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Group B Machine Learning

Assignment 5

Implement K-Nearest Neighbors algorithm on diabetes.csv dataset. Compute confusion matrix, accuracy, error rate, precision and recall on the given dataset.

Dataset link : https://www.kaggle.com/datasets/abdallamahgoub/diabetes

```
import pandas as pd
import numpy as np
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, fbeta_score,confusion_matrix,classification_report
import matplotlib.pyplot as plt
```

```
df = pd.read_csv('diabetes.csv')
df
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	Pedigree	Age	Outcome
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0
2	8	183	64	0	0	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.167	21	0
4	0	137	40	35	168	43.1	2.288	33	1
...	...	...	...	...	...	...	...	...	...
763	10	101	76	48	180	32.9	0.171	63	0
764	2	122	70	27	0	36.8	0.340	27	0
765	5	121	72	23	112	26.2	0.245	30	0
766	1	126	60	0	0	30.1	0.349	47	1
767	1	93	70	31	0	30.4	0.315	23	0

768 rows × 9 columns

```
df.sample(5)
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	Pedigree	Age	Outcome
584	8	124	76	24	600	28.7	0.687	52	1
160	4	151	90	38	0	29.7	0.294	36	0
309	2	124	68	28	205	32.9	0.875	30	1
13	1	189	60	23	846	30.1	0.398	59	1
435	0	141	0	0	0	42.4	0.205	29	1

```
df.shape
```

```
(768, 9)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Pregnancies    768 non-null    int64
 1   Glucose        768 non-null    int64
 2   BloodPressure  768 non-null    int64
 3   SkinThickness  768 non-null    int64
 4   Insulin        768 non-null    int64
 5   BMI            768 non-null    float64
 6   Pedigree       768 non-null    float64
 7   Age            768 non-null    int64
 8   Outcome        768 non-null    int64
dtypes: float64(2), int64(7)
memory usage: 54.1 KB
```

```
df.isnull().sum()
```

```
Pregnancies      0
Glucose          0
BloodPressure    0
SkinThickness    0
Insulin          0
BMI              0
Pedigree         0
Age              0
Outcome          0
dtype: int64
```

```
df.duplicated().sum()
```

```
0
```

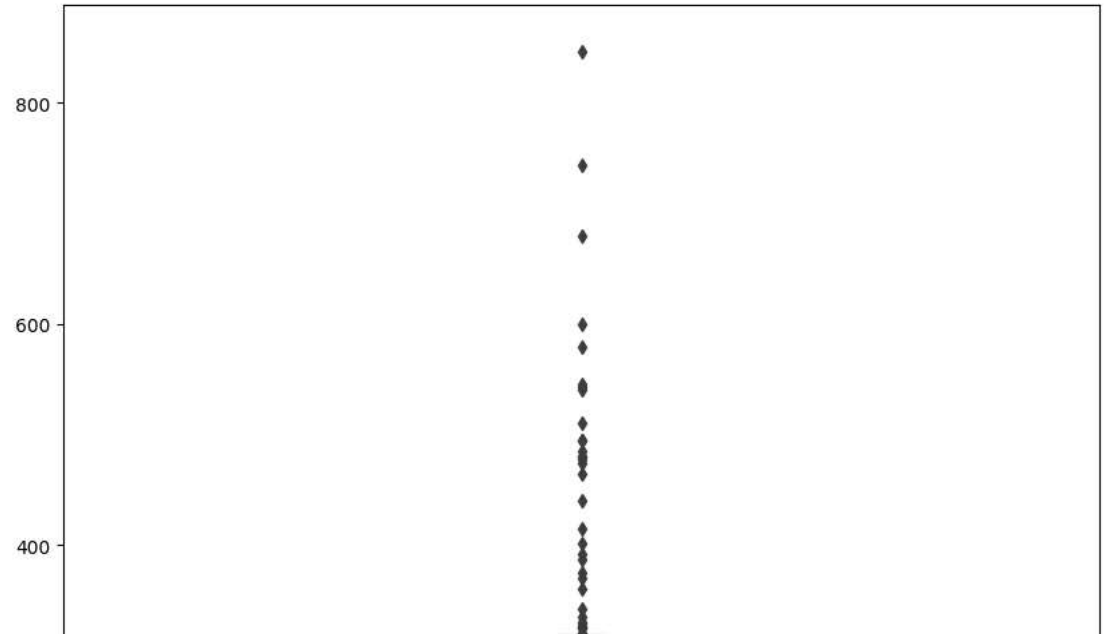
```
df.describe()
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	Pedigree	Age	Outcome
count	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000
mean	3.845052	120.894531	69.105469	20.536458	79.799479	31.992578	0.471876	33.240885	0.348958
std	3.369578	31.972618	19.355807	15.952218	115.244002	7.884160	0.331329	11.760232	0.476951
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.078000	21.000000	0.000000
25%	1.000000	99.000000	62.000000	0.000000	0.000000	27.300000	0.243750	24.000000	0.000000
50%	3.000000	117.000000	72.000000	23.000000	30.500000	32.000000	0.372500	29.000000	0.000000
75%	6.000000	140.250000	80.000000	32.000000	127.250000	36.600000	0.626250	41.000000	1.000000
max	17.000000	199.000000	122.000000	99.000000	846.000000	67.100000	2.420000	81.000000	1.000000

Exploratory Data Analysis

