```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import confusion_matrix, classification_report, accuracy_score
from sklearn import preprocessing
```

Loading the Dataset

First we load the dataset and find out the number of columns, rows, NULL values, etc.

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

```
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.head()
```

	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

Next steps: Generate code with df | View recommended plots | New interactive sheet

Cleaning

```
df.corr().style.background_gradient(cmap='BuGn')
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	Pedigree	Age	Outcome
Pregnancies	1.000000	0.129459	0.141282	-0.081672	-0.073535	0.017683	-0.033523	0.544341	0.221898
Glucose	0.129459	1.000000	0.152590	0.057328	0.331357	0.221071	0.137337	0.263514	0.466581
BloodPressure	0.141282	0.152590	1.000000	0.207371	0.088933	0.281805	0.041265	0.239528	0.065068
SkinThickness	-0.081672	0.057328	0.207371	1.000000	0.436783	0.392573	0.183928	-0.113970	0.074752
Insulin	-0.073535	0.331357	0.088933	0.436783	1.000000	0.197859	0.185071	-0.042163	0.130548
BMI	0.017683	0.221071	0.281805	0.392573	0.197859	1.000000	0.140647	0.036242	0.292695
Pedigree	-0.033523	0.137337	0.041265	0.183928	0.185071	0.140647	1.000000	0.033561	0.173844
Age	0.544341	0.263514	0.239528	-0.113970	-0.042163	0.036242	0.033561	1.000000	0.238356
Outcome	0.221898	0.466581	0.065068	0.074752	0.130548	0.292695	0.173844	0.238356	1.000000

```
df.drop(['BloodPressure', 'SkinThickness'], axis=1, inplace=True)
```

```
df.isna().sum()
```

	0
Pregnancies	0
Glucose	0
Insulin	0
BMI	0
Pedigree	0
Age	0
Outcome	0

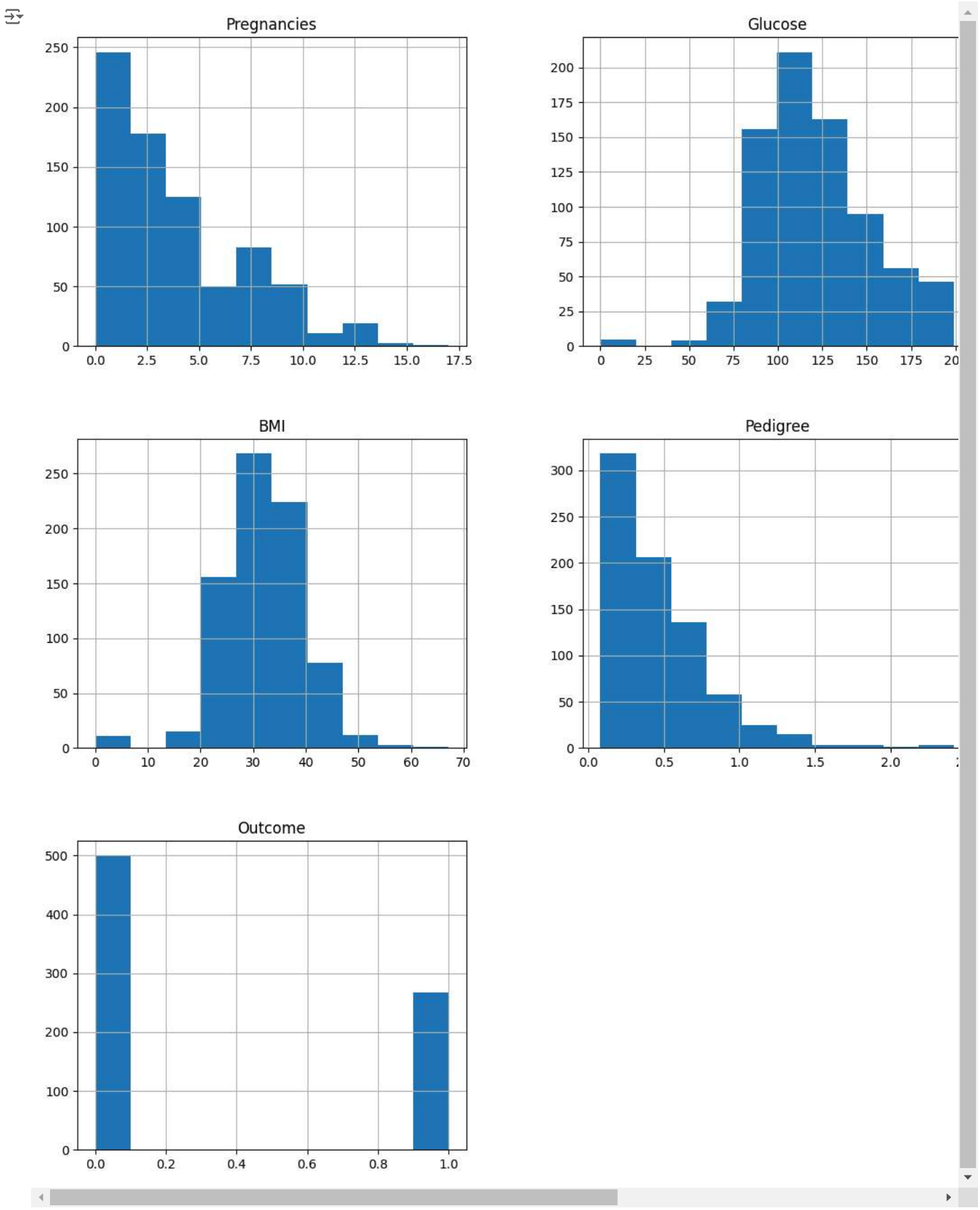
dtype: int64

