```
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```

Group B Machine Learning

Assignment 6

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 (https://www.kaggle.com/datasets/abdallamahgoub/diabetes)

In [1]:
```
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_sco
import matplotlib.pyplot as plt
```

In [2]:
```
df = pd.read_csv('diabetes.csv')
df
```

Out[2]:

	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

In [3]:
```
df.sample(5)
```

Out[3]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	Pedigree	Age	Outcome
282	7	133	88	15	155	32.4	0.262	37	0
458	10	148	84	48	237	37.6	1.001	51	1
420	1	119	88	41	170	45.3	0.507	26	0
66	0	109	88	30	0	32.5	0.855	38	1
385	1	119	54	13	50	22.3	0.205	24	0

In [4]:
```
df.shape
```

Out[4]:
```
(768, 9)
```

In [5]:
```
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
```

In [6]:
```
df.isnull().sum()
```

Out[6]:
```
Pregnancies      0
Glucose          0
BloodPressure    0
SkinThickness    0
Insulin          0
BMI              0
Pedigree         0
Age              0
Outcome          0
dtype: int64
```

In [7]:
```
df.duplicated().sum()
```

Out[7]:
```
0
```

In [8]:
```
df.describe()
```

Out[8]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	Pedigree
count	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.00000
mean	3.845052	120.894531	69.105469	20.536458	79.799479	31.992578	0.47187
std	3.369578	31.972618	19.355807	15.952218	115.244002	7.884160	0.33132
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.07800
25%	1.000000	99.000000	62.000000	0.000000	0.000000	27.300000	0.24375
50%	3.000000	117.000000	72.000000	23.000000	30.500000	32.000000	0.37250
75%	6.000000	140.250000	80.000000	32.000000	127.250000	36.600000	0.62625
max	17.000000	199.000000	122.000000	99.000000	846.000000	67.100000	2.42000

In [9]:
```
x=df.drop(['Outcome'],axis=1)
x.shape
```

Out[9]:
```
(768, 8)
```

In [10]:
```
y=df['Outcome']
y.shape
```

Out[10]:
```
(768,)
```

In [11]:
```
y.value_counts()
```

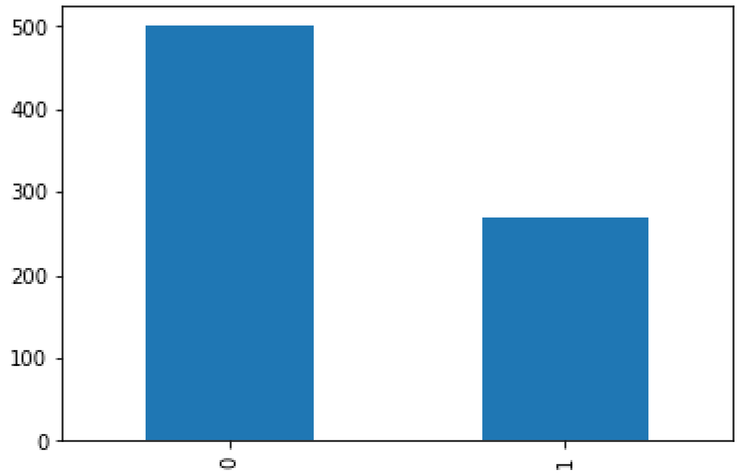
Out[11]:
```
0    500
1    268
Name: Outcome, dtype: int64
```

In [12]:
```
df['Outcome'].value_counts()
```

Out[12]:
```
0    500
1    268
Name: Outcome, dtype: int64
```

In [13]:
```
df['Outcome'].value_counts().plot(kind='bar')
```

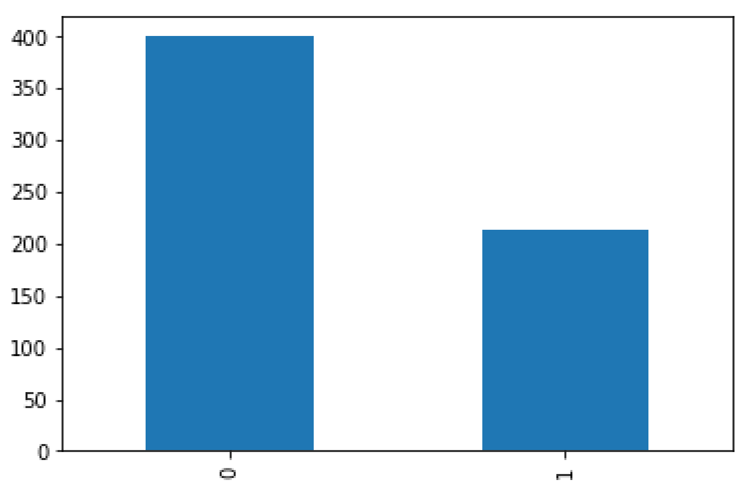
