Diabetes Predictive Model

I. Introduction

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Project Overview: *The rising prevalence of diabetes, particularly among specific populations, necessitates early and accurate diagnosis to manage and mitigate its impact. In this project, the goal is to develop a predictive model using the "Diabetes Dataset" from the Pima Indians, available on Kaggle. This dataset, compiled by the National Institute of Diabetes and Digestive and Kidney Diseases, contains medical records of female patients. The project aims to leverage machine learning techniques to create a reliable and interpretable model that can predict the likelihood of diabetes in female patients based on their health metrics. The outcomes of this project could potentially aid in early detection and contribute to more effective management of diabetes in vulnerable populations.*

II. Dataset

Description of the attributes in the dataset:

- Pregnancies: To express the Number of pregnancies

- Glucose: To express the Glucose level in blood

- BloodPressure: To express the Blood pressure measurement

- SkinThickness: To express the thickness of the skin

- Insulin: To express the Insulin level in blood

- BMI: To express the Body mass index

- DiabetesPedigreeFunction: To express the Diabetes percentage

- Age: To express the age

- Outcome: To express the final result 1 is Yes and 0 is No

III. Data Preprocessing and Exploratory Data Analysis

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
```

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

Out[2]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	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

In [3]:
```
print(f'Dataset shape: Rows: {dia.shape[0]}   Columns: {dia.shape[1]}')
```

