	-6.4633	-7.1513	10.4490	116.73
4	75.1362	30.9205	3.1611	0.3168	0.1832	-5.5277	28.5525	21.8393	4.6480	356.46

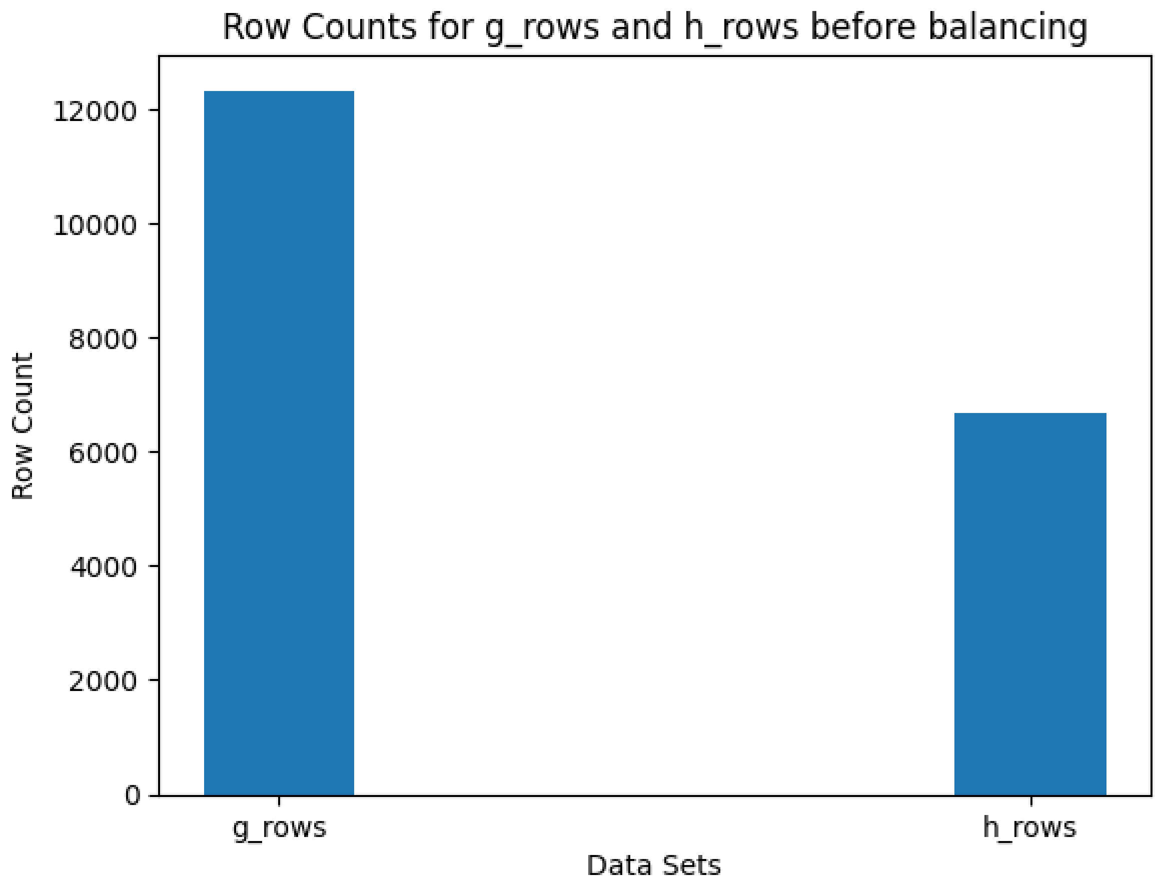
- Create two DataFrames, 'g_rows' and 'h_rows', by filtering rows where the last column of the DataFrame ('iloc[:, -1]') is equal to 'g' or 'h'.
- Calculate the number of rows in each DataFrame using the shape attribute.