Out[13]: <AxesSubplot:>



In [14]:
```
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.2,random_state=
```

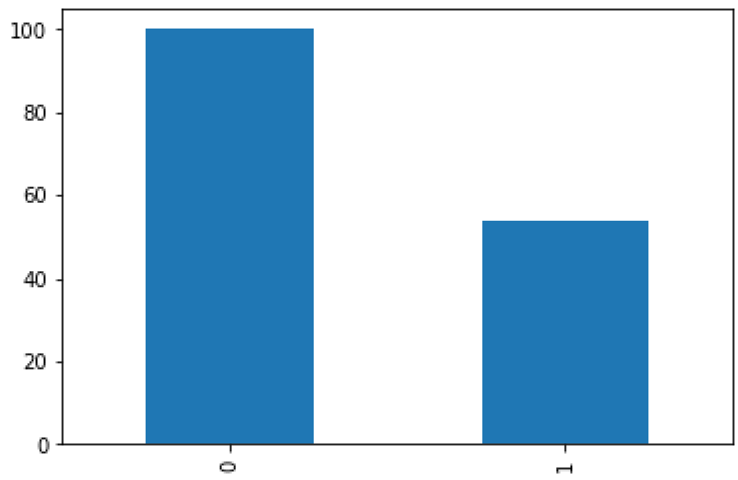
In [15]:
```
y_train.value_counts().plot(kind='bar')
```

Out[15]: <AxesSubplot:>



In [16]:
```
y_test.value_counts().plot(kind='bar')
```

Out[16]: <AxesSubplot:>



In [17]:
```
from sklearn.neighbors import KNeighborsClassifier
knn_model = KNeighborsClassifier()
knn_model.fit(x_train,y_train)
```

Out[17]: KNeighborsClassifier()

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [18]:
```
y_pred = knn_model.predict(x_test)
```

In [19]:
```
accuracy = accuracy_score(y_test,y_pred)
print("Accuracy Score : ",accuracy )
```

```
Accuracy Score :  0.7077922077922078
```

In [20]:
```
recall = recall_score(y_test,y_pred)
print("Recall Score : ",recall)
```

```
Recall Score :  0.5740740740740741
```

In [21]:
```
precision = precision_score(y_test,y_pred)
print("Precision Score : ",precision)
```

```
Precision Score :  0.5849056603773585
```

In [22]:
```
f1_score = f1_score(y_test,y_pred)
print("F1 Score : ",f1_score)
```

```
F1 Score :  0.5794392523364486
```

In [23]:
```