```
Dataset shape: Rows: 768   Columns: 9
```

In [4]:
```
dia.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   DiabetesPedigreeFunction  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
```

-Briefly looking through a few information of the dataset, we can see that this dataset has 9 attributes and 768 records in total.

-Fortunately, it is shown in the info() function that there is no missing value in this dataset. So, we do not need to fill or drop any record.

Now let's look through the records to see if there is any outliers, and then remove it.

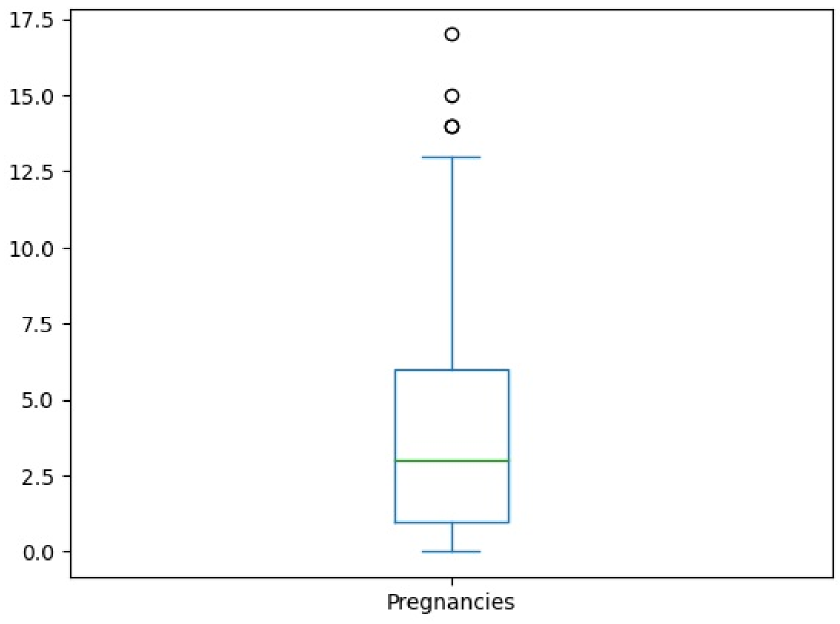
In [5]:
```
dia.describe()
```

Out[5]:

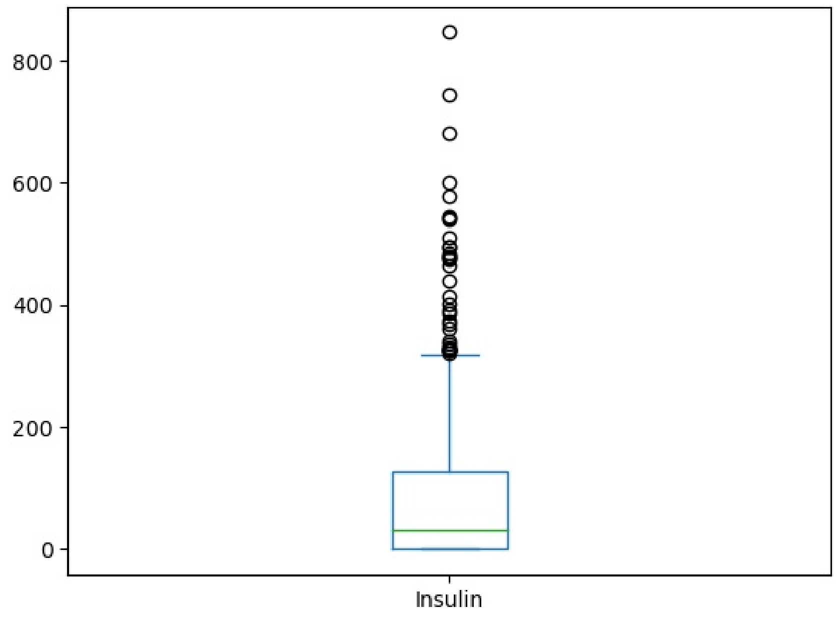
	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	C
count	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768
mean	3.845052	120.894531	69.105469	20.536458	79.799479	31.992578	0.471876	33.240885	(
std	3.369578	31.972618	19.355807	15.952218	115.244002	7.884160	0.331329	11.760232	(
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.078000	21.000000	(
25%	1.000000	99.000000	62.000000	0.000000	0.000000	27.300000	0.243750	24.000000	(
50%	3.000000	117.000000	72.000000	23.000000	30.500000	32.000000	0.372500	29.000000	(
75%	6.000000	140.250000	80.000000	32.000000	127.250000	36.600000	0.626250	41.000000	'
max	17.000000	199.000000	122.000000	99.000000	846.000000	67.100000	2.420000	81.000000	'

We need to use boxplots to spot the outliers. However, we can see that "Outcome" is a kind of label, so we don't need boxplot for it. Moreover, "Pregnancies", "Insulin" and "DiabetesPedigreeFunction" have quite different scales from the others, so we will make different graph for these two attributes.

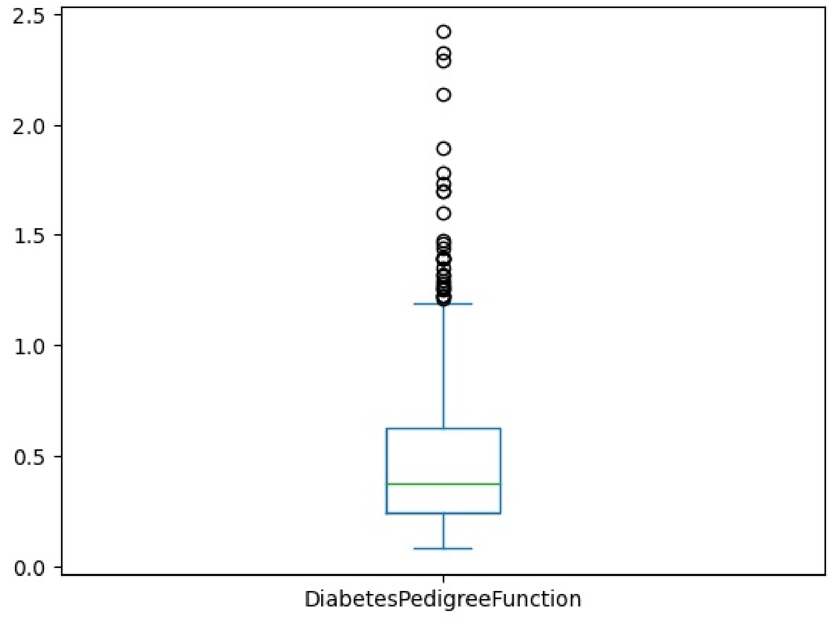
In [6]:
```
dia['Pregnancies'].plot(kind = 'box'); ##For attribute "Pregnancies"
```



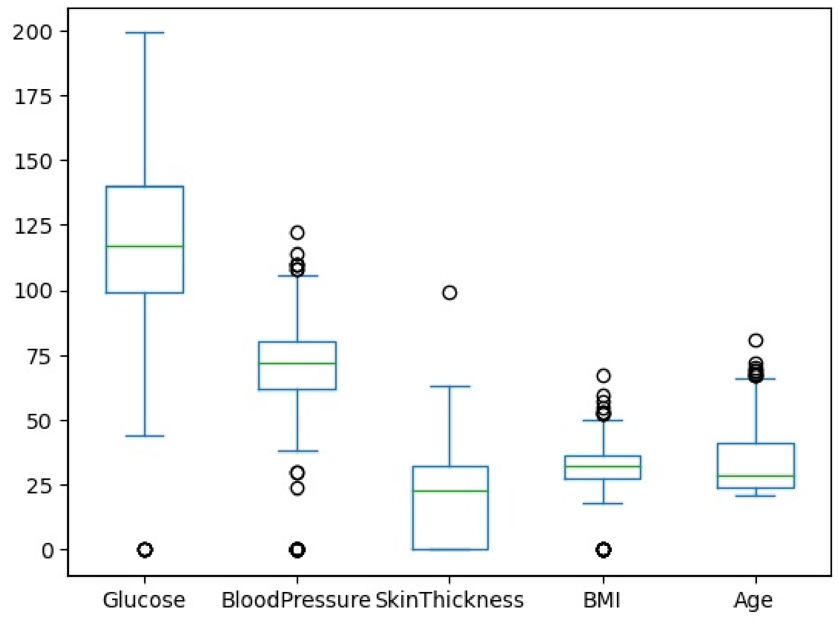
In [7]:
```
dia['Insulin'].plot(kind = 'box'); ##For attribute "Insulin"
```