In [ ]:
```
g_rows = df[df.iloc[:, -1] == 'g']
h_rows = df[df.iloc[:, -1] == 'h']
```

In [ ]:
```
g_row_count = g_rows.shape[0]
h_row_count = h_rows.shape[0]
```

- Use Matplotlib to create a bar chart that displays the counts of 'g_rows' and 'h_rows' before data balancing.

In [ ]:
```
plt.bar(['g_rows', 'h_rows'], [g_row_count, h_row_count], width=0.2)

plt.xlabel('Data Sets')
plt.ylabel('Row Count')
plt.title('Row Counts for g_rows and h_rows before balancing')

plt.show()
```



Dataset Balancing using pandas

- Balance the dataset by randomly selecting 'h_row_count' number of rows from 'g_rows' using sample()
- Using 'random_state' parameter allows you to set a fixed seed value for the random number generator, which ensures that the random processes produce the same results every time you run your code.

In [ ]:
```
new_g_rows = g_rows.sample(h_row_count ,random_state=42)
new_g_rows_count = new_g_rows.shape[0]

new_g_rows.head()
```

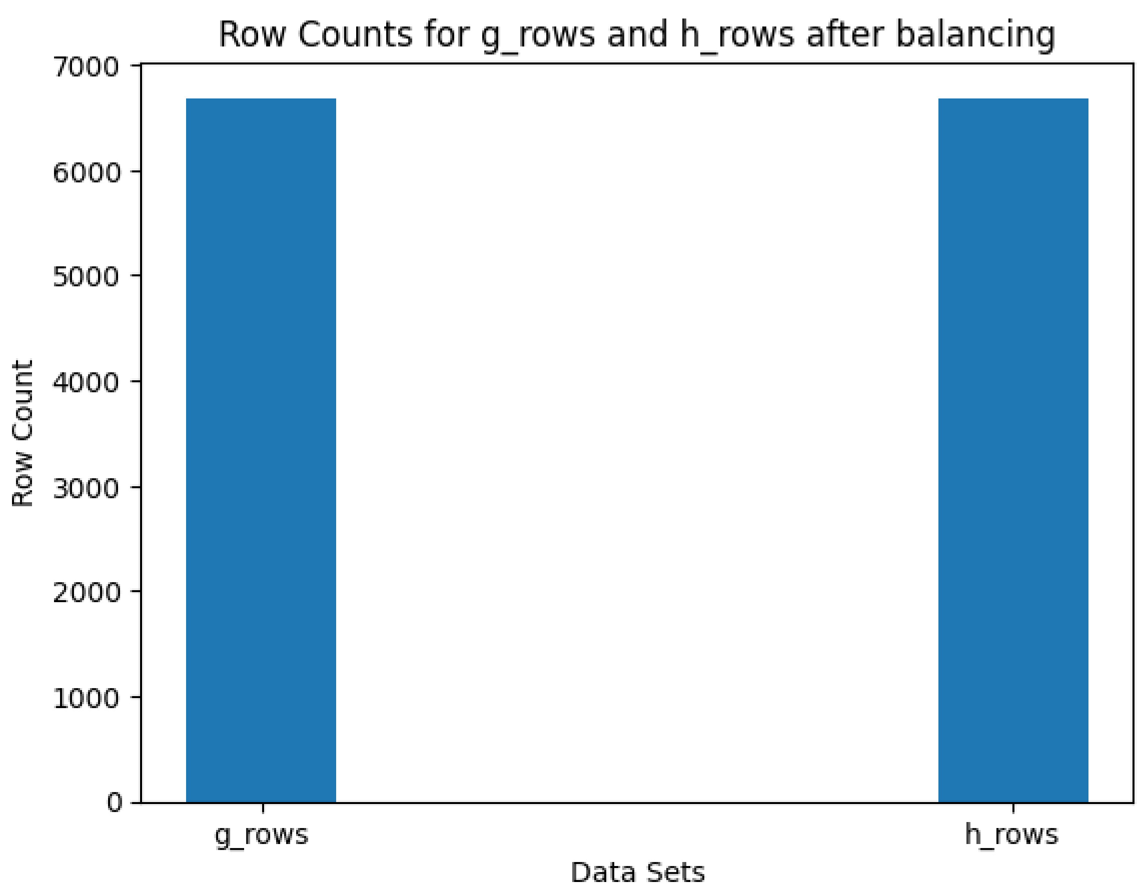
Out[ ]:

	0	1	2	3	4	5	6	7	8	
8917	41.8269	26.3680	3.0422	0.2350	0.1202	24.1335	40.1360	20.4737	29.3920	173.61
772	59.0164	18.0200	3.3073	0.2587	0.1422	57.7010	59.9175	15.4044	1.3107	237.62
12252	15.0205	12.1918	2.3560	0.6608	0.3370	1.9014	-2.0715	3.6258	89.2740	105.21
7793	51.4720	10.4108	2.5453	0.3276	0.1838	73.5451	17.7028	-7.1886	16.7782	176.55
6601	25.3814	15.7361	2.6186	0.4188	0.2419	27.8332	17.8775	5.4552	10.1725	80.39

- Chart to show the counts of 'new_g_rows' and 'h_rows' after balancing.

In [ ]:

```
plt.bar(['g_rows', 'h_rows'], [new_g_rows_count, h_row_count], width=0.2)

plt.xlabel('Data Sets')
plt.ylabel('Row Count')
plt.title('Row Counts for g_rows and h_rows after balancing')

plt.show()
```



- Concatenate 'new_g_rows' and 'h_rows' to create a new balanced DataFrame 'new_df'.

In [ ]:
```
new_df = pd.concat([new_g_rows,h_rows ],axis=0)
```

In [ ]:
```
new_df.head()
```

Out[ ]:

	0	1	2	3	4	5	6	7	8	
8917	41.8269	26.3680	3.0422	0.2350	0.1202	24.1335	40.1360	20.4737	29.3920	173.613
772	59.0164	18.0200	3.3073	0.2587	0.1422	57.7010	59.9175	15.4044	1.3107	237.622
12252	15.0205	12.1918	2.3560	0.6608	0.3370	1.9014	-2.0715	3.6258	89.2740	105.214
7793	51.4720	10.4108	2.5453	0.3276	0.1838	73.5451	17.7028	-7.1886	16.7782	176.559
6601	25.3814	15.7361	2.6186	0.4188	0.2419	27.8332	17.8775	5.4552	10.1725	80.392

Data Split

- Split the data into features (X) and labels (y).
- Then split the data into training, validation, and testing sets.
- 'X_train' and 'y_train' will be used for training your machine learning model with size 70% of the data.
- 'X_val' and 'y_val' will be used for validating and fine-tuning your model with size 15% of the data.
- 'X_test' and 'y_test' will be used for evaluating the final model's performance with size 15% of the data.

In [ ]:
```
X = new_df.iloc[: , :-1].values
y = new_df.iloc[: , -1].values
```

In [ ]:
```
from sklearn.model_selection import train_test_split

X_train, X_temp, y_train, y_temp = train_test_split(X, y, test_size=0.3, random_sta
X_val, X_test, y_val, y_test = train_test_split(X_temp, y_temp, test_size=0.5, rand
```

Feature Scaling

- Different features in your dataset may have different scales and units.Feature scaling is an essential preprocessing step in many machine learning algorithms to ensure that all features (variables) have similar scales.
- The 'StandardScaler' performs a specific type of feature scaling called standardization or (Z-Normalization). Standardization transforms the data such that it has a mean of 0 and a standard deviation of 1. It's done by subtracting the mean and dividing by the standard deviation for each feature.

In [ ]:
```
from sklearn.discriminant_analysis import StandardScaler

sc = StandardScaler()

X_train = sc.fit_transform(X_train)

X_val = sc.transform(X_val)
X_test = sc.transform(X_test)
```

In [ ]:
```
len(new_df)
```

Out[ ]:
```
13376
```

KNN

- Apply KNN model on your data using 'KNeighborsClassifier' with the specified number of neighbors (k) and use the Euclidean distance metric.