fbeta_05 = fbeta_score(y_test,y_pred,beta=0.5)
print("Fbeta_0.5 Score : ",fbeta_05)
```

```
Fbeta_0.5 Score :  0.5827067669172932
```

In [24]:
```
fbeta_1 = fbeta_score(y_test,y_pred,beta=1)
print("Fbeta_1 Score : ",fbeta_1)
```

```
Fbeta_1 Score :  0.5794392523364486
```

In [25]:
```
fbeta_2 = fbeta_score(y_test,y_pred,beta=2)
print("Fbeta_2 Score : ",fbeta_2)
```

```
Fbeta_2 Score :  0.5762081784386617
```

In [26]:
```
matrix = confusion_matrix(y_test,y_pred)
matrix
```

Out[26]:
```
array([[78, 22],
       [23, 31]], dtype=int64)
```

In [27]:
```
report = classification_report(y_test,y_pred)
print(report)
```

```
              precision    recall  f1-score   support

           0       0.77      0.78      0.78       100
           1       0.58      0.57      0.58        54

    accuracy                           0.71       154
   macro avg       0.68      0.68      0.68       154
weighted avg       0.71      0.71      0.71       154
```

In [28]:
```
result = pd.DataFrame(columns=["Accuracy","Precision","Recall","FBeta_0.5","FBeta
result
```

Out[28]:

Accuracy	Precision	Recall	FBeta_0.5	FBeta_1	FBeta_2

In [29]:
```