```
plt.figure(figsize=(10,10))
sns.boxplot(data=df)
```

```
<Axes: >
```



Outlier treatment

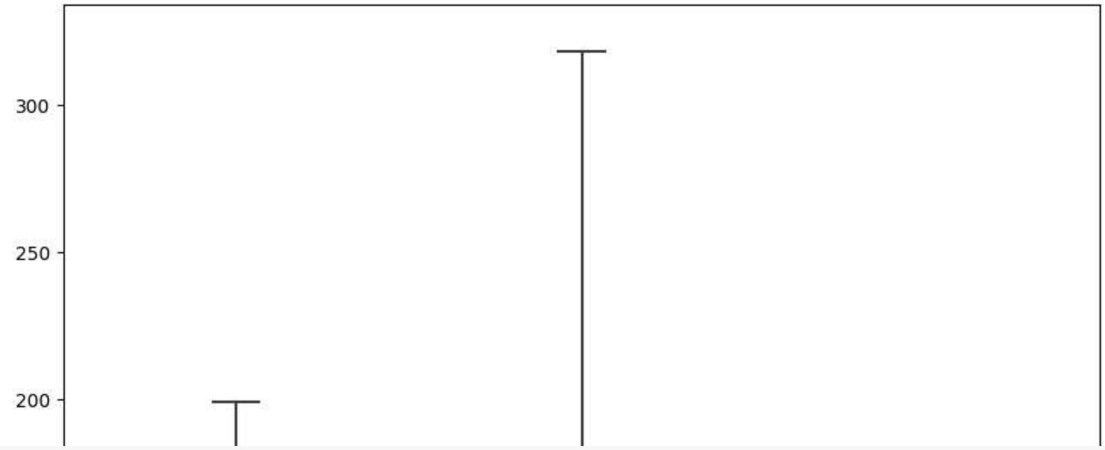
```
def remove_outlier(dataframe , col):
    Q1 = dataframe[col].quantile(0.25)
    Q3 = dataframe[col].quantile(0.75)
    IQR = Q3 - Q1
    lower_whisker = Q1-1.5*IQR
    upper_whisker = Q3+1.5*IQR
    dataframe[col] = np.clip(dataframe[col] , lower_whisker , upper_whisker)
    return dataframe
```

```
def treat_outliers_all(dataframe , col_list):
    for c in col_list:
        dataframe = remove_outlier(dataframe , c)
    return dataframe
```