```
df.describe()
```

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

Visualization

```
hist = df.hist(figsize=(20,16))
```



Separating the features and the labels

```
X=df.iloc[:, :df.shape[1]-1]       #Independent Variables
y=df.iloc[:, -1]                   #Dependent Variable
X.shape, y.shape
```

```
((768, 6), (768,))
```

Splitting the Dataset

Training and Test Set

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=8)
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

Machine Learning model

```
def knn(X_train, X_test, y_train, y_test, neighbors, power):
    model = KNeighborsClassifier(n_neighbors=neighbors, p=power)
    # Fit and predict on model
    # Model is trained using the train set and predictions are made based on the test set. Accuracy scores are calculated for the model.
    y_pred=model.fit(X_train, y_train).predict(X_test)
    print(f"Accuracy for K-Nearest Neighbors model \t: {accuracy_score(y_test, y_pred)}")

    cm = confusion_matrix(y_test, y_pred)
    print(f'''Confusion matrix :\n
    | Positive Prediction\t| Negative Prediction
    ---------------+------------------------+----------------------
    Positive Class | True Positive (TP) {cm[0, 0]}\t| False Negative (FN) {cm[0, 1]}
    ---------------+------------------------+----------------------
    Negative Class | False Positive (FP) {cm[1, 0]}\t| True Negative (TN) {cm[1, 1]}\n''')
    cr = classification_report(y_test, y_pred)
    print('Classification report : \n', cr)
```

Hyperparameter tuning

```
param_grid = {
    'n_neighbors': range(1, 51),
    'p': range(1, 4)
}
grid = GridSearchCV(estimator=KNeighborsClassifier(), param_grid=param_grid, cv=5)
grid.fit(X_train, y_train)
grid.best_estimator_, grid.best_params_, grid.best_score_
```

```
(KNeighborsClassifier(n_neighbors=27),
 {'n_neighbors': 27, 'p': 2},
 0.7719845395175262)
```

```
knn(X_train, X_test, y_train, y_test, grid.best_params_['n_neighbors'], grid.best_params_['p'])
```

```
Accuracy for K-Nearest Neighbors model  : 0.7987012987012987
Confusion matrix :

    | Positive Prediction       | Negative Prediction
    ---------------+------------------------+----------------------
    Positive Class | True Positive (TP) 91      | False Negative (FN) 11
    ---------------+------------------------+----------------------
    Negative Class | False Positive (FP) 20     | True Negative (TN) 32

Classification report :
                precision    recall  f1-score   support
```