result.loc["KNN"] = [accuracy,precision,recall,fbeta_05,fbeta_1,fbeta_2]
result
```

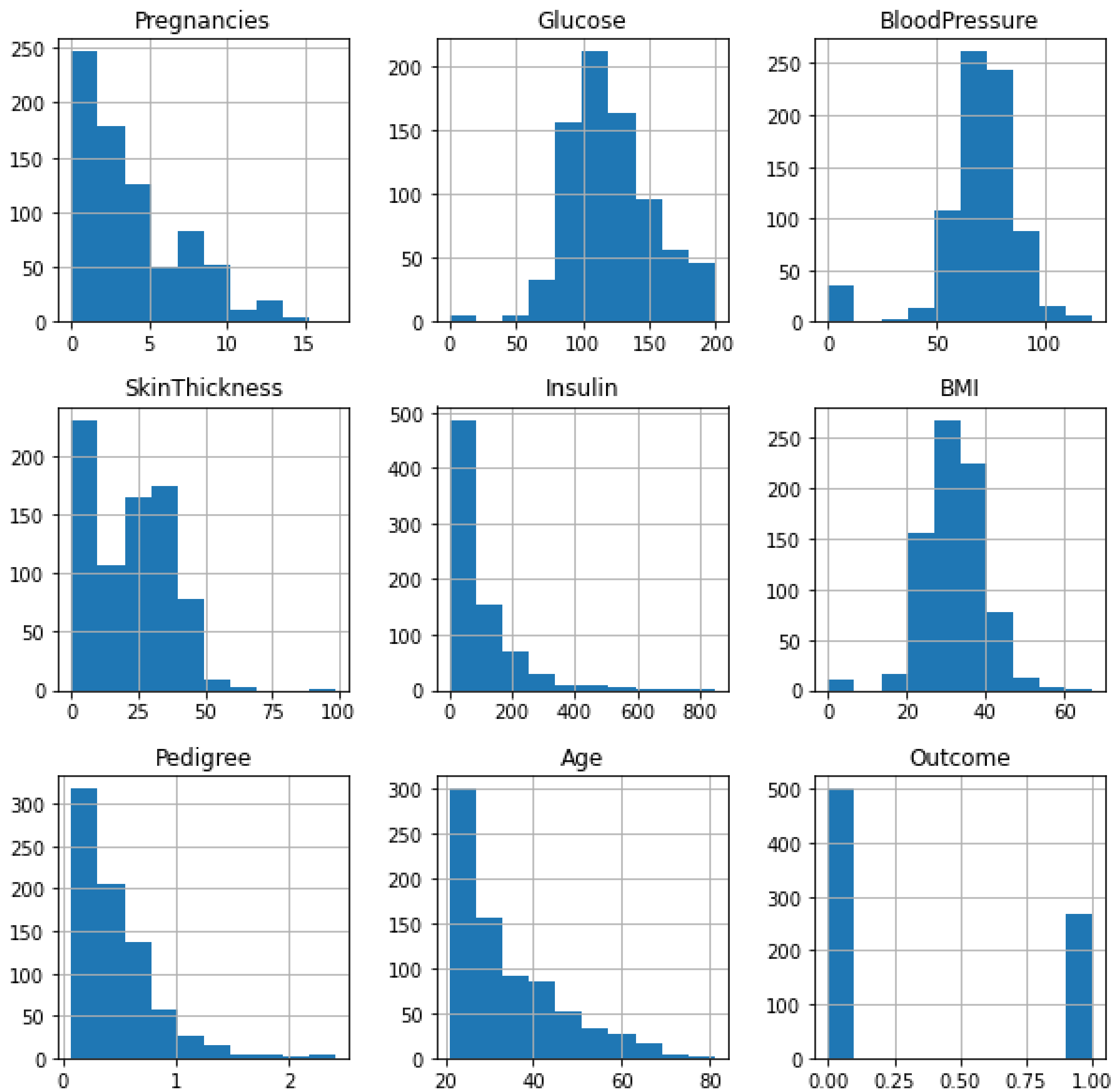
Out[29]:

	Accuracy	Precision	Recall	FBeta_0.5	FBeta_1	FBeta_2
KNN	0.707792	0.584906	0.574074	0.582707	0.579439	0.576208

Exploratory Data Analysis

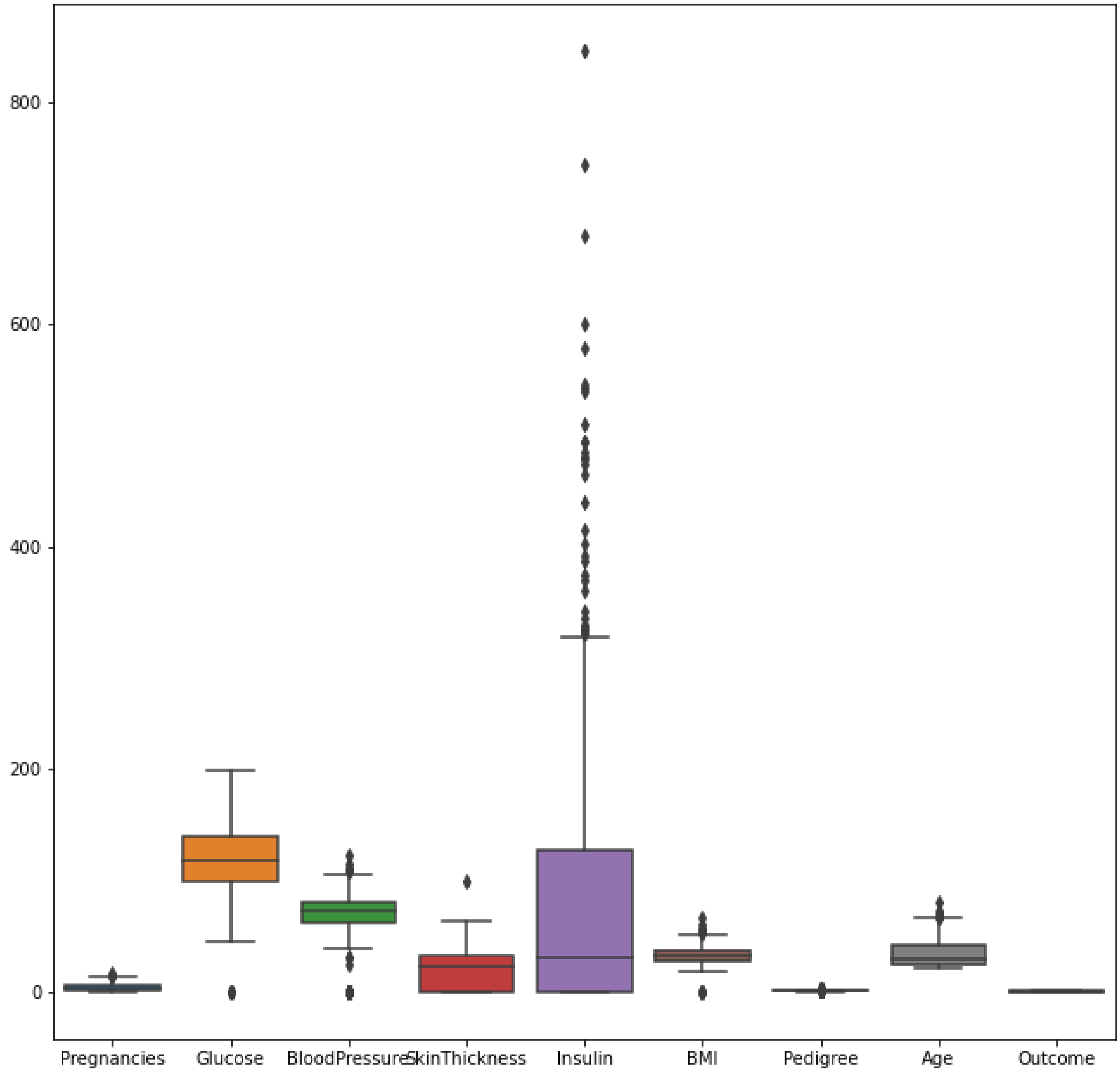
In [30]:
```
fig, axis = plt.subplots(3,3,figsize=(10, 10))
df.hist(ax=axis)
```

Out[30]:
```
array([[<AxesSubplot:title={'center':'Pregnancies'}>,
        <AxesSubplot:title={'center':'Glucose'}>,
        <AxesSubplot:title={'center':'BloodPressure'}>],
       [<AxesSubplot:title={'center':'SkinThickness'}>,
        <AxesSubplot:title={'center':'Insulin'}>,
        <AxesSubplot:title={'center':'BMI'}>],
       [<AxesSubplot:title={'center':'Pedigree'}>,
        <AxesSubplot:title={'center':'Age'}>,
        <AxesSubplot:title={'center':'Outcome'}>]], dtype=object)
```



In [31]:
```
plt.figure(figsize=(11,11))
sns.boxplot(data=df)
```

Out[31]: <AxesSubplot:>



Outlier treatment

In [32]:
```
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
```

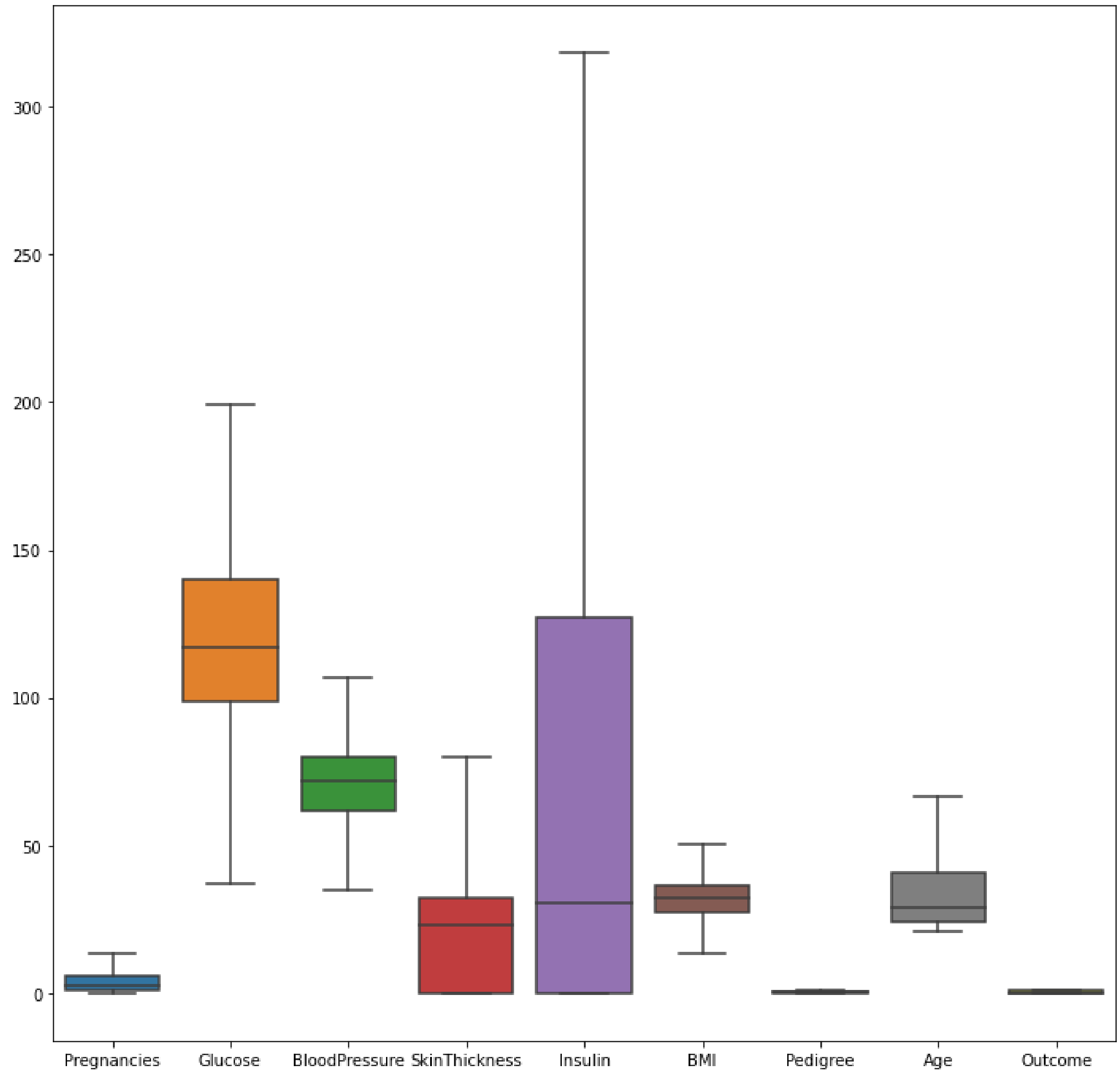
```
np.clip(a, a_min, a_max)
Clip (limit) the values in an array.