- Return the following performance measures:

    - 1-Accuracy:

        - Measures overall correctness of the model's predictions and indicates how well the model classifies instances correctly.
        - It is the ratio of correct predictions to total predictions.
    - 2-Precision:

        - Focuses on positive class accuracy as it measures the accuracy of the positive predictions made by the model.
        - It is the ratio of true positives to (true positives + false positives).
        - Important when minimizing false positives (e.g., medical diagnosis).
    - 3-Recall:

        - Measures the model's ability to identify all relevant instances in the dataset.
        - It is the ratio of true positives to (true positives + false negatives).
        - Critical when minimizing false negatives (e.g., disease identification).
    - 4-F1 Score:

        - Harmonic mean of precision and recall.
        - It provides a single metric that balances precision and recall.
        - Useful when finding a trade-off between precision and recall is necessary, especially with imbalanced data.
    - 5-Confusion Matrix:

        - A confusion matrix is a table that is often used to describe the performance of the classification model.

- It provides a detailed breakdown of the model's predictions, including true positives, true negatives, false positives, and false negatives.

In [ ]:
```
from sklearn.metrics import accuracy_score,precision_score,recall_score,f1_score,co
from sklearn.neighbors import KNeighborsClassifier

def KNN(k, train_X,train_y,test_X,test_y):
    knn = KNeighborsClassifier(n_neighbors=k,metric='euclidean')
    knn.fit(train_X,train_y)
    pred = knn.predict(test_X)

    accuracy = accuracy_score(test_y,pred)
    precision = precision_score(test_y,pred , pos_label='g')
    recall = recall_score(test_y, pred, pos_label='g')
    f1 = f1_score(test_y, pred, pos_label='g')
    conf_matrix = confusion_matrix(test_y,pred)

    result = {'k': k , 'accuracy' : accuracy , 'precision' : precision , 'conf_matr
               'recall' : recall , 'f1_score' : f1 }
    return result
```

- Store the results of KNN classification for different values of 'k' in 'k_scores'.

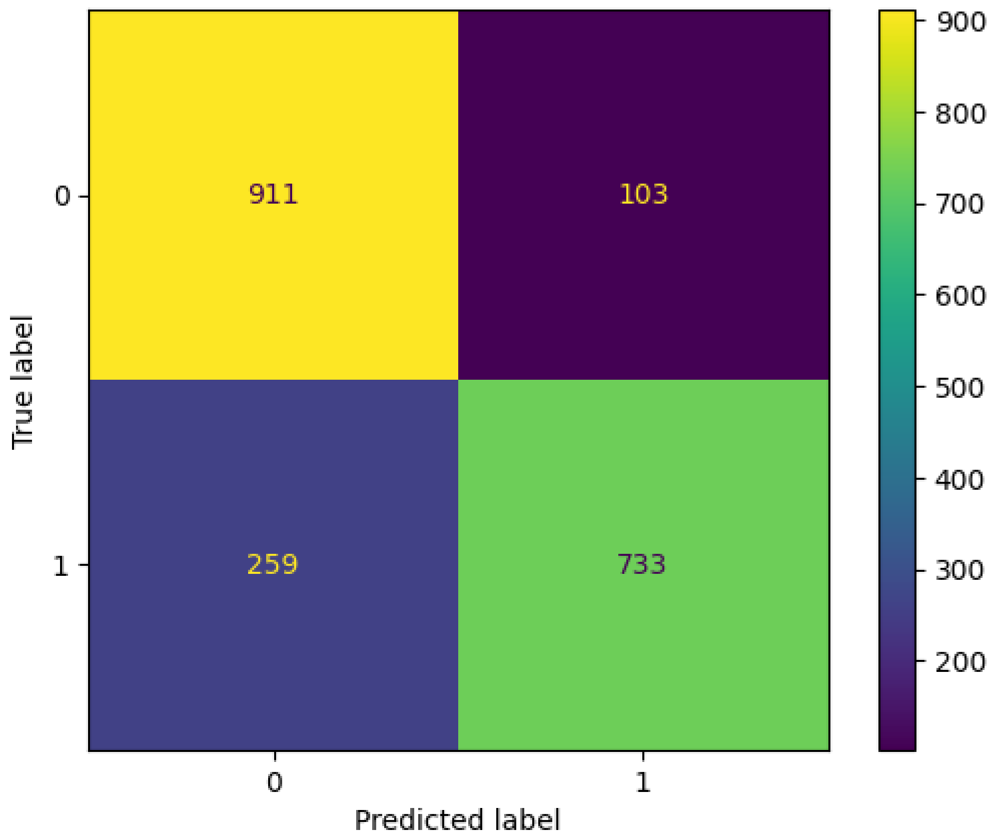
In [ ]:
```
k_scores = []
for i in range(1,115,2):
    k_result = KNN(i,X_train,y_train,X_val,y_val)
    k_scores.append(k_result)
```