```
df1 = treat_outliers_all(df, df.columns)
```

```
plt.figure(figsize=(10,10))
sns.boxplot(data=df1)
```

```
<Axes: >
```

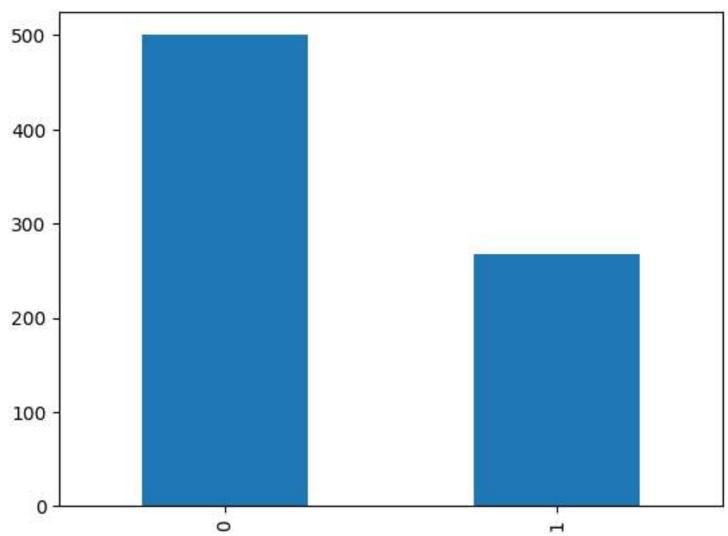



```
df1['Outcome'].value_counts()
```

```
0    500
1    268
Name: Outcome, dtype: int64
```

```
# imbalance classifier
df1['Outcome'].value_counts().plot(kind='bar')
```

```
<Axes: >
```



Define independent variable (x) & dependent variable (y)

```
x=df1.drop('Outcome',axis=1)
y=df1['Outcome']
print(x.shape)
print(y.shape)
```

```
(768, 8)
(768,)
```

Splitting dataset into training and testing set

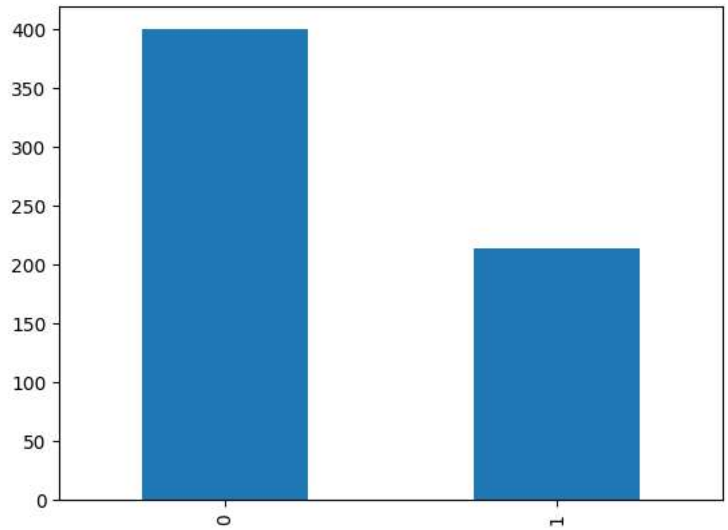
```
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.2,random_state=31,stratify=y)
```