```
In [8]: dia['DiabetesPedigreeFunction'].plot(kind = 'box'); ##For attribute "DiabetesPedigreeFunction"
```



```
In [9]: col = dia[['Glucose', 'BloodPressure', 'SkinThickness', 'BMI', 'Age']]
        col.plot(kind = 'box'); ##For the other attributes
```



From the above plots, we can conclude the outlier for each attributes are:

- Pregnancies: > 13

- Insulin: > 400

- DiabetesPedigreeFunction: > 1.5

- Glucose: < 25

- BloodPressure: < 25

- SkinThickness: > 75

- BMI: > 50 and < 5

- Age: >75

Now we remove these outliers.

In [10]:
```
remove_index = dia.loc[(dia['Pregnancies'] > 13) |
                        (dia['Insulin'] > 400) |
                        (dia['DiabetesPedigreeFunction'] > 1.5) |
                        (dia['Glucose'] < 25) |
                        (dia['BloodPressure'] < 25) |
                        (dia['SkinThickness'] > 75) |
                        ((dia['BMI'] > 50) & (dia['BMI'] < 5)) |
                        (dia['Age'] > 75)
                       ].index
dia = dia.drop(remove_index)
print(f'Dataset shape after removal: {dia.shape}')
```
```
Dataset shape after removal: (693, 9)
```

IV. Model Training

1. Linear Regression:

In this section, we will train a model to diagnose if a patient has diabetes using the dataset.

First, I will try something simple, I will train a Linear Regression Model.

Model Training:

In [11]:
```
from sklearn.model_selection import train_test_split
from sklearn import linear_model
from sklearn.metrics import r2_score
```

In [12]:
```
X = dia.iloc[:,:-1]
y = dia.iloc[:,-1:]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 42)
```

In [13]:
```
reg = linear_model.LinearRegression()
reg.fit(X_train, y_train);
```

Model Evaluation:

In [14]:
```
print('Report on train set:')
y_predict = reg.predict(X_train)
mse = ((np.array(y_train) - y_predict) ** 2).sum()/len(y_train)
r2 = r2_score(y_train, y_predict)
print("MSE:", mse)
print("R Squared:", r2)
```
```
Report on train set:
MSE: 0.1529467360684823
R Squared: 0.30068081270474034
```

In [15]:
```
print('Report on test set:')
y_predict = reg.predict(X_test)
mse = ((np.array(y_test) - y_predict) ** 2).sum()/len(y_test)
r2 = r2_score(y_test, y_predict)
print("MSE:", mse)
print("R Squared:", r2)
```
```
Report on test set:
MSE: 0.15229660827254976
R Squared: 0.3443576719175726
```

In the report on train set we can see that the MSE is not quite close to 0, and R Squared is not quite close to 1. This means that the model is not accurate enough. Moreover, look into the report on test set, the scores is even worse. Therefore, we can say that the Linear Regression Model is underfitting.

To fix this problem, we can train a more complex model.

2. Classification Models:

Diagnosing a diabetes patient can be considered as a classification work. Therefore, we should use classification models to improve performance of the model.

Now let's try Logistic Regression Model, a simple model for classification.

A. Logistic Regression:

Model training:

In [16]:
```
reg = linear_model.LogisticRegression()
reg.fit(X_train, y_train);
```

Model Evaluation:

To evaluate this classifier model, we will use accuracy score and confusion matrix.

In [17]:
```
from sklearn.metrics import confusion_matrix, accuracy_score
```

In [18]:
```
y_pred = reg.predict(X_test)
print('Report on Logistic Regression Model:\n')
print(f'    Accuracy rate: {accuracy_score(y_test, y_pred)}')
tn, fp, fn, tp = confusion_matrix(y_test, y_pred).ravel()
print(f'    Confusion matrix: TrueNev:{tn}   FalsePos:{fp}   FalseNev:{fn}   TruePos:{tp}')
print(f'    Precision rate: {tp / (tp + fp)}')
```

```
Report on Logistic Regression Model:

    Accuracy rate: 0.7697841726618705
    Confusion matrix: TrueNev:80   FalsePos:8   FalseNev:24   TruePos:27
    Precision rate: 0.7714285714285715
```

As reported, the accuracy and precision score of this model is quite reasonable. However, it is just right above average, so this model is still not accurate enough.

This may happen when there are too many feature and the model starts to learn from the noises. Therefore, we will perform feature selection and train the model once more to see if it is improved. In this report, I will use RFE feature selection model.

We have 8 attributes in total for X, now I will try select only 4 best features to train the Logistic Regression Model.

In [19]:
```
from sklearn.feature_selection import RFE
lr = linear_model.LogisticRegression()
rfe = RFE(estimator = lr, n_features_to_select = 4)
rfe.fit(X, y);
for i in range(len(X.columns)):
    print(f'{X.columns[i]}: {rfe.support_[i]}')
```

```
Pregnancies: True
Glucose: True
BloodPressure: False
SkinThickness: False
Insulin: False
BMI: True
DiabetesPedigreeFunction: True
Age: False
```

The result shows that "Pregnancies", "Glucose", "BMI" and "DiabetesPedigreeFunction" is selected. Now we will train the Logistic Regression Model again using only these 4 features.

Model Training:

In [20]:
```
X_new = dia[["Pregnancies", "Glucose", "BMI", "DiabetesPedigreeFunction"]]
X_train, X_test, y_train, y_test = train_test_split(X_new, y, test_size = 0.2, random_state = 42)
lr.fit(X_train, y_train)
```

Out[20]:
```
LogisticRegression()
```

Model Evaluation:

In [21]:
```
y_pred = lr.predict(X_test)
print('Report on Logistic Regression Model:\n')
print(f'    Accuracy rate: {accuracy_score(y_test, y_pred)}')
tn, fp, fn, tp = confusion_matrix(y_test, y_pred).ravel()
print(f'    Confusion matrix: TrueNev:{tn}   FalsePos:{fp}   FalseNev:{fn}   TruePos:{tp}')
print(f'    Precision rate: {tp / (tp + fp)}')
```

```
Report on Logistic Regression Model:

    Accuracy rate: 0.7697841726618705
    Confusion matrix: TrueNev:80   FalsePos:8   FalseNev:24   TruePos:27
    Precision rate: 0.7714285714285715
```

Obviously, even when we select best features to train Logistic Regression Model, the results remain the same. Therefore, we can see that the problem are not from the noises. This shows that the model is still too simple for such dataset. We can conclude that linear models is not suitable for this dataset.

To fix this, we will try a different classifier model: K-Nearest Neighbors (KNN).

B. K-Nearest Neighbors:

Parameter Tuning:

Since we do not know what is the value of K that gives the best performance on the model, we need to performm a parameter tuning technique to find the best K, and then we train the model using that value of K.

In this report, I will use GridSearchCV for parameter tuning.

In [22]:
```python
from sklearn.model_selection import GridSearchCV
from sklearn.neighbors import KNeighborsClassifier
clf = KNeighborsClassifier()
grid_search = GridSearchCV(clf, {'n_neighbors': range(1, 200, 5)}, cv = 10, scoring = 'accuracy')
grid_search.fit(X, y)
print(f'Best K: {grid_search.best_estimator_}')
```