Performance measures

- Find the KNN result with the highest accuracy.
- Print the best 'k' value and the corresponding accuracy, precision, recall, and F1 score.
- Plot its confusion matrix.

In [ ]:
```
best_k_scores = max(k_scores, key=lambda x: x['accuracy'])
print(f"K : {best_k_scores['k']}")
print(f"Accuracy : {best_k_scores['accuracy']:.3f}")
print(f"Precision : {best_k_scores['precision']:.3f}")
print(f"Recall : {best_k_scores['recall']:.3f}")
print(f"f1_score : {best_k_scores['f1_score']:.3f}")
print("Confusion Matrix : ")
print(best_k_scores['conf_matrix'])
ConfusionMatrixDisplay(best_k_scores['conf_matrix']).plot()
plt.show()
```

```
K : 15
Accuracy : 0.820
Precision : 0.779
Recall : 0.898
f1_score : 0.834
Confusion Matrix :
[[911 103]
 [259 733]]
```

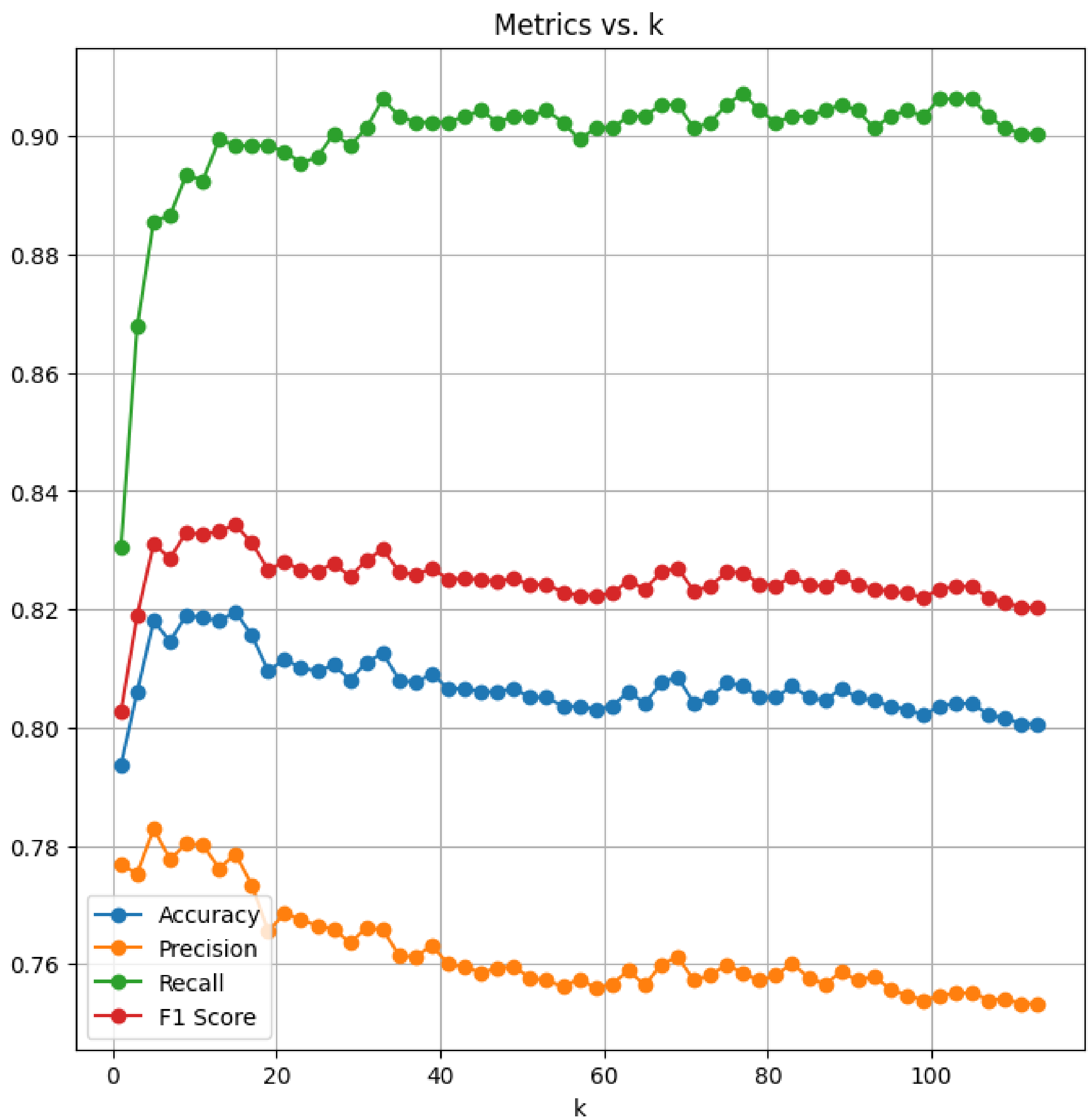


Comparing performance measures for diffrent k values

- Create line plots for accuracy, precision, recall, and F1 score as a function of 'k'.
- Display the plot to compare how different 'k' values affect these performance metrics.

In [ ]:
```
k_values = [item['k'] for item in k_scores]
accuracy_values = [item['accuracy'] for item in k_scores]
precision_values = [item['precision'] for item in k_scores]