```
y_train.value_counts()
```

```
0    400
1    214
Name: Outcome, dtype: int64
```

```
y_train.value_counts().plot(kind='bar')
```

```
<Axes: >
```

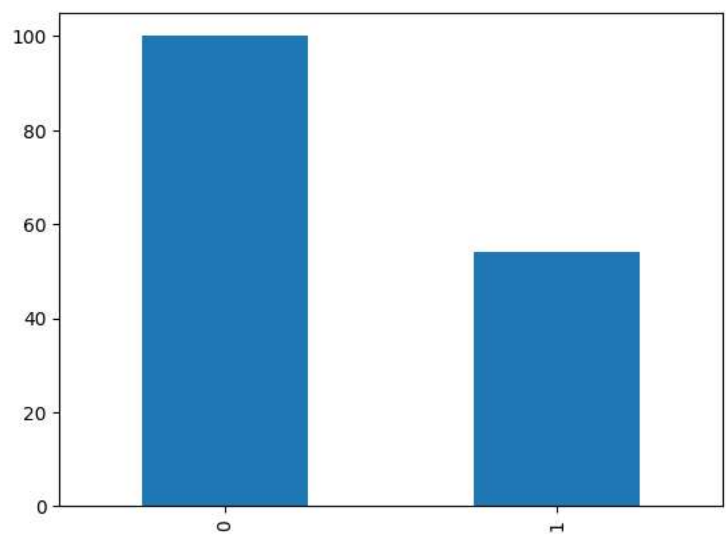



```
y_test.value_counts()
```

```
0    100
1     54
Name: Outcome, dtype: int64
```

```
y_test.value_counts().plot(kind='bar')
```

```
<Axes: >
```



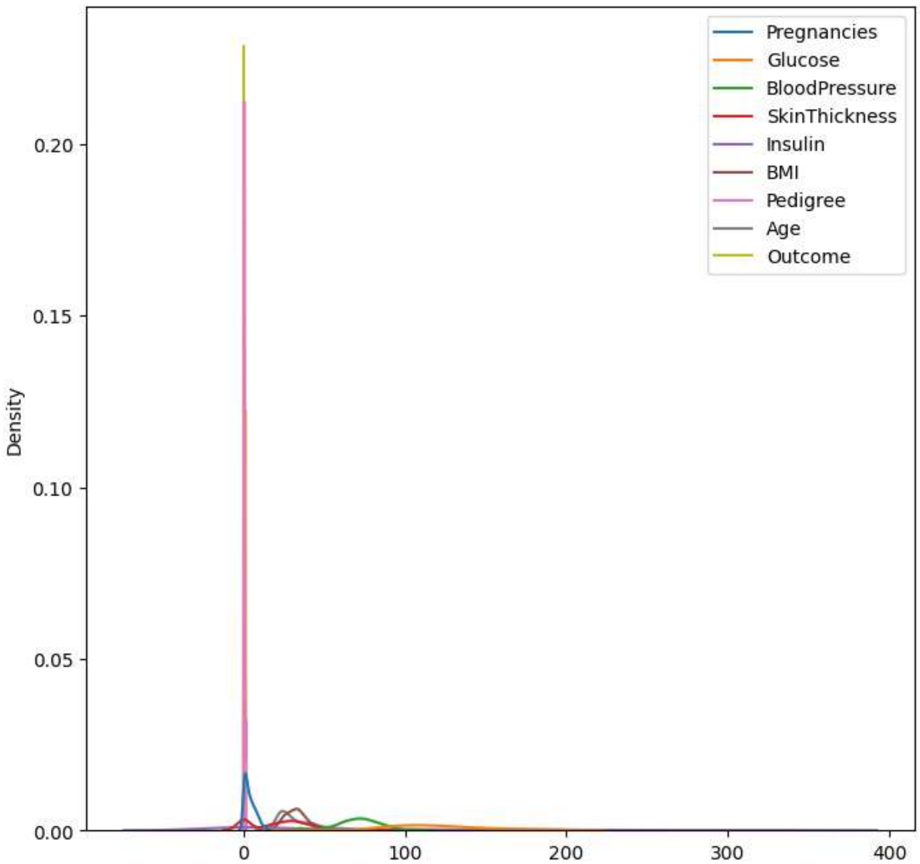
Feature Scaling

```
sns.histplot(data=df1)
```

```
<Axes: ylabel='Count'>
```


```
plt.figure(figsize=(8,8))
sns.kdeplot(data=df1)
```

```
<Axes: ylabel='Density'>
```




```
# Use StandardScaler for normally distributed data, otherwise use MinMaxScaler.
scaler = MinMaxScaler()
x_train_scaled = scaler.fit_transform(x_train)
x_test_scaled = scaler.transform(x_test)
```

```
x_train_scaled
```

```
array([[0.22222222, 0.42548263, 0.26388889, ..., 0.47177419, 0.19073084,
        0.06593407],
       [0.2962963 , 0.33899614, 0.625     , ..., 0.77553763, 0.14171123,
        0.17582418],
       [0.2962963 , 0.55521236, 0.73611111, ..., 0.56854839, 0.46345811,
        0.15384615],
       ...,
       [0.2962963 , 0.9011583 , 0.        , ..., 0.40456989, 0.11942959,
        0.32967033],
       [0.51851852, 0.87644788, 0.83333333, ..., 0.56048387, 0.07664884,
        0.85714286],
       [0.74074074, 0.68494208, 0.68055556, ..., 0.65188172, 0.82263815,
        0.65934066]])
```