Given an interval, values outside the interval are clipped to the interval
edges.
```

In [33]:
```
def treat_outliers_all(dataframe , col_list):
    for c in col_list:
        dataframe = remove_outlier(dataframe , c)
    return dataframe
```

In [34]:
```
df1 = treat_outliers_all(df, df.columns)
```

In [35]:
```
plt.figure(figsize=(12,12))
sns.boxplot(data= df1)
```

Out[35]: <AxesSubplot:>

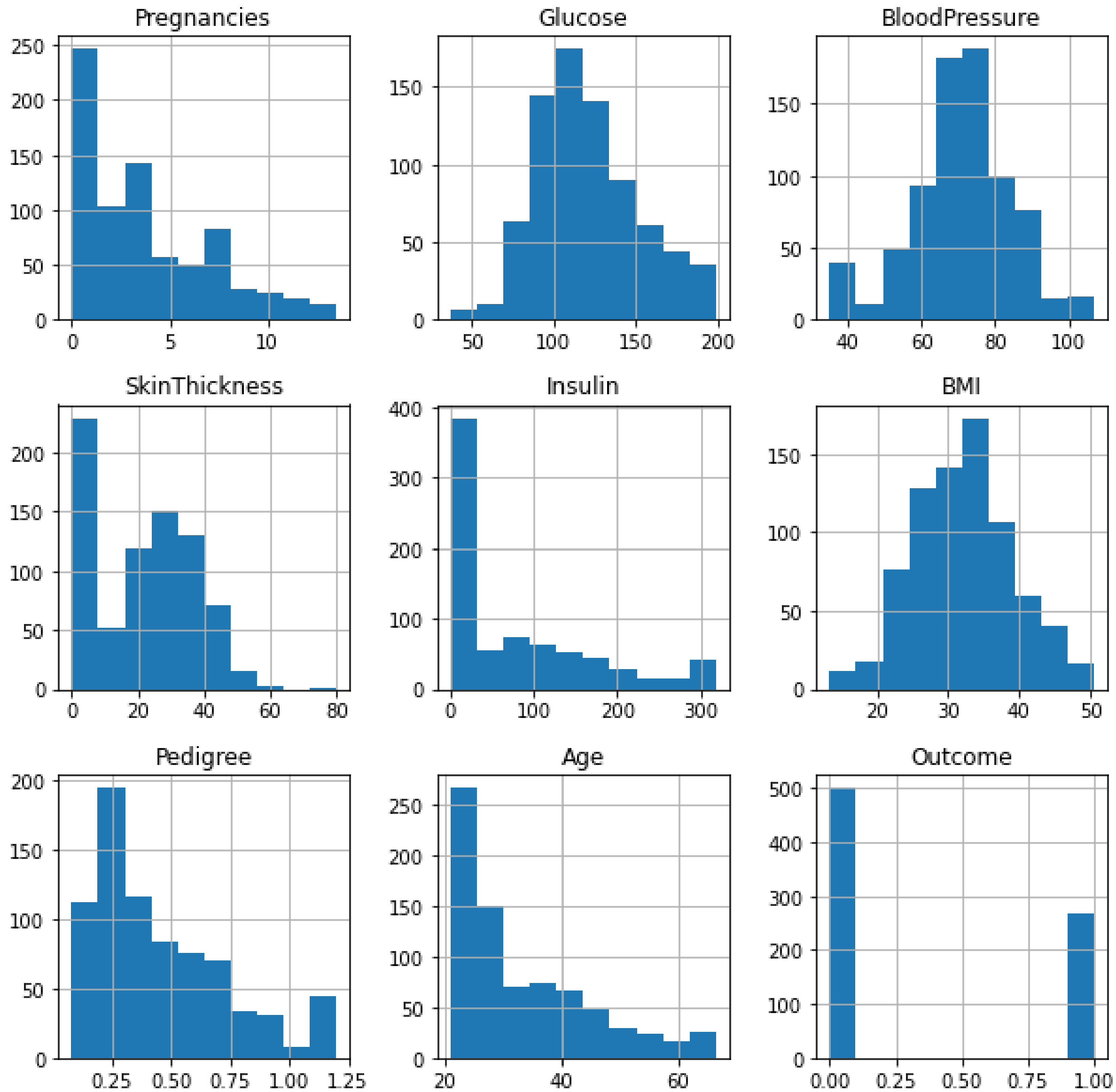


Features Scaling

```
 it is always advisable to bring all the features to the same scale for
applying distance based algorithms like KNN or K-Means.