```
Best K: KNeighborsClassifier(n_neighbors=16)
```

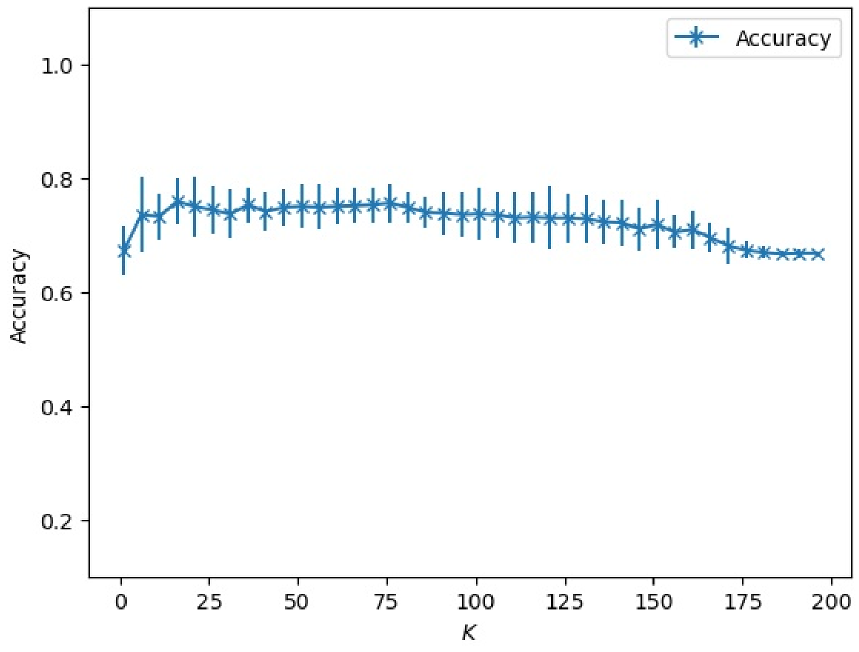
We can see that GridSearchCV tells us that K = 16 is the best K in this case. Let's take a look at the whole process to see how it's come to this conclusion.

In [23]:
```python
cv_results = pd.DataFrame(grid_search.cv_results_)
cv_results.loc[cv_results['param_n_neighbors'] == 16]
```

Out[23]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_n_neighbors	params	split0_test_score	split1_test_s
3	0.002994	0.000002	0.004044	0.00034	16	{'n_neighbors': 16}	0.785714	0.77

In [24]:
```python
plt.errorbar(cv_results['param_n_neighbors'], cv_results['mean_test_score'], yerr= cv_results['std_test_score']
plt.ylim([0.1, 1.1])
plt.xlabel('$K$')
plt.ylabel('Accuracy')
plt.legend(loc='best');
```



We can see from the above graph that the performance of K increases from 1 and reach the peak at 16, after that it starts decreasing continuosly. However, if we look into the mean test score of K = 16, it is only 0.795, not seems to be accurate enough for a medical diagnose system.

Nevertheless, let's try training the model and evaluate it with unseen data to see how well it works.

Model Training:

In [25]:
```
clf = clf = KNeighborsClassifier(n_neighbors = 16)
clf.fit(X_train, y_train)
```

Out[25]:
```
KNeighborsClassifier(n_neighbors=16)
```

Model Evaluation:

I will use K-fold cross validation technique to evaluate the model.

In [26]:
```
from sklearn.model_selection import cross_val_score, KFold
KNN_scores = cross_val_score(clf, X_test, y_test, scoring='accuracy', cv = KFold(n_splits=10, shuffle=True))
print(f'Mean accuracy score: {KNN_scores.mean()}    Standard deviation: {KNN_scores.std()}')
```

```
Mean accuracy score: 0.7703296703296703    Standard deviation: 0.07576841396016788
```

It is obvious that the performance for this model is even higher than expected. However, let's perform K-fold cross validation on the previous Logistic Regression Model, and compare the accuracy score to the KNN Model. Then, we will conclude which model is better.

In [27]:
```
lr_scores = cross_val_score(lr, X_test, y_test, scoring='accuracy', cv = KFold(n_splits=10, shuffle=True))
print(f'Mean accuracy score: {lr_scores.mean()}    Standard deviation: {lr_scores.std()}')
```

```
Mean accuracy score: 0.7906593406593407    Standard deviation: 0.08939173755795328
```

V. Conclusion

Clearly, the Logistic Regression Model is the best model for the diagnose system until now with the accuracy up to 80%.