```
x_train_scaled_df = pd.DataFrame(x_train_scaled,columns=x_train.columns)
x_train_scaled_df
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	Pedigree	Age
0	0.222222	0.425483	0.263889	0.333333	0.496660	0.471774	0.190731	0.065934
1	0.296296	0.338996	0.625000	0.000000	0.000000	0.775538	0.141711	0.175824
2	0.296296	0.555212	0.736111	0.174603	0.487230	0.568548	0.463458	0.153846
3	0.518519	0.697297	0.597222	0.460317	0.396071	0.587366	0.547237	0.725275
4	0.148148	0.332819	0.375000	0.000000	0.000000	0.375000	0.398396	0.021978
...	...	...	...	...	...	...	...	...
609	0.074074	0.388417	0.513889	0.190476	0.220039	0.321237	0.516934	0.153846
610	0.518519	0.505792	0.000000	0.000000	0.000000	0.318548	0.116756	0.351648
611	0.296296	0.901158	0.000000	0.000000	0.000000	0.404570	0.119430	0.329670
612	0.518519	0.876448	0.833333	0.492063	0.000000	0.560484	0.076649	0.857143
613	0.740741	0.684942	0.680556	0.761905	0.744990	0.651882	0.822638	0.659341

```
x_test_scaled_df = pd.DataFrame(x_test_scaled,columns=x_test.columns)
x_test_scaled_df
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	Pedigree	Age
0	0.148148	0.629344	0.555556	0.000000	0.000000	0.329301	0.079323	0.175824
1	0.666667	0.530502	0.486111	0.698413	0.295481	0.530914	0.263815	0.417582
2	0.000000	0.864093	0.347222	0.460317	1.000000	0.571237	0.885918	0.000000
3	0.296296	0.666409	0.652778	0.285714	0.000000	0.514785	0.139929	1.000000
4	0.222222	0.456371	0.291667	0.619048	0.000000	0.450269	0.426916	0.197802
...	...	...	...	...	...	...	...	...
149	0.000000	0.351351	0.000000	0.000000	0.000000	0.000000	0.158645	0.087912
150	0.074074	0.369884	0.430556	0.238095	0.440079	0.264785	0.364528	0.021978
151	0.592593	0.388417	0.569444	0.000000	0.000000	0.681452	0.099822	0.461538
152	0.666667	0.215444	0.597222	0.396825	0.000000	0.490591	0.180036	0.373626
153	0.148148	0.511969	0.263889	0.000000	0.000000	0.361559	0.336007	0.131868

154 rows × 8 columns

SMOTE for Imbalanced classification

```
from imblearn.over_sampling import SMOTE
```

```
smote_object = SMOTE()
```

```
x_sampled, y_sampled = smote_object.fit_resample(x_train_scaled_df,y_train)
```

```
x_sampled.shape
```

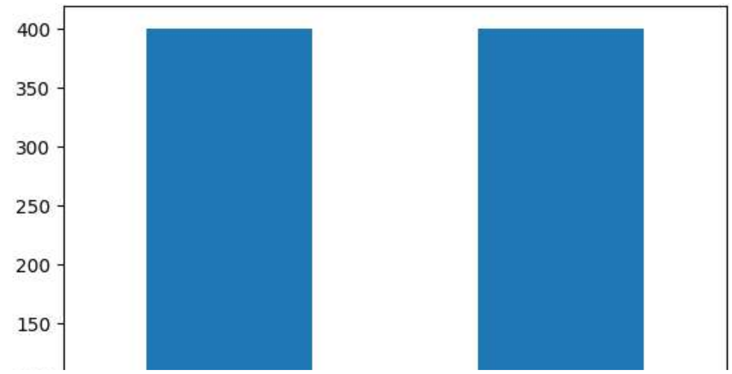
```
(800, 8)
```

```
y_sampled.shape
```

```
(800,)
```

```
y_sampled.value_counts().plot(kind='bar')
```

```
<Axes: >
```



Build a model

```
from sklearn.neighbors import KNeighborsClassifier
```

```
x_train_sampled,x_test_sampled,y_train_sampled,y_test_sampled = train_test_split(x_sampled,y_sampled,test_size=0.2,random_state=42)
```

```
knn_model = KNeighborsClassifier()
knn_model.fit(x_train_sampled,y_train_sampled)
y_pred = knn_model.predict(x_test_sampled)
```

```
accuracy = accuracy_score(y_test_sampled,y_pred)
print('Accuracy:',accuracy)
```

```
Accuracy: 0.73125
```

```
recall = recall_score(y_test_sampled,y_pred)
print('Recall:',recall)
```

```
Recall: 0.7682926829268293
```

```
precision = precision_score(y_test_sampled,y_pred)
print('Precision:',precision)
```

```
Precision: 0.7241379310344828
```

```
matrix = confusion_matrix(y_test_sampled,y_pred)
matrix
```

```
array([[54, 24],
       [19, 63]])
```