```

In [36]:
```
fig, axis = plt.subplots(3,3,figsize=(10, 10))
df1.hist(ax=axis)
```

Out[36]:
```
array([[<AxesSubplot:title={'center':'Pregnancies'}>,
        <AxesSubplot:title={'center':'Glucose'}>,
        <AxesSubplot:title={'center':'BloodPressure'}>],
       [<AxesSubplot:title={'center':'SkinThickness'}>,
        <AxesSubplot:title={'center':'Insulin'}>,
        <AxesSubplot:title={'center':'BMI'}>],
       [<AxesSubplot:title={'center':'Pedigree'}>,
        <AxesSubplot:title={'center':'Age'}>,
        <AxesSubplot:title={'center':'Outcome'}>]], dtype=object)
```



In [37]:
```
x1=df1.drop('Outcome',axis=1)
y1=df1['Outcome']
print(x1.shape)
print(y1.shape)
```

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

In [38]:
```
x_train1,x_test1,y_train1,y_test1 = train_test_split(x1,y1,test_size=0.2,random_s
```

In [39]:
```
# std_scaler = StandardScaler()
# x_train_scaled = std_scaler.fit_transform(x_train1)
# x_test_scaled = std_scaler.fit_transform(x_test1)
```

In [40]:
```
# x_train_scaled
```

In [41]:
```
scaler = MinMaxScaler()
x_train_scaled = scaler.fit_transform(x_train1)
x_test_scaled = scaler.transform(x_test1)
```

In [42]:
```
x_train_scaled
```

Out[42]:
```
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]])
```

In [43]:
```
x_test_scaled
```

Out[43]:
```
array([[0.14814815, 0.62934363, 0.55555556, ..., 0.32930108, 0.07932264,
        0.17582418],
       [0.66666667, 0.53050193, 0.48611111, ..., 0.53091398, 0.26381462,
        0.41758242],
       [0.        , 0.86409266, 0.34722222, ..., 0.57123656, 0.885918  ,
        0.        ],
       ...,
       [0.59259259, 0.38841699, 0.56944444, ..., 0.68145161, 0.09982175,
        0.46153846],
       [0.66666667, 0.21544402, 0.59722222, ..., 0.4905914 , 0.18003565,
        0.37362637],
       [0.14814815, 0.51196911, 0.26388889, ..., 0.36155914, 0.33600713,
        0.13186813]])
```

In [44]:
```
x_train_scaled_ = pd.DataFrame(x_train_scaled,columns=x_train.columns)
x_train_scaled_
```

Out[44]:

	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

614 rows × 8 columns

In [45]:
```
x_test_scaled_ = pd.DataFrame(x_test_scaled,columns=x_test.columns)
x_test_scaled_
```

Out[45]:

	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

In [46]:
```
from imblearn.over_sampling import SMOTE
```

In [47]:
```
smote_object = SMOTE()
```

In [48]:
```
x_sampled, y_sampled = smote_object.fit_resample(x1,y1)
```

In [49]:
```
x_sampled
```

Out[49]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	Pedigree	
0	6.000000	148.000000	72.000000	35.000000	0.000000	33.600000	0.627000	50.