recall_values = [item['recall'] for item in k_scores]
f1_score_values = [item['f1_score'] for item in k_scores]

plt.figure(figsize=(8, 8))

# Plot accuracy
plt.plot(k_values, accuracy_values, label='Accuracy', marker='o', linestyle='-')

# Plot precision
```

```
plt.plot(k_values, precision_values, label='Precision', marker='o', linestyle='-')

# Plot recall
plt.plot(k_values, recall_values, label='Recall', marker='o', linestyle='-')

# Plot F1-score
plt.plot(k_values, f1_score_values, label='F1 Score', marker='o', linestyle='-')

plt.title('Metrics vs. k')
plt.xlabel('k')
plt.grid(True)

plt.legend()

plt.show()
```



In [ ]:
```
knn_model = KNeighborsClassifier(n_neighbors=best_k_scores['k'],metric='euclidean')
```

Testing

- Using the best 'k' value to perform KNN classification on the test set and print the testing results

In [ ]:
```
testing_result = KNN(best_k_scores['k'], X_train,y_train,X_test,y_test)
print("Testing Result: ", testing_result)
```

```
Testing Result:  {'k': 15, 'accuracy': 0.8236173393124065, 'precision': 0.7798634812
286689, 'conf_matrix': array([[914,  96],
       [258, 739]], dtype=int64), 'recall': 0.904950495049505, 'f1_score': 0.8377635
19706691}
```