1	1.000000	85.000000	66.000000	29.000000	0.000000	26.600000	0.351000	31.
2	8.000000	183.000000	64.000000	0.000000	0.000000	23.300000	0.672000	32.
3	1.000000	89.000000	66.000000	23.000000	94.000000	28.100000	0.167000	21.
4	0.000000	137.000000	40.000000	35.000000	168.000000	43.100000	1.200000	33.
...	...	...	...	...	...	...	...	
995	1.816354	171.455764	70.721178	48.047588	318.125000	41.828553	0.713565	29.
996	0.000000	137.301212	46.024242	35.000000	167.698788	40.539697	0.999393	29.
997	0.081125	151.011589	89.976821	45.976821	0.000000	42.191555	0.370606	21.
998	6.546964	132.709393	74.324857	0.000000	0.000000	33.335911	0.308360	40.
999	3.434282	173.868565	78.651424	37.045729	185.759994	34.027998	0.928309	33.

1000 rows × 8 columns

In [50]:
```
x_sampled.shape
```

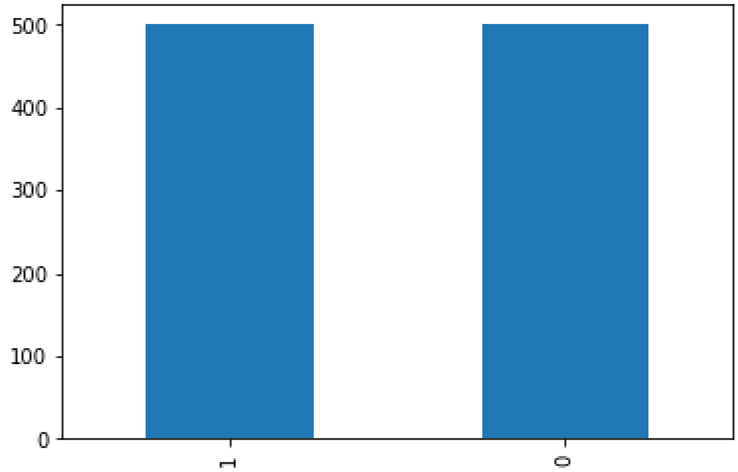
Out[50]: (1000, 8)

In [51]:
```
y_sampled.shape
```

Out[51]: (1000,)

In [52]:
```
y_sampled.value_counts().plot(kind='bar')
```

Out[52]: <AxesSubplot:>



Build a model

In [53]:
```
x_train_sampled,x_test_sampled,y_train_sampled,y_test_sampled = train_test_split(
```

In [54]:
```
knn_model = KNeighborsClassifier()
knn_model.fit(x_train_sampled,y_train_sampled)
y_pred1 = knn_model.predict(x_test_sampled)
accuracy = accuracy_score(y_test_sampled,y_pred1)
recall = recall_score(y_test_sampled,y_pred1)
precision = precision_score(y_test_sampled,y_pred1)
fbeta_05 = fbeta_score(y_test_sampled,y_pred1,beta = 0.5)
fbeta_1 = fbeta_score(y_test_sampled,y_pred1,beta = 1)
fbeta_2 = fbeta_score(y_test_sampled,y_pred1,beta = 2)
result.loc["KNN SMOTE"] = [accuracy,precision,recall,fbeta_05,fbeta_1,fbeta_2]
result
```

Out[54]:

	Accuracy	Precision	Recall	FBeta_0.5	FBeta_1	FBeta_2
KNN	0.707792	0.584906	0.574074	0.582707	0.579439	0.576208
KNN SMOTE	0.765000	0.732759	0.841584	0.752212	0.783410	0.817308

In [55]:
```
matrix = confusion_matrix(y_test_sampled,y_pred1)
matrix
```

Out[55]:
```
array([[68, 31],
       [16, 85]], dtype=int64)
```

In [56]:
```
report = classification_report(y_test_sampled,y_pred1)
print(report)
```

```
              precision    recall  f1-score   support

           0       0.81      0.69      0.74        99
           1       0.73      0.84      0.78       101

    accuracy                           0.77       200
   macro avg       0.77      0.76      0.76       200
weighted avg       0.77      0.77      0.76       200
```

In [ ]: