Diabetes Prediction using Machine Learning

Importing Necessary Libraries

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

```
import warnings
warnings.filterwarnings('ignore')
```

Data Collection

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

EDA

```
df.head()
```

```
   Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin
BMI  \
0            6      148             72             35        0  33.6

1            1       85             66             29        0  26.6

2            8      183             64              0        0  23.3

3            1       89             66             23       94  28.1

4            0      137             40             35      168  43.1


   DiabetesPedigreeFunction  Age  Outcome
0                     0.627   50        1
1                     0.351   31        0
2                     0.672   32        1
3                     0.167   21        0
4                     2.288   33        1
```

```
df.tail()
```

```
     Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI
\
763           10      101             76             48      180  32.9

764            2      122             70             27        0  36.8

765            5      121             72             23      112  26.2

766            1      126             60              0        0  30.1

767            1       93             70             31        0  30.4


     DiabetesPedigreeFunction  Age  Outcome
763                     0.171   63        0
```

```
764                      0.340   27        0
765                      0.245   30        0
766                      0.349   47        1
767                      0.315   23        0
```

```
df.shape
```

```
(768, 9)
```

```
df.columns
```

```
Index(['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness',
'Insulin',
       'BMI', 'DiabetesPedigreeFunction', 'Age', 'Outcome'],
      dtype='object')
```

About the Dataset

Context

The dataset originates from the National Institute of Diabetes and Digestive and Kidney Diseases. The primary aim is to predict whether a patient has diabetes based on several diagnostic measurements. This dataset is crucial for developing models that can assist in early diagnosis and intervention for diabetes, potentially improving patient outcomes and reducing healthcare costs.

Content

The dataset includes several constraints and specifics regarding the patient selection:

- **Patient Demographics**:
  - All patients are females.
  - Patients are at least 21 years old.
  - All patients are of Pima Indian heritage.

The dataset comprises the following features:

1. **Pregnancies**:
   - **Description**: Number of times the patient has been pregnant.
   - **Type**: Numeric (Integer)
   - **Relevance**: Previous pregnancies can impact the likelihood of diabetes due to physiological changes during pregnancy.
2. **Glucose**:
   - **Description**: Plasma glucose concentration measured two hours after an oral glucose tolerance test.
   - **Type**: Numeric (Float)
   - **Relevance**: High plasma glucose levels are a key indicator of diabetes.
3. **BloodPressure**:
   - **Description**: Diastolic blood pressure in millimeters of mercury (mm Hg).

   - **Type**: Numeric (Float)
   - **Relevance**: Blood pressure levels can be indicative of overall cardiovascular health, which is often linked to diabetes.
4. **SkinThickness**:
   - **Description**: Triceps skin fold thickness in millimeters.
   - **Type**: Numeric (Float)
   - **Relevance**: This measurement can indicate subcutaneous fat levels, which may be associated with insulin resistance and diabetes.
5. **Insulin**:
   - **Description**: 2-hour serum insulin in micro-units per milliliter (mu U/ml).
   - **Type**: Numeric (Float)
   - **Relevance**: Insulin levels are crucial for understanding insulin resistance, a precursor to diabetes.
6. **BMI (Body Mass Index)**:
   - **Description**: Weight in kilograms divided by the square of height in meters (kg/m^2).
   - **Type**: Numeric (Float)
   - **Relevance**: BMI is a significant indicator of obesity, which is a major risk factor for diabetes.
7. **DiabetesPedigreeFunction**:
   - **Description**: A function that scores the likelihood of diabetes based on family history.
   - **Type**: Numeric (Float)
   - **Relevance**: Family history is a strong predictor of diabetes risk.
8. **Age**:
   - **Description**: Age of the patient in years.
   - **Type**: Numeric (Integer)
   - **Relevance**: Age is a risk factor, as the likelihood of developing diabetes increases with age.
9. **Outcome**:
   - **Description**: Class variable indicating the presence of diabetes.
     - 0: Non-diabetic
     - 1: Diabetic
   - **Type**: Categorical (Binary)
   - **Relevance**: This is the target variable that models aim to predict.

Data Summary

The dataset is structured to include comprehensive features that can contribute to the predictive modeling of diabetes. By analyzing these features, one can develop various machine learning models to classify patients based on their likelihood of having diabetes. The features represent a mix of personal medical history, physiological measurements, and family history, all of which are critical in understanding and predicting diabetes.

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

```
0
```

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

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

```
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   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
```

```
df.describe()
```

```
       Pregnancies     Glucose  BloodPressure  SkinThickness  \
Insulin  \
count   768.000000  768.000000     768.000000     768.000000  
768.000000
mean      3.845052  120.894531      69.105469      20.536458  
79.799479
std       3.369578   31.972618      19.355807      15.952218  
115.244002
min       0.000000    0.000000       0.000000       0.000000  
0.000000
25%       1.000000   99.000000      62.000000       0.000000  
0.000000
50%       3.000000  117.000000      72.000000      23.000000  
30.500000
75%       6.000000  140.250000      80.000000      32.000000
```

```
127.250000
max      17.000000  199.000000     122.000000      99.000000
846.000000

              BMI  DiabetesPedigreeFunction         Age     Outcome
count  768.000000                768.000000  768.000000  768.000000
mean    31.992578                  0.471876   33.240885    0.348958
std      7.884160                  0.331329   11.760232    0.476951
min      0.000000                  0.078000   21.000000    0.000000
25%     27.300000                  0.243750   24.000000    0.000000
50%     32.000000                  0.372500   29.000000    0.000000
75%     36.600000                  0.626250   41.000000    1.000000
max     67.100000                  2.420000   81.000000    1.000000
```

```
df.nunique()
```

```
Pregnancies                 17
Glucose                    136
BloodPressure               47
SkinThickness               51
Insulin                    186
BMI                        248
DiabetesPedigreeFunction   517
Age                         52
Outcome                      2
dtype: int64
```

```
object_columns = df.select_dtypes(include=['object']).columns
print("Object type columns:")
print(object_columns)

numerical_columns = df.select_dtypes(include=['int64',
'float64']).columns
print("\nNumerical type columns:")
print(numerical_columns)
```

```
Object type columns:
Index([], dtype='object')

Numerical type columns:
Index(['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness',
'Insulin',
       'BMI', 'DiabetesPedigreeFunction', 'Age', 'Outcome'],
      dtype='object')
```

```
def classify_features(df):
    categorical_features = []
    non_categorical_features = []
    discrete_features = []
    continuous_features = []
```

```
    for column in df.columns:
        if df[column].dtype == 'object':
            if df[column].nunique() < 20:
                categorical_features.append(column)
            else:
                non_categorical_features.append(column)
        elif df[column].dtype in ['int64', 'float64']:
            if df[column].nunique() < 10:
                discrete_features.append(column)
            else:
                continuous_features.append(column)

    return categorical_features, non_categorical_features,
discrete_features, continuous_features

categorical, non_categorical, discrete, continuous =
classify_features(df)

print("Categorical Features:", categorical)
print("Non-Categorical Features:", non_categorical)
print("Discrete Features:", discrete)
print("Continuous Features:", continuous)
```

```
Categorical Features: []
Non-Categorical Features: []
Discrete Features: ['Outcome']
Continuous Features: ['Pregnancies', 'Glucose', 'BloodPressure',
'SkinThickness', 'Insulin', 'BMI', 'DiabetesPedigreeFunction', 'Age']
```

```
df['Outcome'].unique()
```

```
array([1, 0], dtype=int64)
```

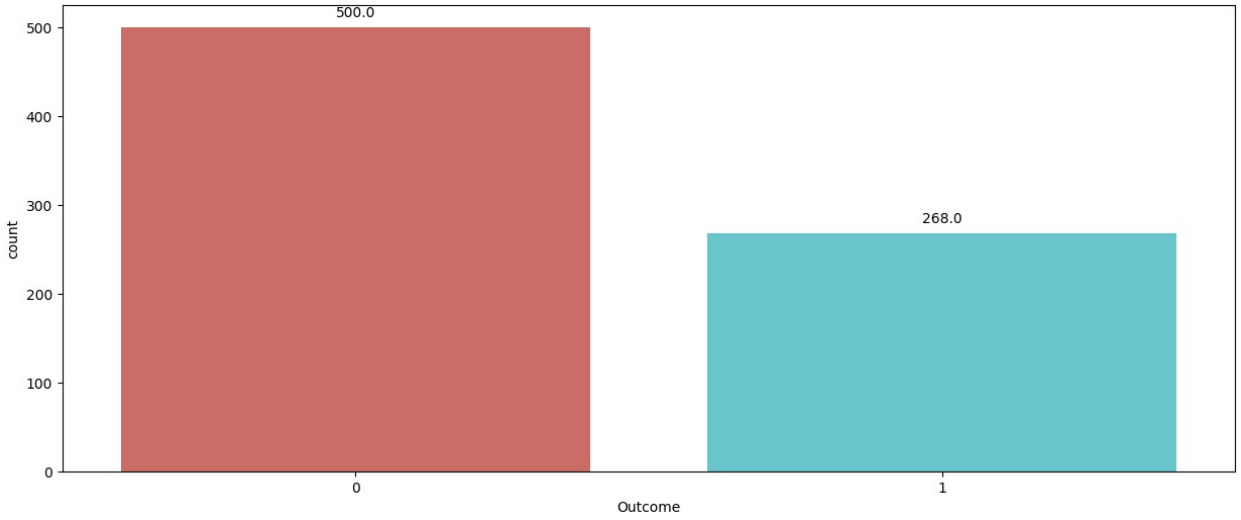
```
df['Outcome'].value_counts()
```

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

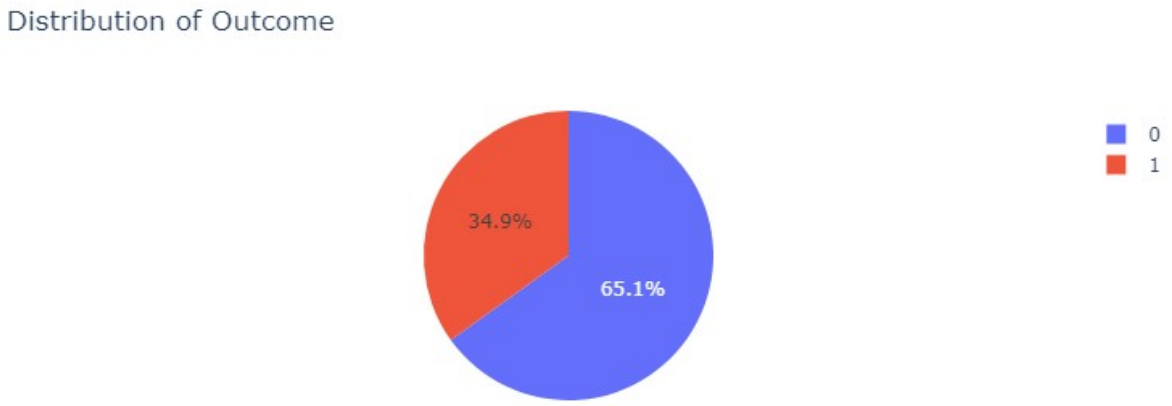
Data Visualization

```
for i in discrete:
    plt.figure(figsize=(15, 6))
    ax = sns.countplot(x=i, data=df, palette='hls')

    for p in ax.patches:
        height = p.get_height()
        ax.annotate(f'{height}',
```

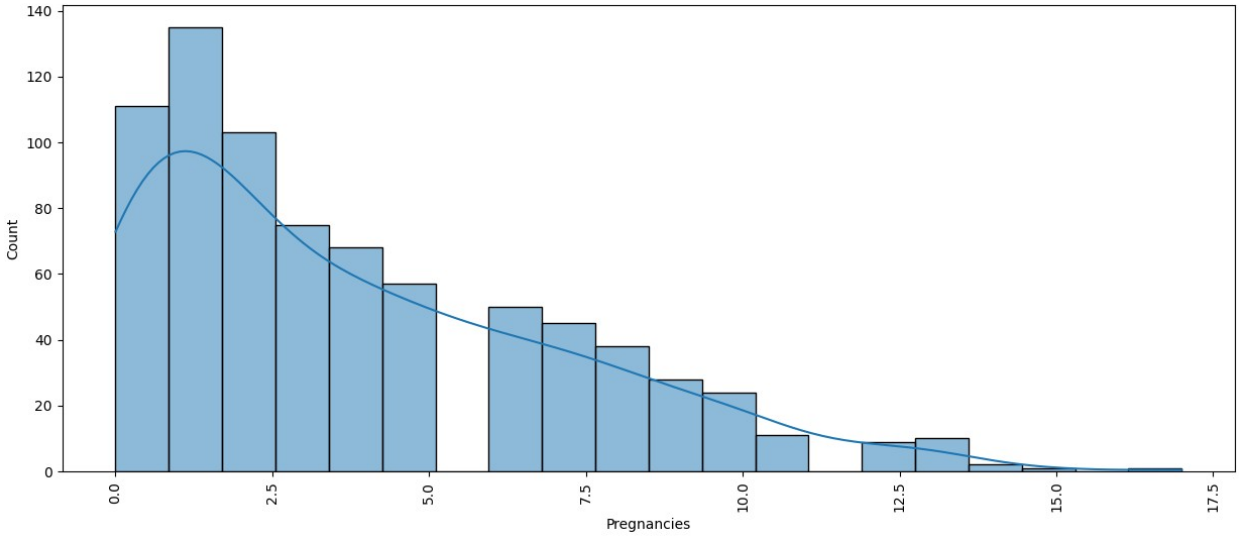
```
                    xy=(p.get_x() + p.get_width() / 2., height),
                    xytext=(0, 10),
                    textcoords='offset points',
                    ha='center', va='center')

    plt.show()
```

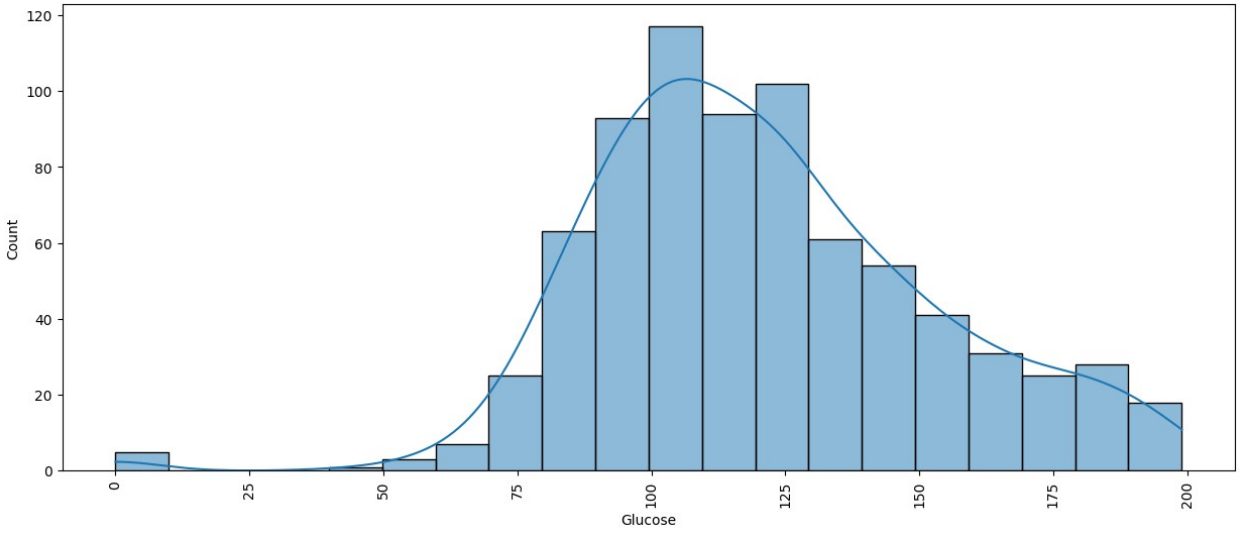


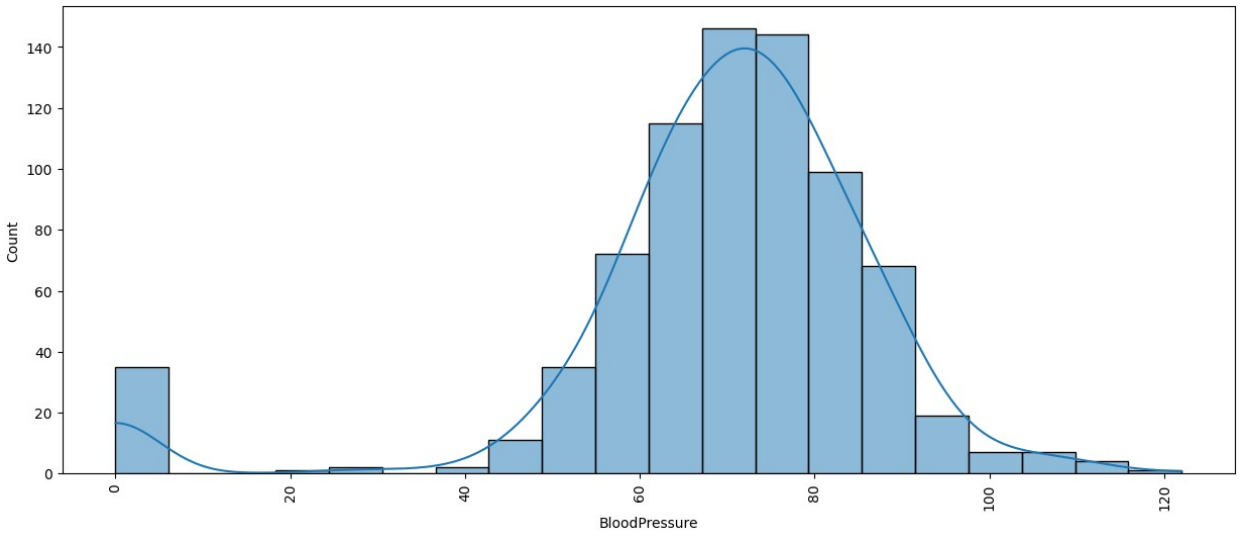

```
import plotly.express as px

for i in discrete:
    counts = df[i].value_counts()
    fig = px.pie(counts, values=counts.values, names=counts.index,
title=f'Distribution of {i}')
    fig.show()
```

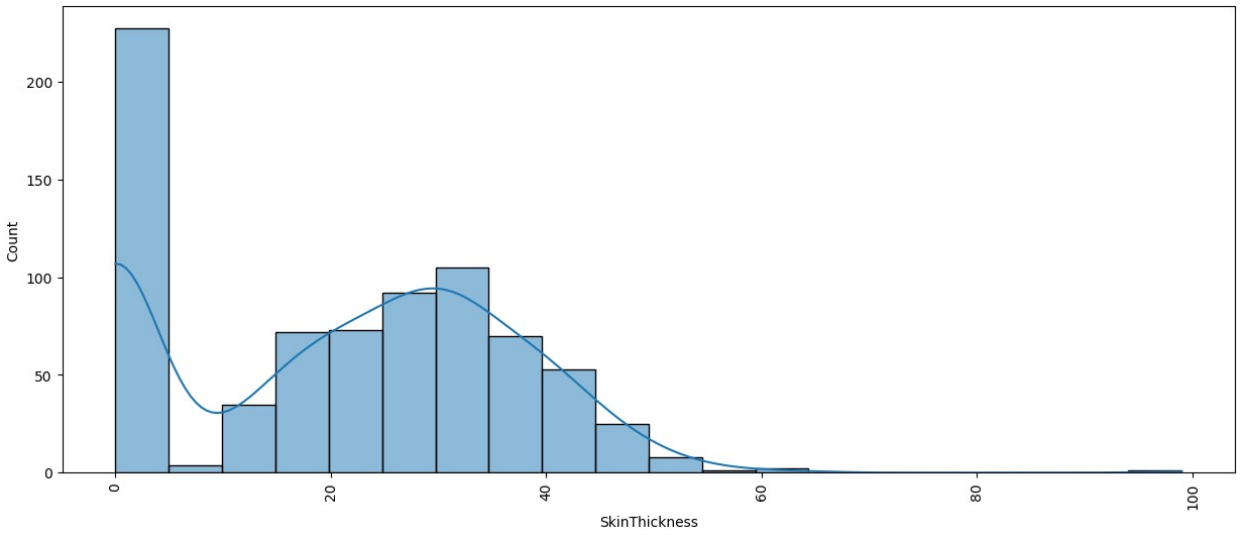


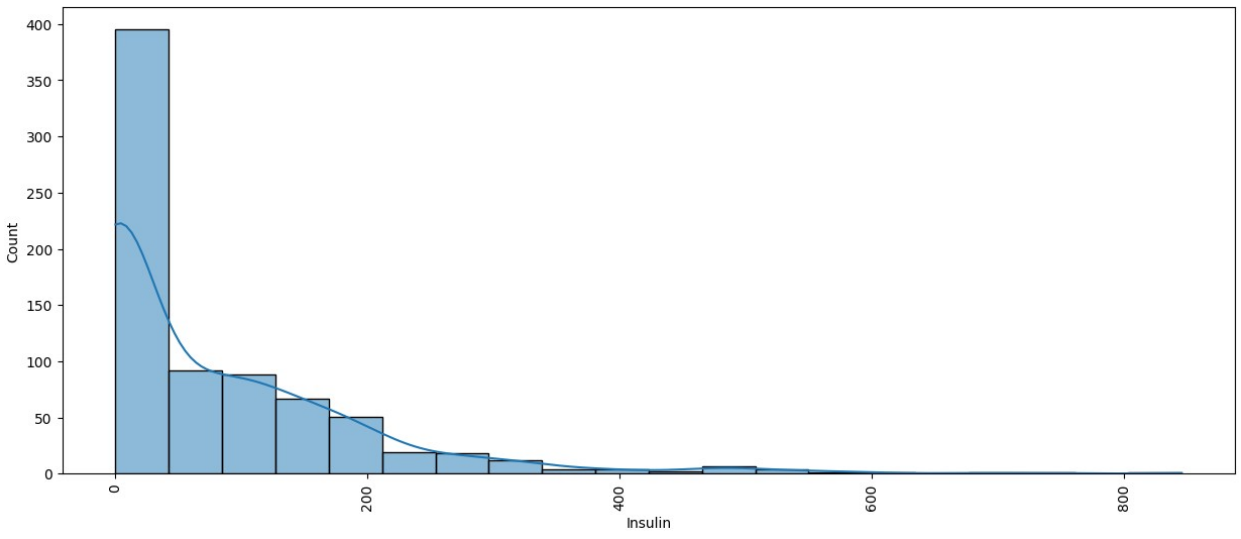
```
for i in continuous:
    plt.figure(figsize=(15,6))
    sns.histplot(df[i], bins = 20, kde = True, palette='hls')
    plt.xticks(rotation = 90)
    plt.show()
```

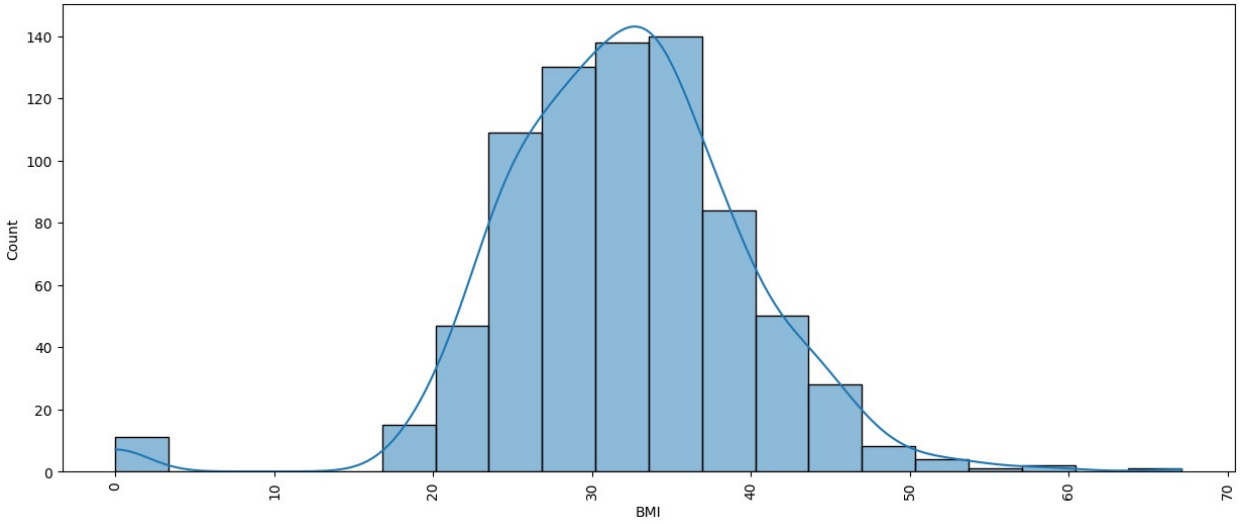


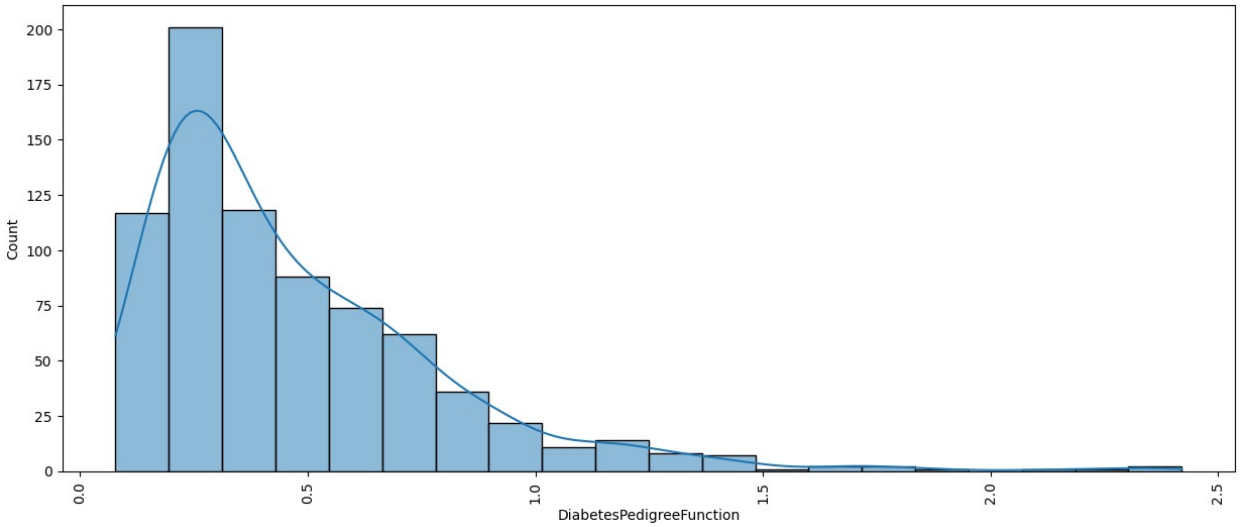


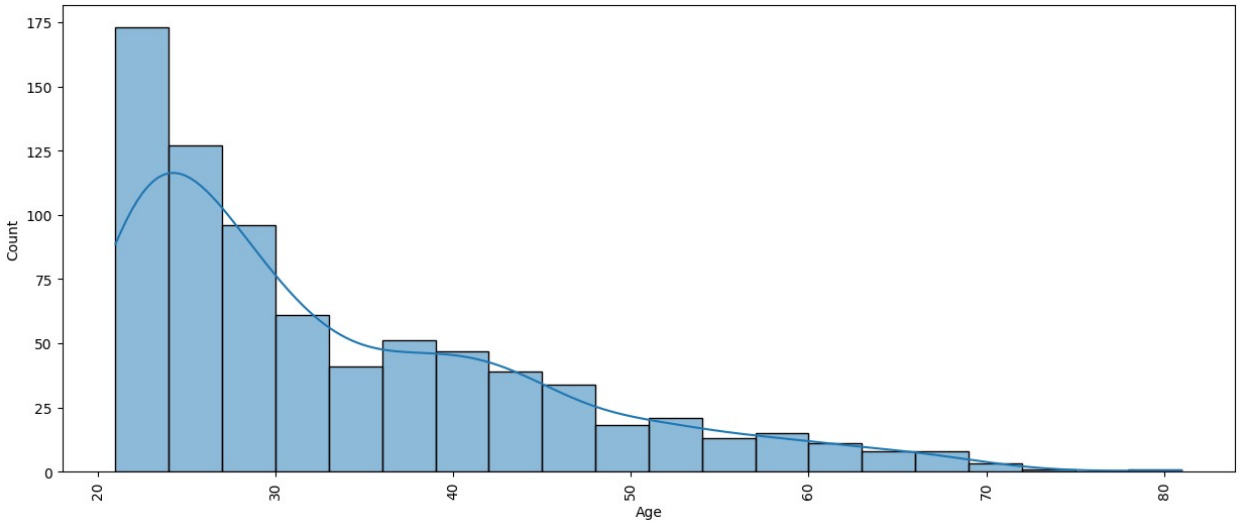

Count
0
20
40
60
80
100
120
140
BloodPressure


Count
0
50
100
150
200
0
20
40
60
80
100
SkinThickness

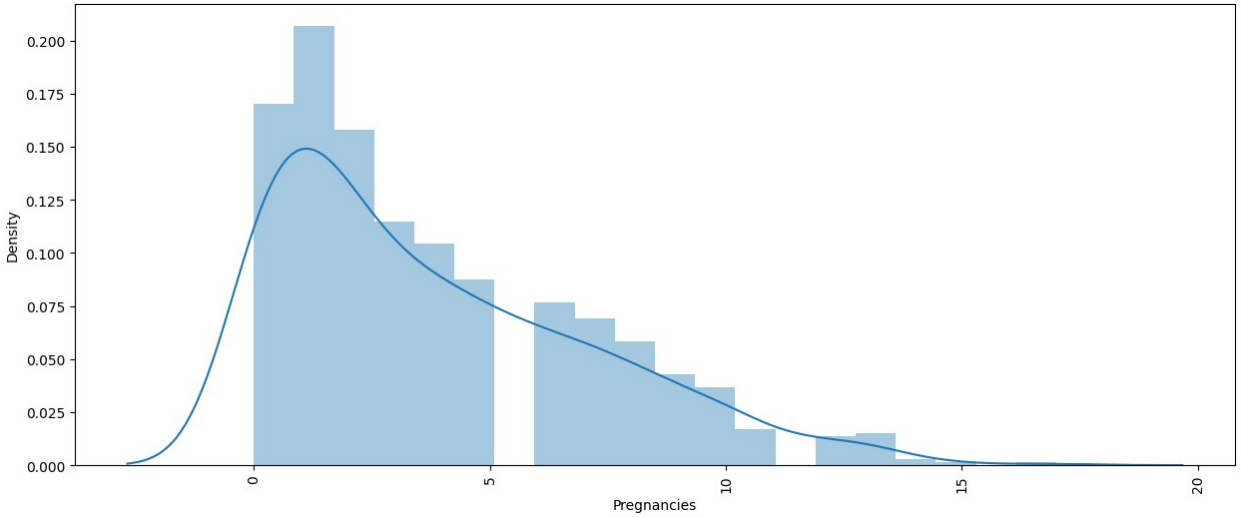

Count
0
50
100
150
200
250
300
350
400
0
200
400
600
800
Insulin

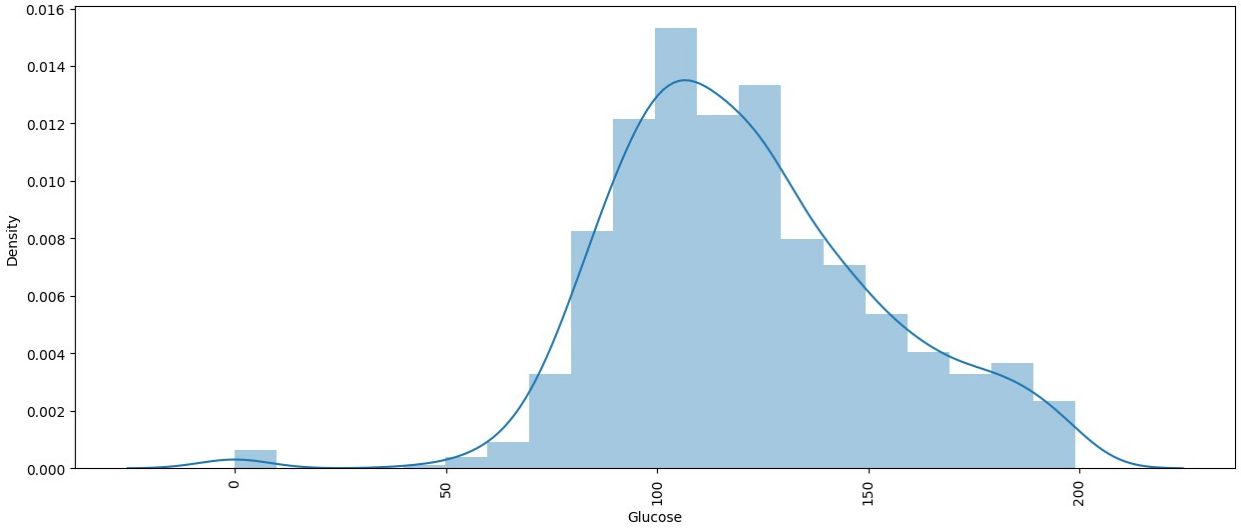

Count
BMI

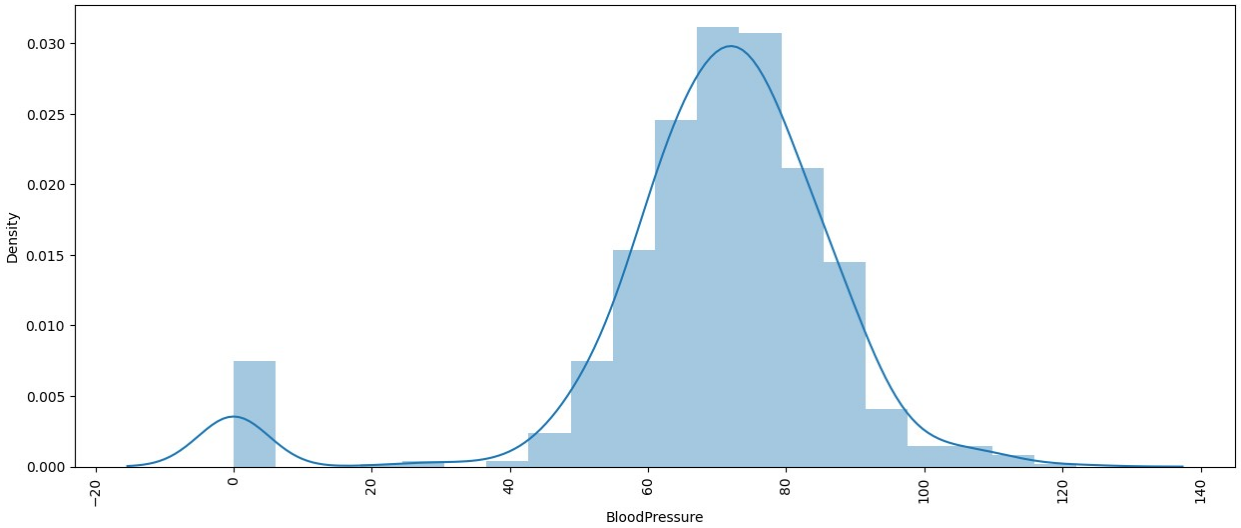

Count
DiabetesPedigreeFunction

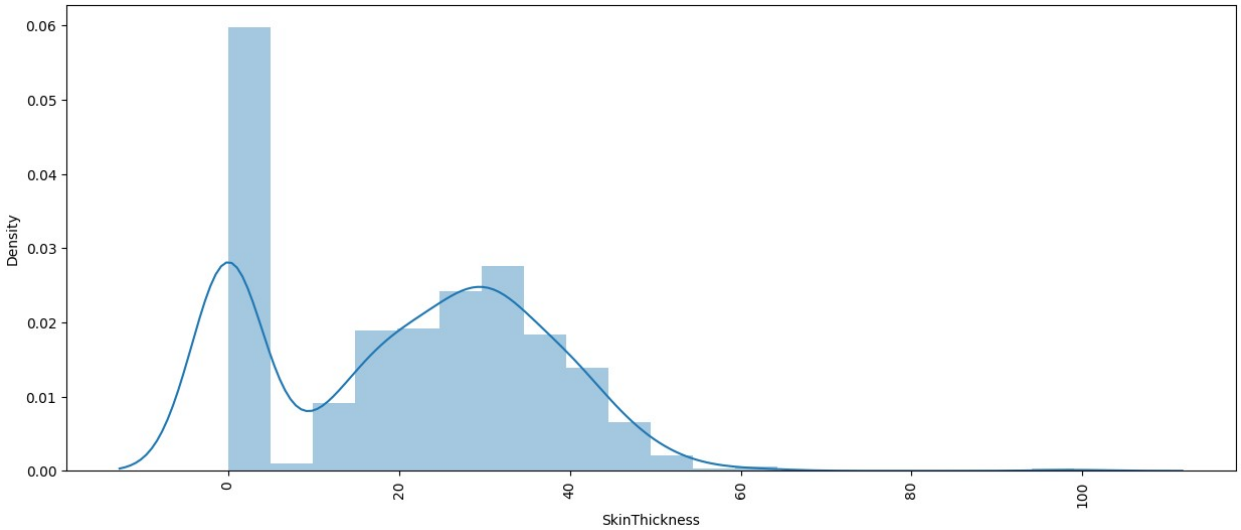

Count
Age

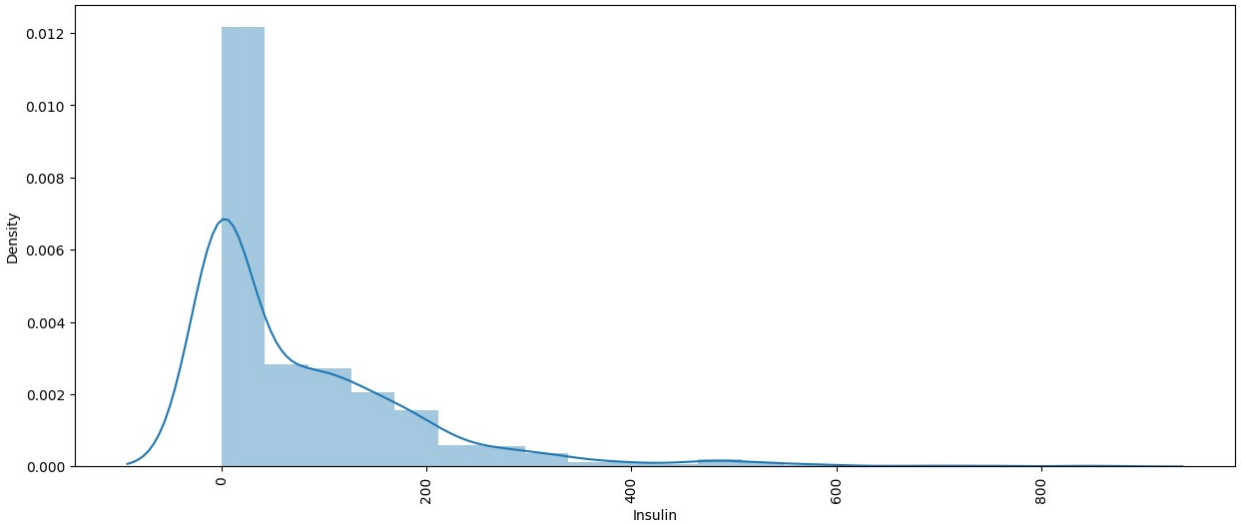
```
for i in continuous:
    plt.figure(figsize=(15,6))
    sns.distplot(df[i], bins = 20, kde = True)
    plt.xticks(rotation = 90)
    plt.show()
```

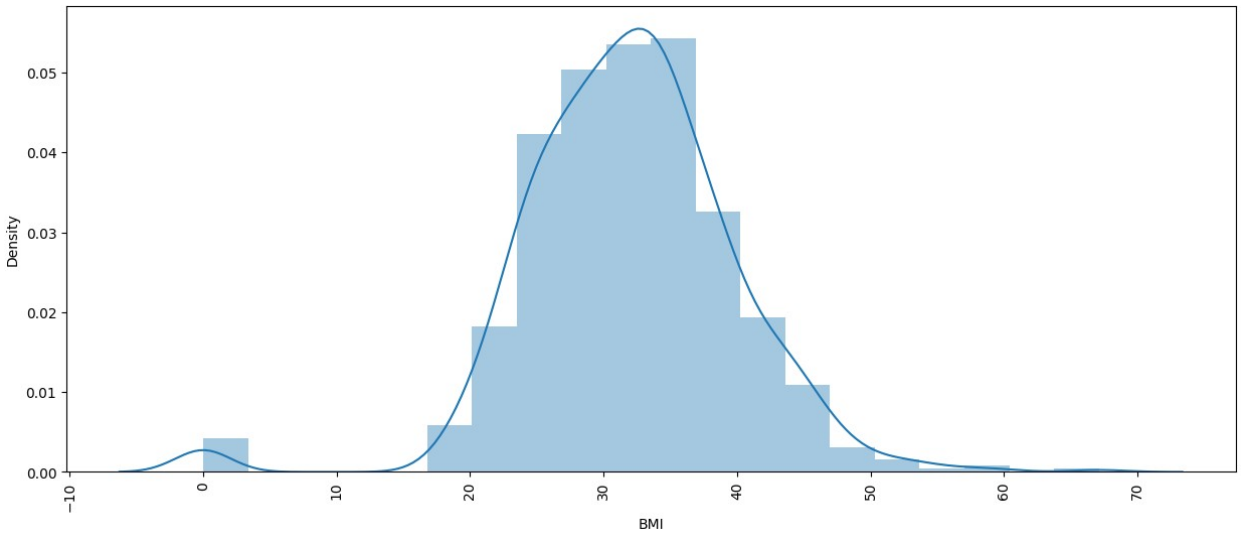


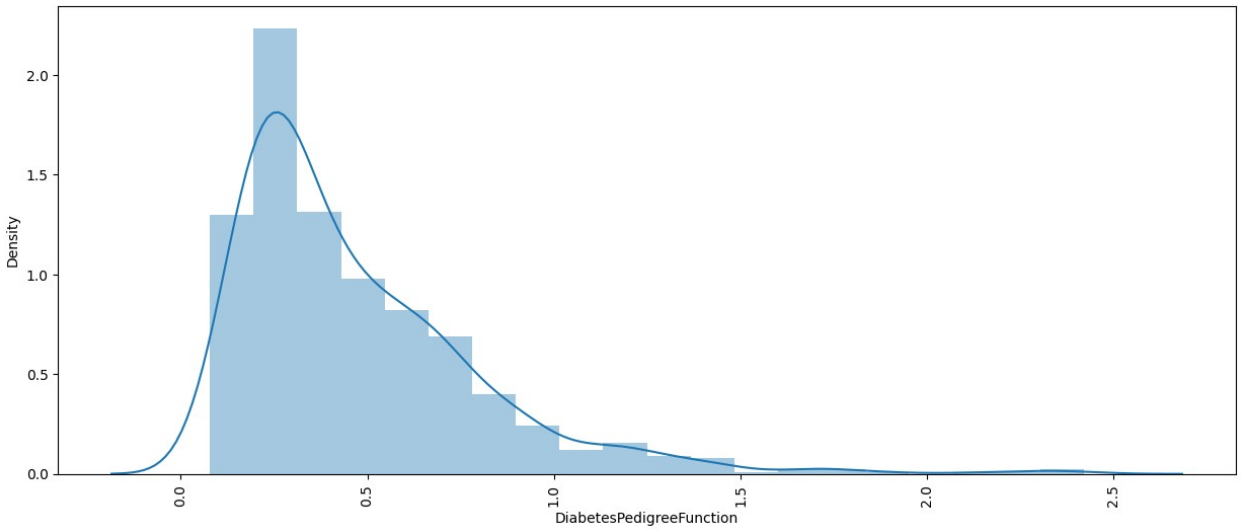


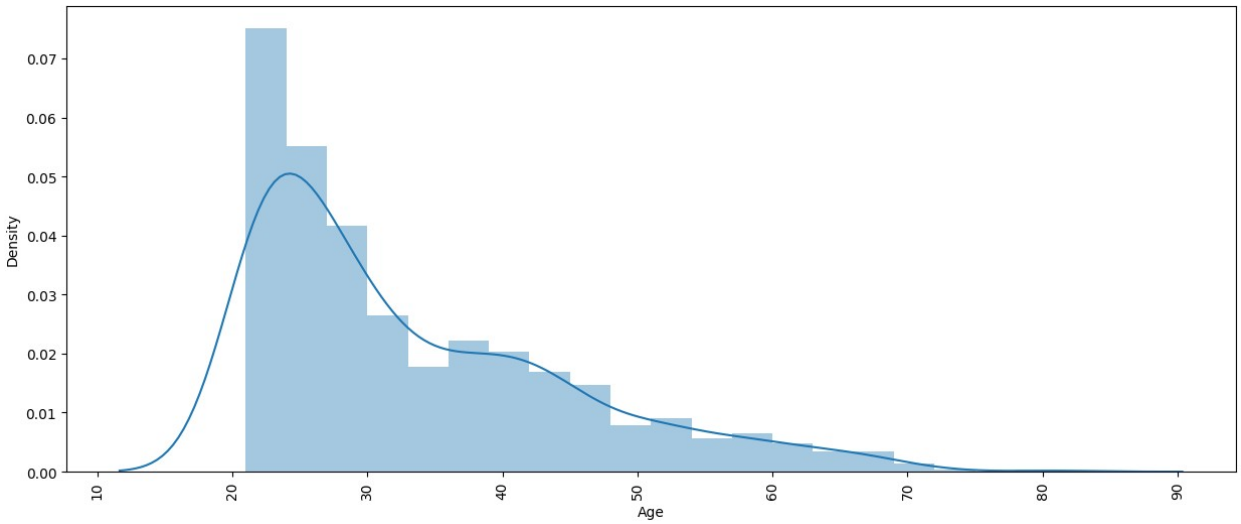

Density
0.030
0.025
0.020
0.015
0.010
0.005
0.000
−20
0
20
40
60
80
100
120
140
BloodPressure


Density
0.06
0.05
0.04
0.03
0.02
0.01
0.00
0
20
40
60
80
100
SkinThickness

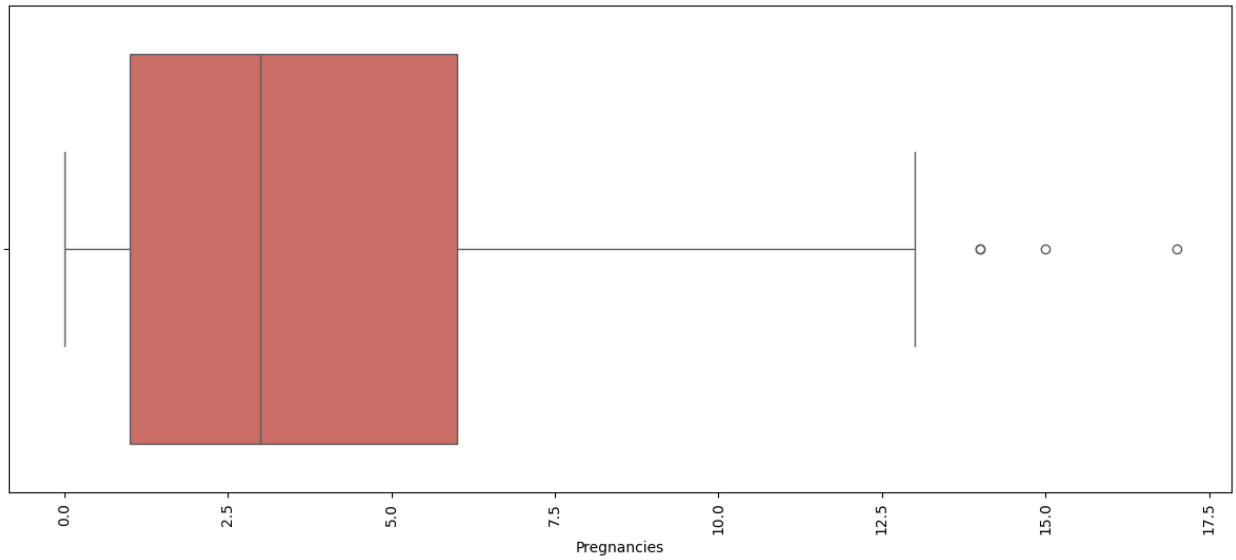

Density
0.012
0.010
0.008
0.006
0.004
0.002
0.000
0
200
400
600
800
Insulin

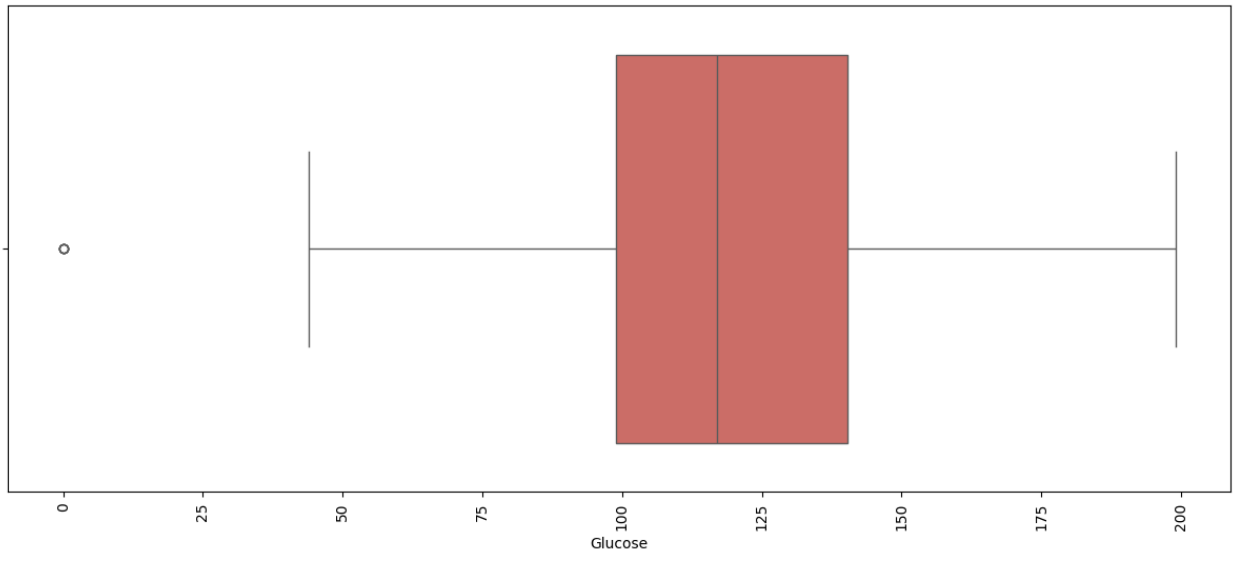

Density
0.00
0.01
0.02
0.03
0.04
0.05
−10
0
10
20
30
40
50
60
70
BMI

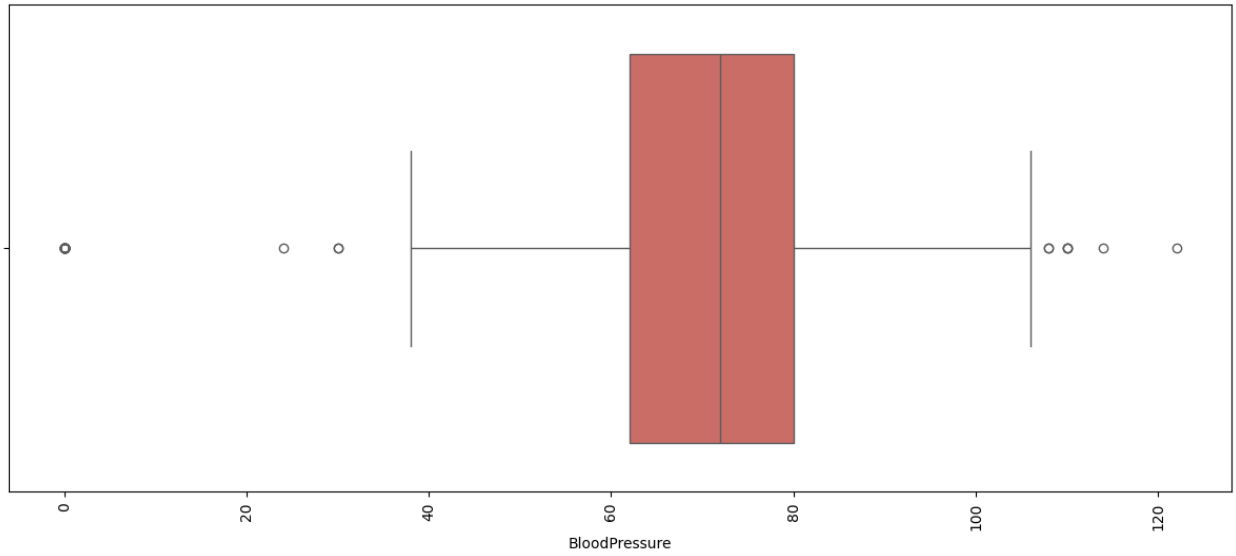

Density
0.0
0.5
1.0
1.5
2.0
0.0
0.5
1.0
1.5
2.0
2.5
DiabetesPedigreeFunction

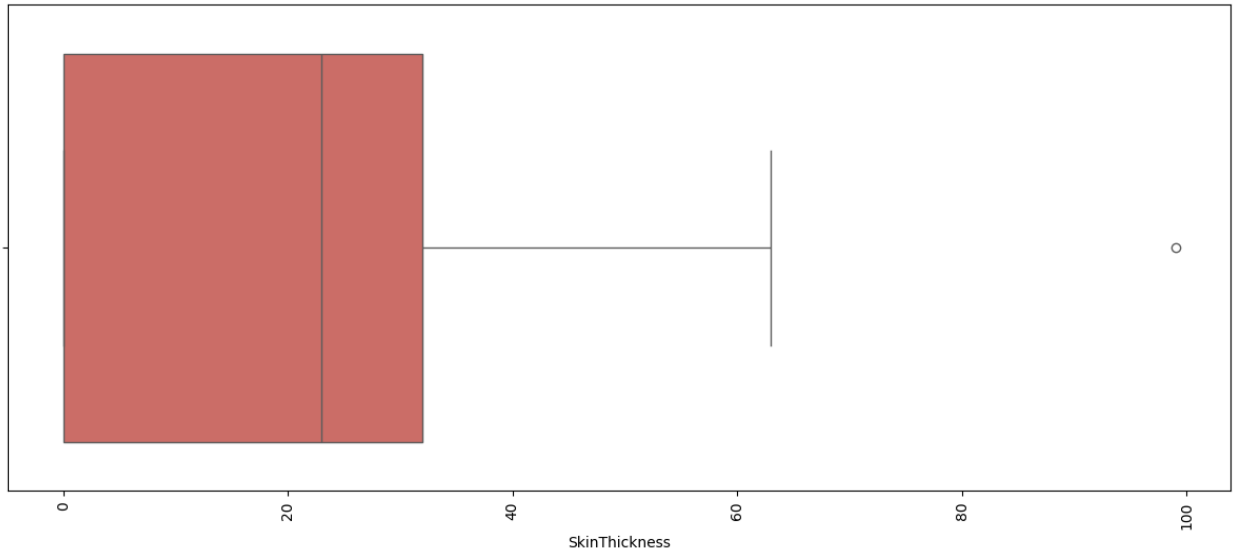

Density
0.00
0.01
0.02
0.03
0.04
0.05
0.06
0.07
10
20
30
40
50
60
70
80
90
Age

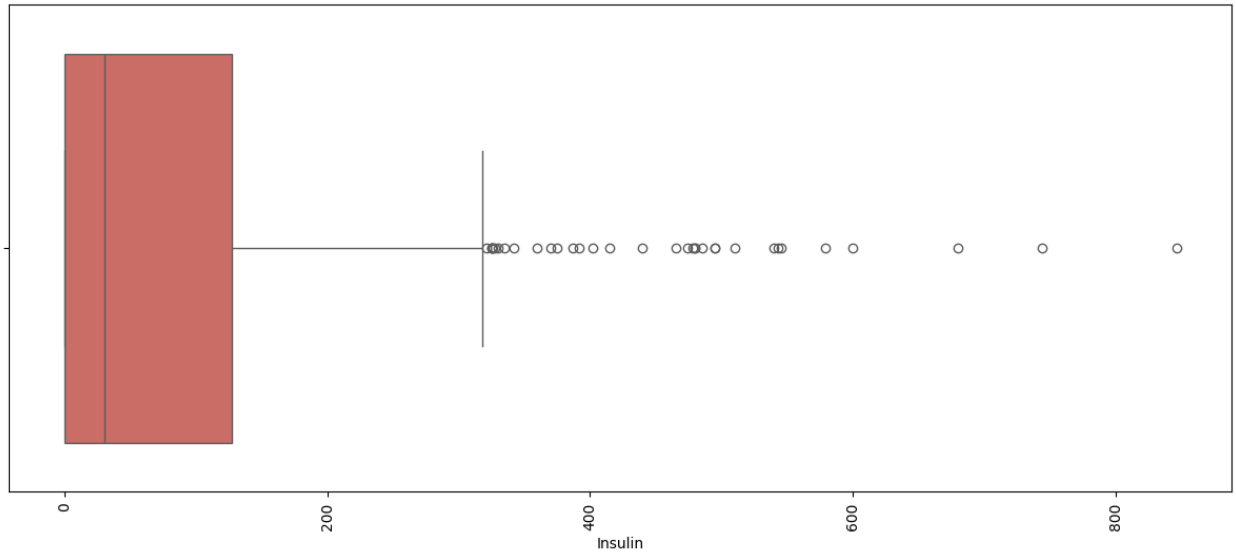
```
for i in continuous:
    plt.figure(figsize=(15, 6))
    sns.boxplot(x=i, data=df, palette='hls')
    plt.xticks(rotation=90)
    plt.show()
```

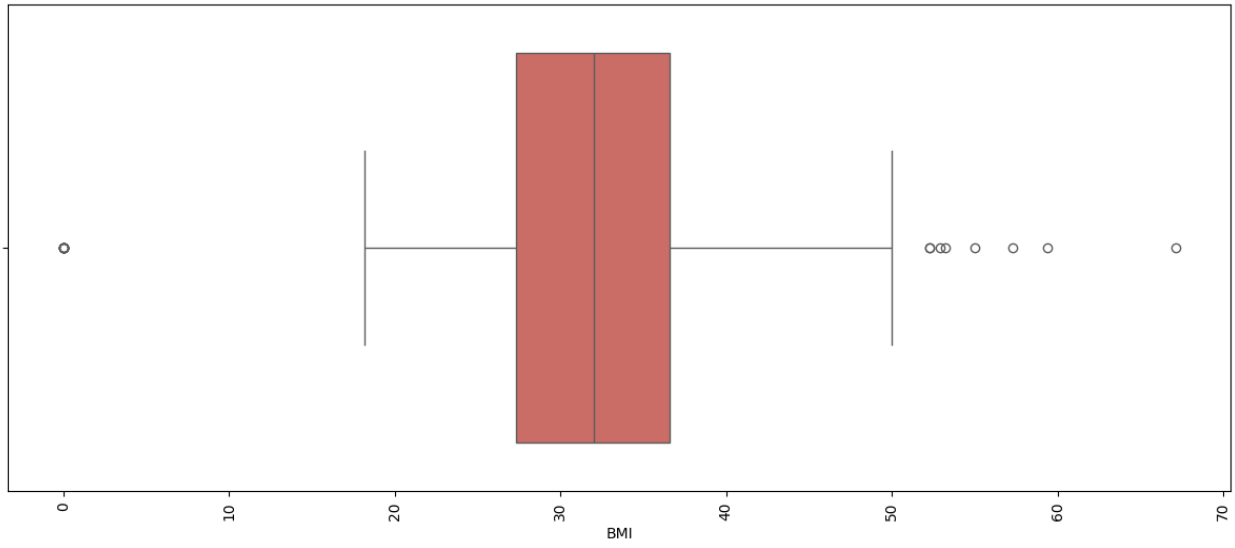


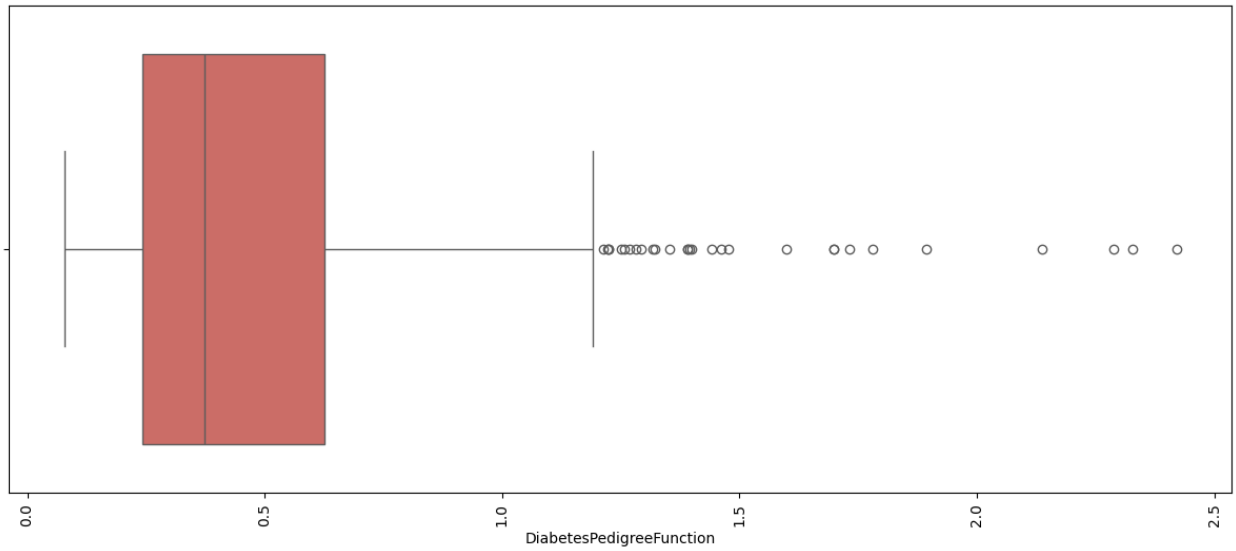


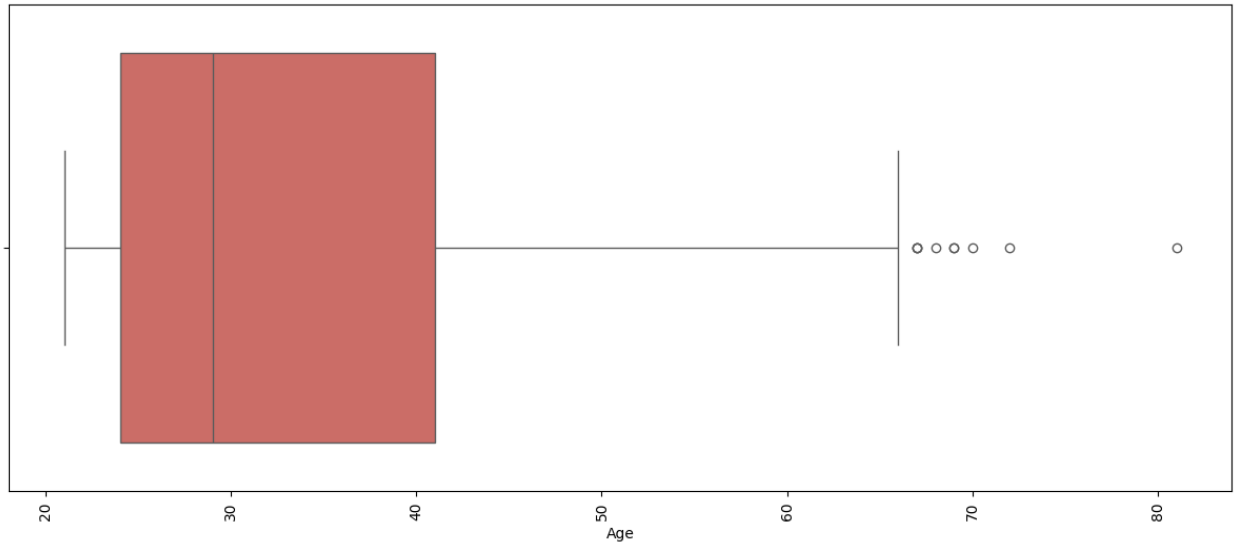

0
20
40
60
80
100
120
BloodPressure


0
20
40
60
80
100
SkinThickness

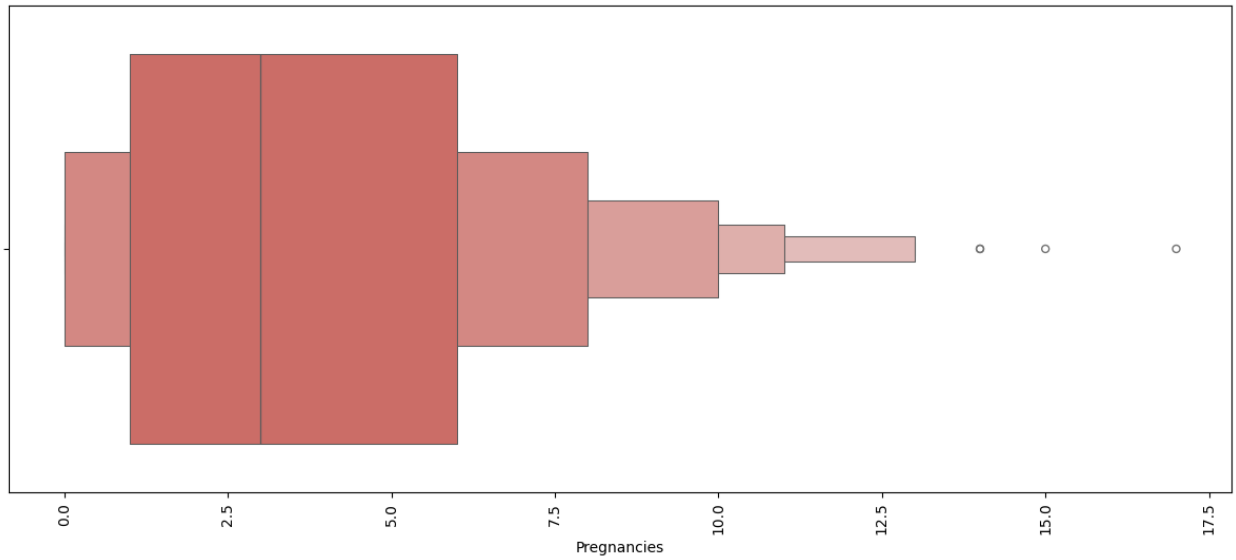

0
200
400
600
800
Insulin

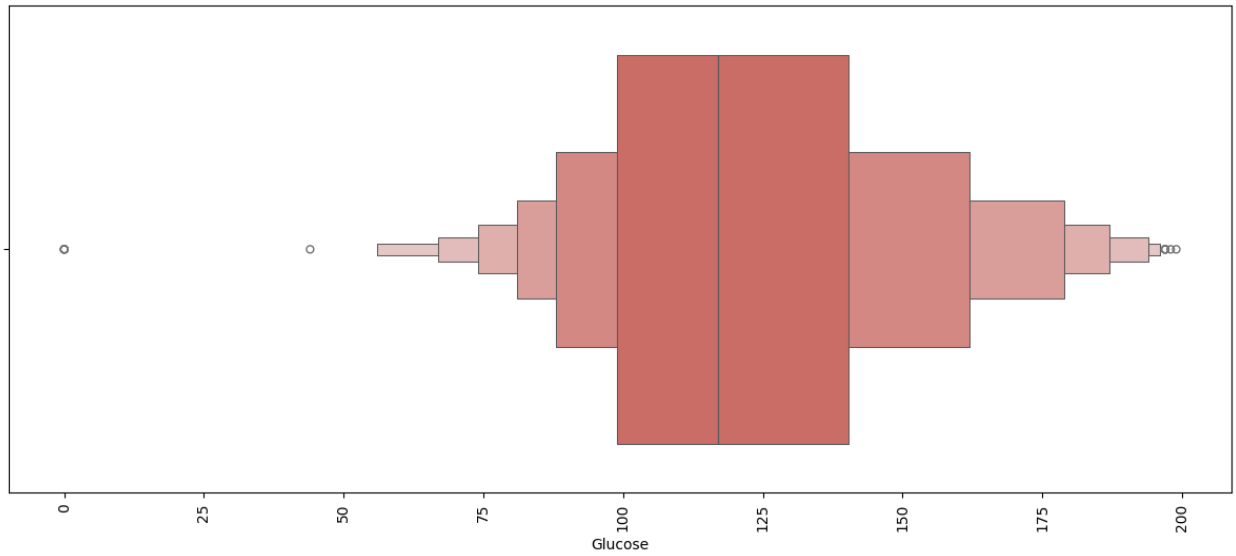

0
10
20
30
40
50
60
70
BMI

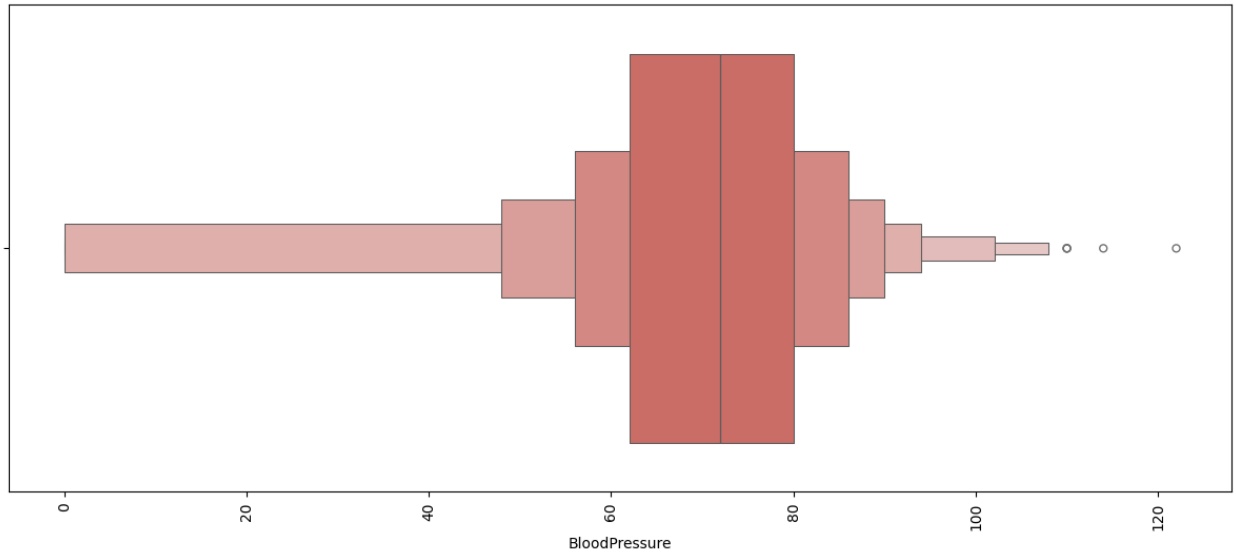


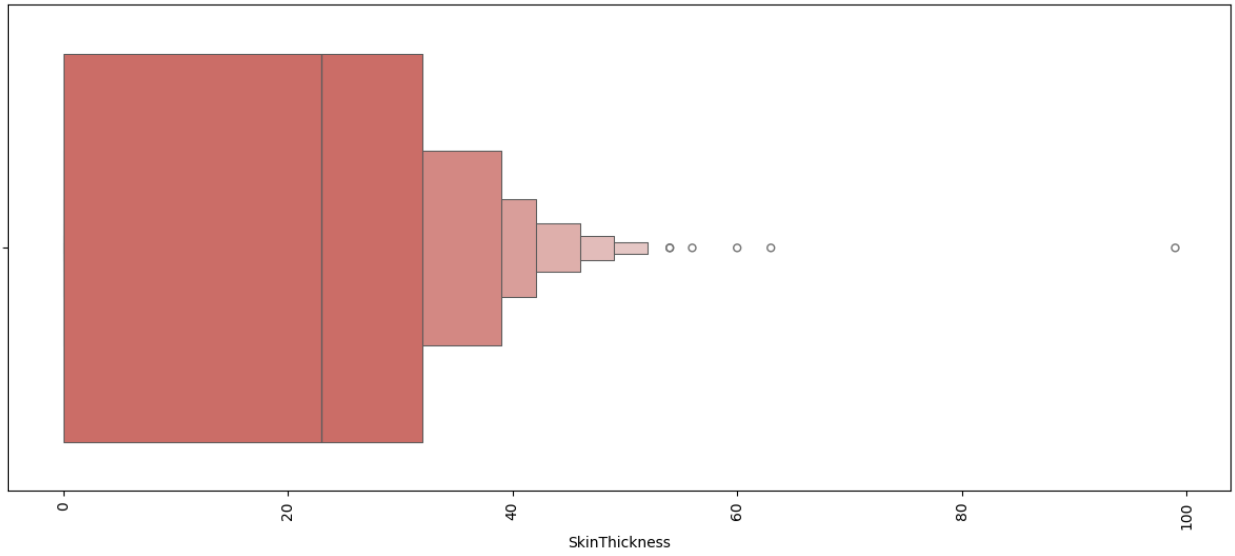


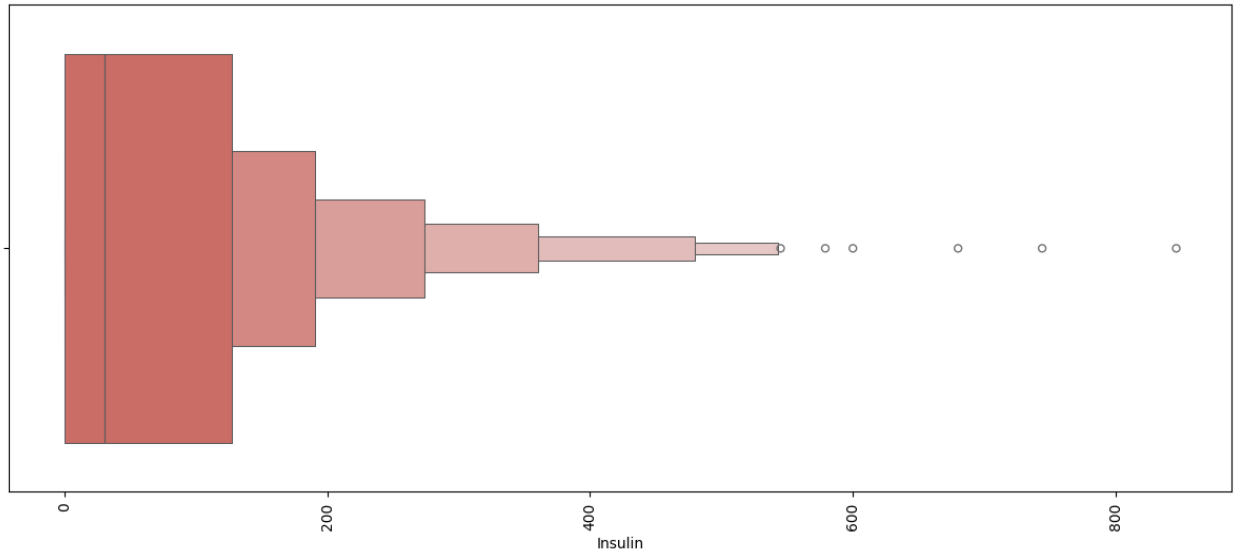

```
for i in continuous:
    plt.figure(figsize=(15, 6))
    sns.boxenplot(x=i, data=df, palette='hls')
    plt.xticks(rotation=90)
    plt.show()
```

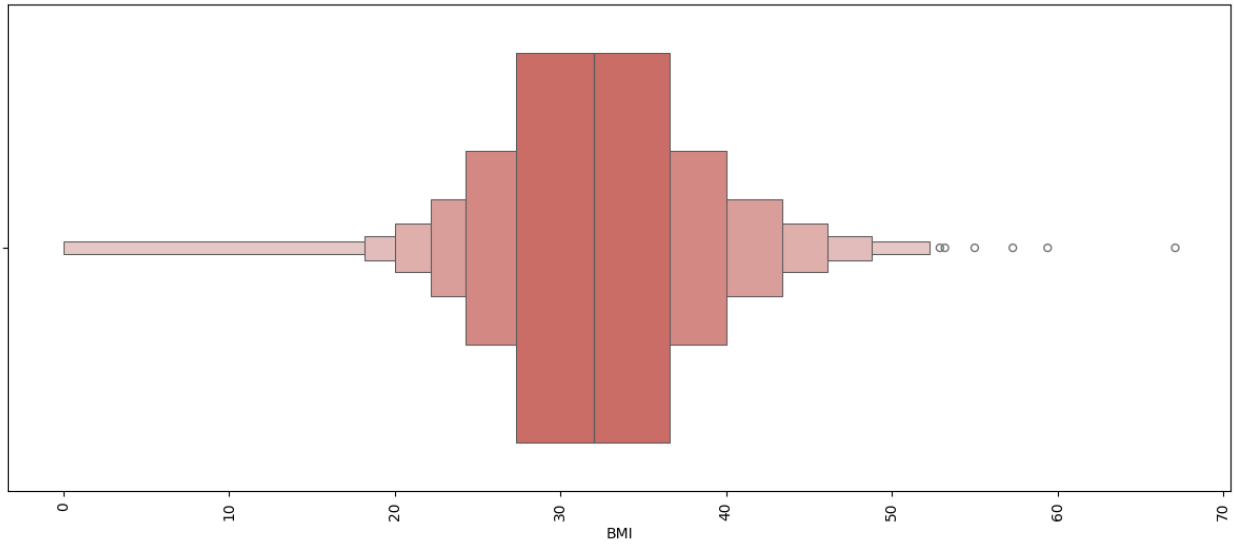

0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
Pregnancies

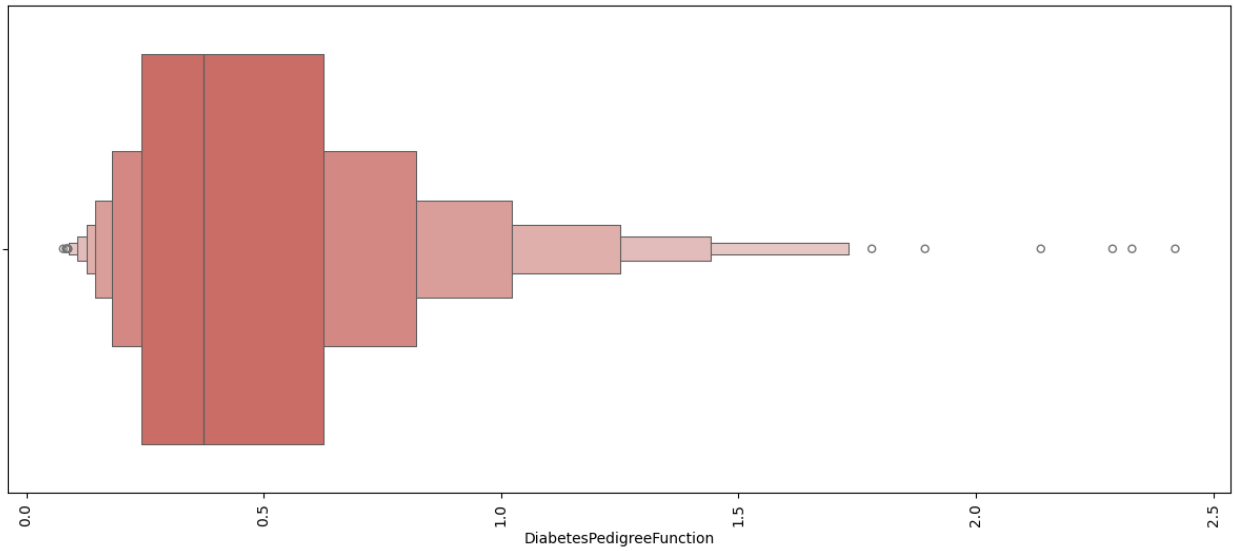

0
25
50
75
100
125
150
175
200
Glucose

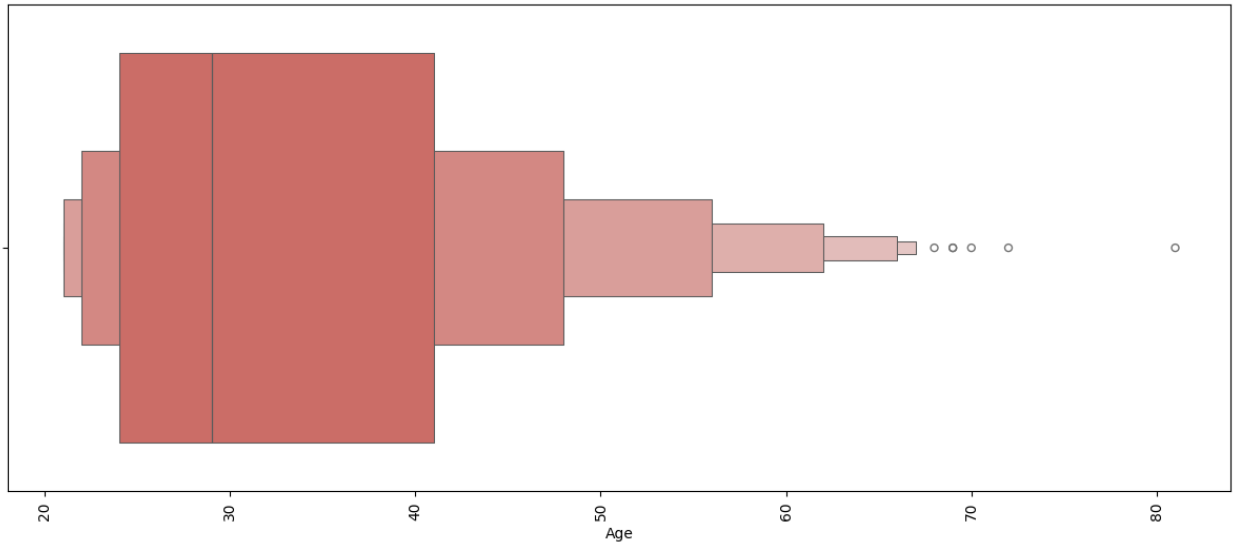

0
20
40
60
80
100
120
BloodPressure


0
20
40
60
80
100
SkinThickness

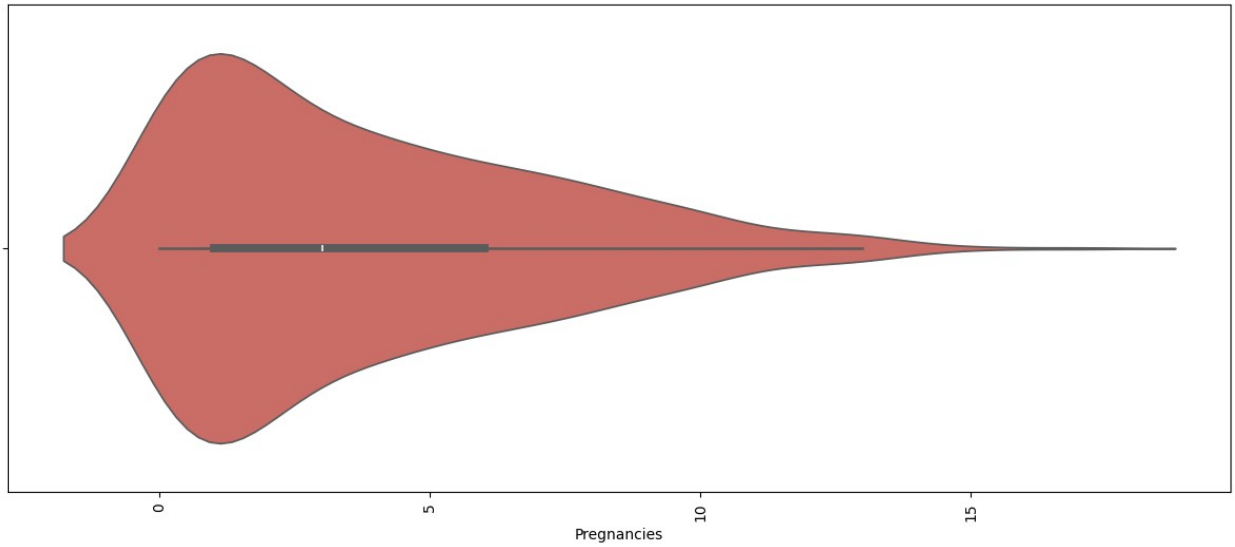

0
200
400
600
800
Insulin

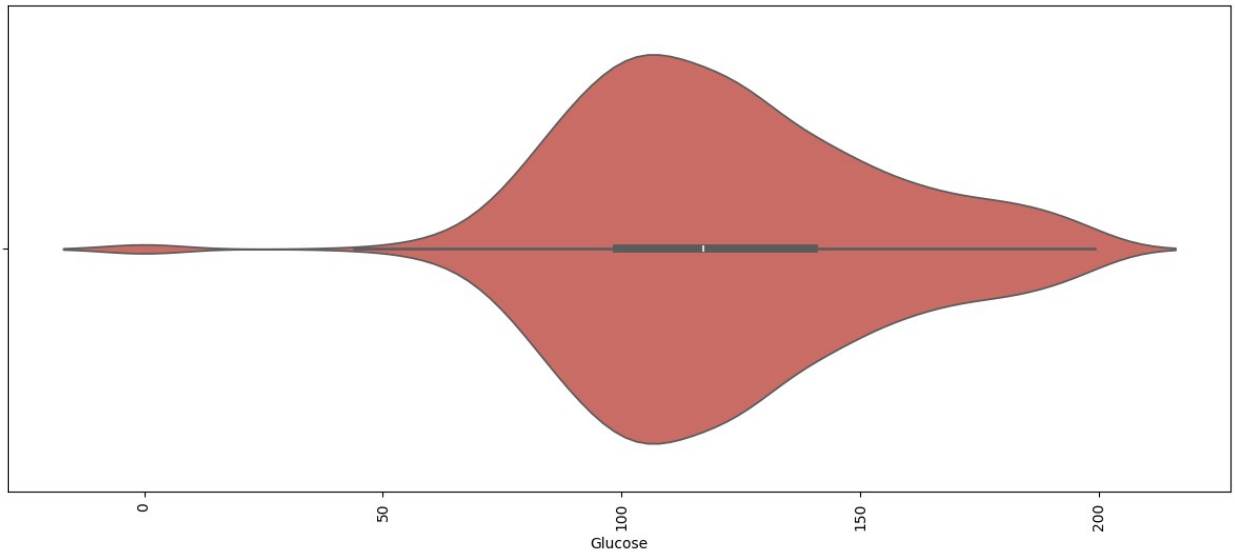

0
10
20
30
40
50
60
70
BMI

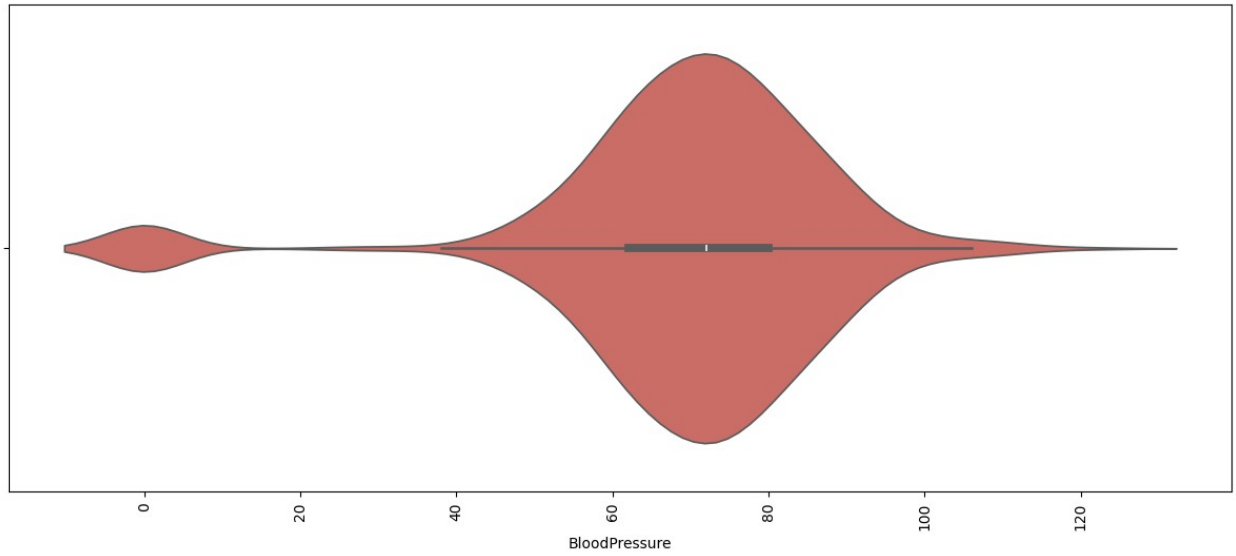


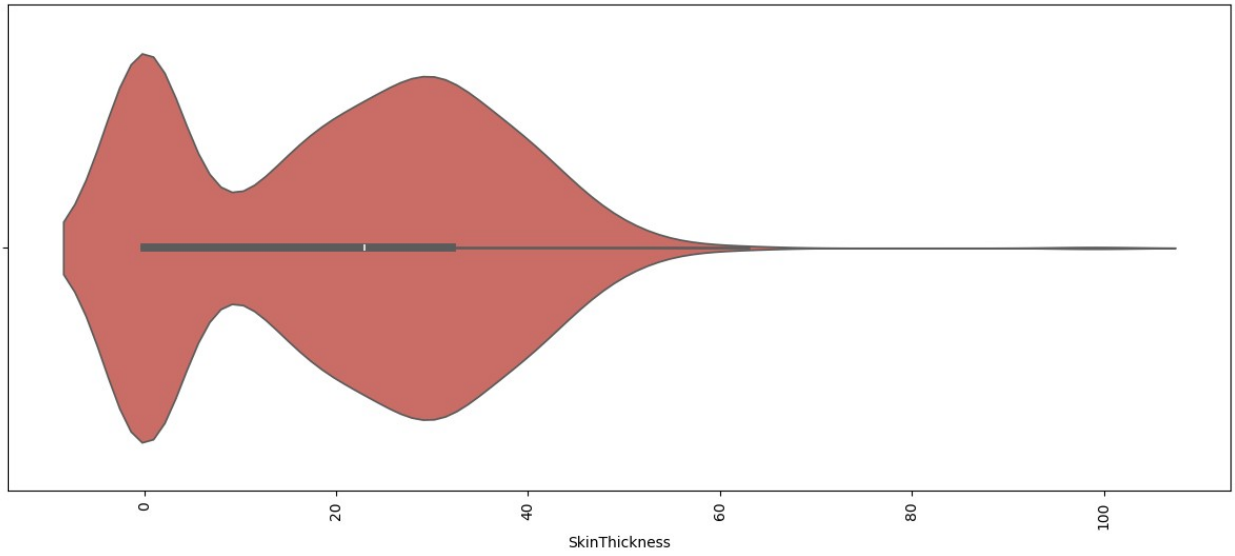


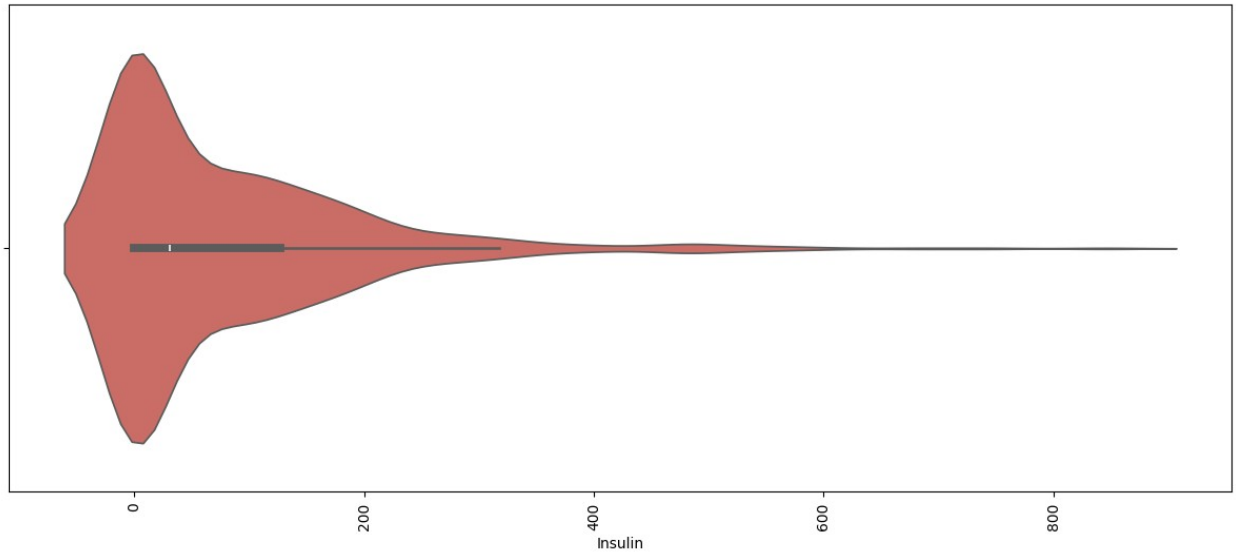

```
for i in continuous:
    plt.figure(figsize=(15, 6))
    sns.violinplot(x=i, data=df, palette='hls')
    plt.xticks(rotation=90)
    plt.show()
```

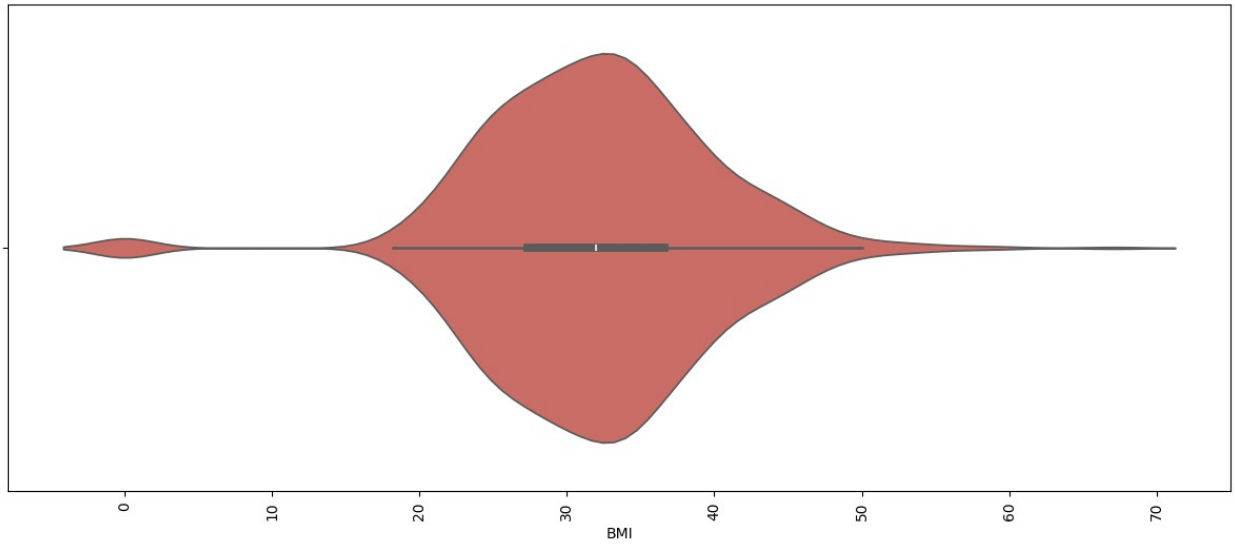

0
5
10
15
Pregnancies

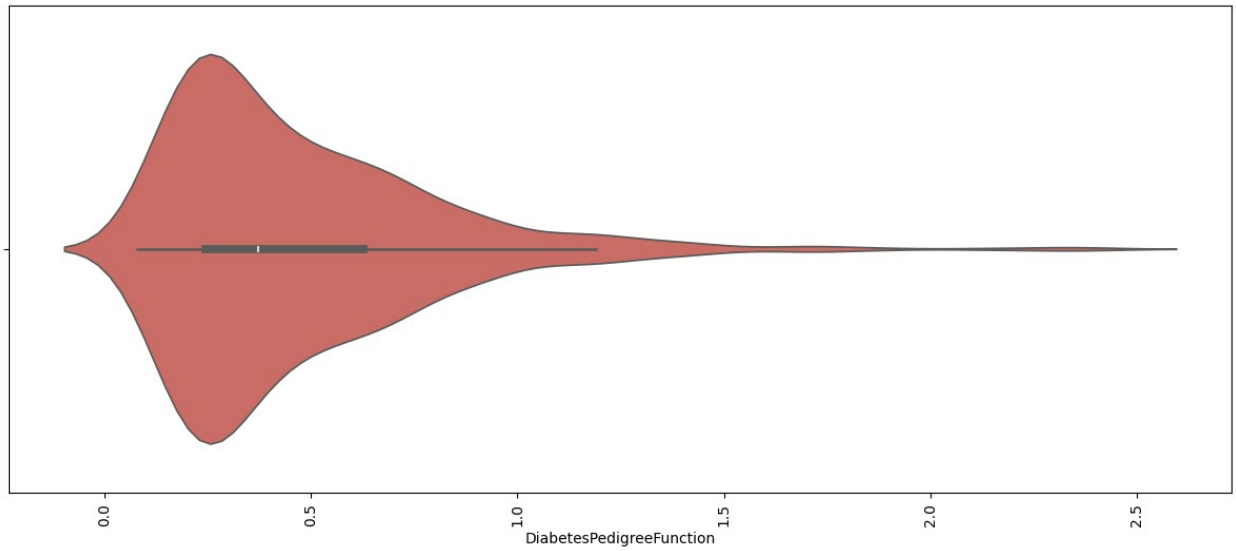

0
50
100
150
200
Glucose

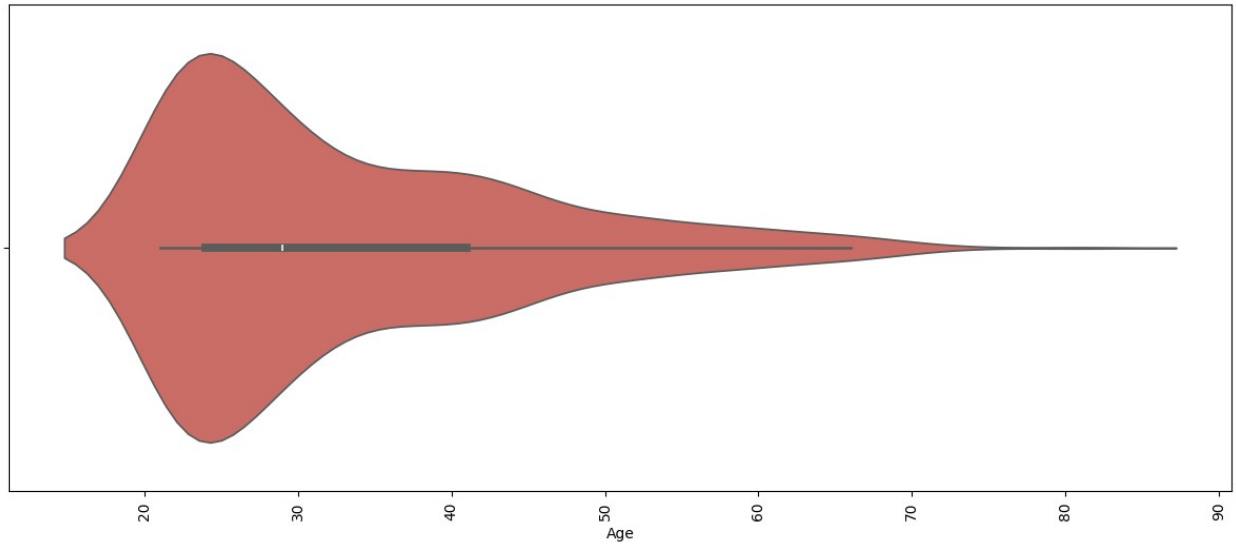

0
20
40
60
80
100
120
BloodPressure


0
20
40
60
80
100
SkinThickness

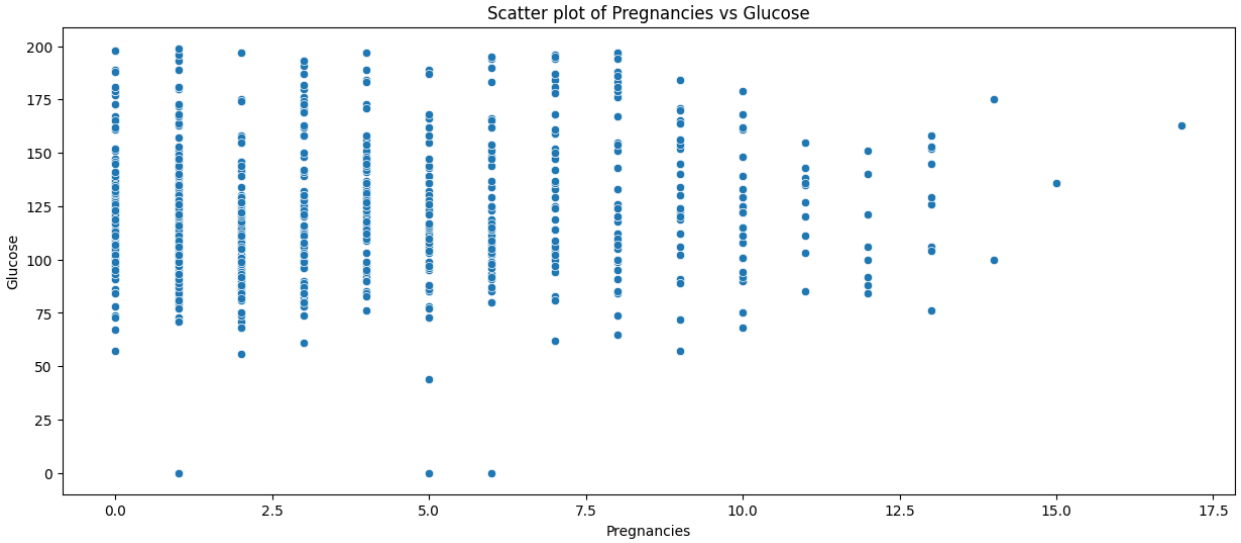

0
200
400
600
800
Insulin

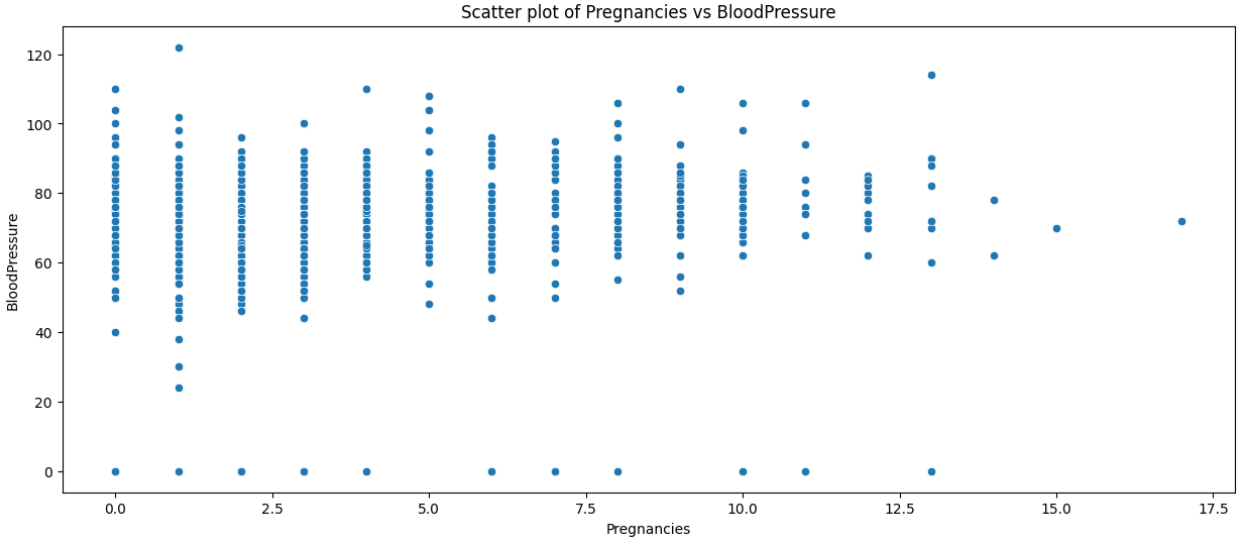

0
10
20
30
40
50
60
70
BMI

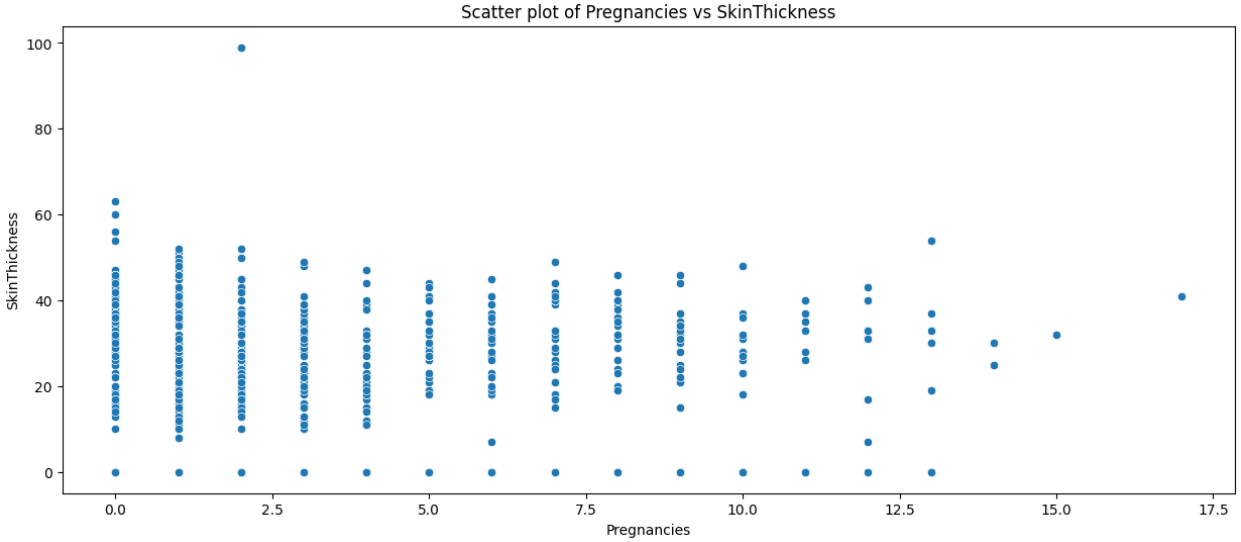


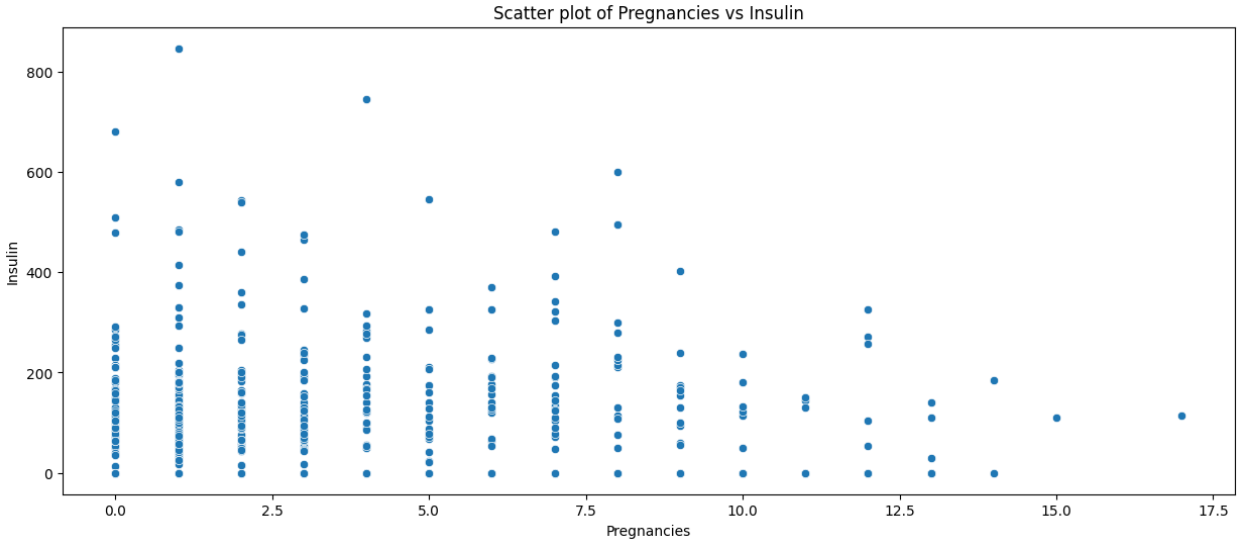


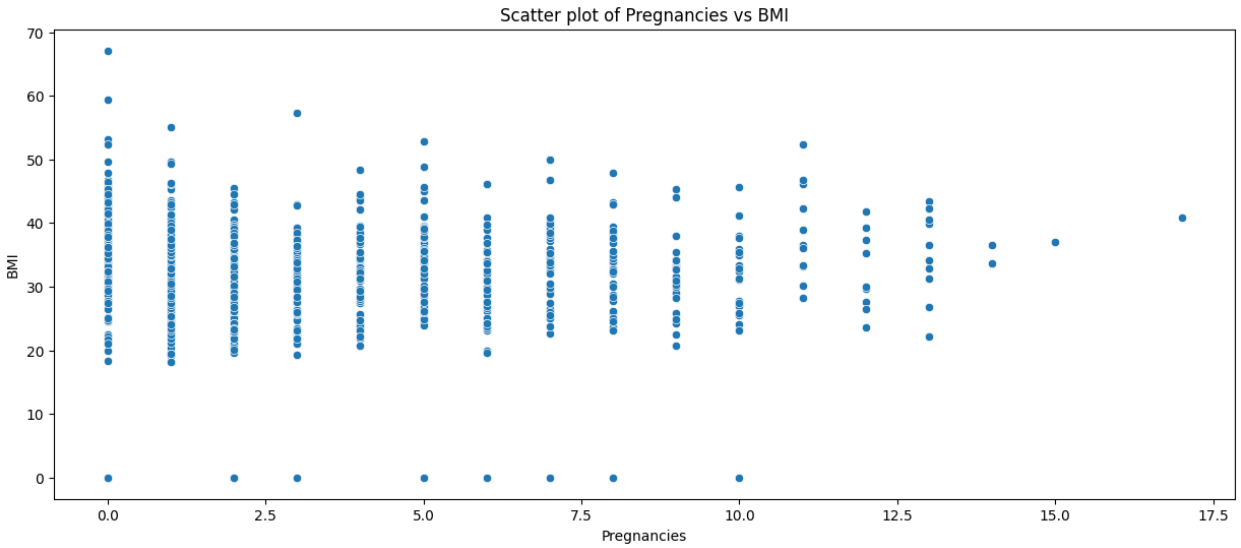

```
for i in range(len(continuous)):
    for j in range(i + 1, len(continuous)):
        plt.figure(figsize=(15, 6))
        sns.scatterplot(x=continuous[i], y=continuous[j], data=df,
palette='hls')
        plt.title(f'Scatter plot of {continuous[i]} vs
{continuous[j]}')
        plt.show()
```

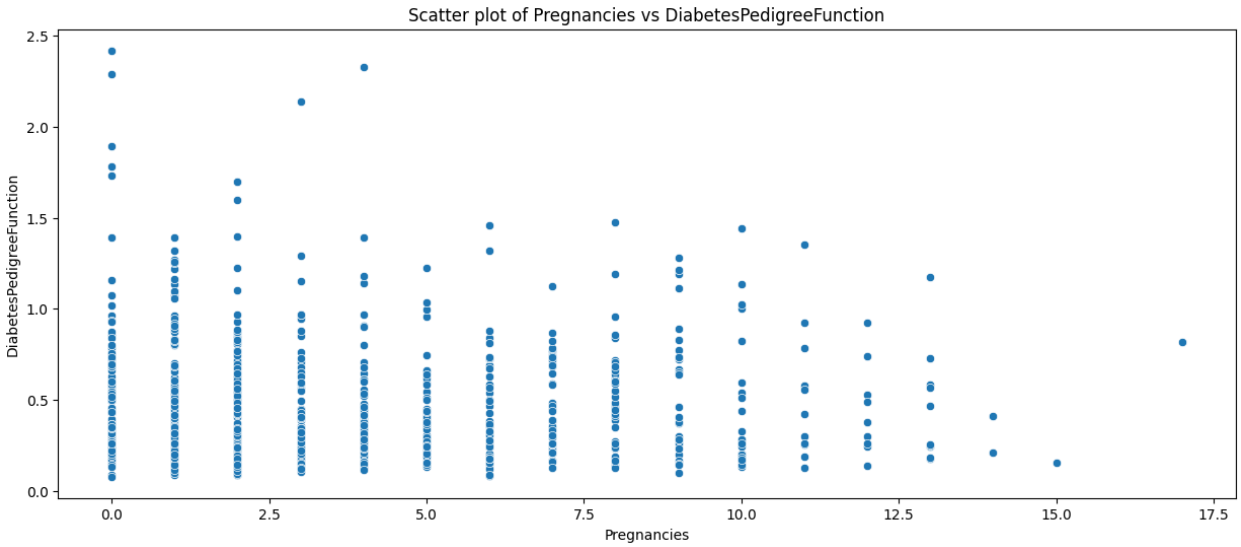

Scatter plot of Pregnancies vs Glucose
Glucose
Pregnancies
200
175
150
125
100
75
50
25
0
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5

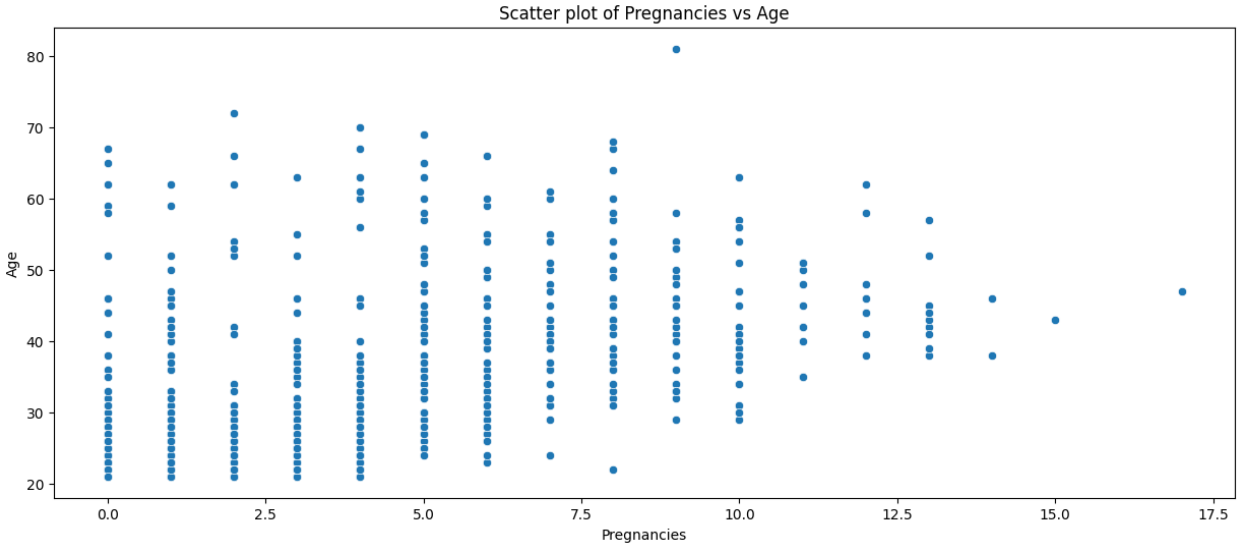

Scatter plot of Pregnancies vs BloodPressure
BloodPressure
Pregnancies
120
100
80
60
40
20
0
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5

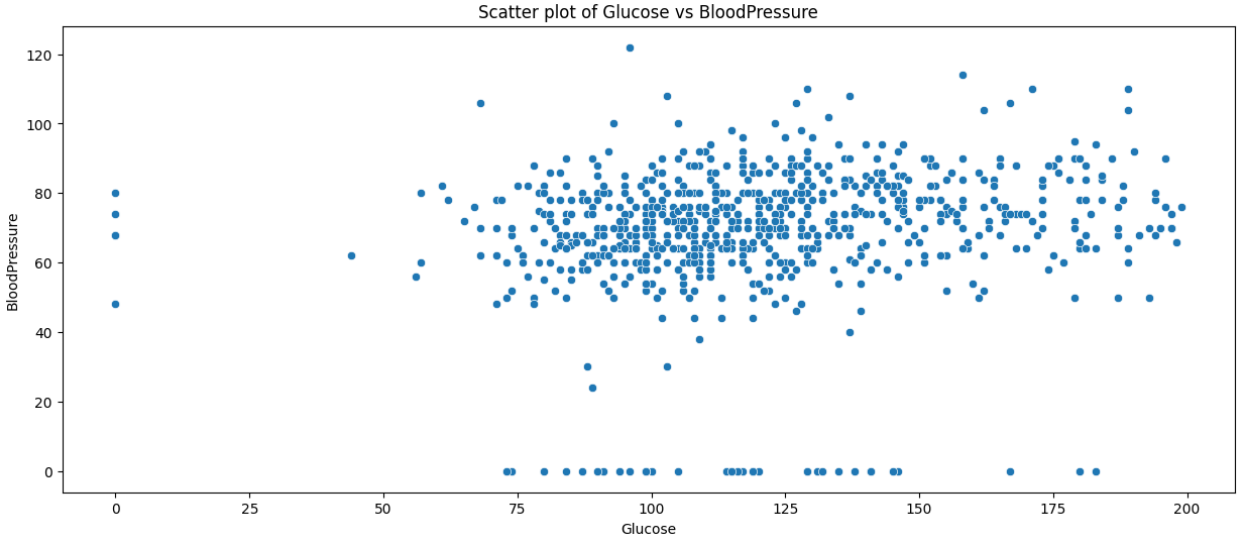

Scatter plot of Pregnancies vs SkinThickness
SkinThickness
Pregnancies
100
80
60
40
20
0
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5

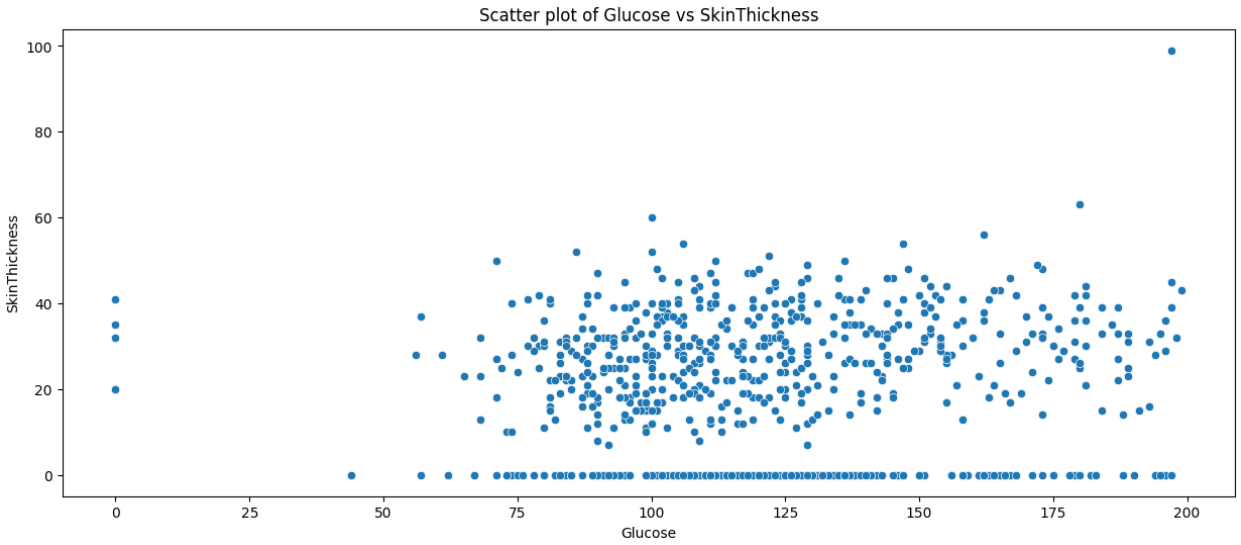

Scatter plot of Pregnancies vs Insulin
Insulin
Pregnancies
0
200
400
600
800
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5

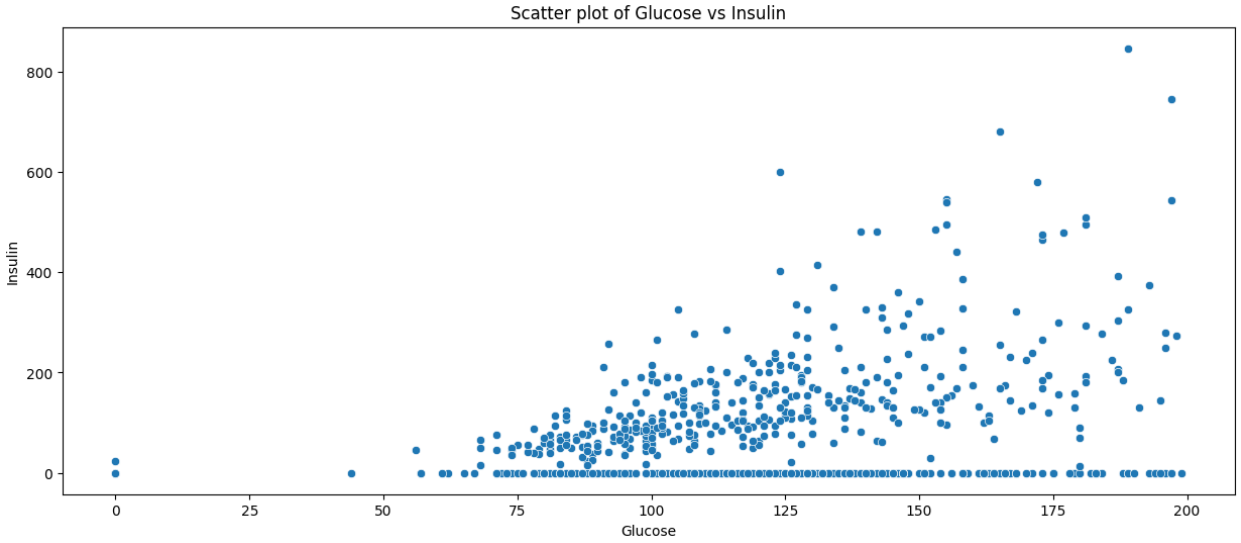

Scatter plot of Pregnancies vs BMI
BMI
Pregnancies
0
10
20
30
40
50
60
70
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5

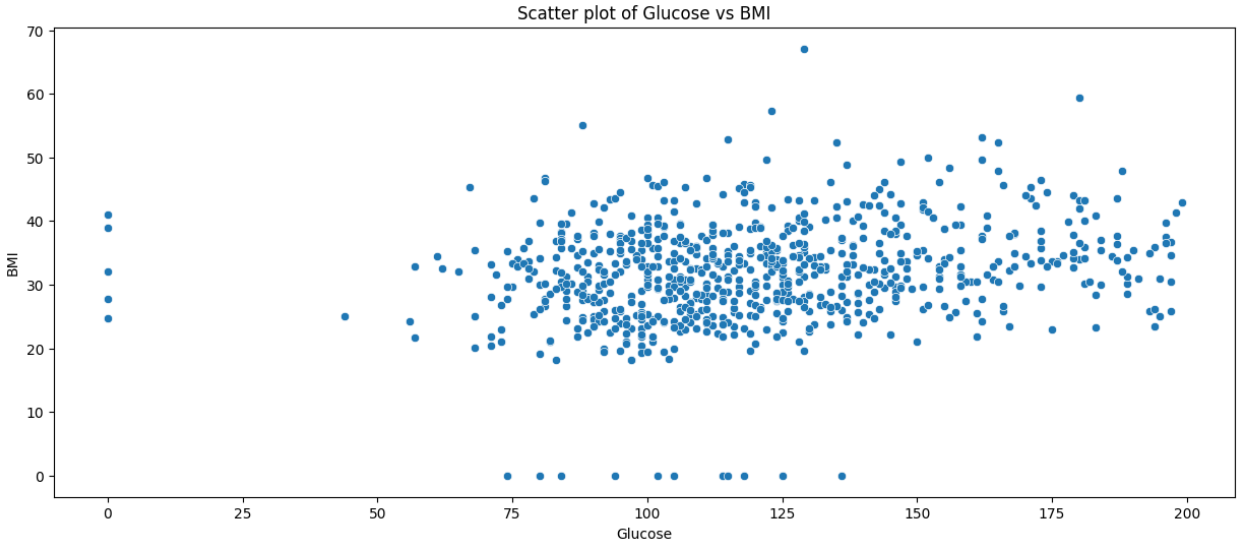

Scatter plot of Pregnancies vs DiabetesPedigreeFunction
DiabetesPedigreeFunction
Pregnancies
0.0
0.5
1.0
1.5
2.0
2.5
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5

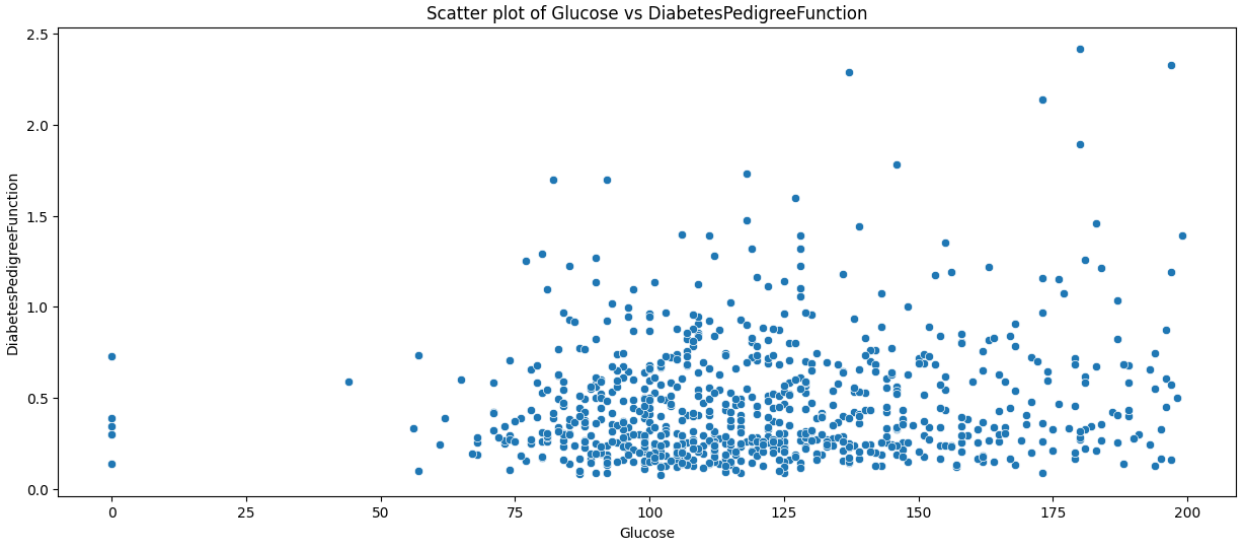

Scatter plot of Pregnancies vs Age
Age
Pregnancies
80
70
60
50
40
30
20
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5

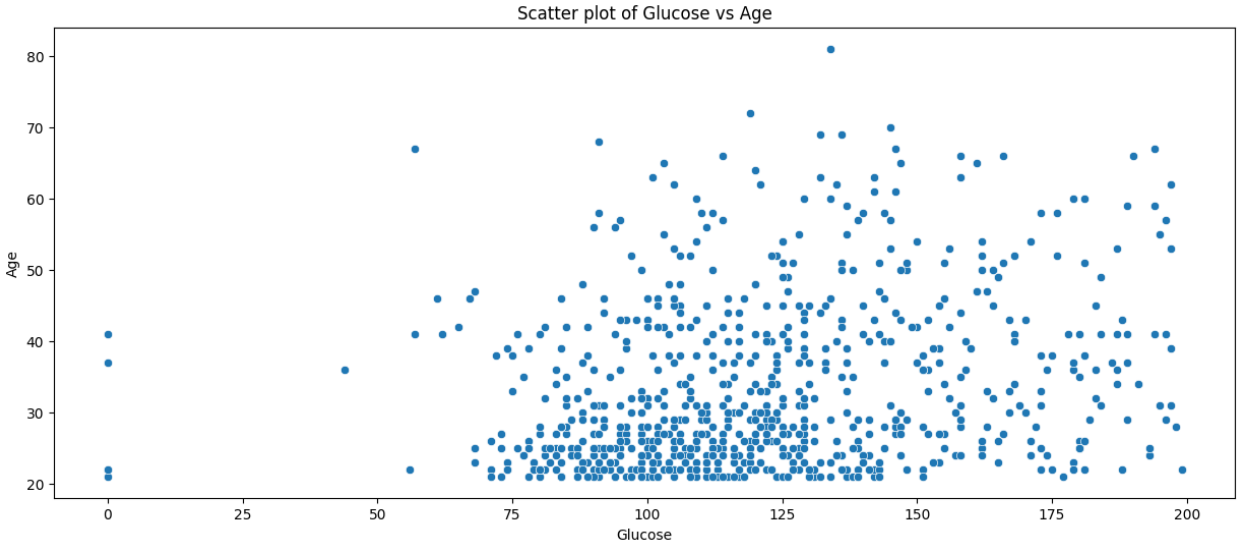

Scatter plot of Glucose vs BloodPressure
BloodPressure
Glucose
120
100
80
60
40
20
0
0
25
50
75
100
125
150
175
200

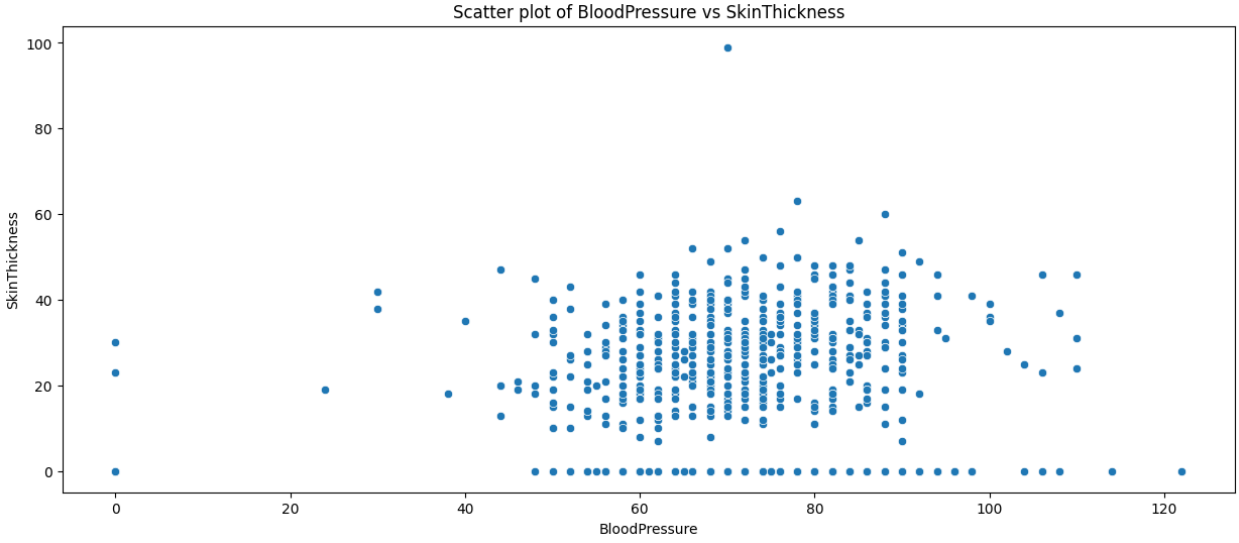

Scatter plot of Glucose vs SkinThickness
SkinThickness
Glucose
100
80
60
40
20
0
0
25
50
75
100
125
150
175
200

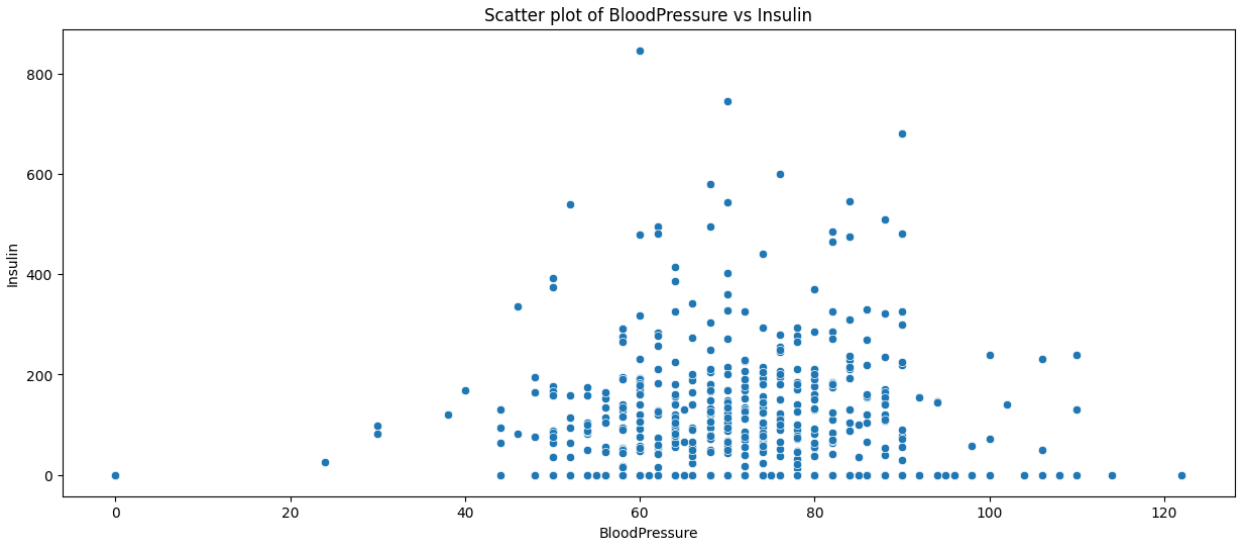

Scatter plot of Glucose vs Insulin
Insulin
Glucose
0
200
400
600
800
0
25
50
75
100
125
150
175
200

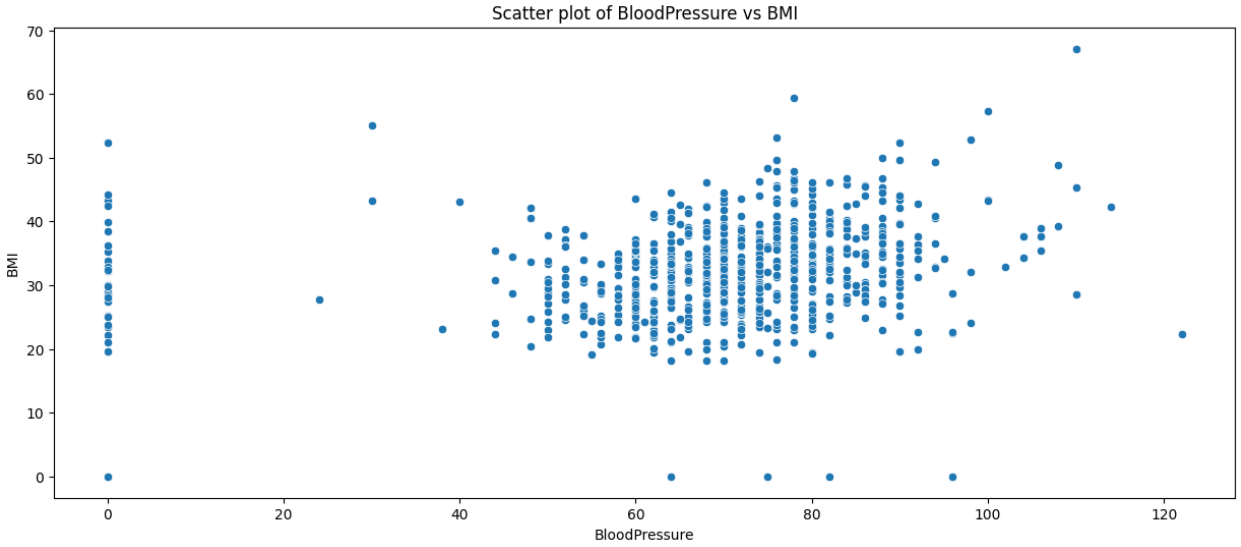

Scatter plot of Glucose vs BMI
BMI
Glucose
0
10
20
30
40
50
60
70
0
25
50
75
100
125
150
175
200

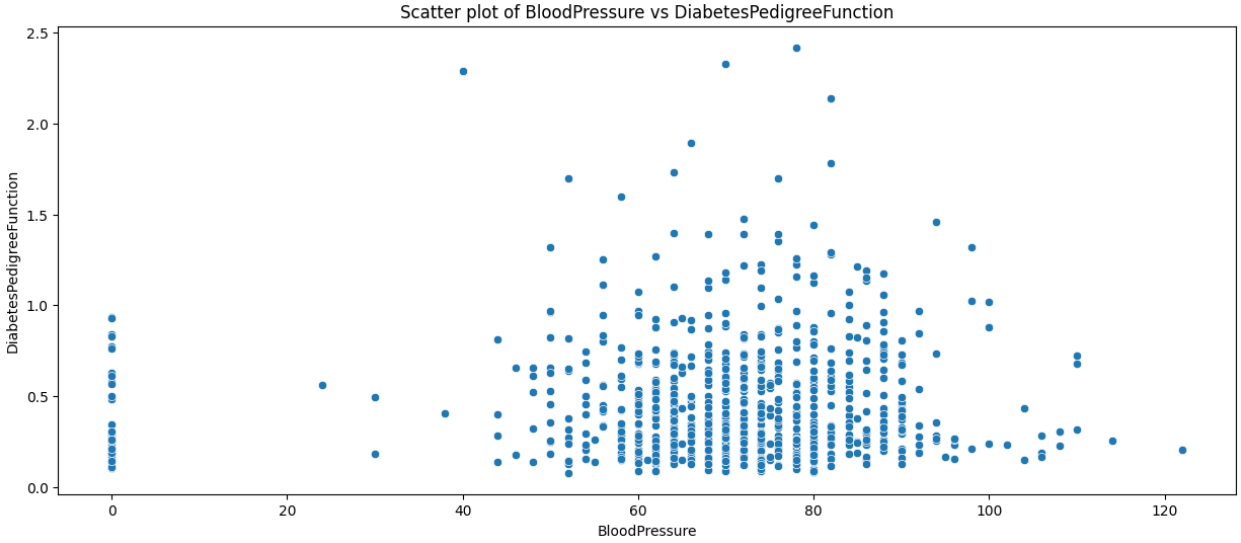

Scatter plot of Glucose vs DiabetesPedigreeFunction
DiabetesPedigreeFunction
Glucose
0.0
0.5
1.0
1.5
2.0
2.5
0
25
50
75
100
125
150
175
200

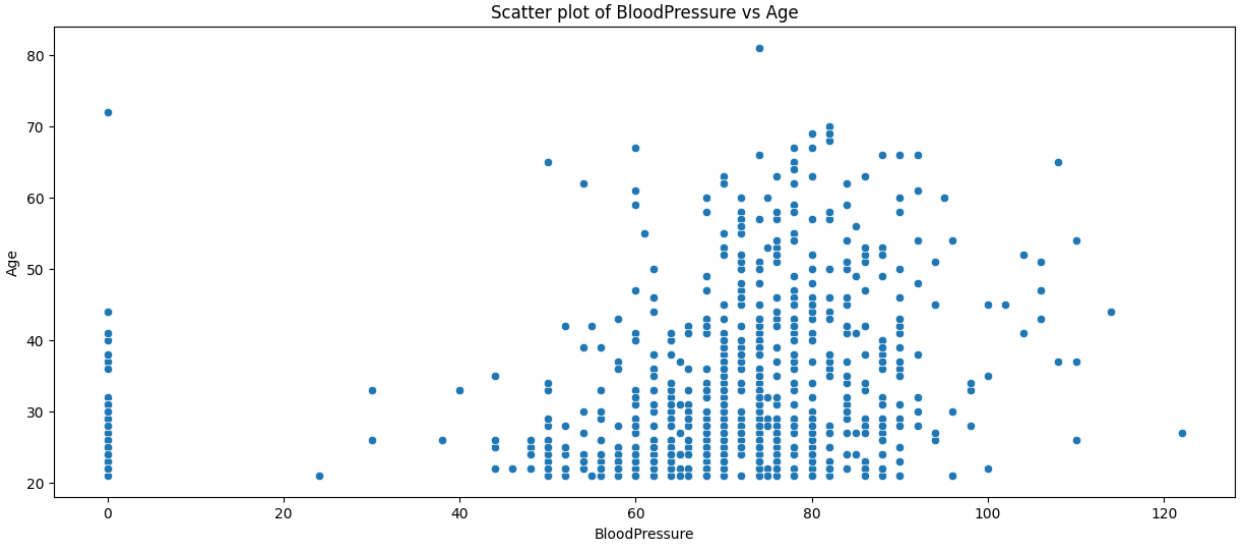

Scatter plot of Glucose vs Age
Age
Glucose
80
70
60
50
40
30
20
0
25
50
75
100
125
150
175
200

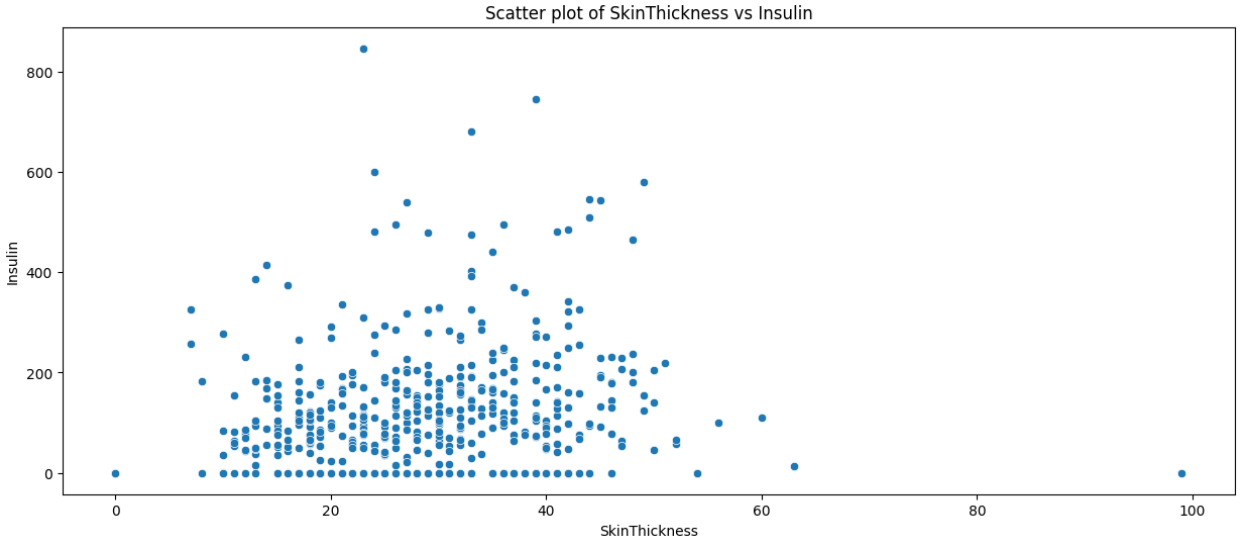

Scatter plot of BloodPressure vs SkinThickness
SkinThickness
BloodPressure
100
80
60
40
20
0
0
20
40
60
80
100
120

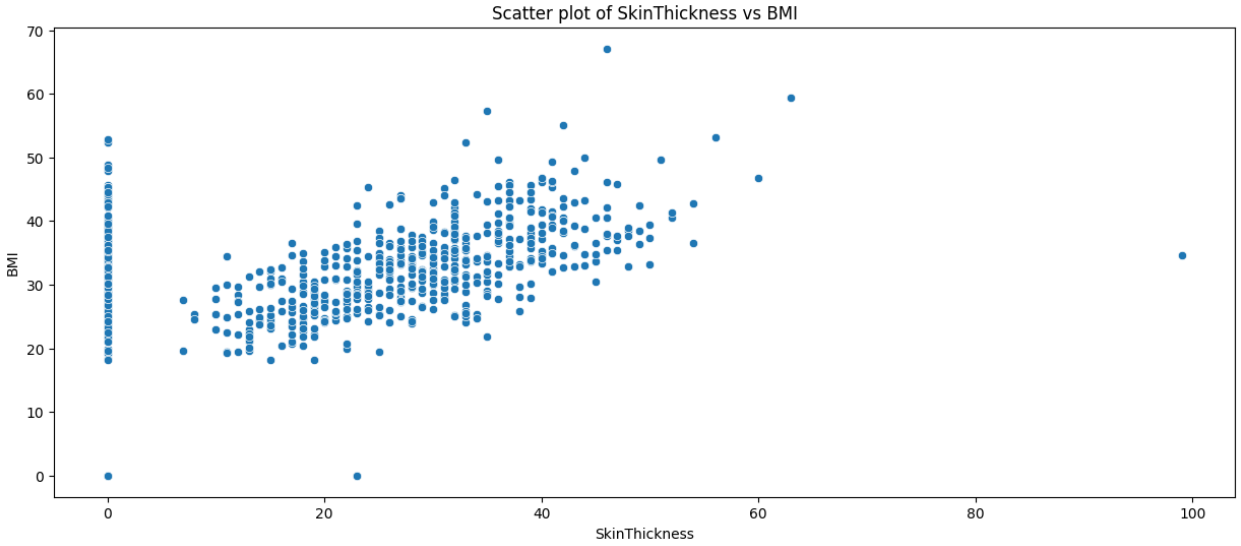

Scatter plot of BloodPressure vs Insulin
Insulin
BloodPressure
800
600
400
200
0
0
20
40
60
80
100
120

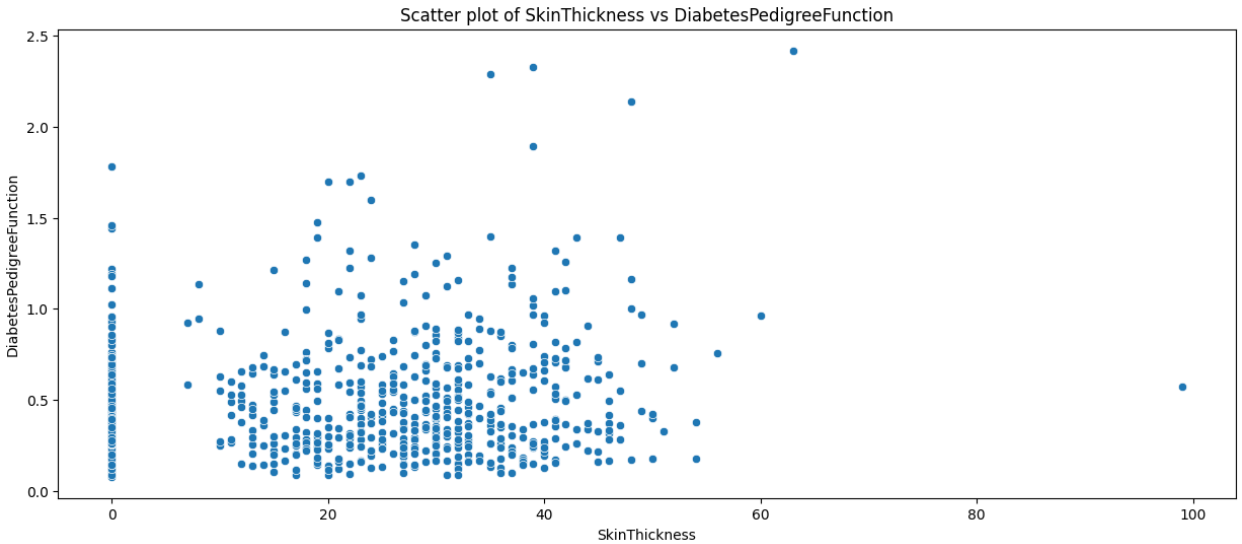

Scatter plot of BloodPressure vs BMI
BMI
BloodPressure
0
10
20
30
40
50
60
70
0
20
40
60
80
100
120

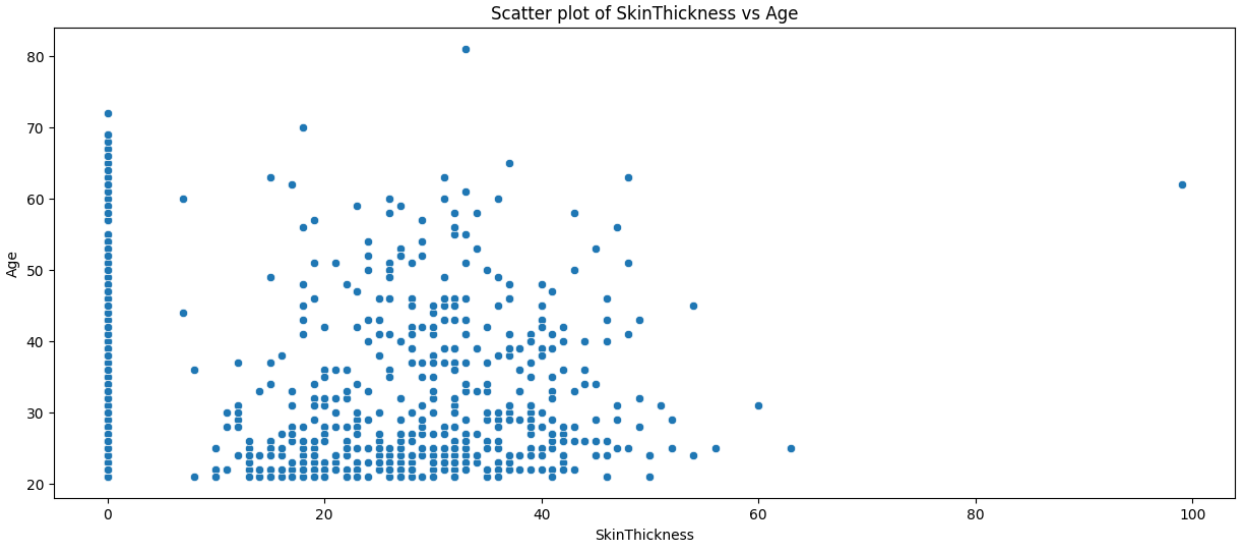

Scatter plot of BloodPressure vs DiabetesPedigreeFunction
DiabetesPedigreeFunction
BloodPressure
0.0
0.5
1.0
1.5
2.0
2.5
0
20
40
60
80
100
120

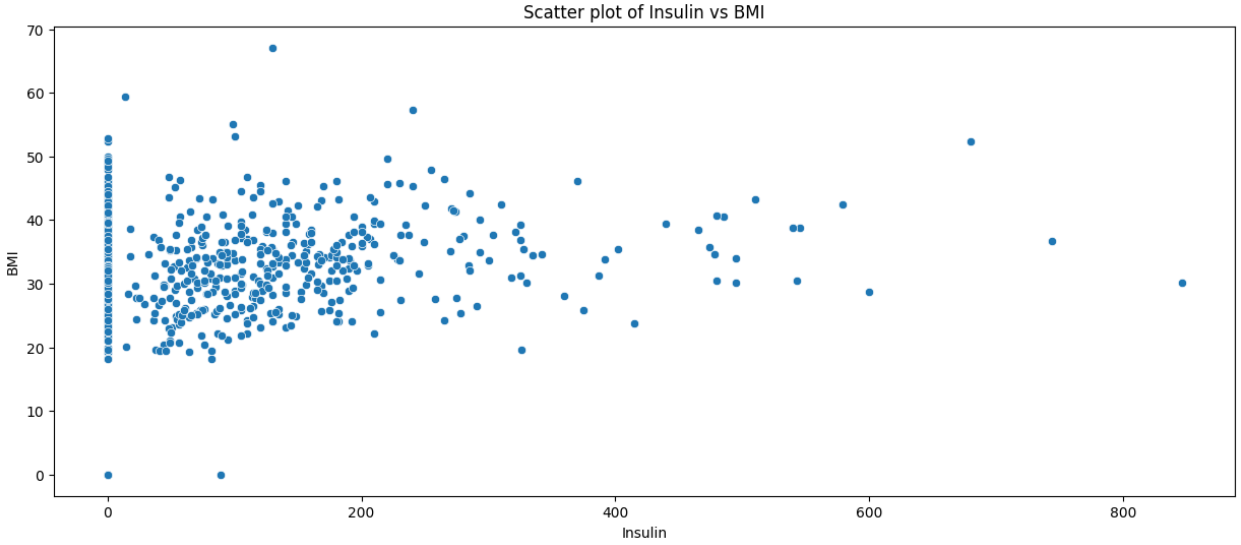

Scatter plot of BloodPressure vs Age
Age
BloodPressure
20
30
40
50
60
70
80
0
20
40
60
80
100
120

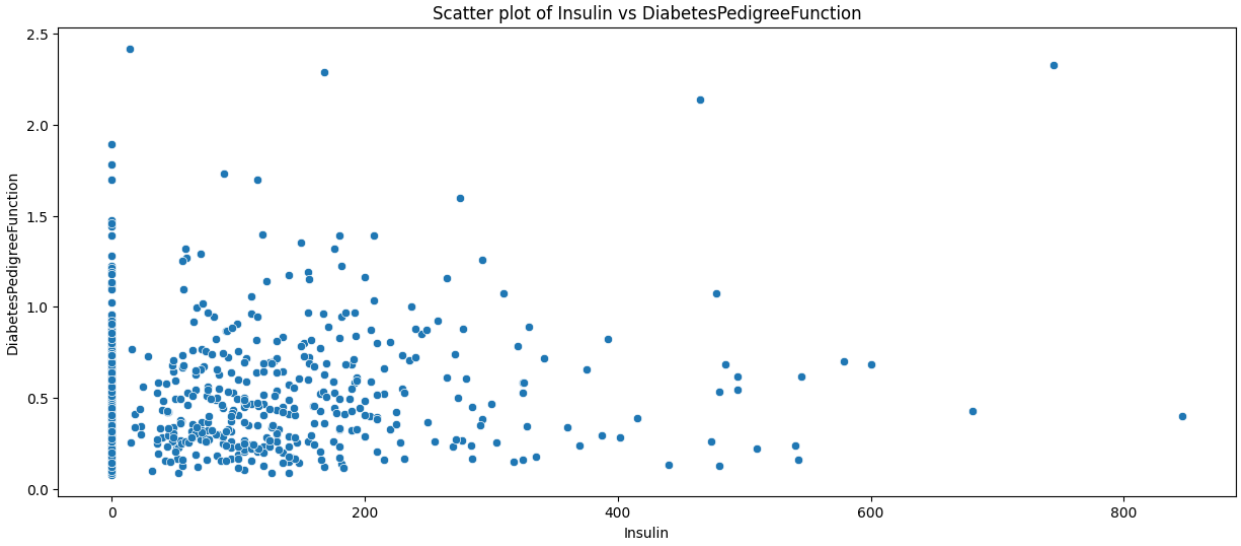

Scatter plot of SkinThickness vs Insulin
Insulin
SkinThickness
0
200
400
600
800
0
20
40
60
80
100

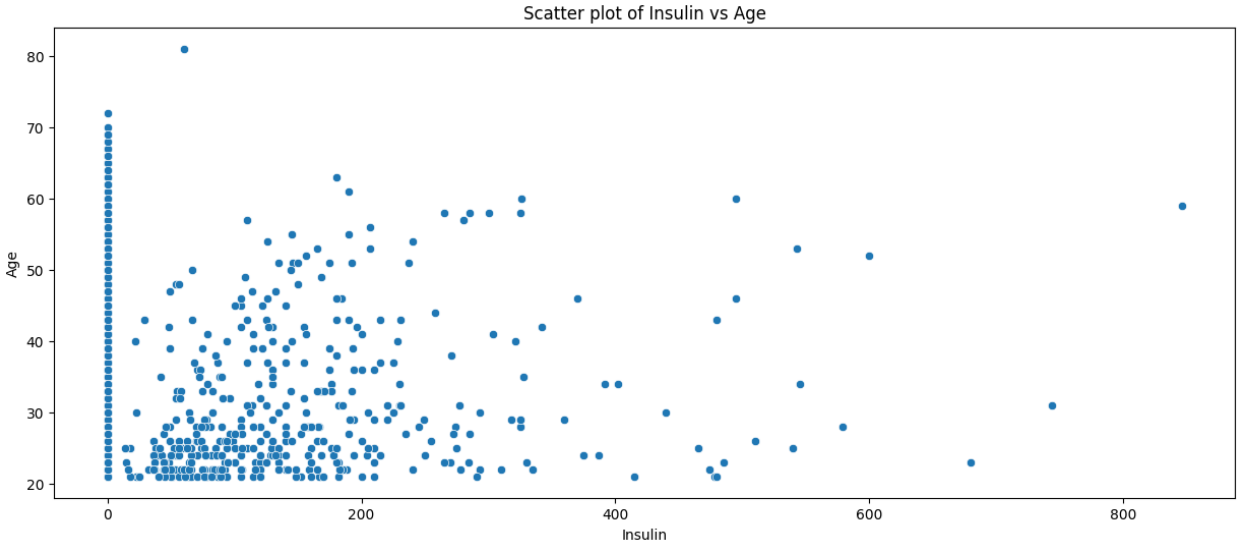

Scatter plot of SkinThickness vs BMI
BMI
SkinThickness
0
10
20
30
40
50
60
70
0
20
40
60
80
100

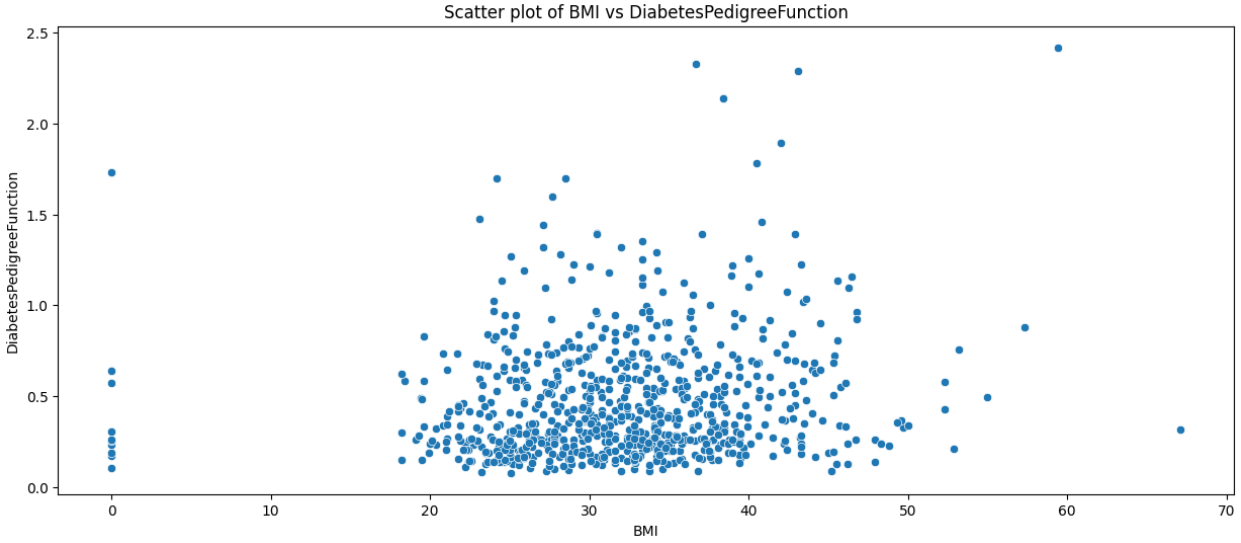

Scatter plot of SkinThickness vs DiabetesPedigreeFunction
DiabetesPedigreeFunction
SkinThickness
0.0
0.5
1.0
1.5
2.0
2.5
0
20
40
60
80
100

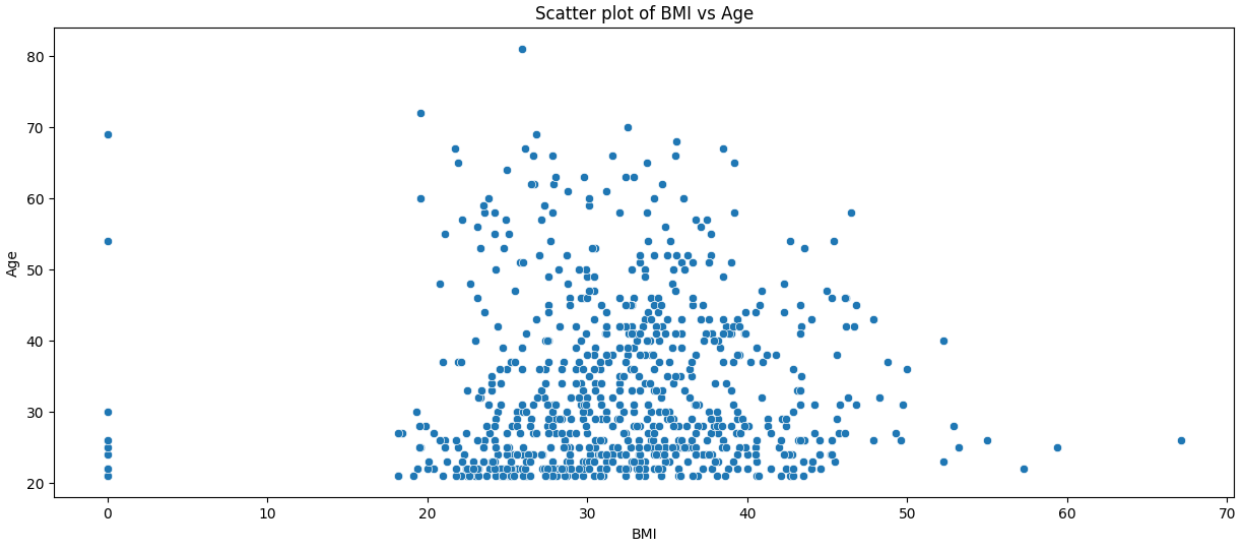

Scatter plot of SkinThickness vs Age
Age
SkinThickness
80
70
60
50
40
30
20
0
20
40
60
80
100

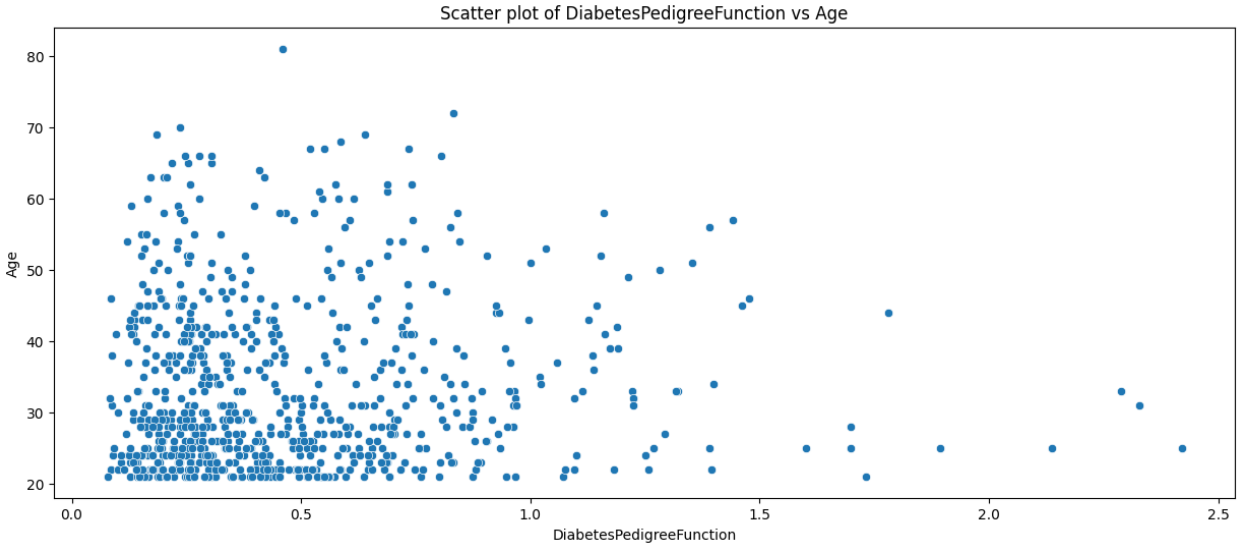

Scatter plot of Insulin vs BMI
BMI
Insulin
70
60
50
40
30
20
10
0
0
200
400
600
800


Scatter plot of Insulin vs DiabetesPedigreeFunction
DiabetesPedigreeFunction
Insulin
2.5
2.0
1.5
1.0
0.5
0.0
0
200
400
600
800

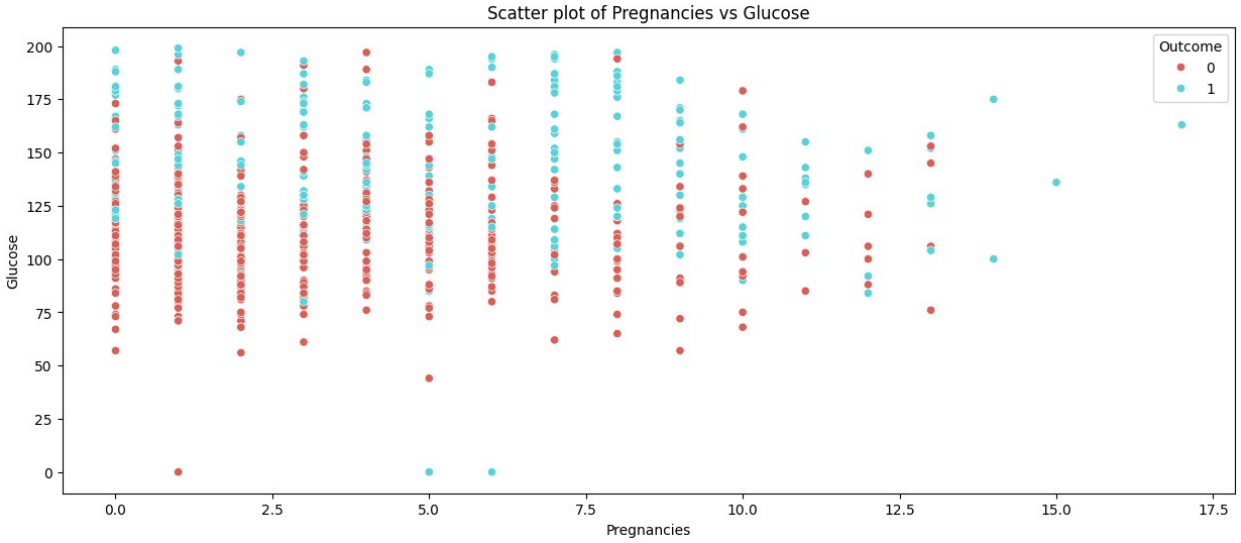

Scatter plot of Insulin vs Age
Age
Insulin
80
70
60
50
40
30
20
0
200
400
600
800

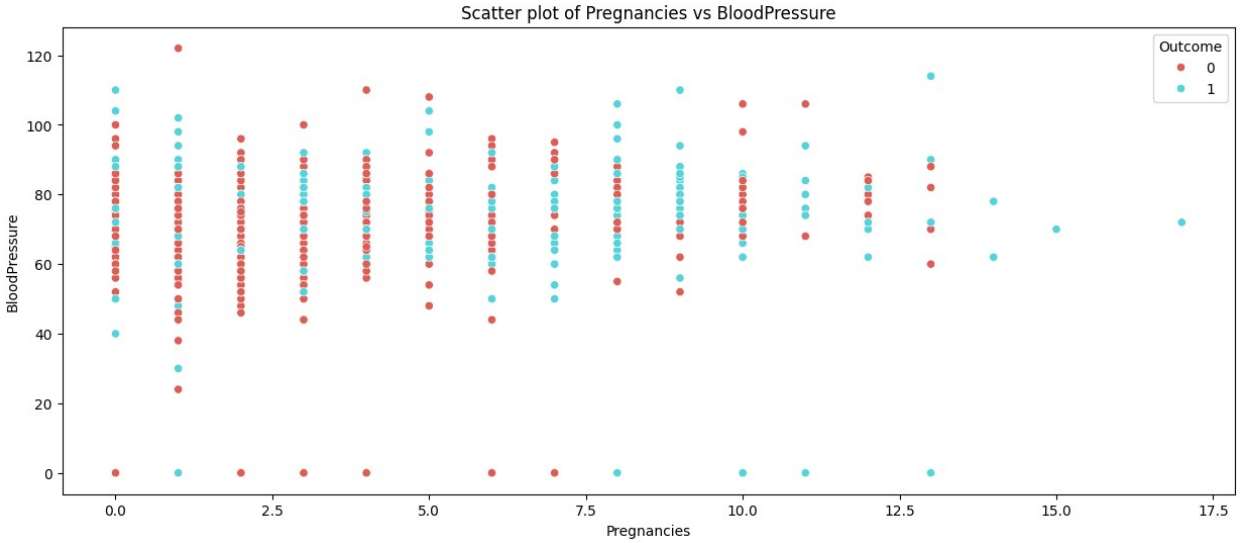

Scatter plot of BMI vs DiabetesPedigreeFunction
DiabetesPedigreeFunction
BMI
2.5
2.0
1.5
1.0
0.5
0.0
0
10
20
30
40
50
60
70

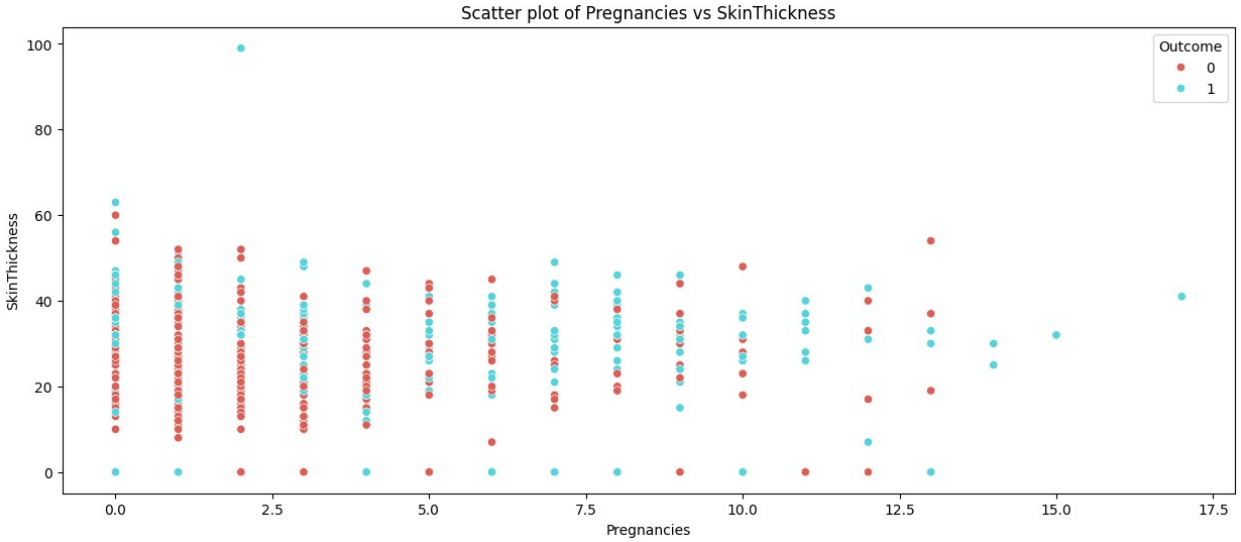

Scatter plot of BMI vs Age
Age
BMI
80
70
60
50
40
30
20
0
10
20
30
40
50
60
70

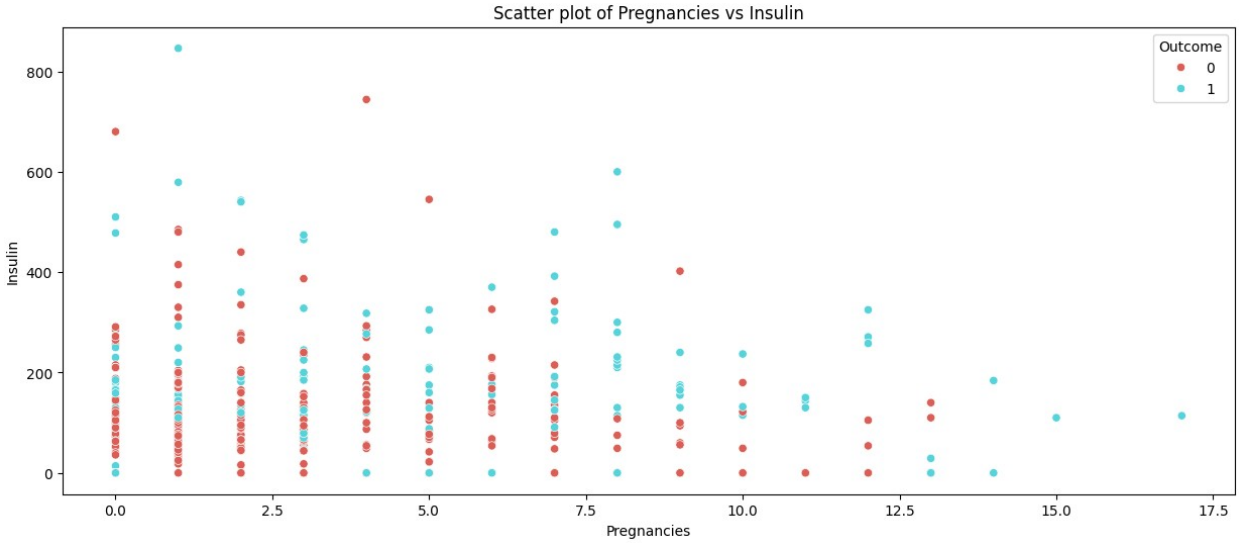


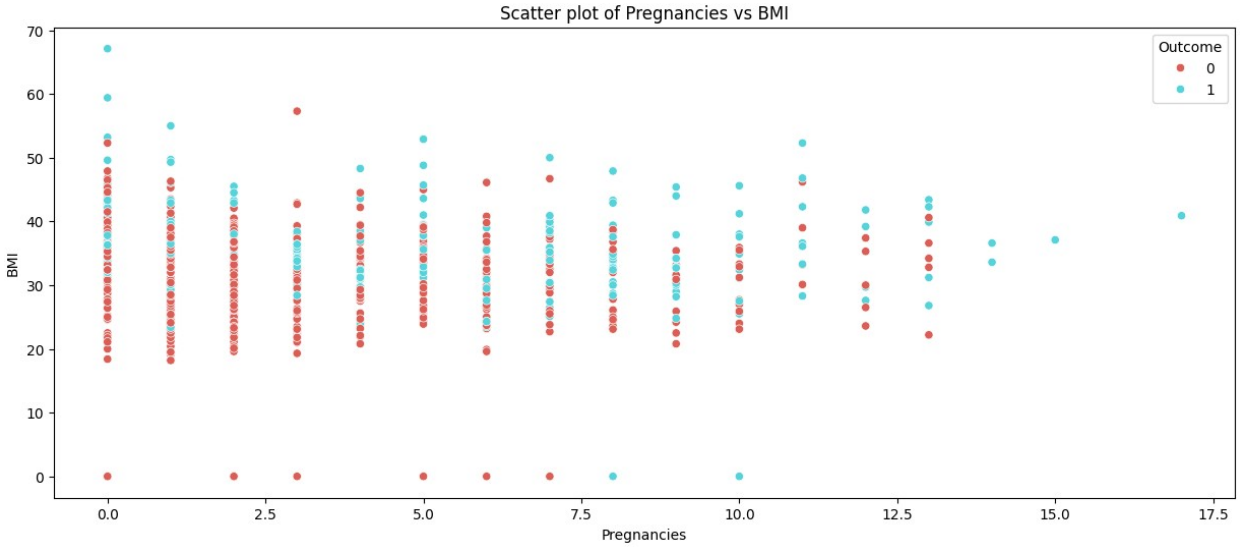

```
for i in range(len(continuous)):
    for j in range(i + 1, len(continuous)):
        plt.figure(figsize=(15, 6))
        sns.scatterplot(x=continuous[i], y=continuous[j], data=df, hue
= 'Outcome', palette='hls')
        plt.title(f'Scatter plot of {continuous[i]} vs
{continuous[j]}')
        plt.show()
```

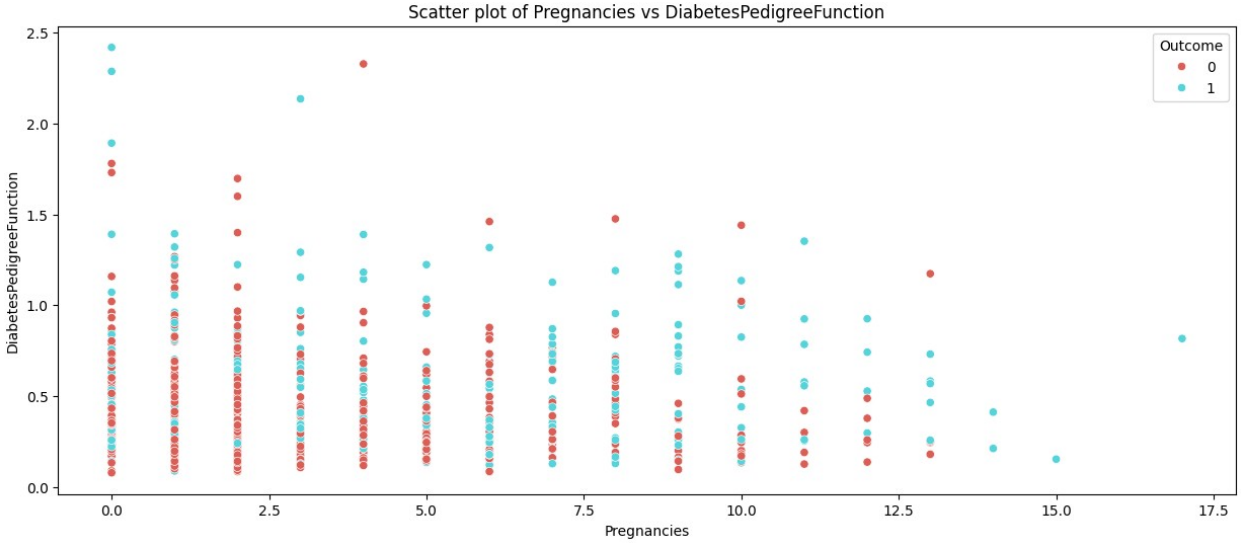


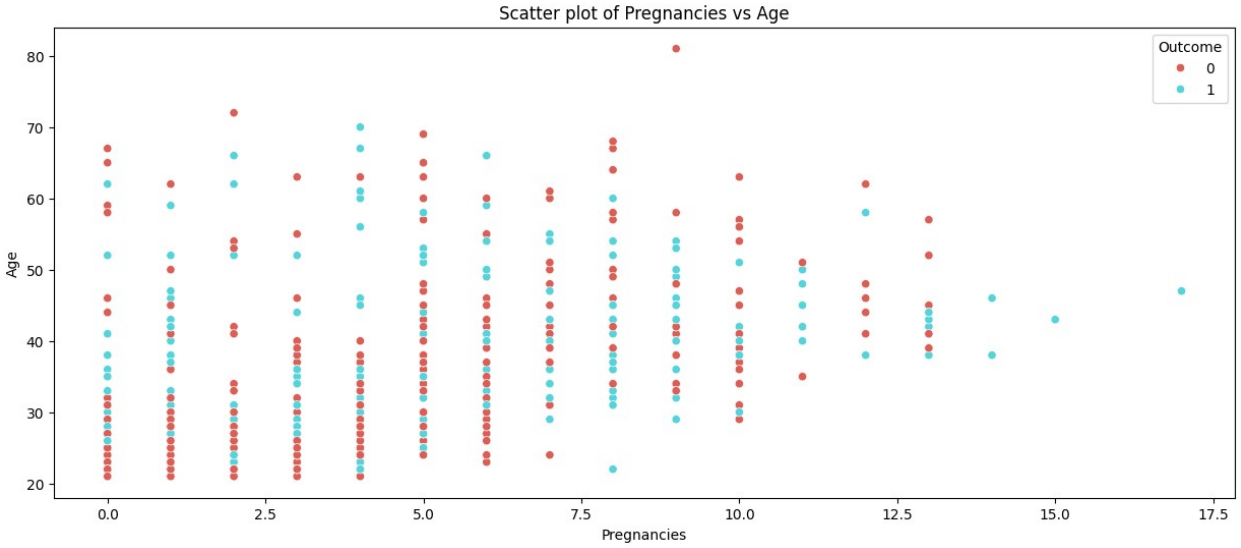

Scatter plot of Pregnancies vs BloodPressure
Outcome
0
1
BloodPressure
Pregnancies
0
20
40
60
80
100
120
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5

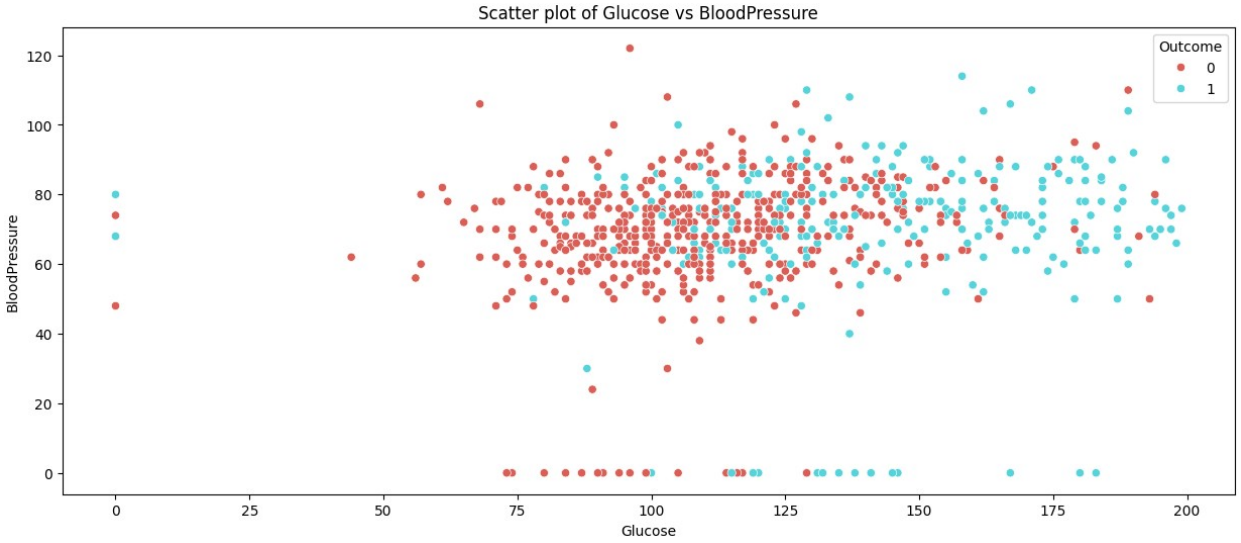

Scatter plot of Pregnancies vs SkinThickness
Outcome
0
1
SkinThickness
Pregnancies
0
20
40
60
80
100
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5


Scatter plot of Pregnancies vs Insulin
Outcome
0
1
Insulin
Pregnancies
0
200
400
600
800
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5

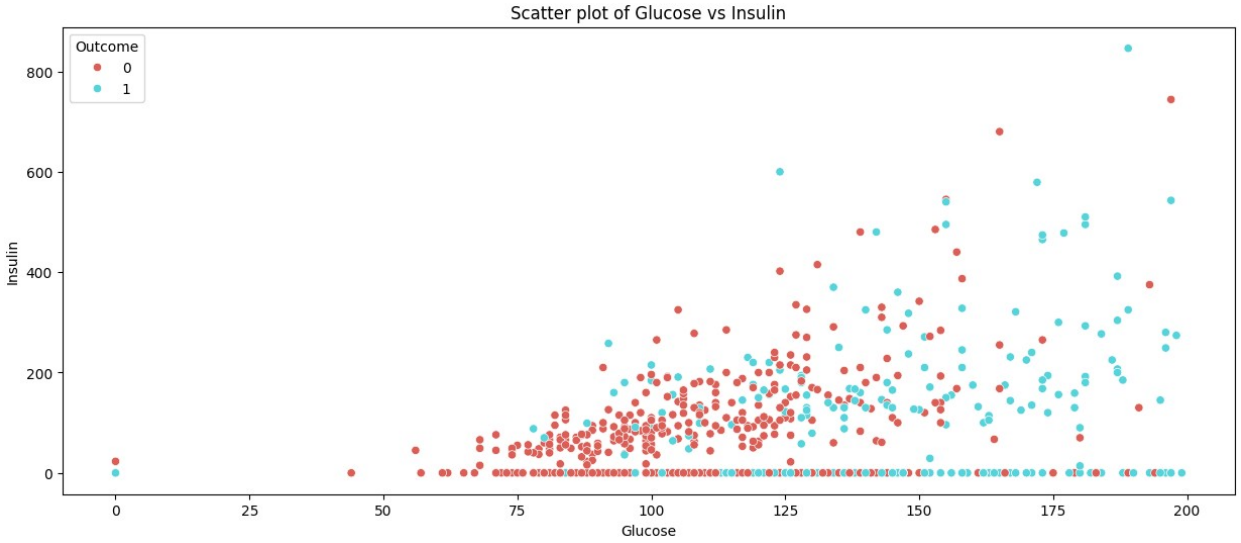

Scatter plot of Pregnancies vs BMI
Outcome
0
1
BMI
Pregnancies

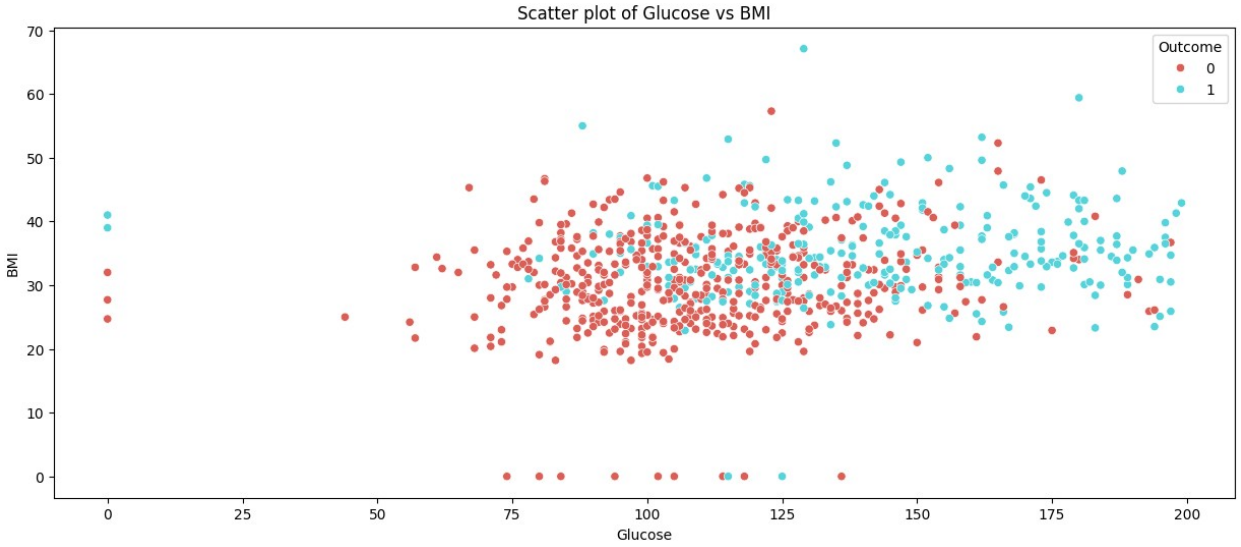

Scatter plot of Pregnancies vs DiabetesPedigreeFunction
Outcome
0
1
DiabetesPedigreeFunction
Pregnancies


Scatter plot of Pregnancies vs Age
Outcome
0
1
Age
Pregnancies

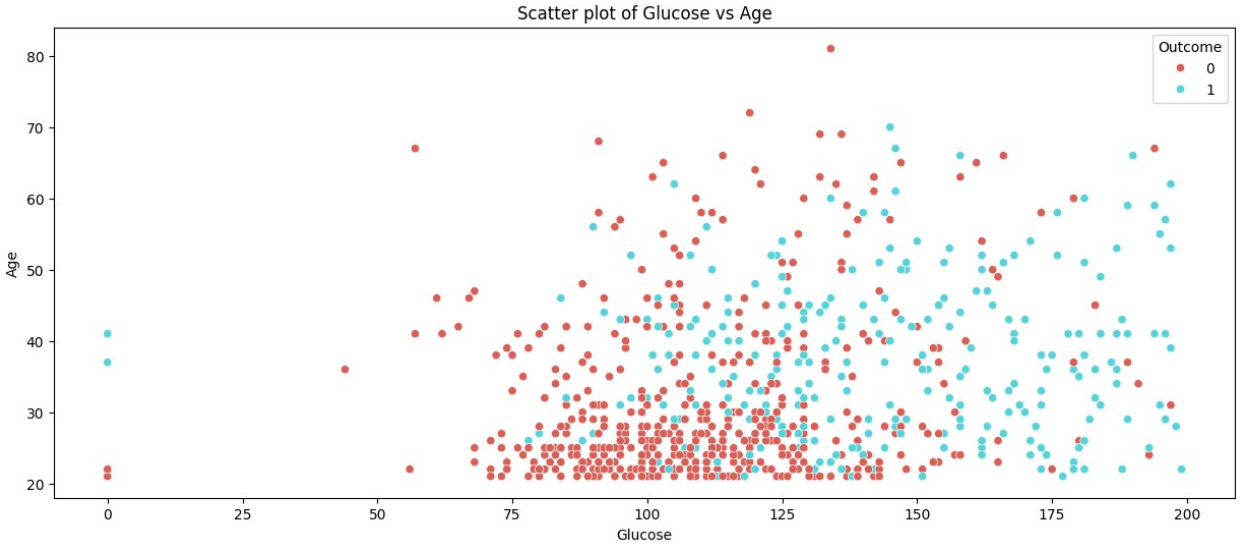

Scatter plot of Glucose vs BloodPressure
Outcome
0
1
BloodPressure
Glucose
0
20
40
60
80
100
120
0
25
50
75
100
125
150
175
200


Scatter plot of Glucose vs SkinThickness
Outcome
0
1
SkinThickness
Glucose
0
20
40
60
80
100
0
25
50
75
100
125
150
175
200

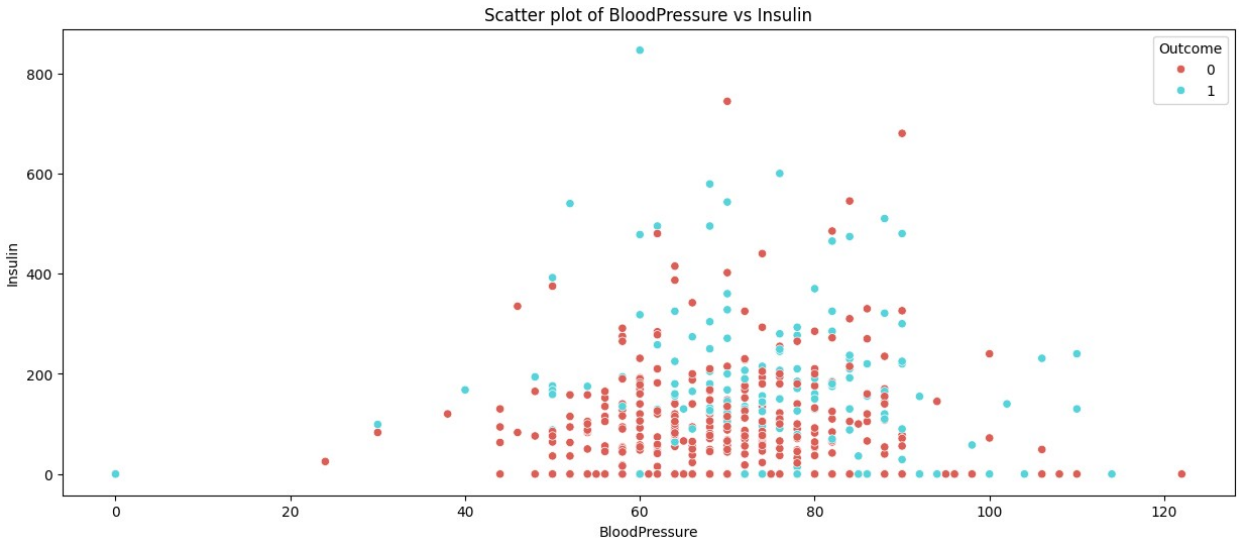

Scatter plot of Glucose vs Insulin
Outcome
0
1
Insulin
Glucose
0
200
400
600
800
0
25
50
75
100
125
150
175
200

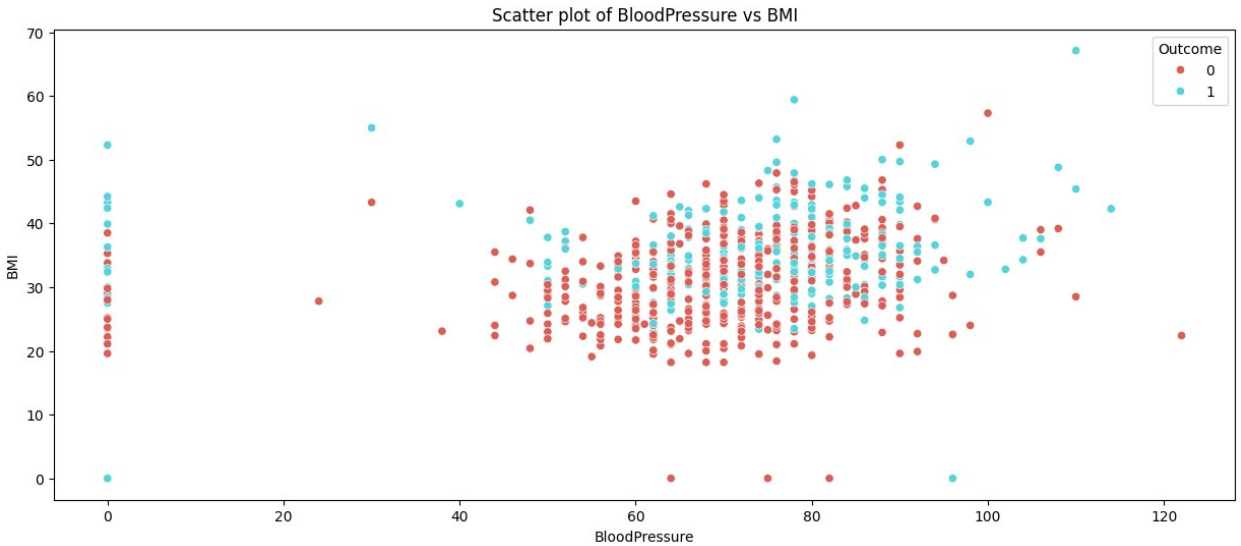

Scatter plot of Glucose vs BMI
Outcome
0
1
BMI
Glucose
0
10
20
30
40
50
60
70
0
25
50
75
100
125
150
175
200

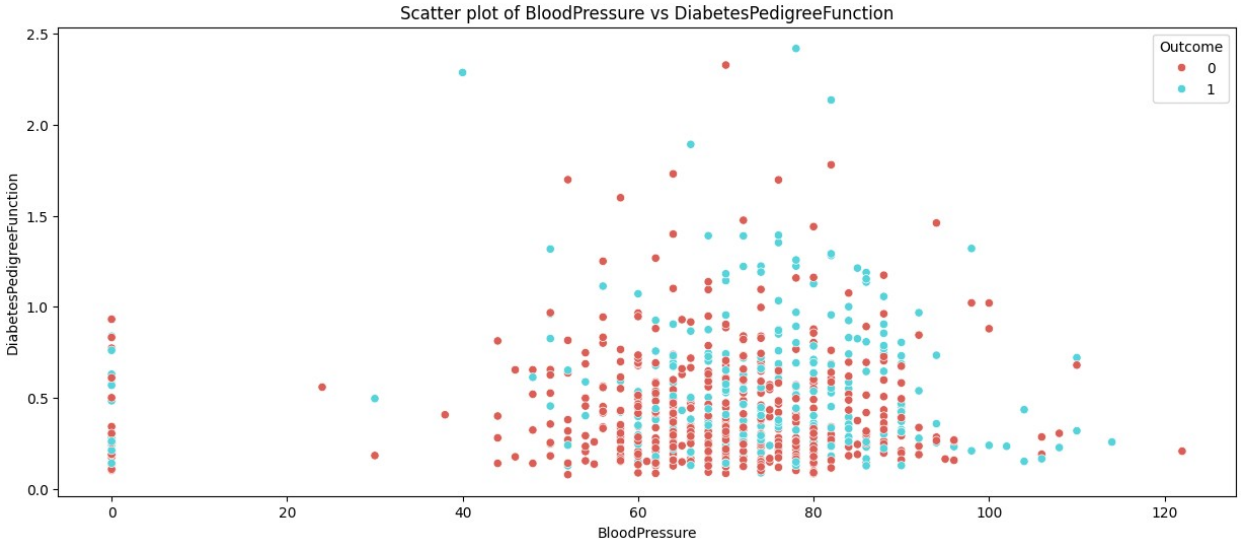

Scatter plot of Glucose vs DiabetesPedigreeFunction
Outcome
0
1
DiabetesPedigreeFunction
Glucose
0.0
0.5
1.0
1.5
2.0
2.5
0
25
50
75
100
125
150
175
200


Scatter plot of Glucose vs Age
Outcome
0
1
Age
Glucose
20
30
40
50
60
70
80
0
25
50
75
100
125
150
175
200

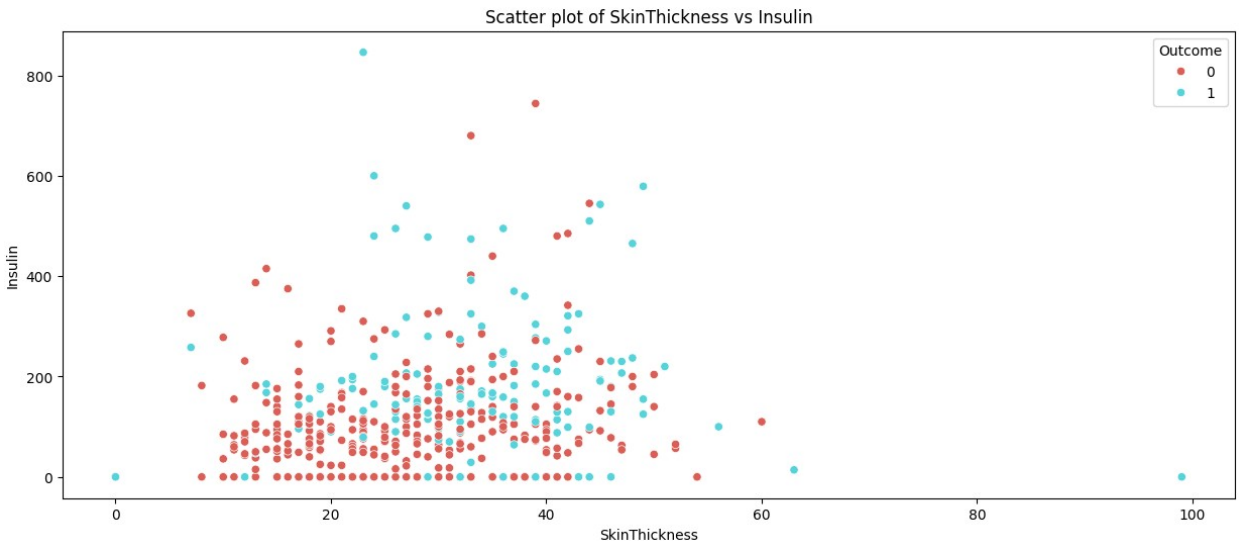

Scatter plot of BloodPressure vs SkinThickness
Outcome
0
1
SkinThickness
BloodPressure
0
20
40
60
80
100
120

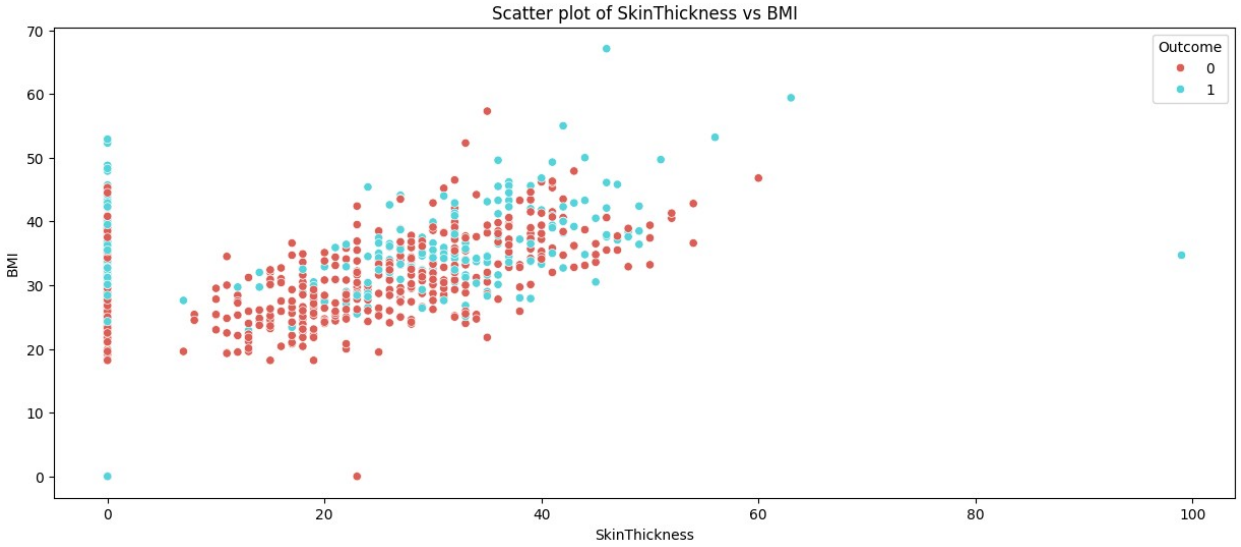

Scatter plot of BloodPressure vs Insulin
Outcome
0
1
Insulin
BloodPressure
0
200
400
600
800
0
20
40
60
80
100
120

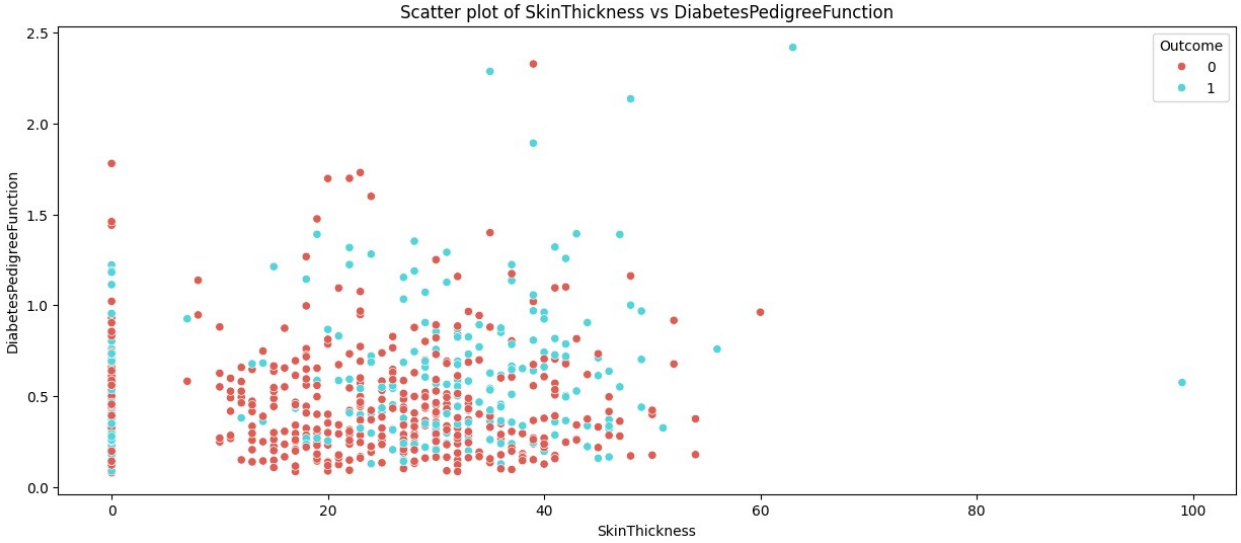

Scatter plot of BloodPressure vs BMI
Outcome
0
1
BMI
BloodPressure
0
10
20
30
40
50
60
70
0
20
40
60
80
100
120

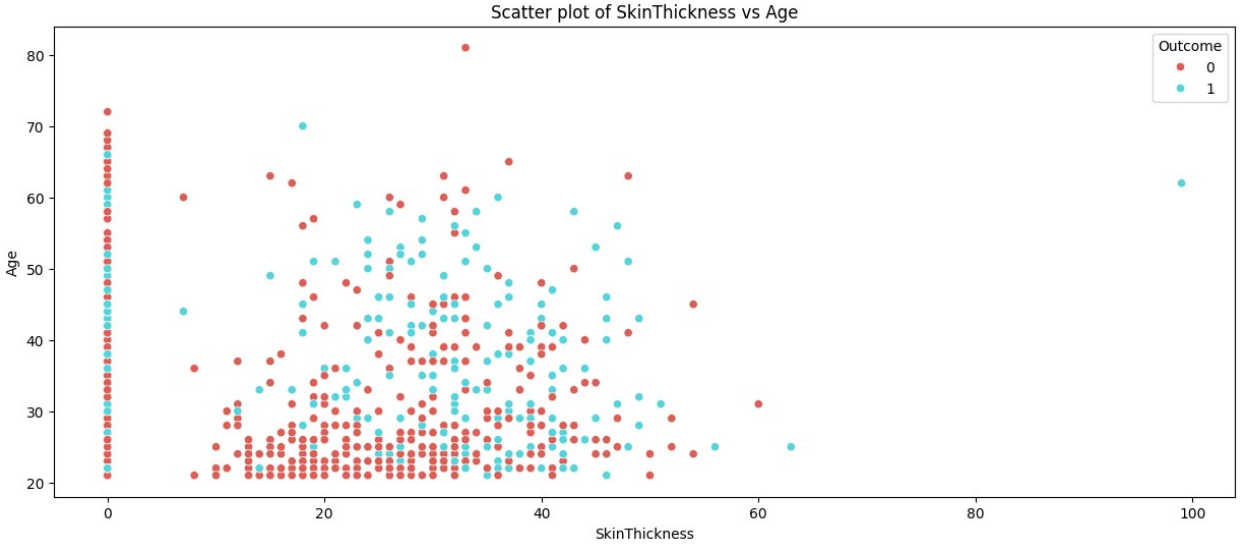

Scatter plot of BloodPressure vs DiabetesPedigreeFunction
Outcome
0
1
DiabetesPedigreeFunction
BloodPressure
0.0
0.5
1.0
1.5
2.0
2.5
0
20
40
60
80
100
120

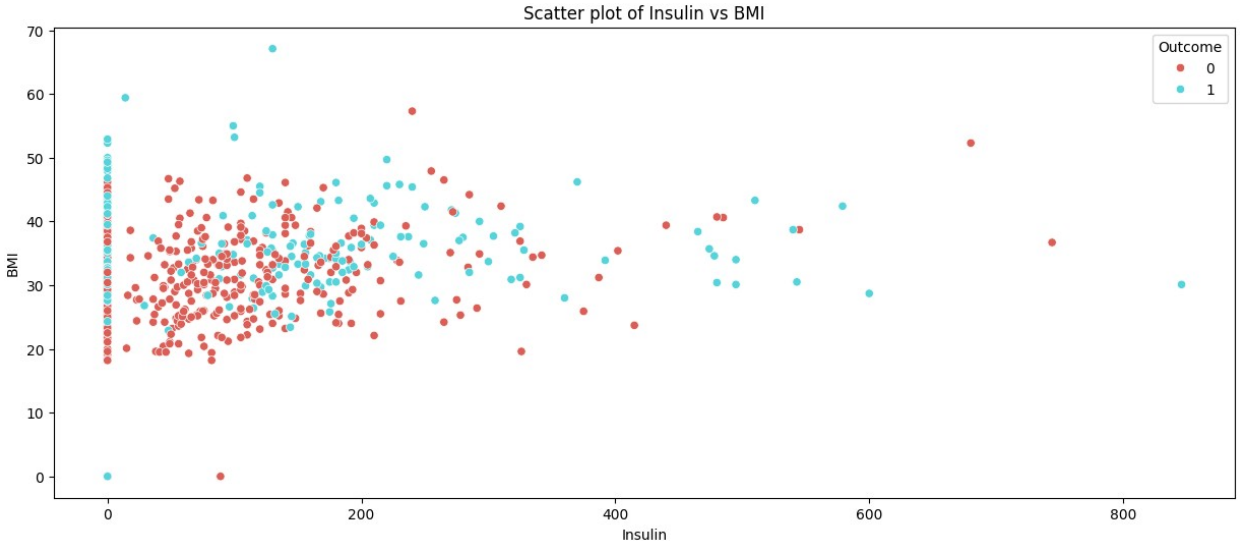

Scatter plot of BloodPressure vs Age
Outcome
0
1
Age
BloodPressure
20
30
40
50
60
70
80
0
20
40
60
80
100
120

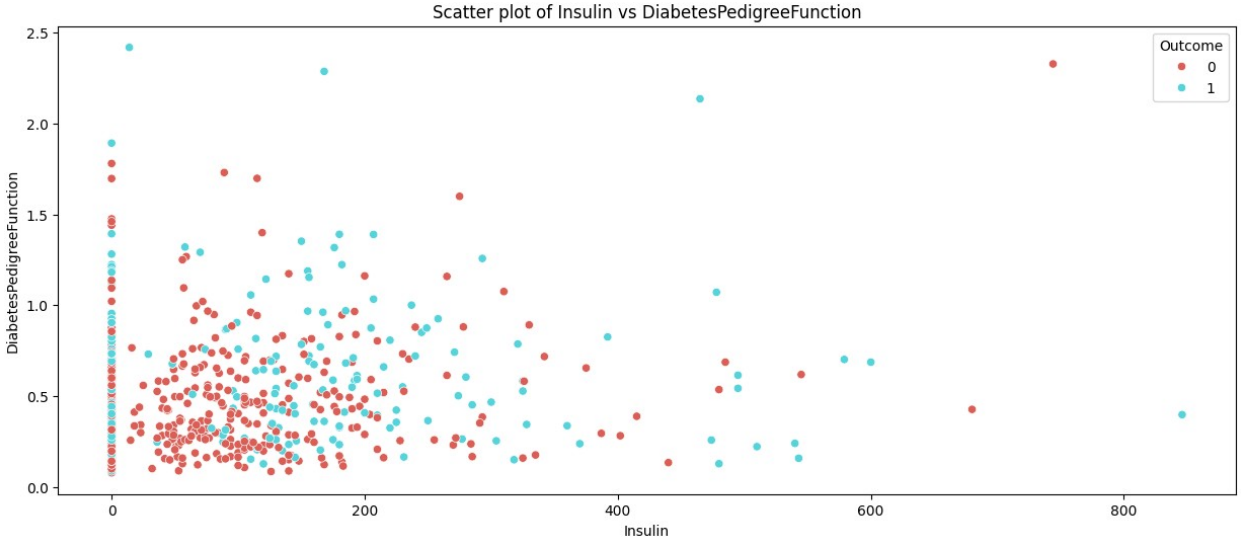

Scatter plot of SkinThickness vs Insulin
Outcome
0
1
Insulin
SkinThickness
0
200
400
600
800
0
20
40
60
80
100

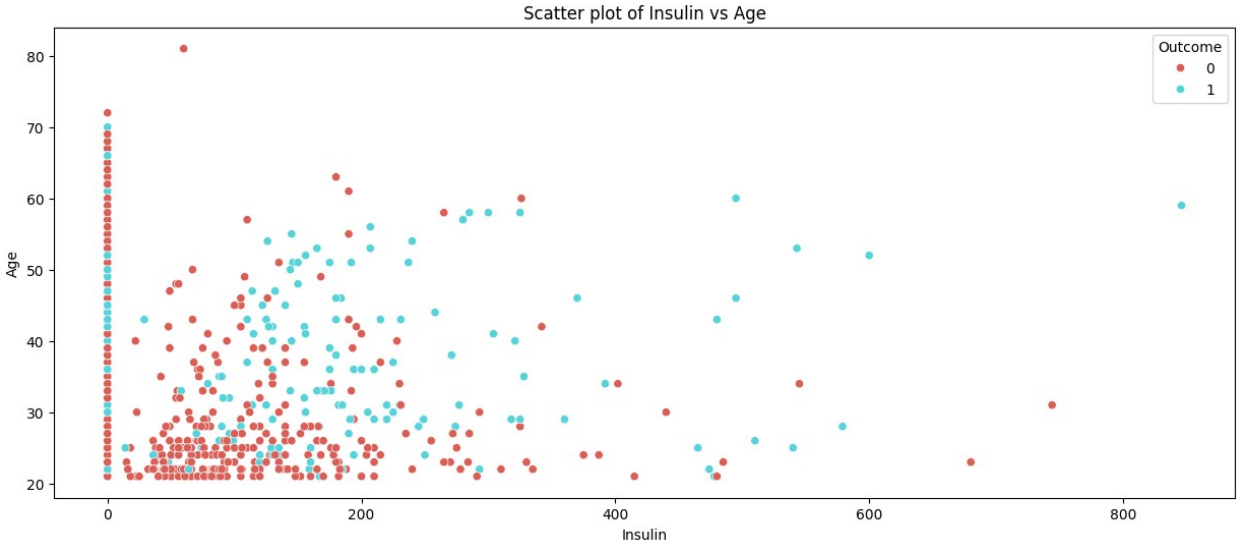

Scatter plot of SkinThickness vs BMI
Outcome
0
1
BMI
SkinThickness
0
10
20
30
40
50
60
70
0
20
40
60
80
100


Scatter plot of SkinThickness vs DiabetesPedigreeFunction
Outcome
0
1
DiabetesPedigreeFunction
SkinThickness
0.0
0.5
1.0
1.5
2.0
2.5
0
20
40
60
80
100


Scatter plot of SkinThickness vs Age
Outcome
0
1
Age
SkinThickness
20
30
40
50
60
70
80
0
20
40
60
80
100

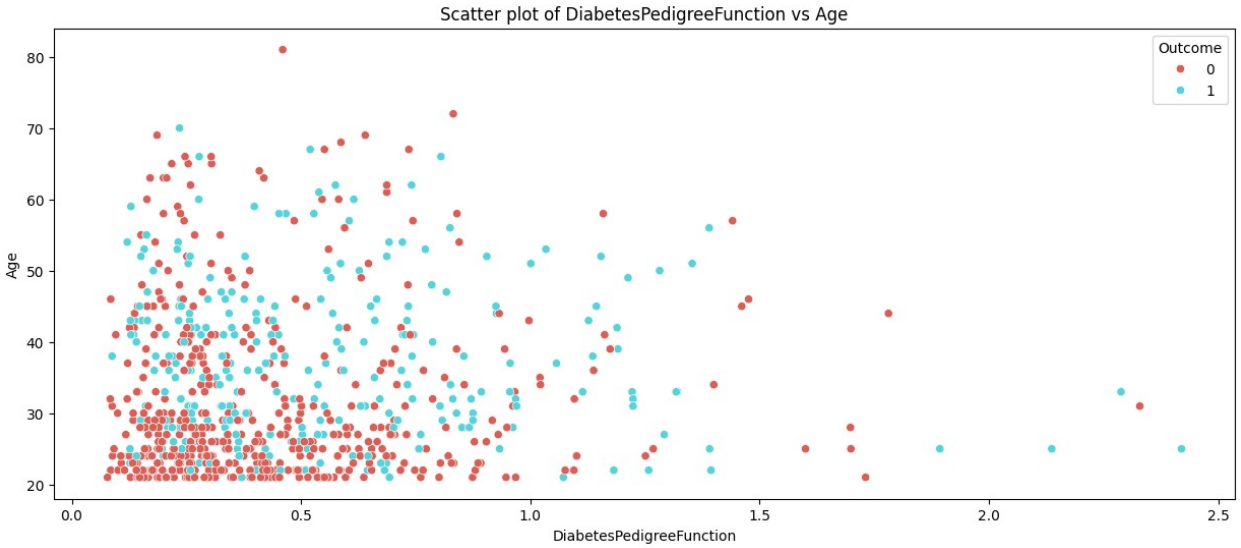

Scatter plot of Insulin vs BMI
Outcome
0
1
BMI
Insulin
0
10
20
30
40
50
60
70
0
200
400
600
800


Scatter plot of Insulin vs DiabetesPedigreeFunction
Outcome
0
1
DiabetesPedigreeFunction
Insulin
0.0
0.5
1.0
1.5
2.0
2.5
0
200
400
600
800

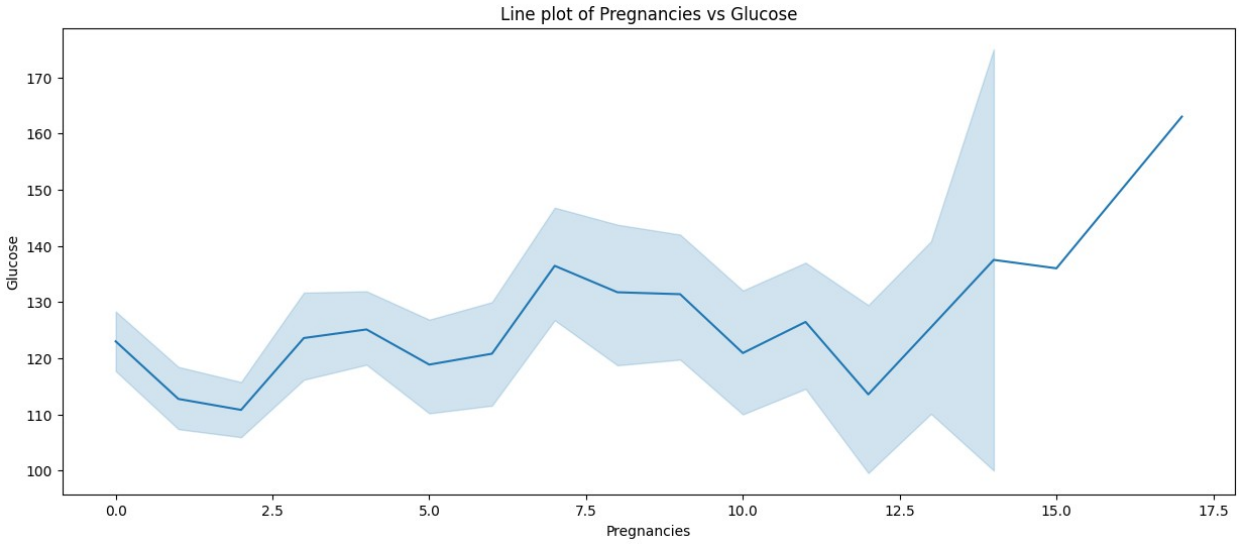

Scatter plot of Insulin vs Age
Outcome
0
1
Age
Insulin
20
30
40
50
60
70
80
0
200
400
600
800

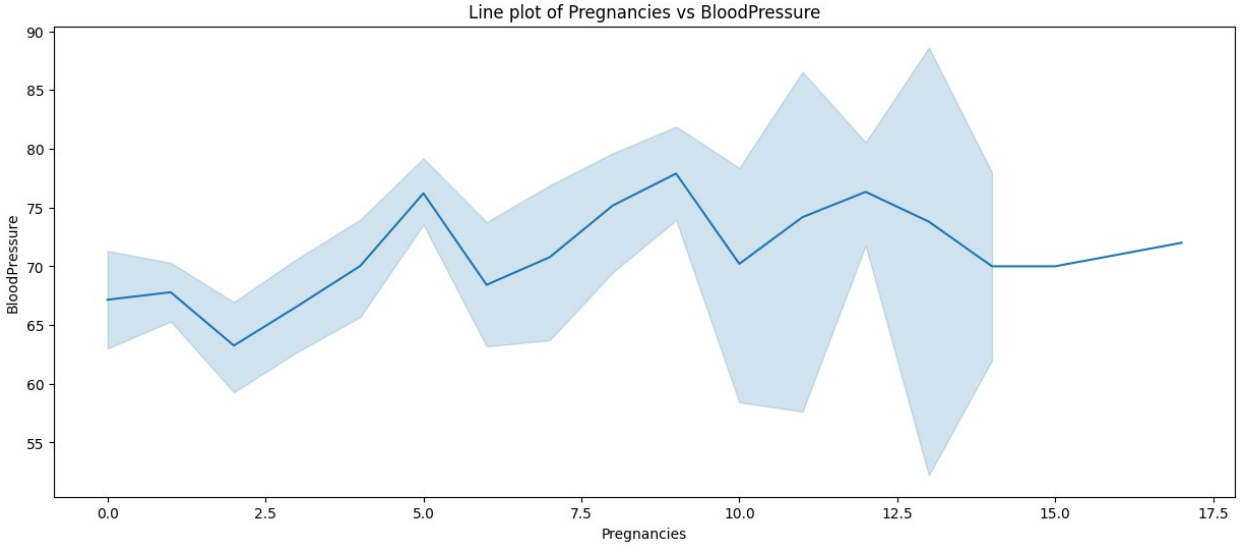

Scatter plot of BMI vs DiabetesPedigreeFunction
Outcome
0
1
DiabetesPedigreeFunction
BMI
0.0
0.5
1.0
1.5
2.0
2.5
0
10
20
30
40
50
60
70

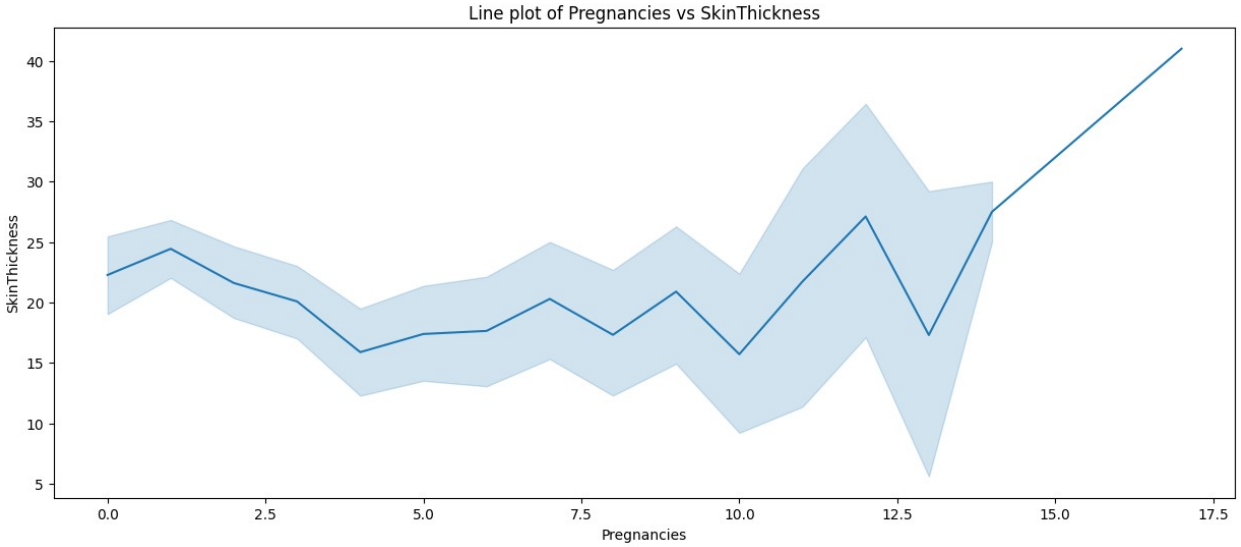

Scatter plot of BMI vs Age
Outcome
0
1
Age
BMI
20
30
40
50
60
70
80
0
10
20
30
40
50
60
70

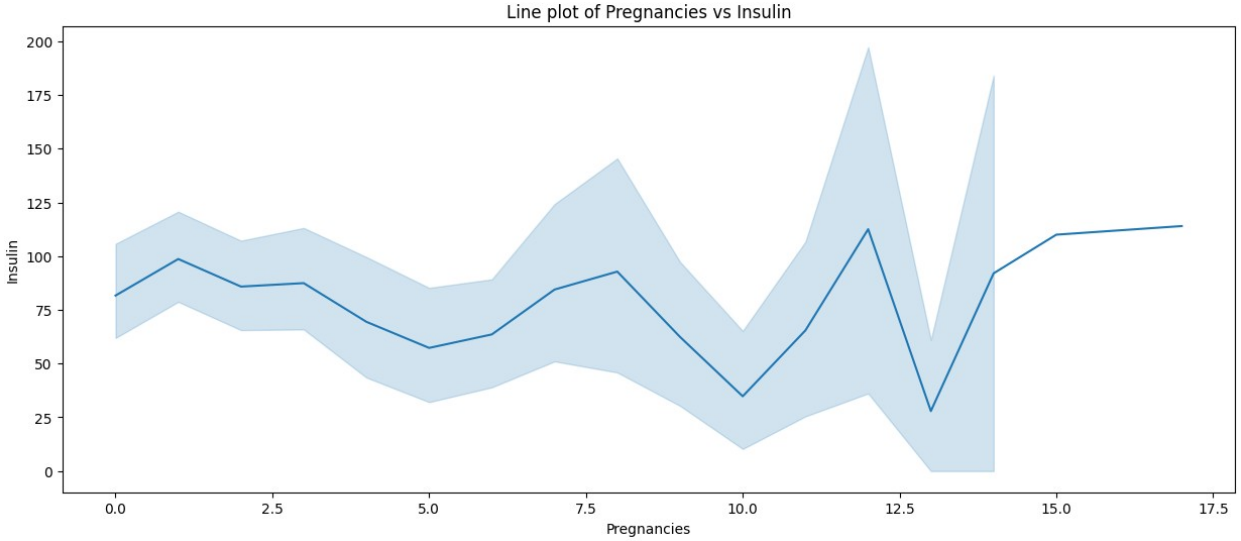

Scatter plot of DiabetesPedigreeFunction vs Age
Outcome
0
1
Age
DiabetesPedigreeFunction
20
30
40
50
60
70
80
0.0
0.5
1.0
1.5
2.0
2.5

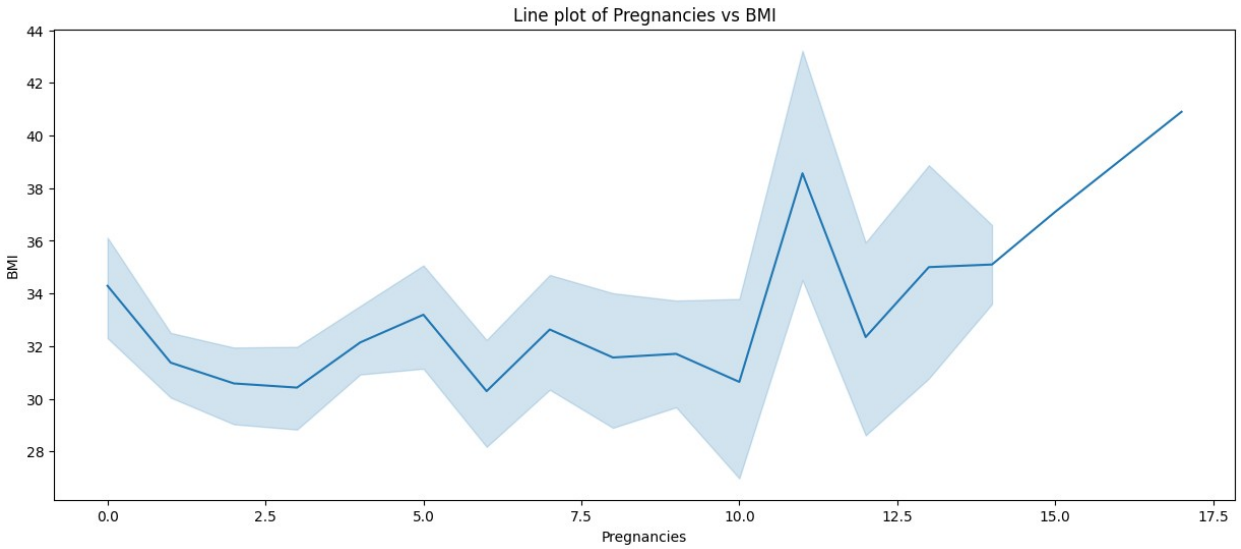
```
for i in range(len(continuous)):
    for j in range(i + 1, len(continuous)):
        plt.figure(figsize=(15, 6))
        sns.lineplot(x=continuous[i], y=continuous[j], data=df,
palette='hls')
        plt.title(f'Line plot of {continuous[i]} vs {continuous[j]}')
        plt.show()
```

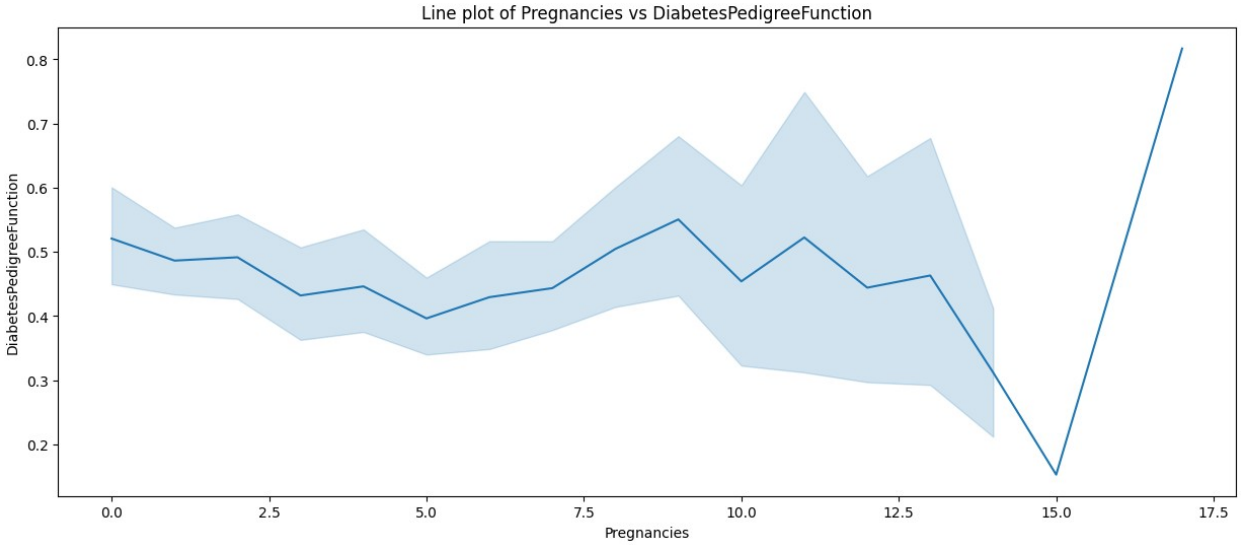


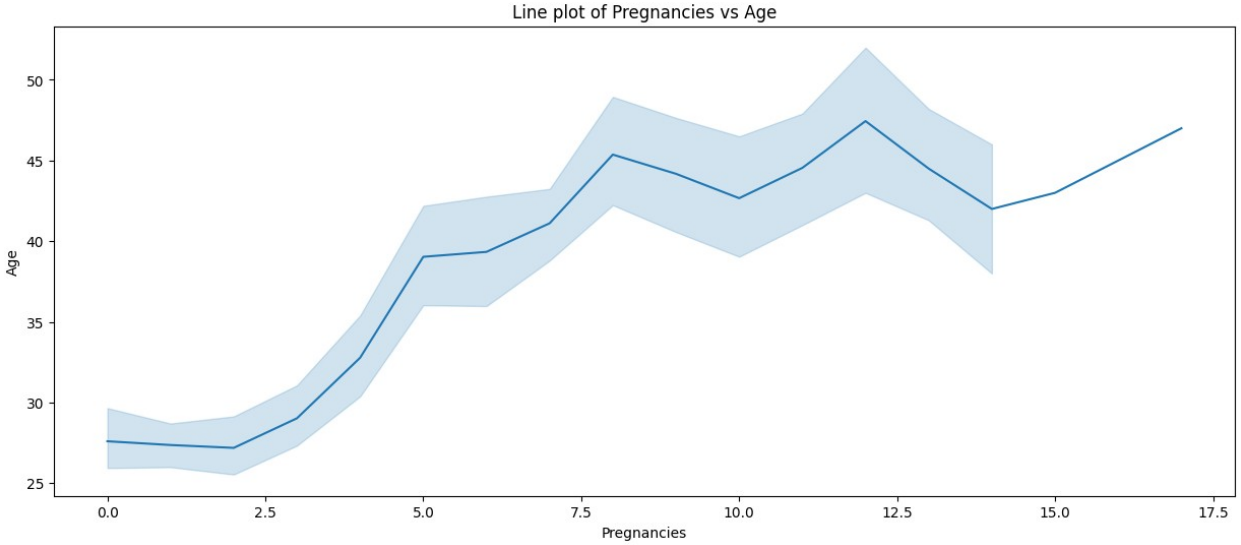


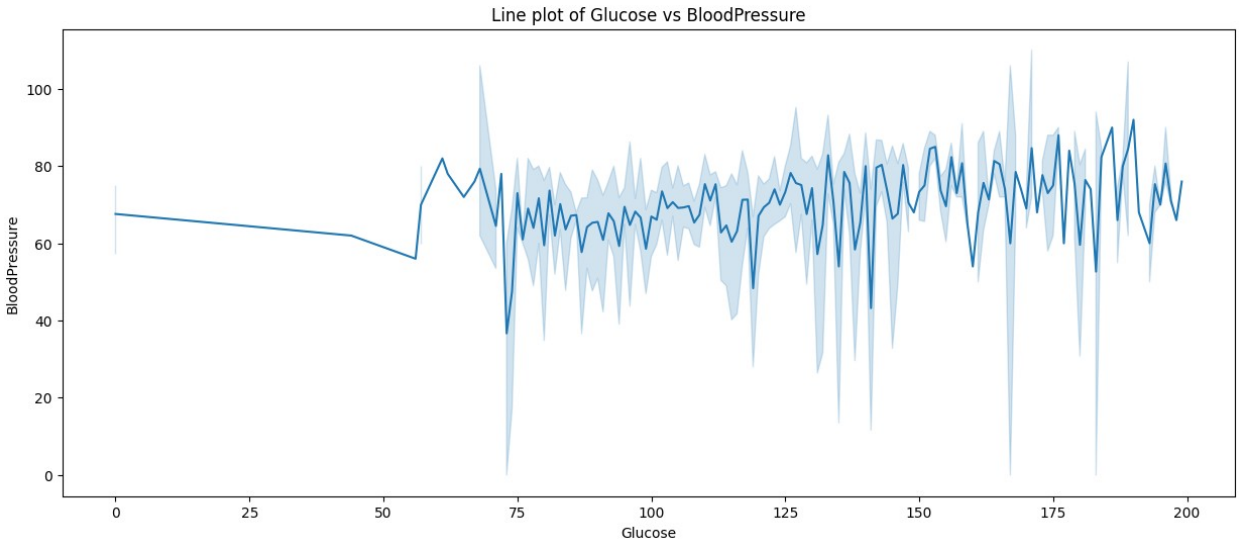

Line plot of Pregnancies vs SkinThickness
SkinThickness
Pregnancies
40
35
30
25
20
15
10
5
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5

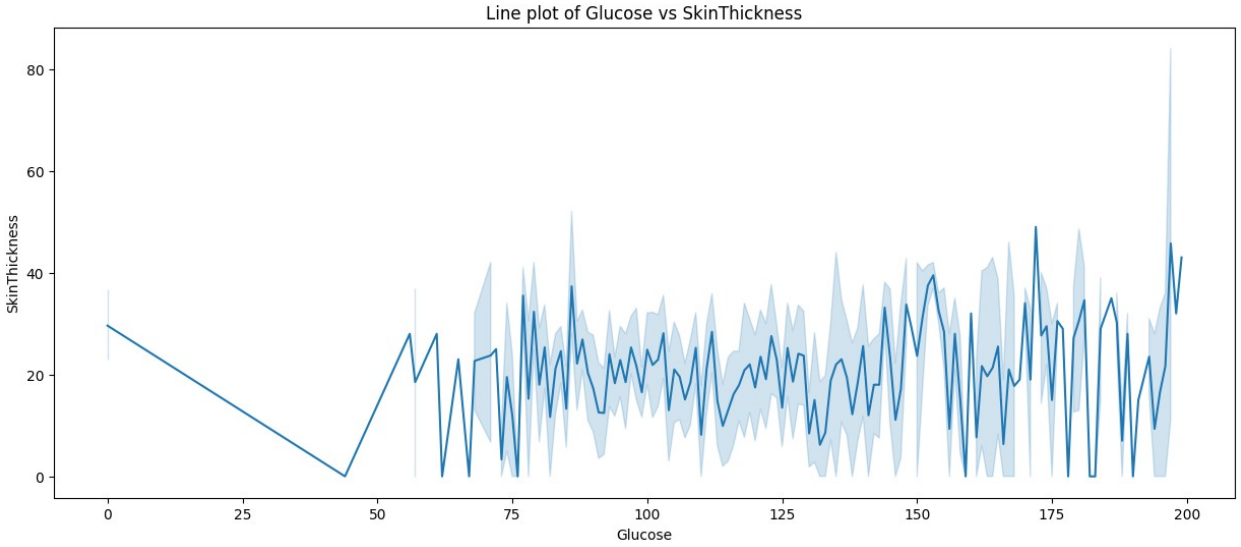

Line plot of Pregnancies vs Insulin
Insulin
Pregnancies
200
175
150
125
100
75
50
25
0
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5

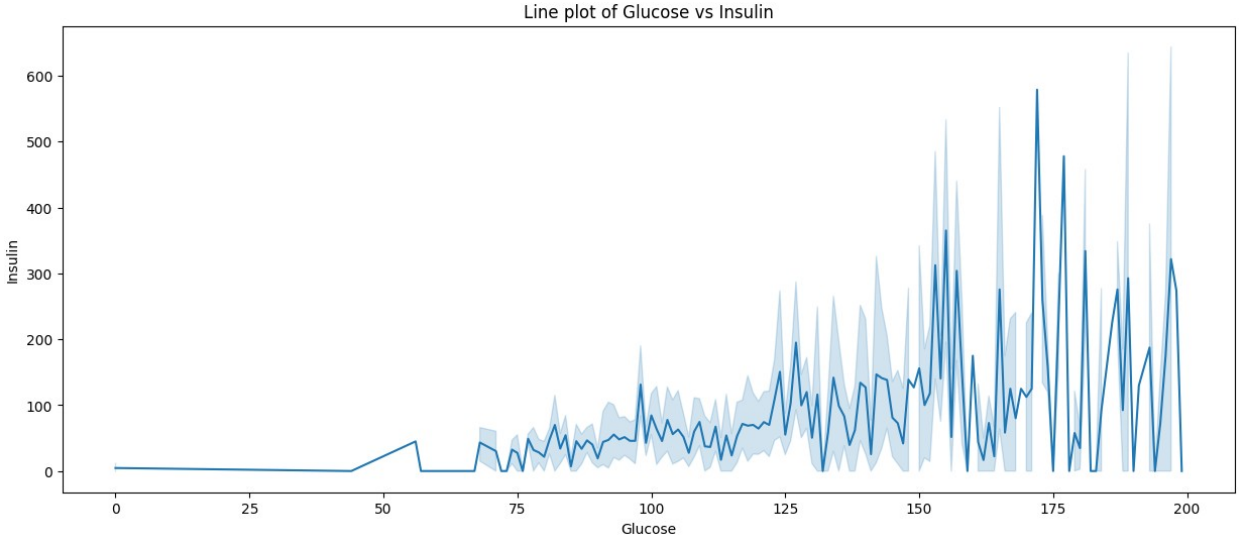

Line plot of Pregnancies vs BMI
BMI
Pregnancies
44
42
40
38
36
34
32
30
28
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5

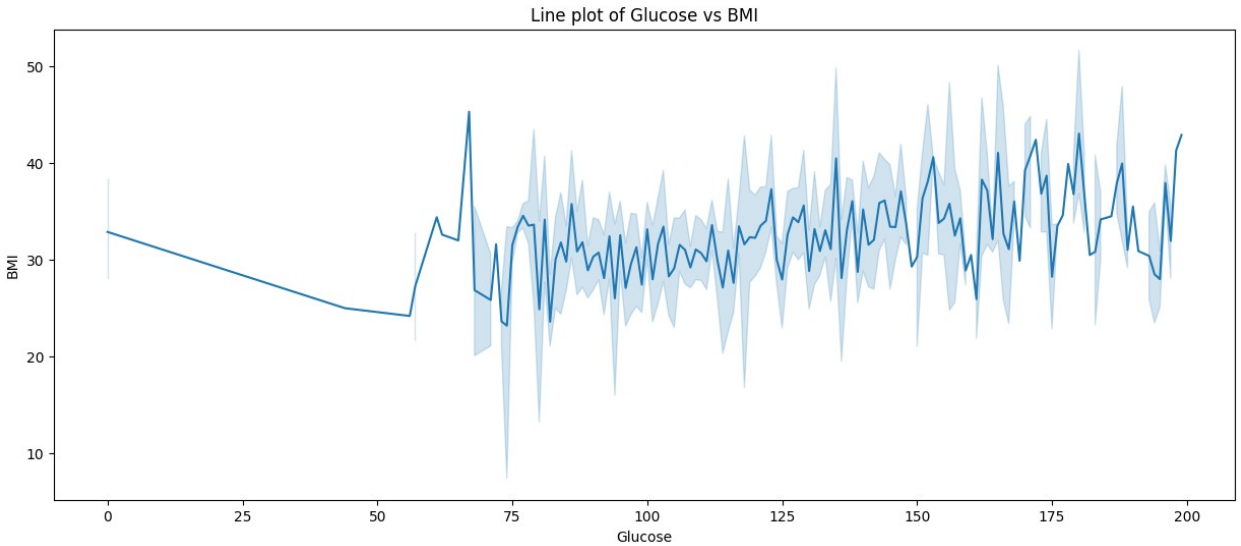

Line plot of Pregnancies vs DiabetesPedigreeFunction
DiabetesPedigreeFunction
Pregnancies
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5

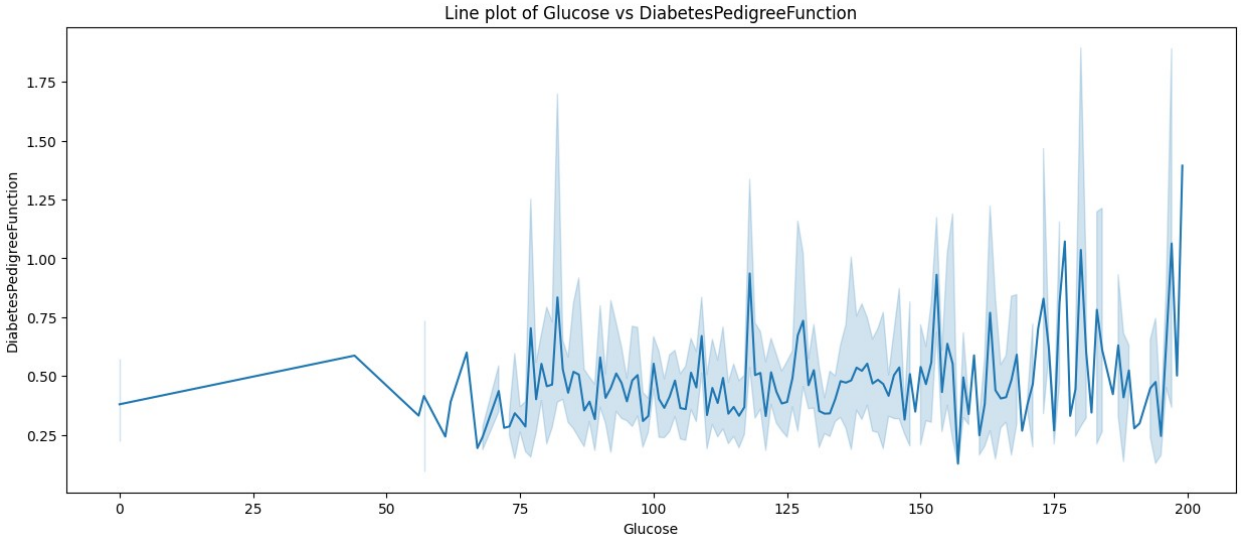

Line plot of Pregnancies vs Age
Age
Pregnancies
25
30
35
40
45
50
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5

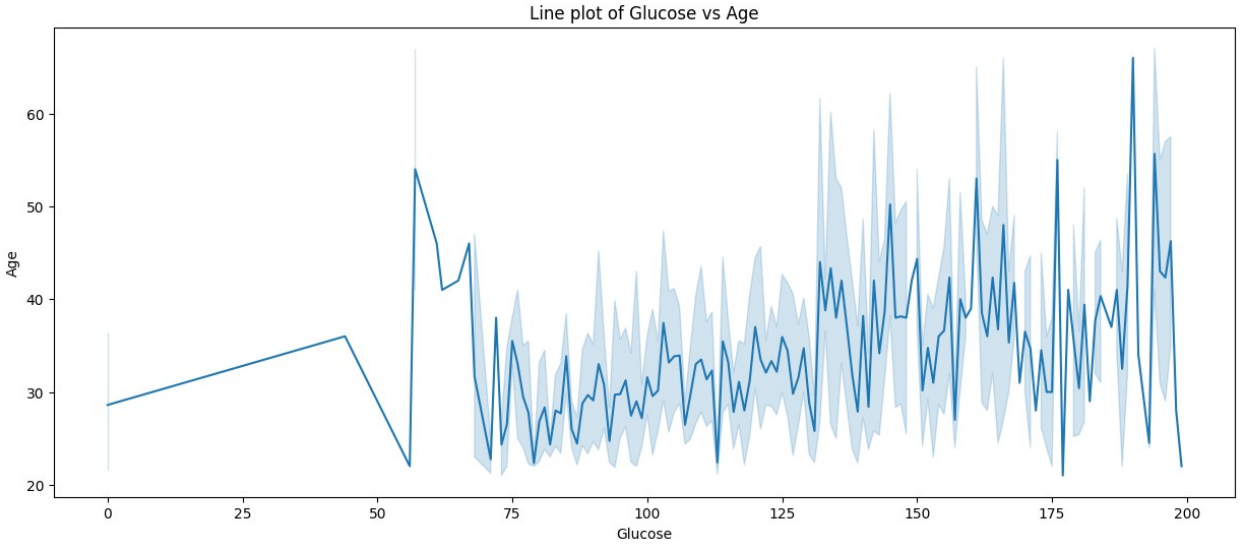

Line plot of Glucose vs BloodPressure
BloodPressure
Glucose
0
20
40
60
80
100
0
25
50
75
100
125
150
175
200

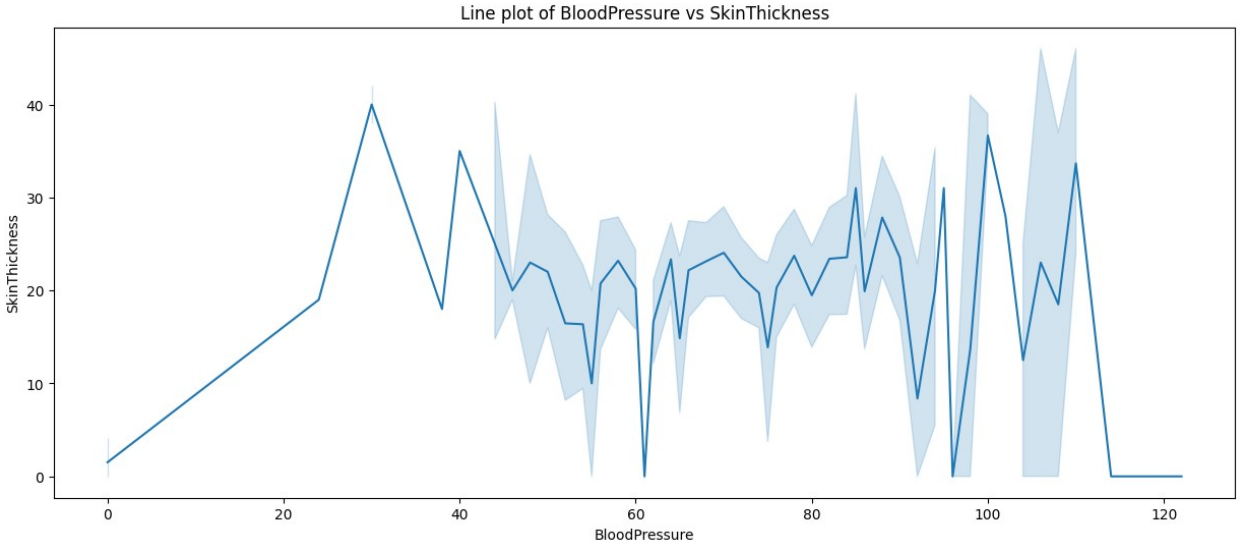

Line plot of Glucose vs SkinThickness
SkinThickness
Glucose
0
20
40
60
80
0
25
50
75
100
125
150
175
200

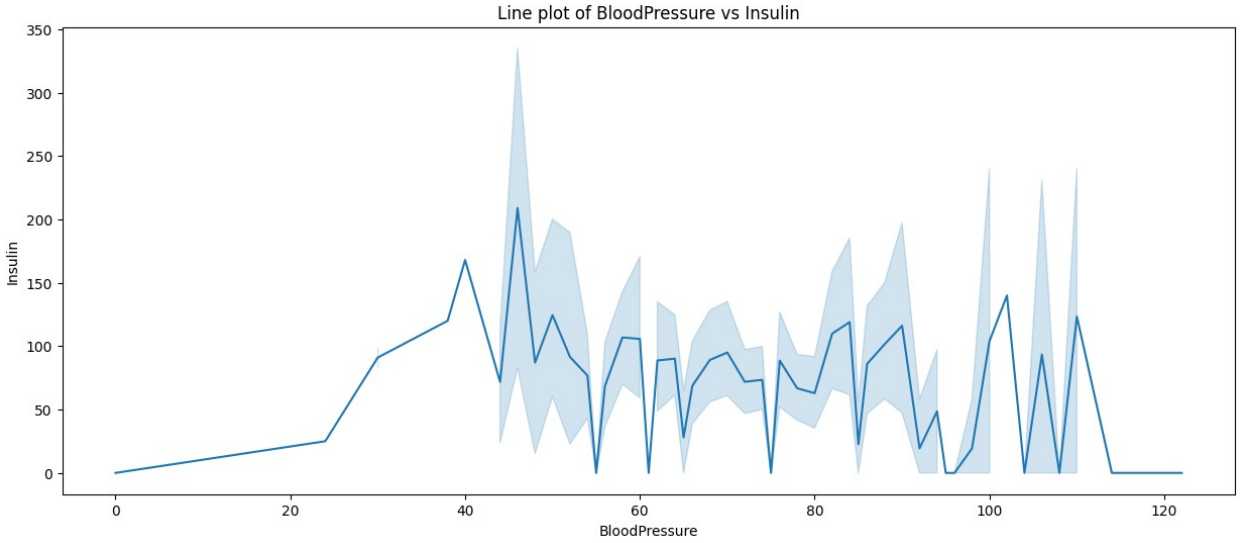

Line plot of Glucose vs Insulin
Insulin
Glucose
0
100
200
300
400
500
600
0
25
50
75
100
125
150
175
200

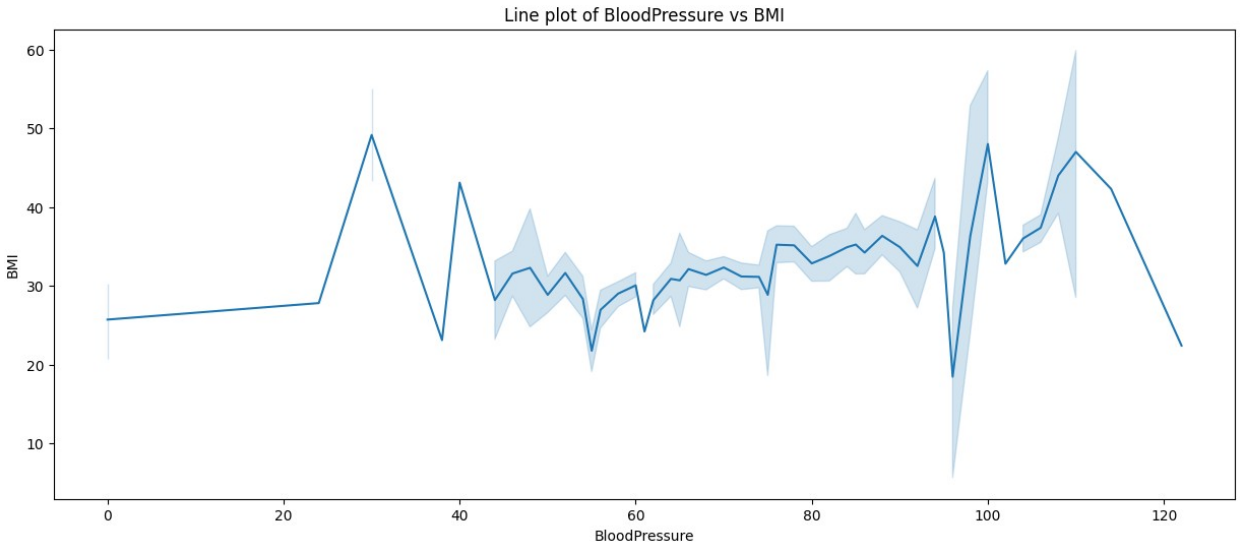

Line plot of Glucose vs BMI
BMI
Glucose
10
20
30
40
50
0
25
50
75
100
125
150
175
200

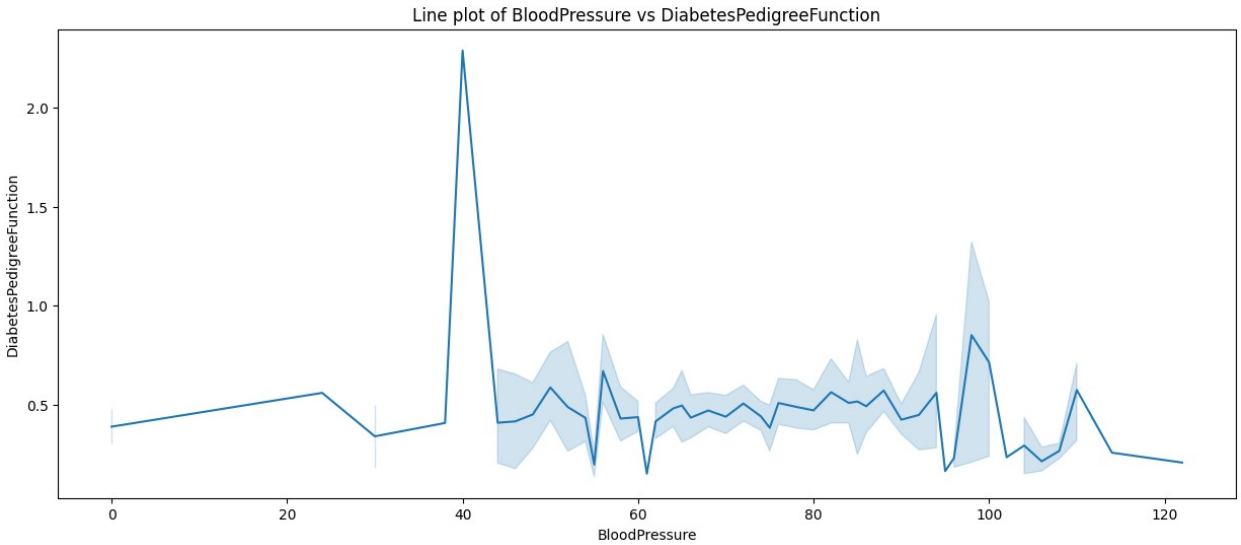

Line plot of Glucose vs DiabetesPedigreeFunction
DiabetesPedigreeFunction
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0
25
50
75
100
125
150
175
200
Glucose

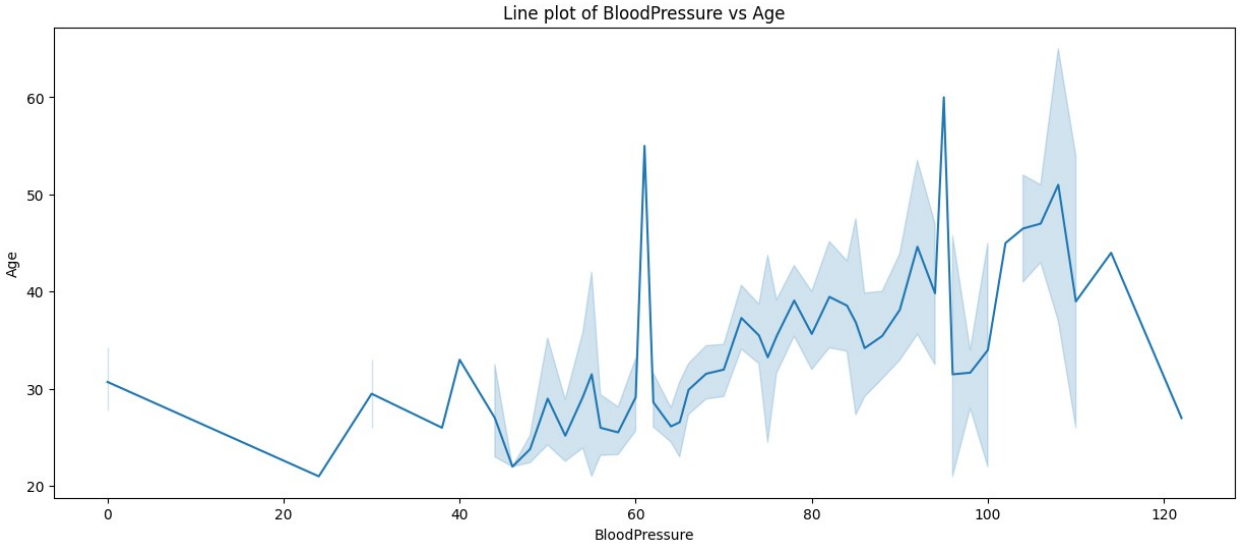

Line plot of Glucose vs Age
Age
60
50
40
30
20
0
25
50
75
100
125
150
175
200
Glucose

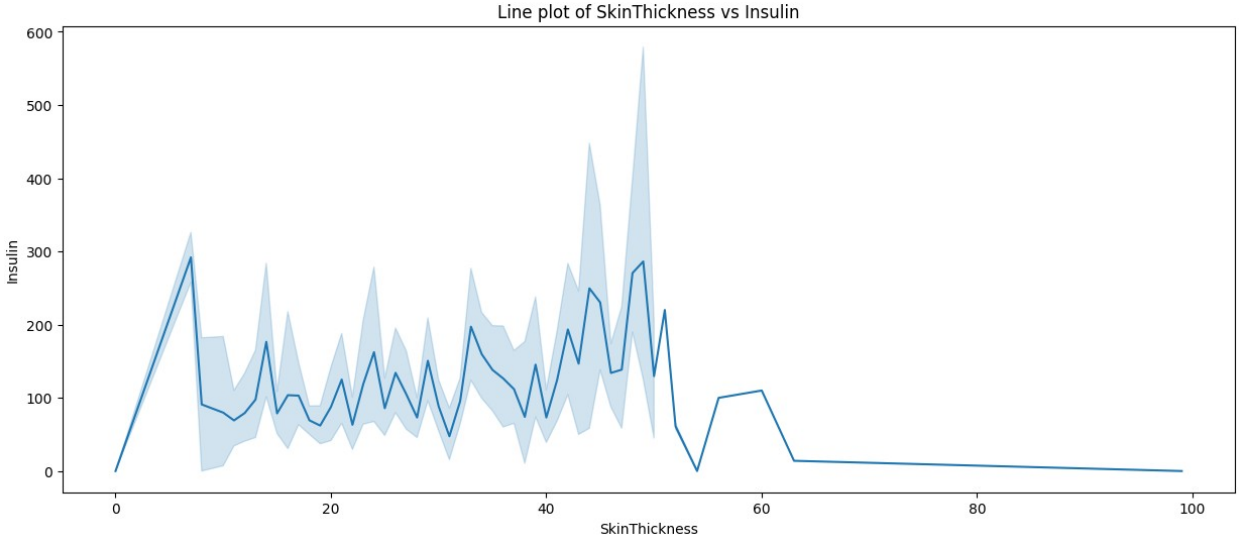

Line plot of BloodPressure vs SkinThickness
SkinThickness
40
30
20
10
0
0
20
40
60
80
100
120
BloodPressure

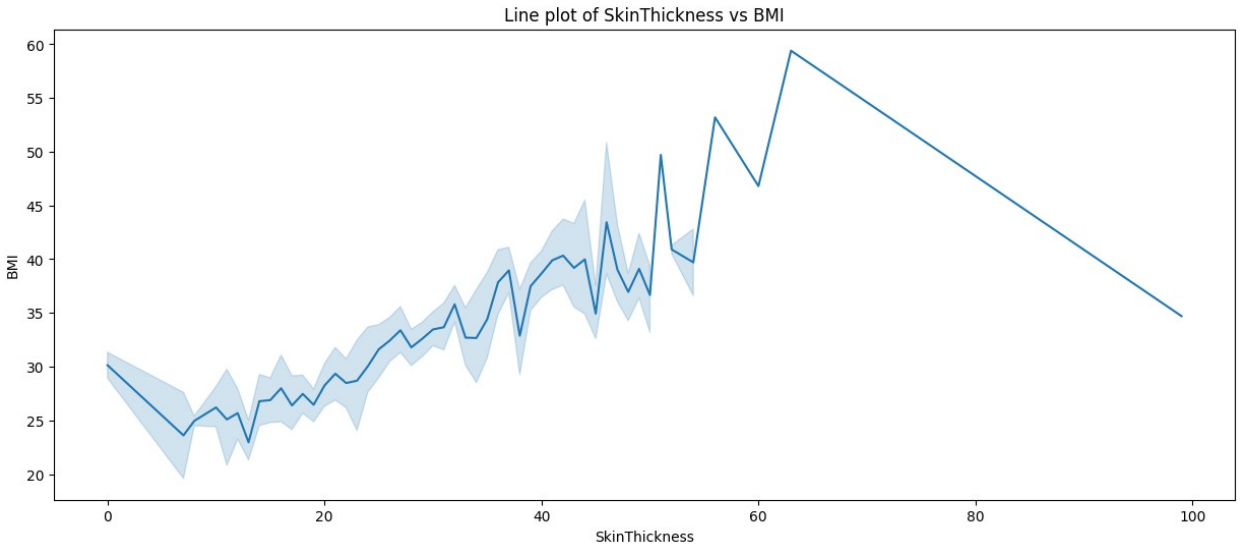

Line plot of BloodPressure vs Insulin
Insulin
BloodPressure
0
50
100
150
200
250
300
350
0
20
40
60
80
100
120

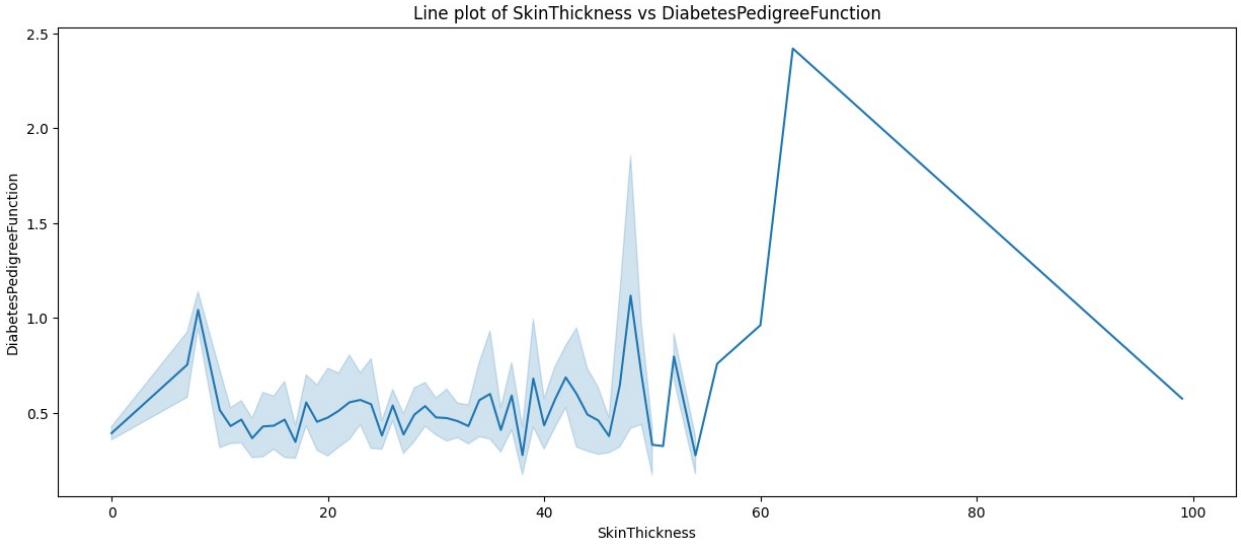

Line plot of BloodPressure vs BMI
BMI
BloodPressure
10
20
30
40
50
60
0
20
40
60
80
100
120

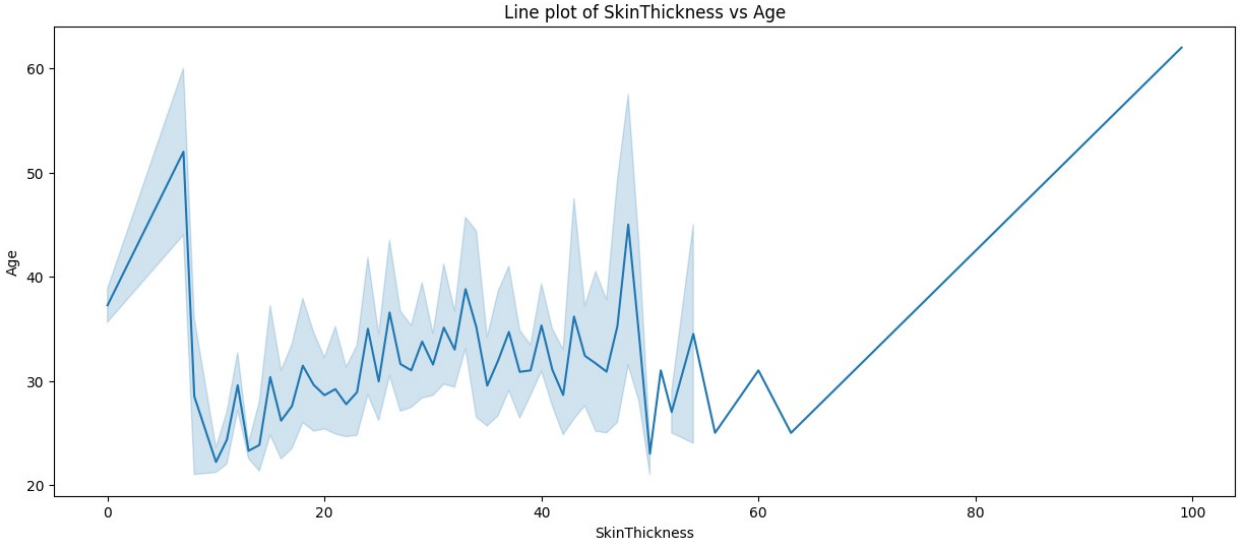

Line plot of BloodPressure vs DiabetesPedigreeFunction
DiabetesPedigreeFunction
BloodPressure
0.5
1.0
1.5
2.0
0
20
40
60
80
100
120

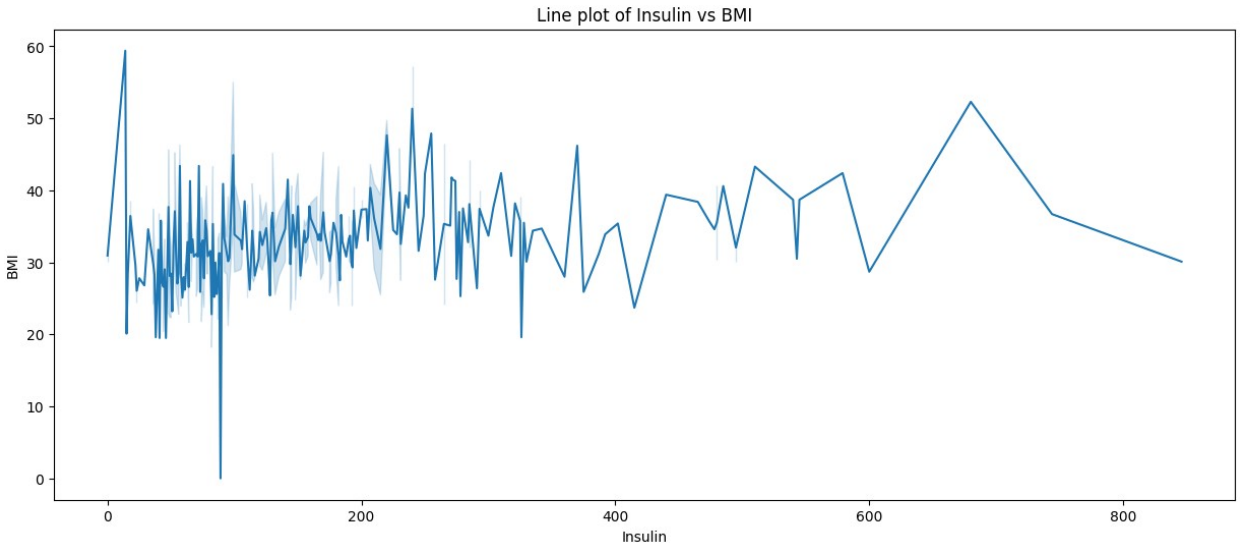

Line plot of BloodPressure vs Age
Age
BloodPressure
20
30
40
50
60
0
20
40
60
80
100
120

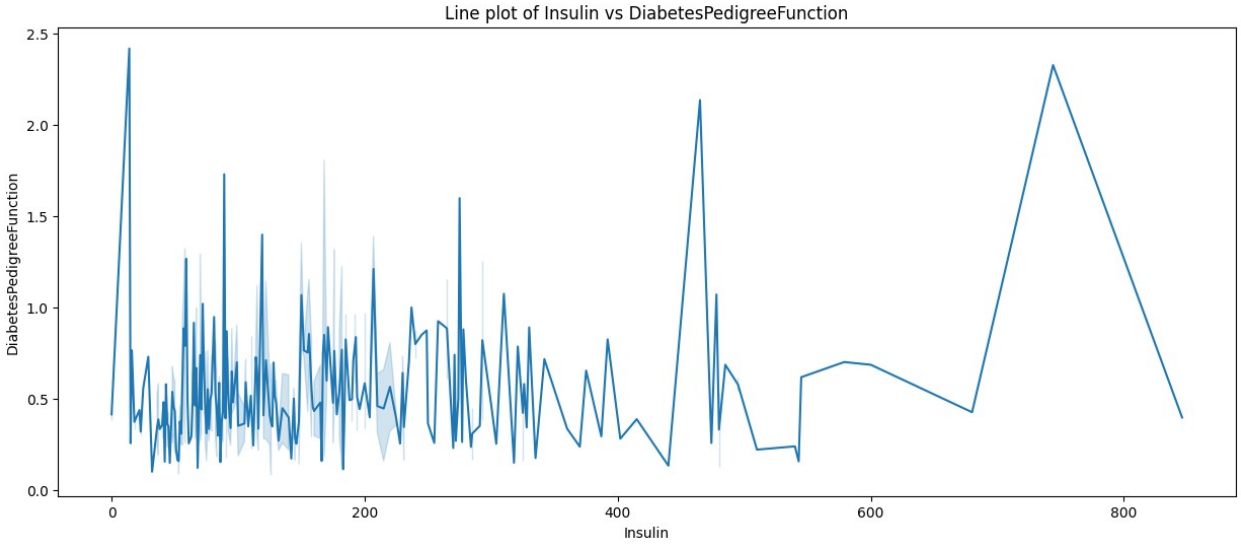

Line plot of SkinThickness vs Insulin
Insulin
SkinThickness
0
100
200
300
400
500
600
0
20
40
60
80
100

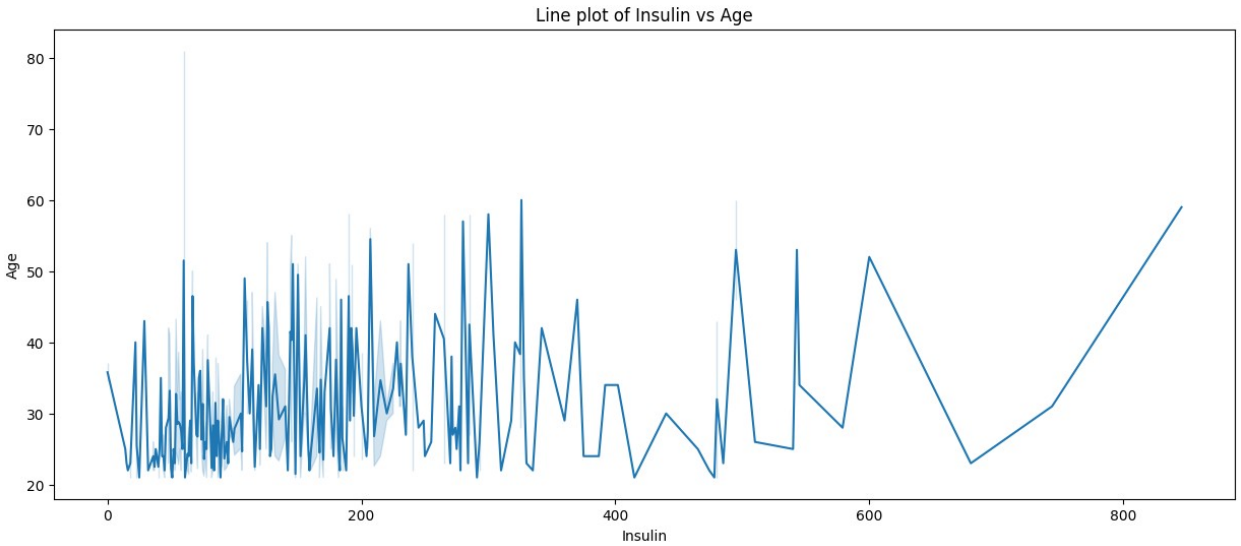

Line plot of SkinThickness vs BMI
BMI
SkinThickness
20
25
30
35
40
45
50
55
60
0
20
40
60
80
100

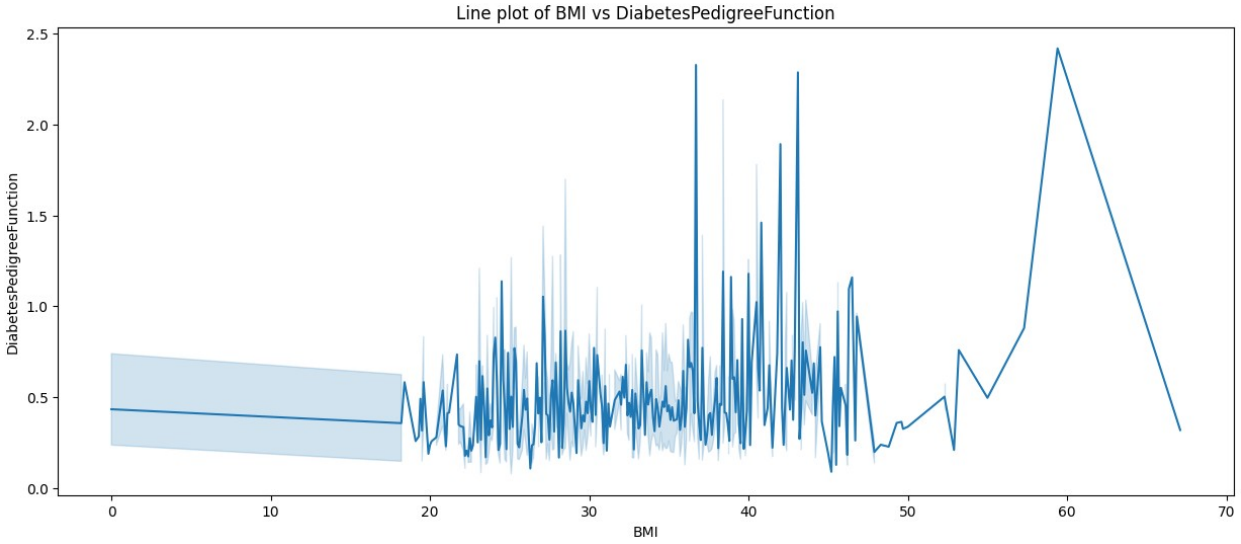

Line plot of SkinThickness vs DiabetesPedigreeFunction
DiabetesPedigreeFunction
SkinThickness
2.5
2.0
1.5
1.0
0.5
0
20
40
60
80
100

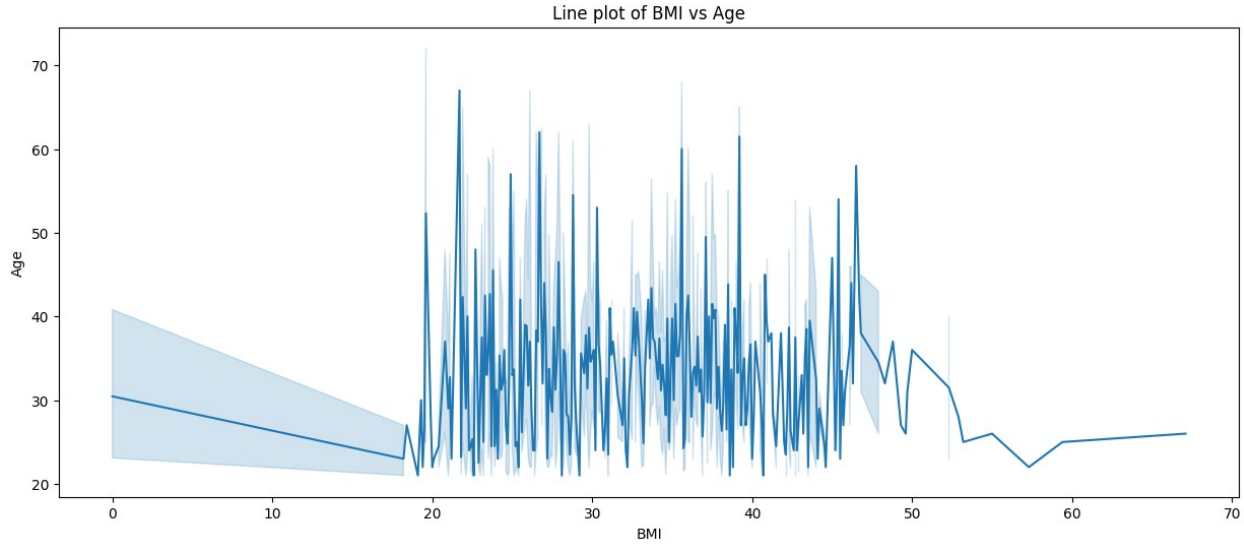

Line plot of SkinThickness vs Age
Age
SkinThickness
60
50
40
30
20
0
20
40
60
80
100

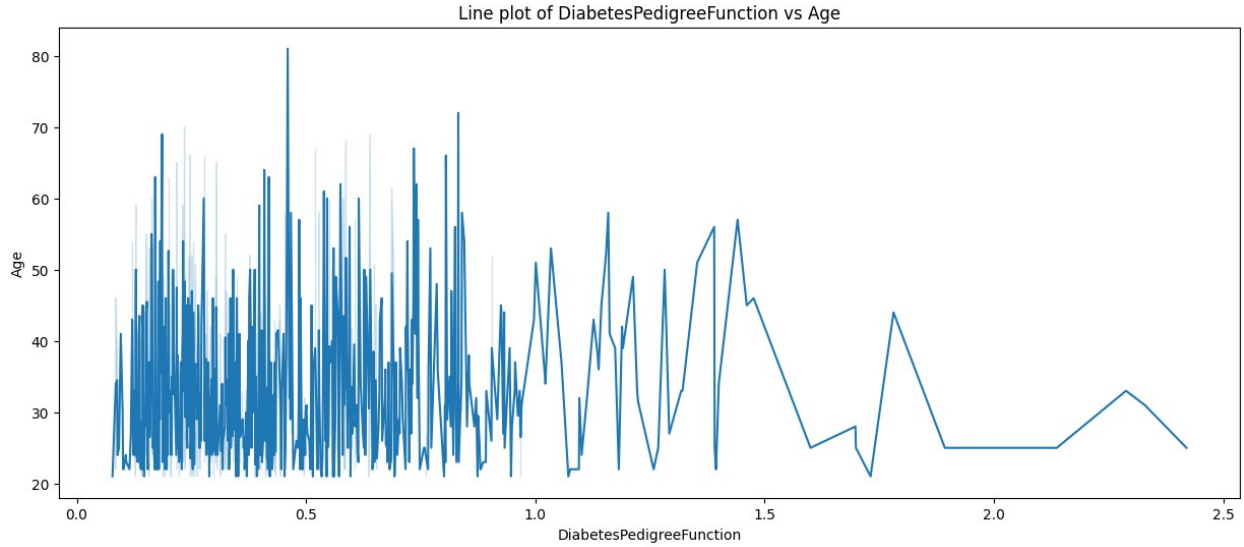

Line plot of Insulin vs BMI
BMI
Insulin
60
50
40
30
20
10
0
0
200
400
600
800


Line plot of Insulin vs DiabetesPedigreeFunction
DiabetesPedigreeFunction
Insulin
0.0
0.5
1.0
1.5
2.0
2.5
0
200
400
600
800

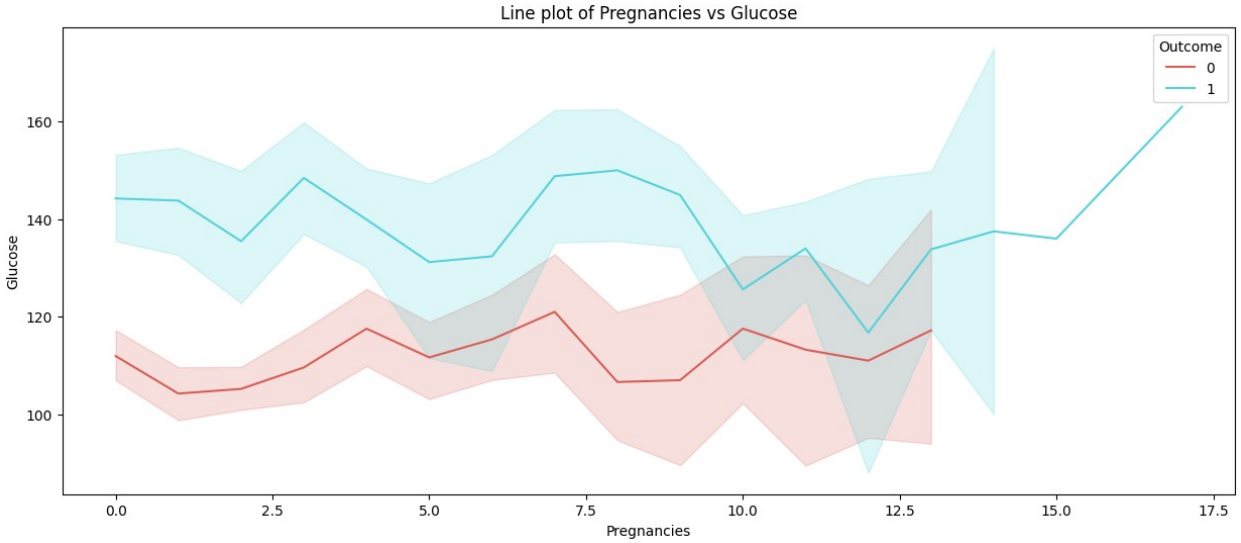

Line plot of Insulin vs Age
Age
Insulin
20
30
40
50
60
70
80
0
200
400
600
800

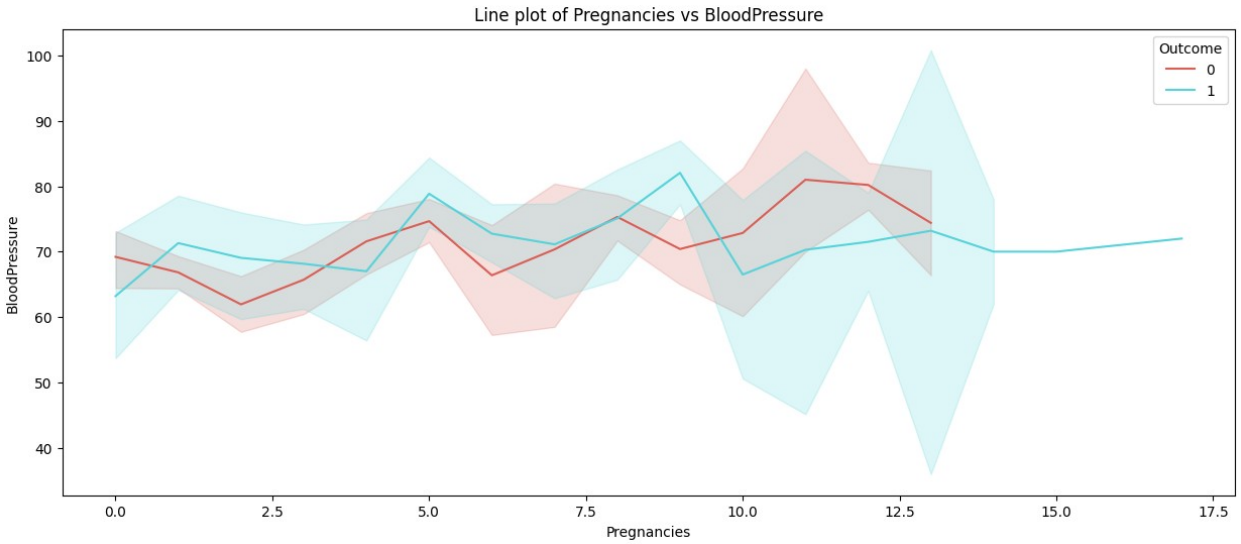

Line plot of BMI vs DiabetesPedigreeFunction
DiabetesPedigreeFunction
BMI
0.0
0.5
1.0
1.5
2.0
2.5
0
10
20
30
40
50
60
70

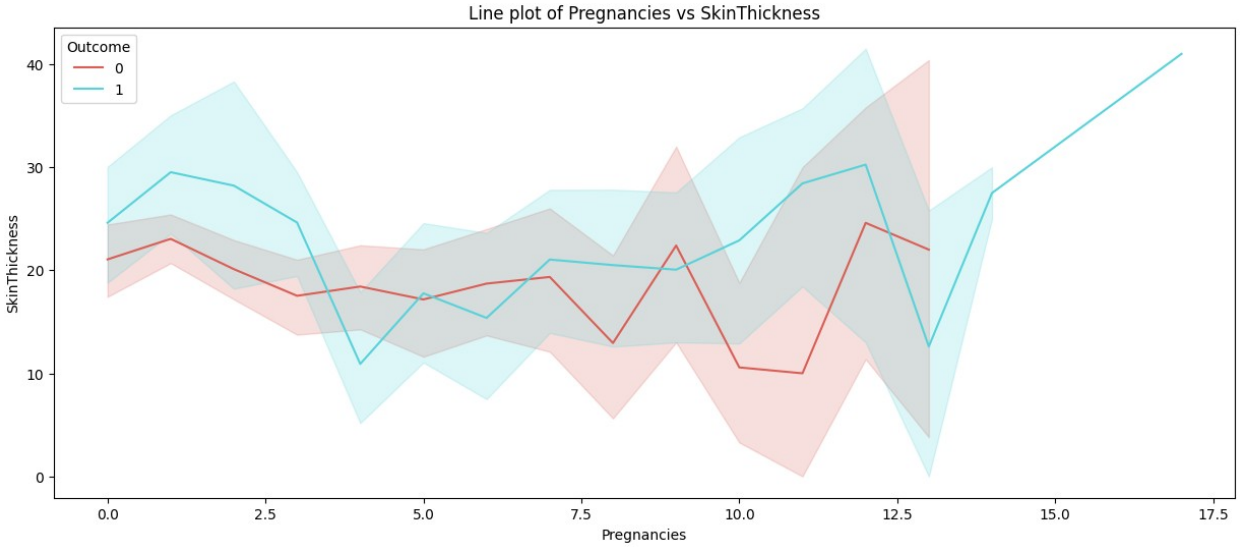


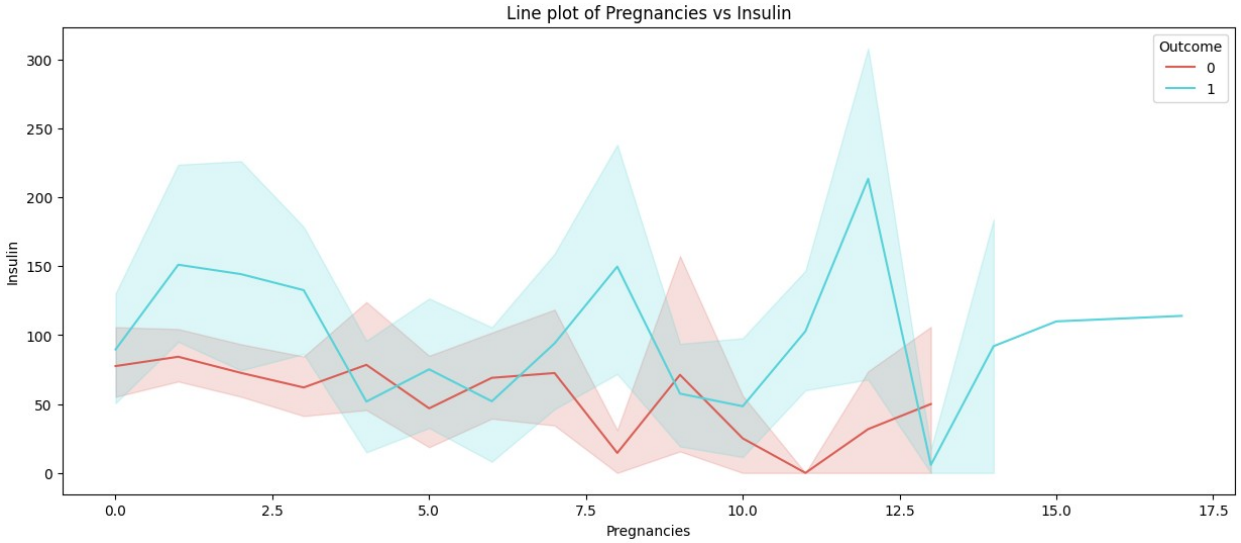


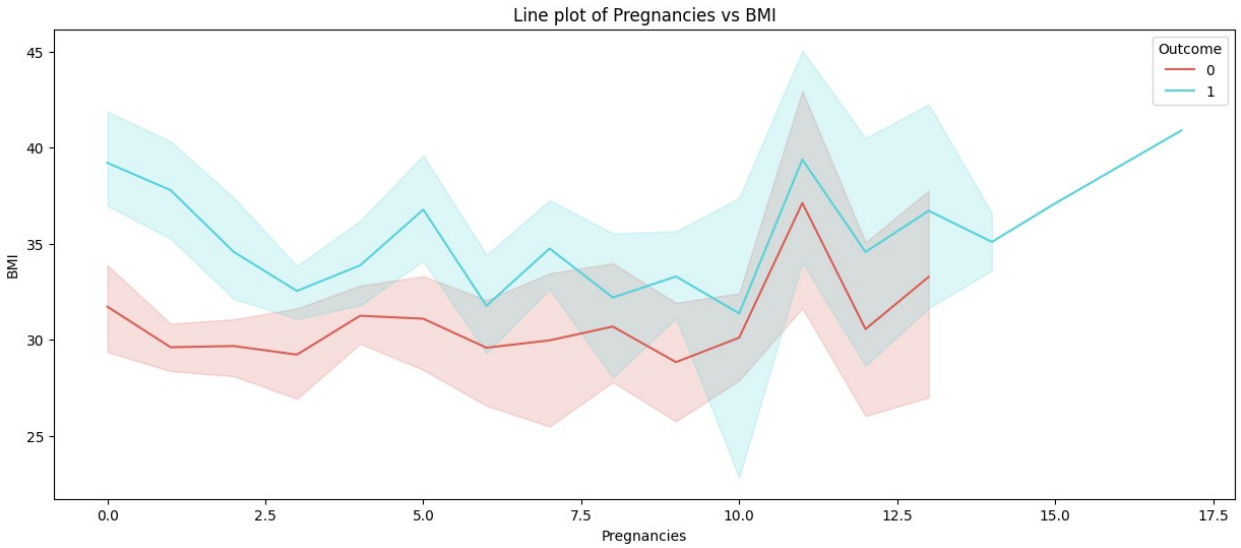

```
for i in range(len(continuous)):
    for j in range(i + 1, len(continuous)):
        plt.figure(figsize=(15, 6))
        sns.lineplot(x=continuous[i], y=continuous[j], data=df, hue =
'Outcome', palette='hls')
        plt.title(f'Line plot of {continuous[i]} vs {continuous[j]}')
        plt.show()
```

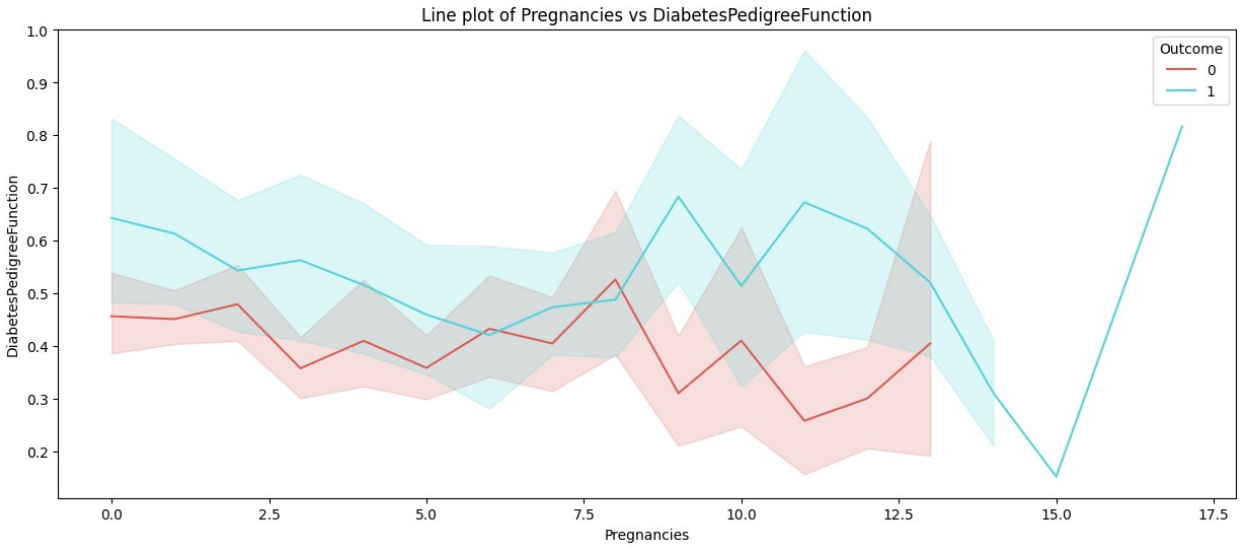

Line plot of Pregnancies vs Glucose
Outcome
0
1
Glucose
160
140
120
100
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
Pregnancies

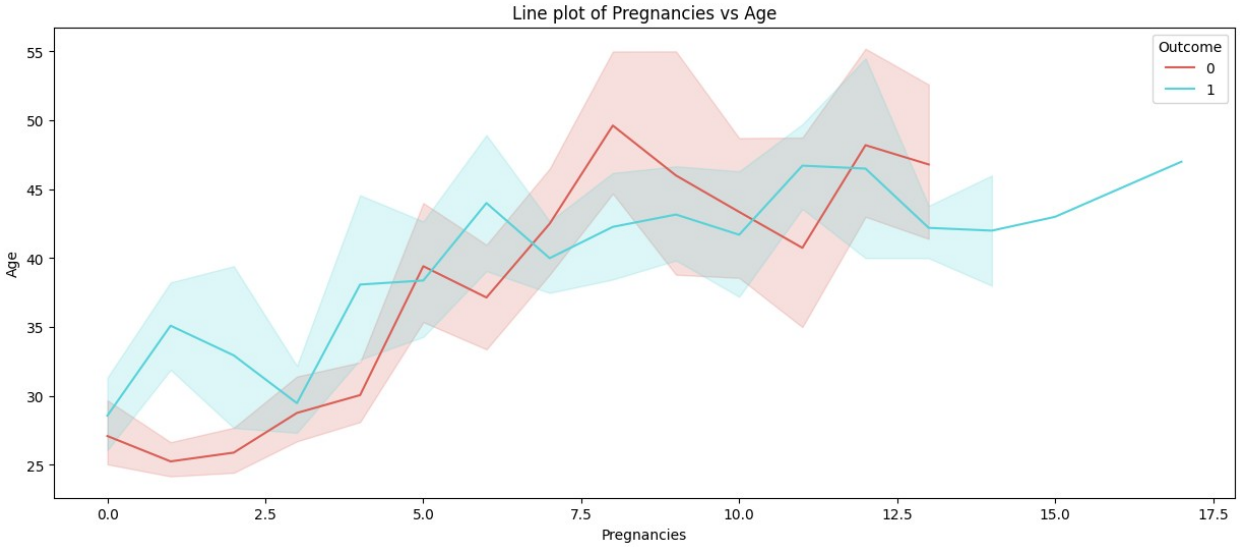

Line plot of Pregnancies vs BloodPressure
Outcome
0
1
BloodPressure
100
90
80
70
60
50
40
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
Pregnancies

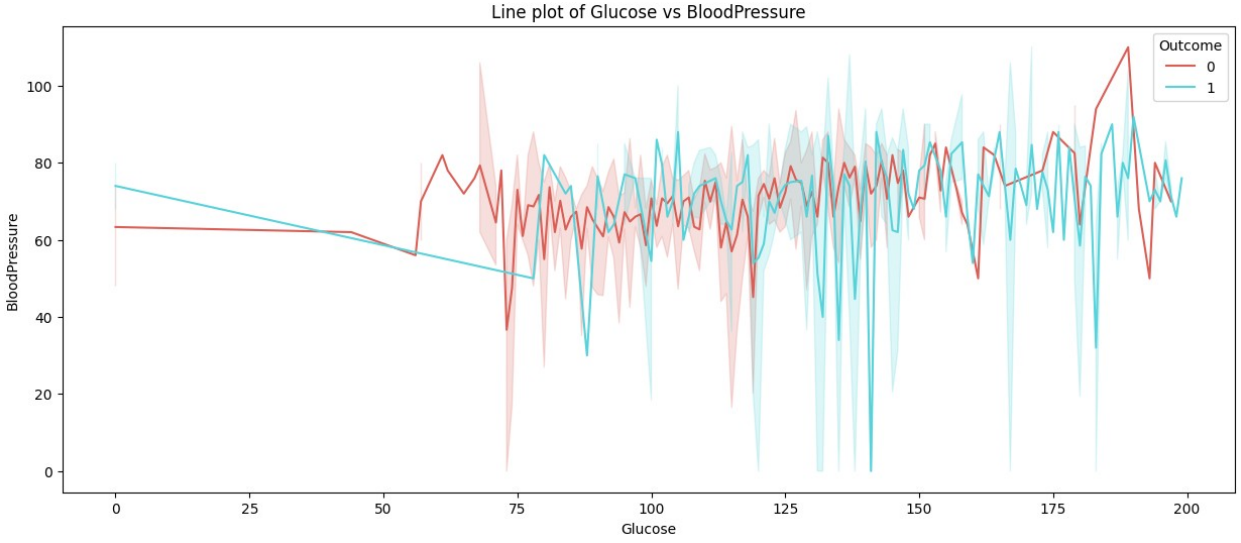

Line plot of Pregnancies vs SkinThickness
Outcome
0
1
SkinThickness
40
30
20
10
0
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
Pregnancies

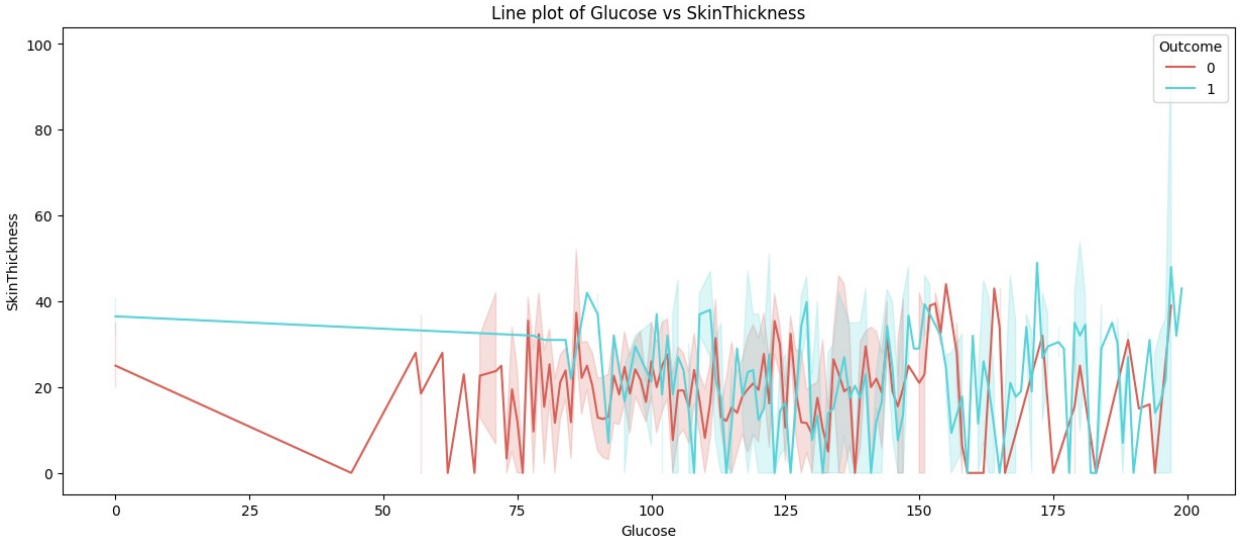

Line plot of Pregnancies vs Insulin
Outcome
0
1
Insulin
Pregnancies
0
50
100
150
200
250
300
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5

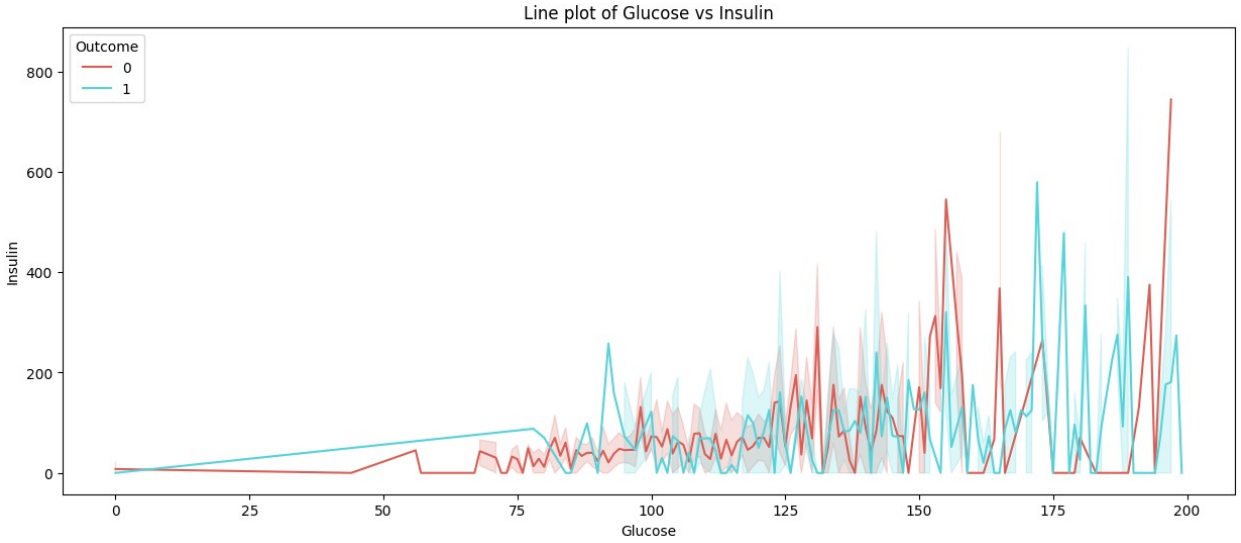

Line plot of Pregnancies vs BMI
Outcome
0
1
BMI
Pregnancies
25
30
35
40
45
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5

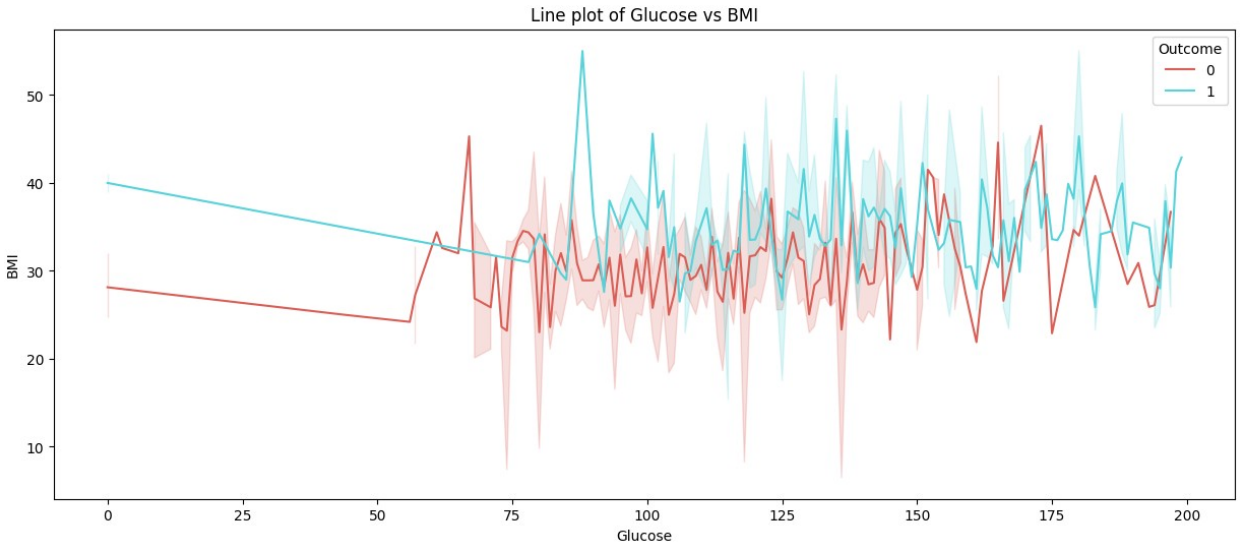

Line plot of Pregnancies vs DiabetesPedigreeFunction
Outcome
0
1
DiabetesPedigreeFunction
Pregnancies
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5

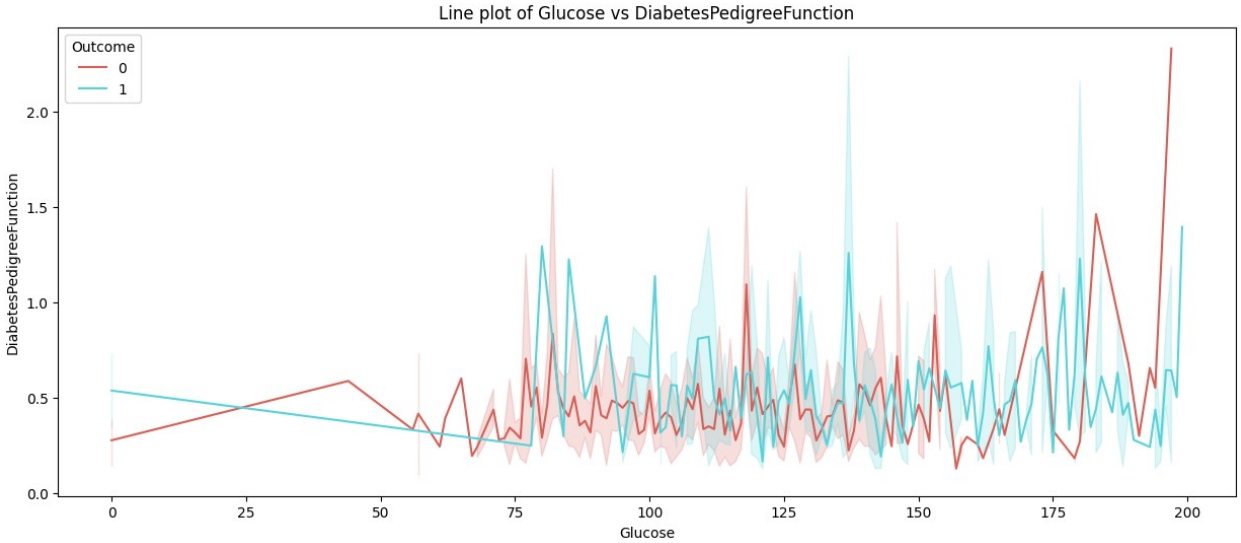

Line plot of Pregnancies vs Age
Outcome
0
1
Age
Pregnancies
55
50
45
40
35
30
25
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5

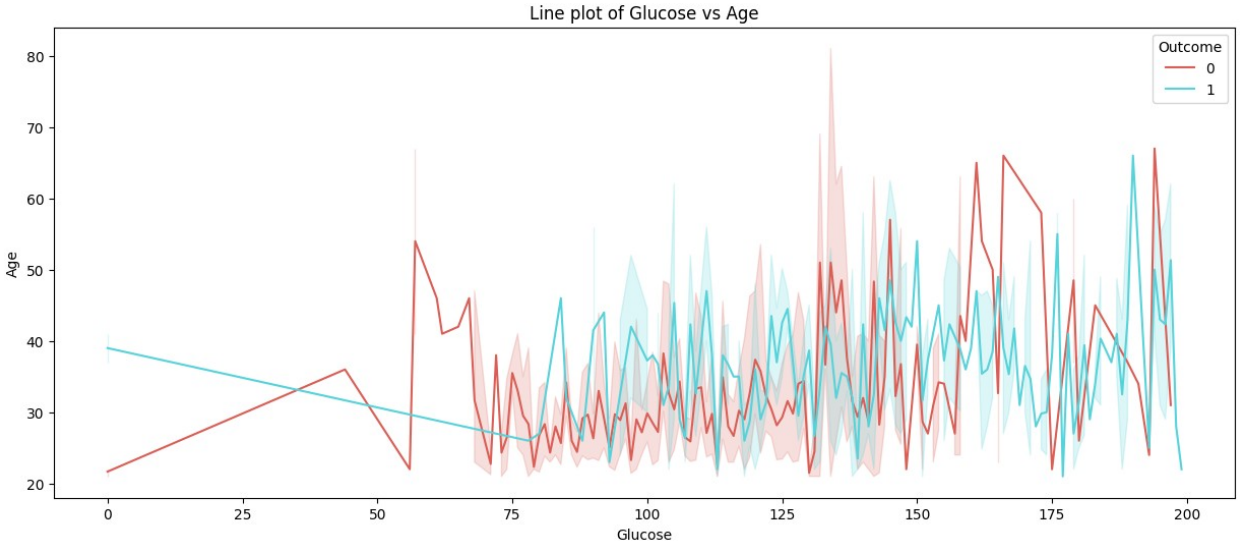

Line plot of Glucose vs BloodPressure
Outcome
0
1
BloodPressure
Glucose
100
80
60
40
20
0
0
25
50
75
100
125
150
175
200

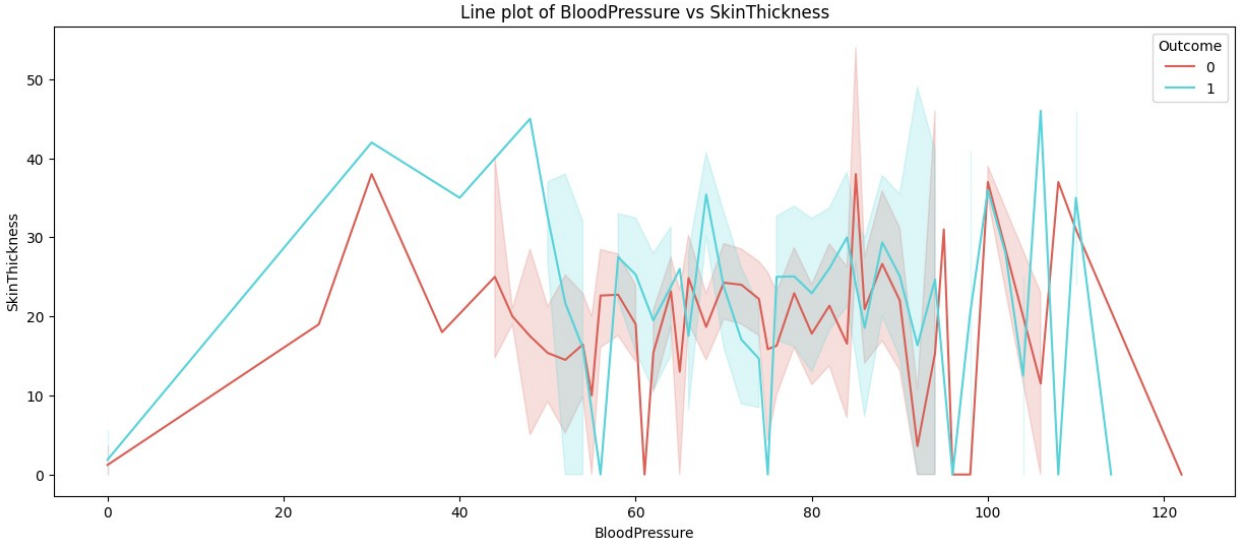

Line plot of Glucose vs SkinThickness
Outcome
0
1
SkinThickness
Glucose
100
80
60
40
20
0
0
25
50
75
100
125
150
175
200

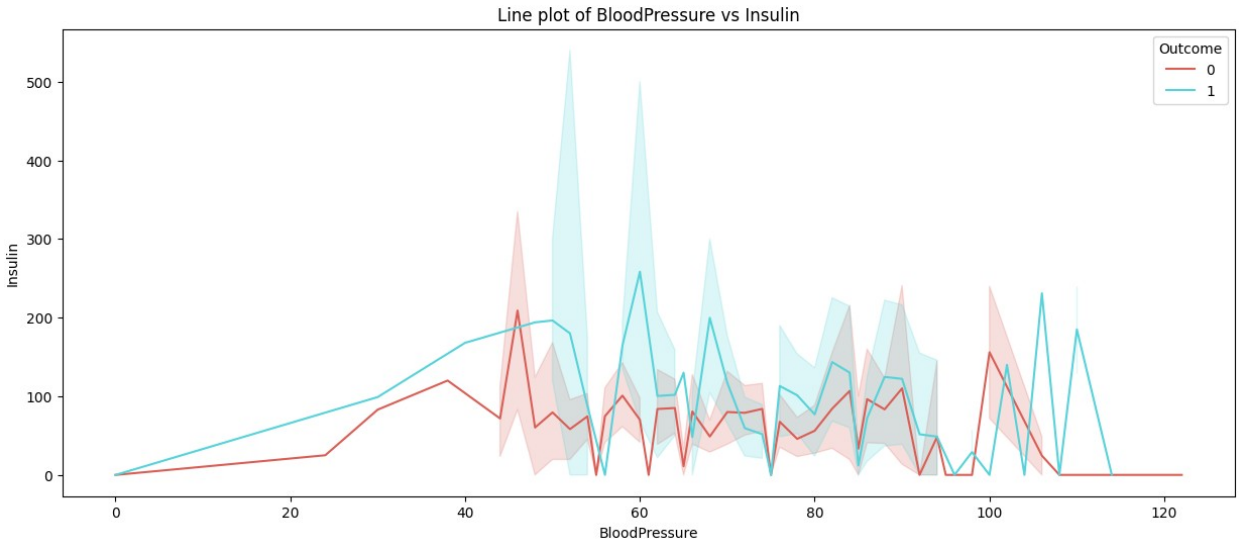

Line plot of Glucose vs Insulin
Outcome
0
1
Insulin
Glucose
0
200
400
600
800
0
25
50
75
100
125
150
175
200

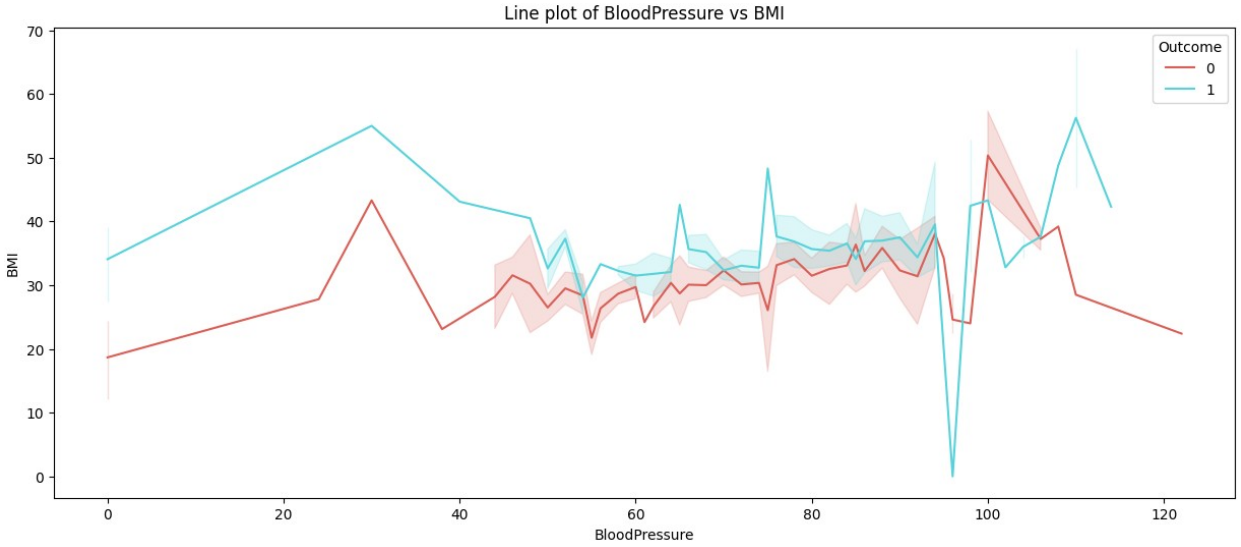

Line plot of Glucose vs BMI
Outcome
0
1
BMI
Glucose
10
20
30
40
50
0
25
50
75
100
125
150
175
200

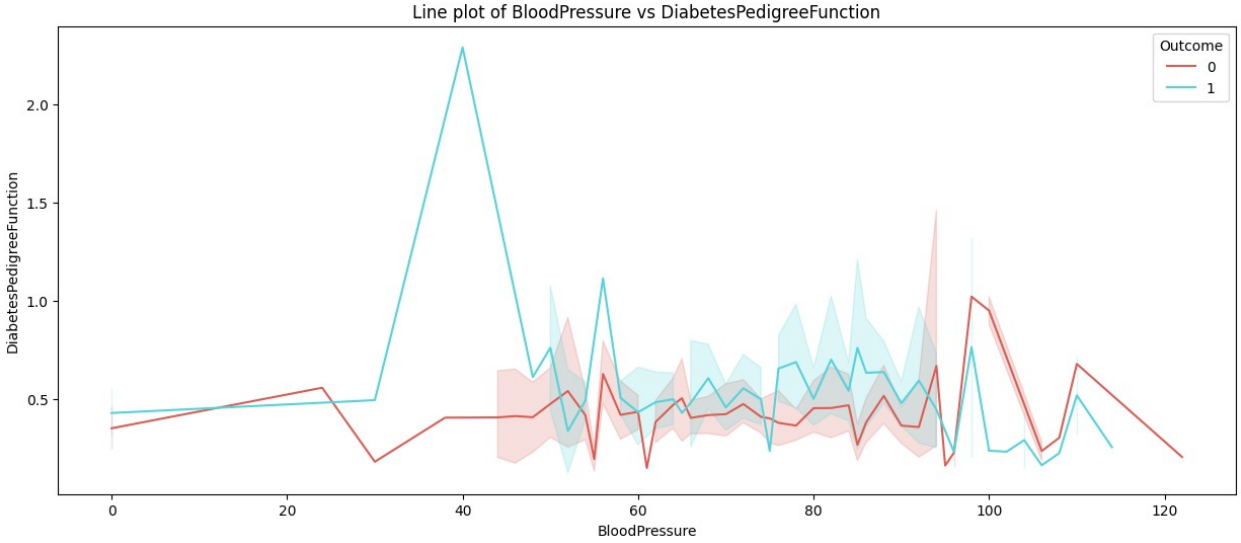

Line plot of Glucose vs DiabetesPedigreeFunction
Outcome
0
1
DiabetesPedigreeFunction
Glucose
0.0
0.5
1.0
1.5
2.0
0
25
50
75
100
125
150
175
200

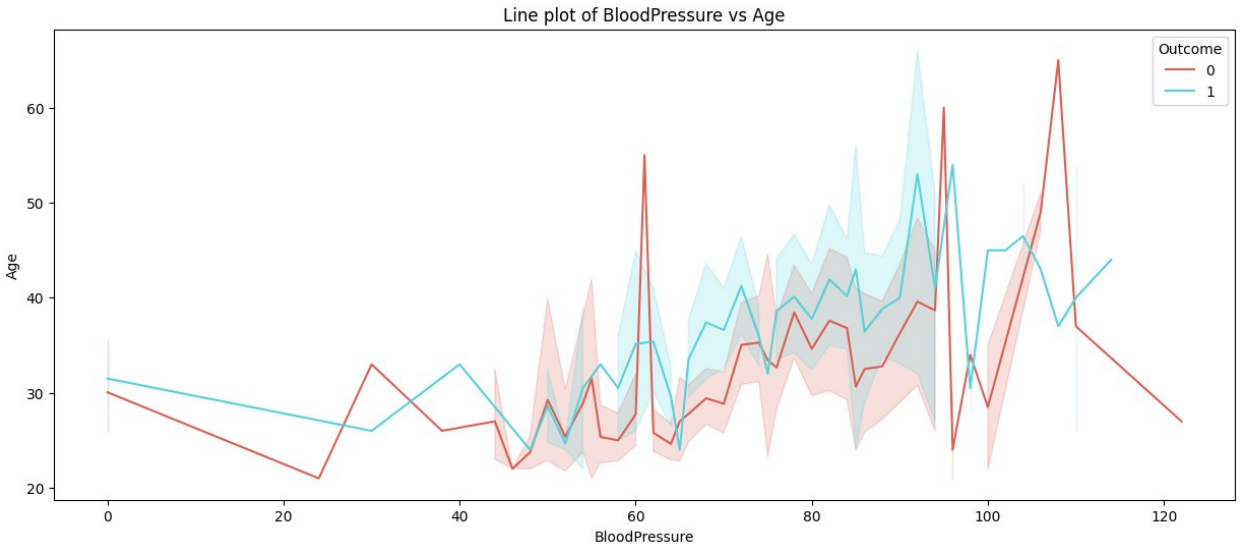

Line plot of Glucose vs Age
Outcome
0
1
Age
Glucose
20
30
40
50
60
70
80
0
25
50
75
100
125
150
175
200

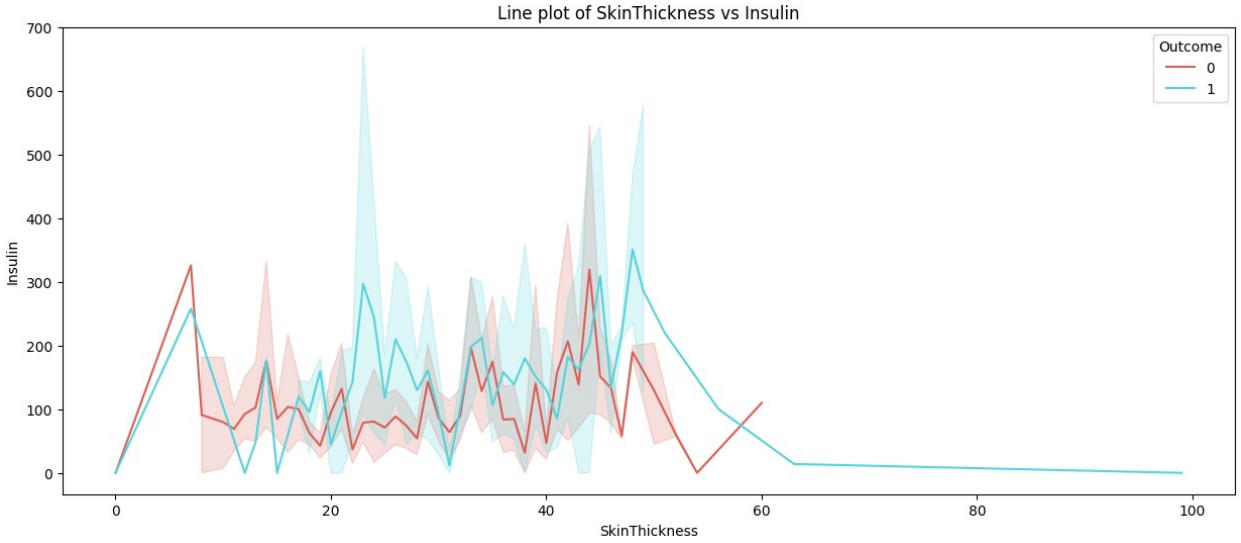

Line plot of BloodPressure vs SkinThickness
Outcome
0
1
SkinThickness
BloodPressure
0
10
20
30
40
50
0
20
40
60
80
100
120

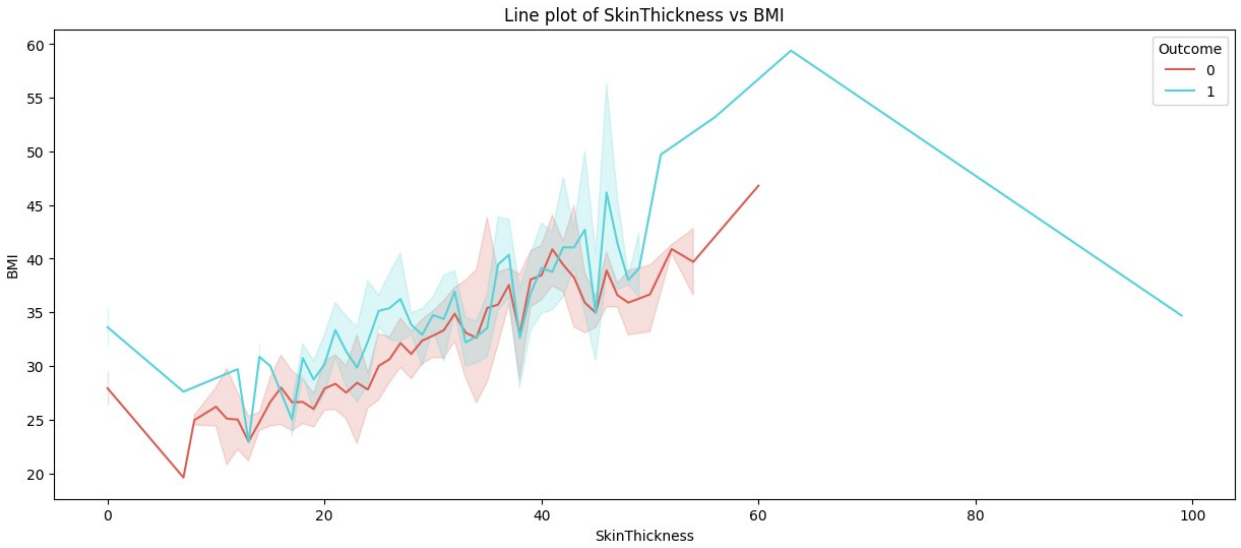

Line plot of BloodPressure vs Insulin
Outcome
0
1
Insulin
BloodPressure
0
100
200
300
400
500
0
20
40
60
80
100
120

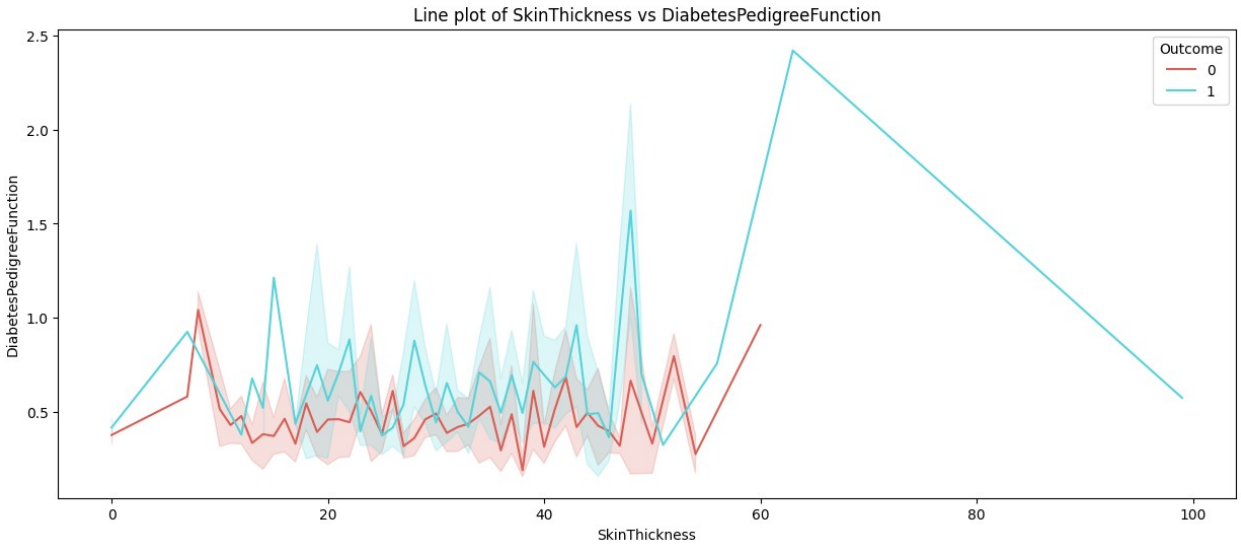

Line plot of BloodPressure vs BMI
Outcome
0
1
BMI
BloodPressure
0
10
20
30
40
50
60
70
0
20
40
60
80
100
120

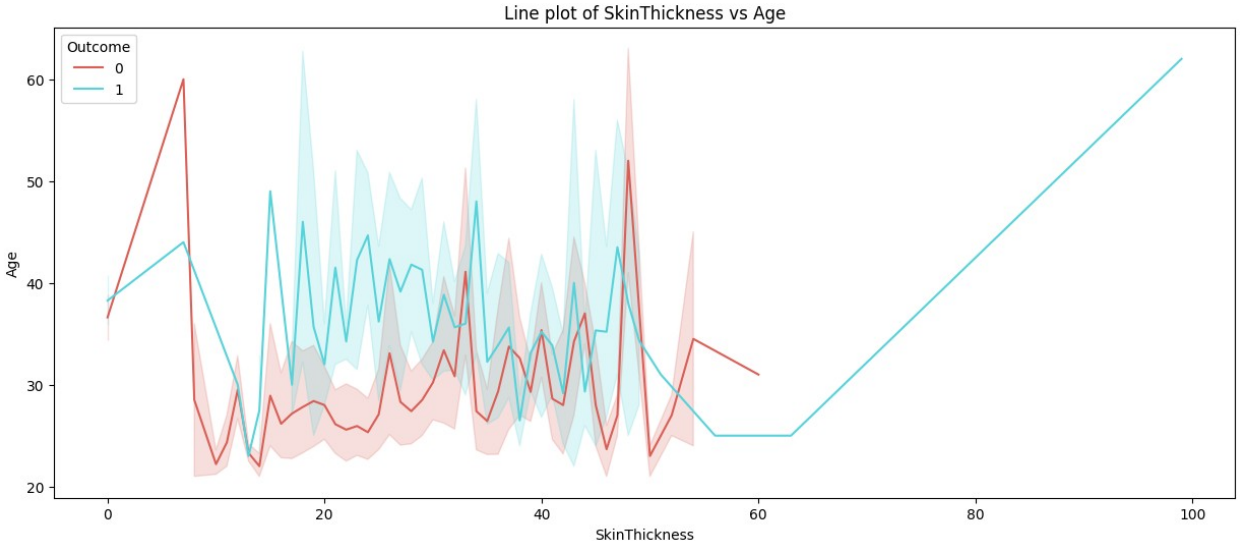

Line plot of BloodPressure vs DiabetesPedigreeFunction
Outcome
0
1
DiabetesPedigreeFunction
BloodPressure
0.5
1.0
1.5
2.0
0
20
40
60
80
100
120

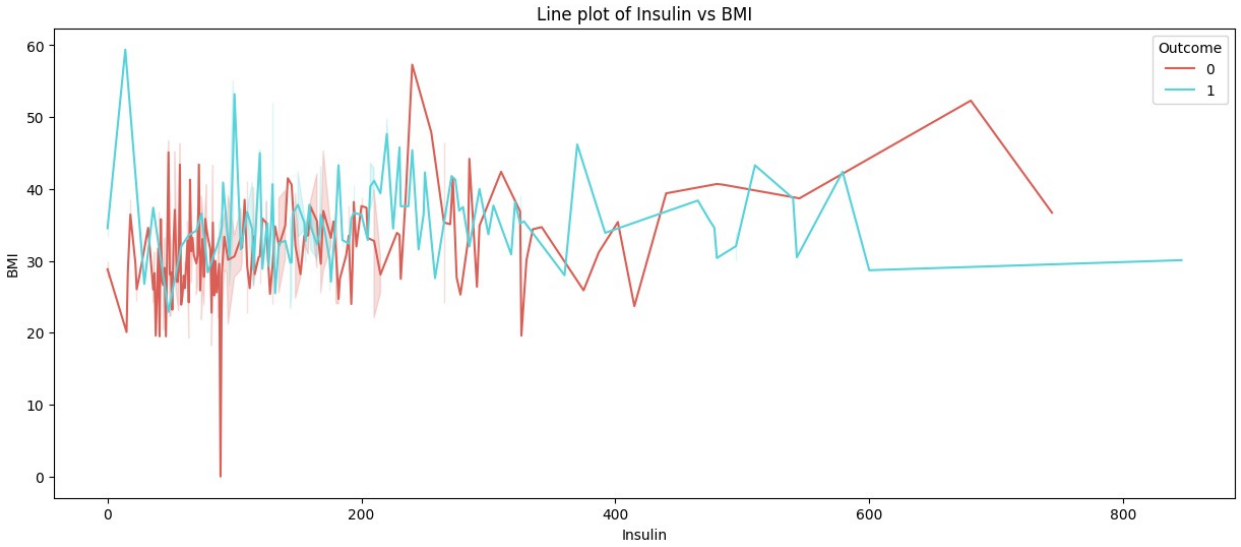

Line plot of BloodPressure vs Age
Outcome
0
1
Age
BloodPressure
20
30
40
50
60
0
20
40
60
80
100
120


Line plot of SkinThickness vs Insulin
Outcome
0
1
Insulin
SkinThickness
0
100
200
300
400
500
600
700
0
20
40
60
80
100

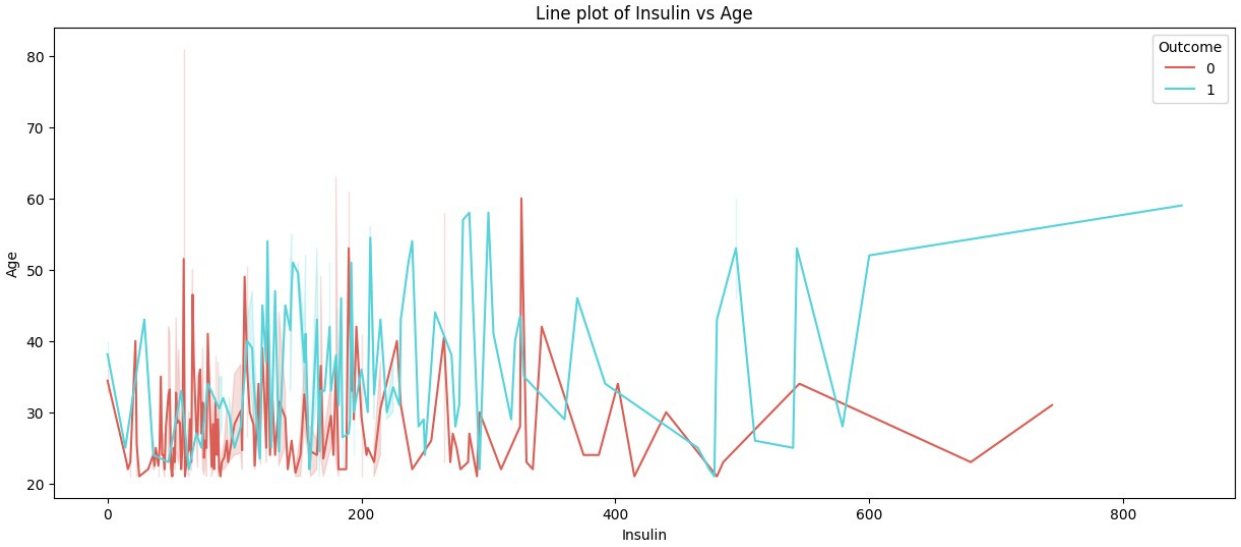

Line plot of SkinThickness vs BMI
Outcome
0
1
BMI
SkinThickness
20
25
30
35
40
45
50
55
60
0
20
40
60
80
100

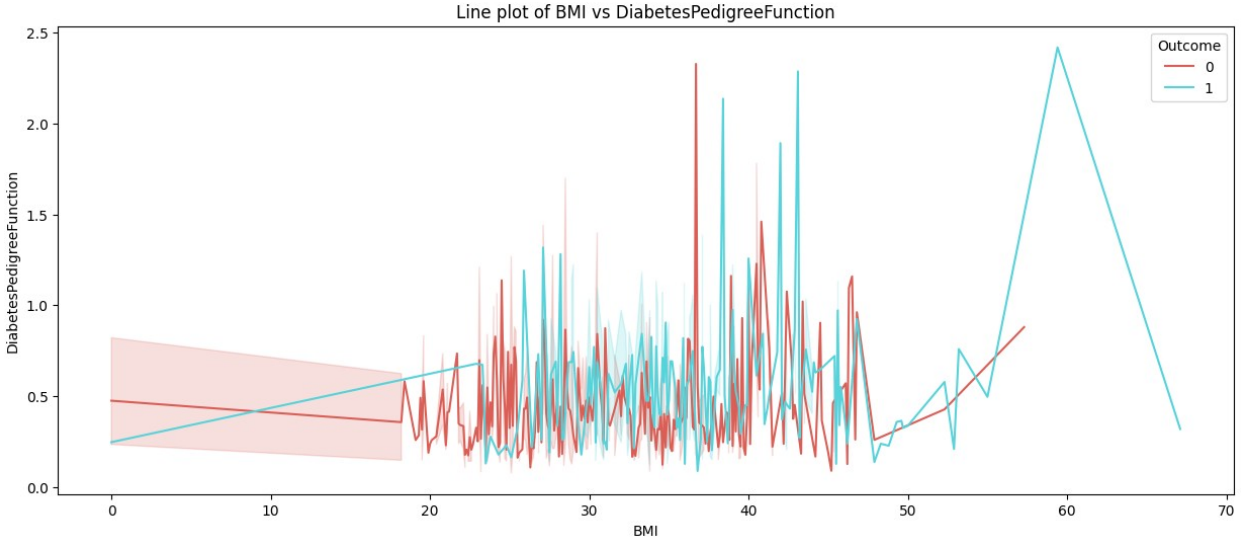

Line plot of SkinThickness vs DiabetesPedigreeFunction
Outcome
0
1
DiabetesPedigreeFunction
SkinThickness
0.5
1.0
1.5
2.0
2.5
0
20
40
60
80
100

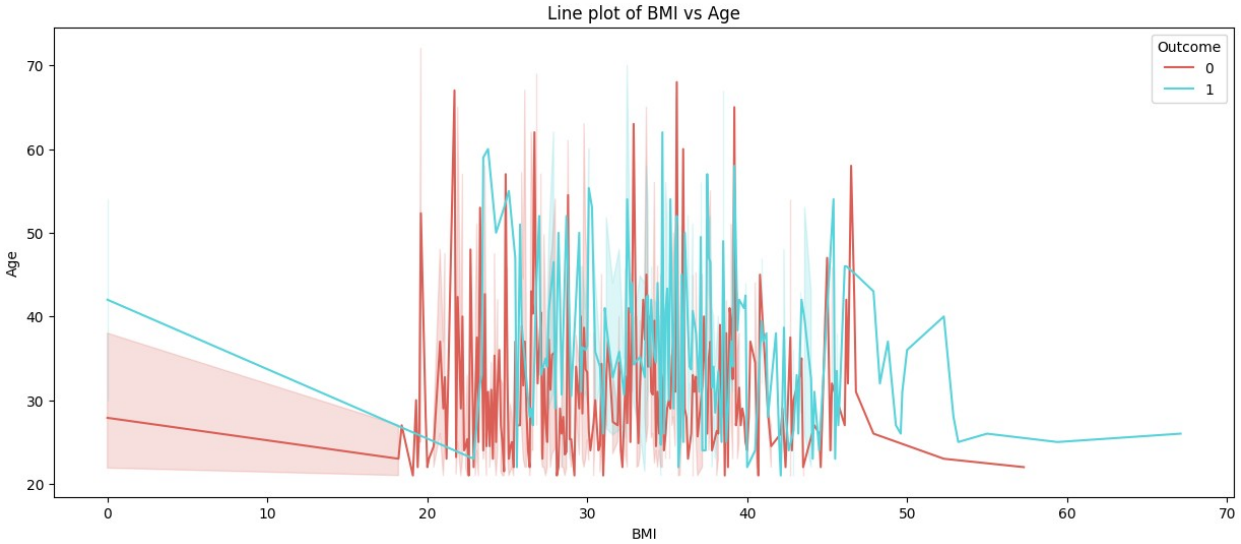

Line plot of SkinThickness vs Age
Outcome
0
1
Age
SkinThickness
20
30
40
50
60
0
20
40
60
80
100

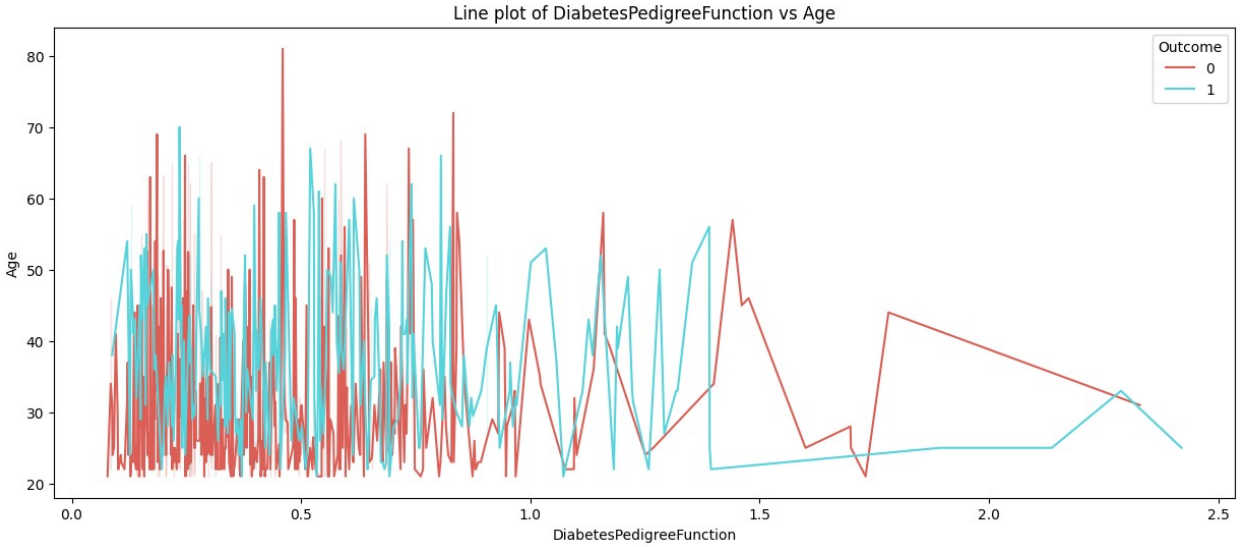

Line plot of Insulin vs BMI
Outcome
0
1
BMI
Insulin
0
10
20
30
40
50
60
0
200
400
600
800


Line plot of Insulin vs DiabetesPedigreeFunction
Outcome
0
1
DiabetesPedigreeFunction
Insulin
0.0
0.5
1.0
1.5
2.0
2.5
0
200
400
600
800

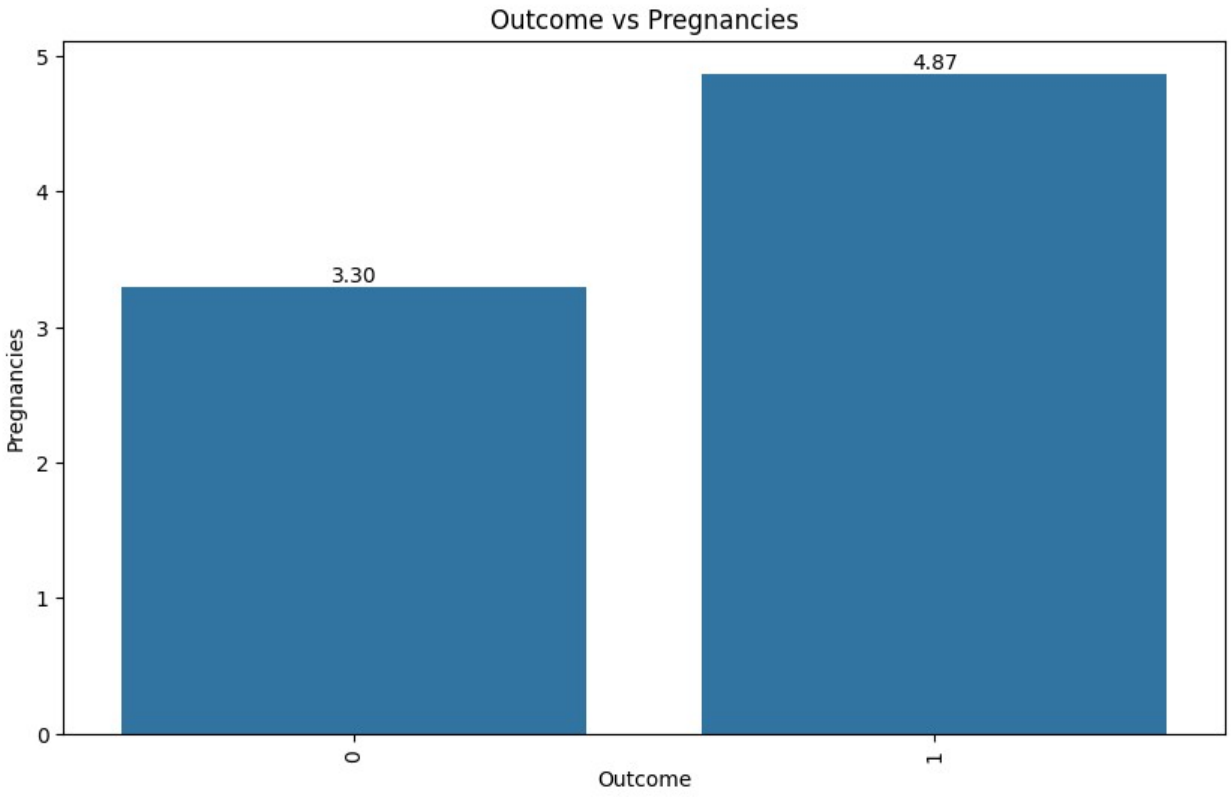

Line plot of Insulin vs Age
Outcome
0
1
Age
Insulin
20
30
40
50
60
70
80
0
200
400
600
800

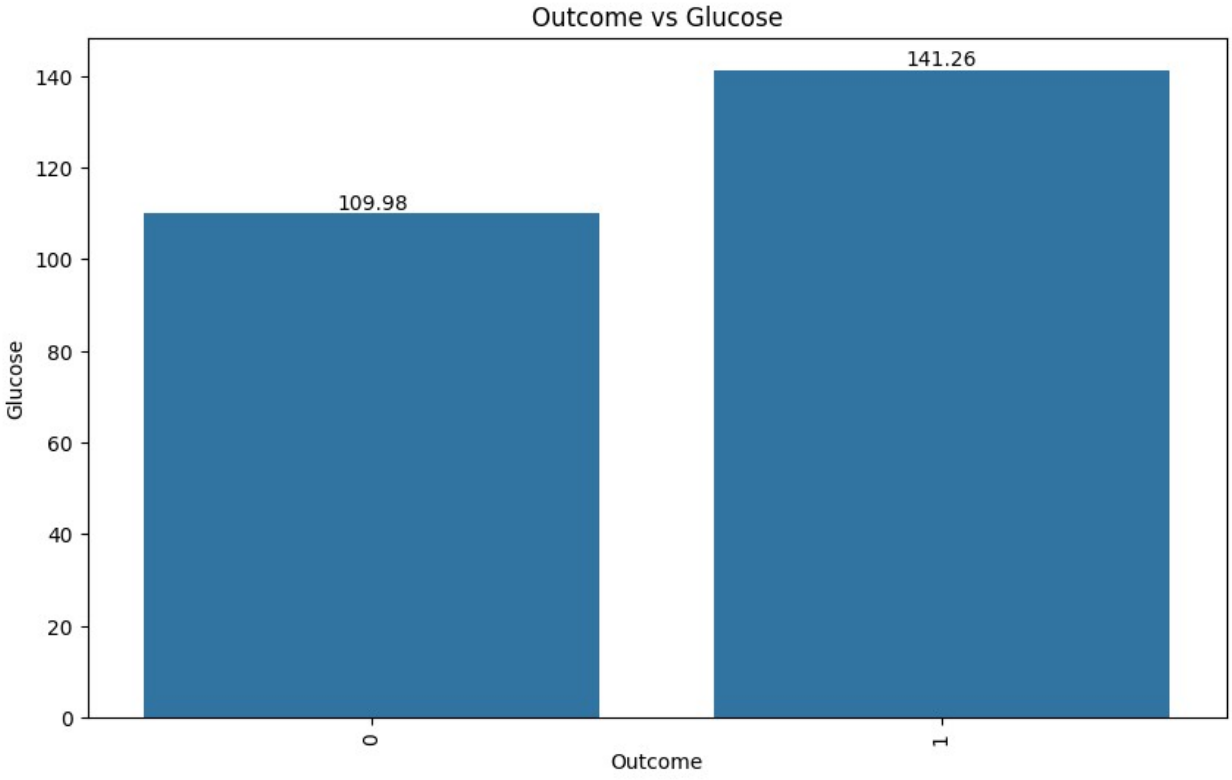

Line plot of BMI vs DiabetesPedigreeFunction
Outcome
0
1
DiabetesPedigreeFunction
BMI
0.0
0.5
1.0
1.5
2.0
2.5
0
10
20
30
40
50
60
70

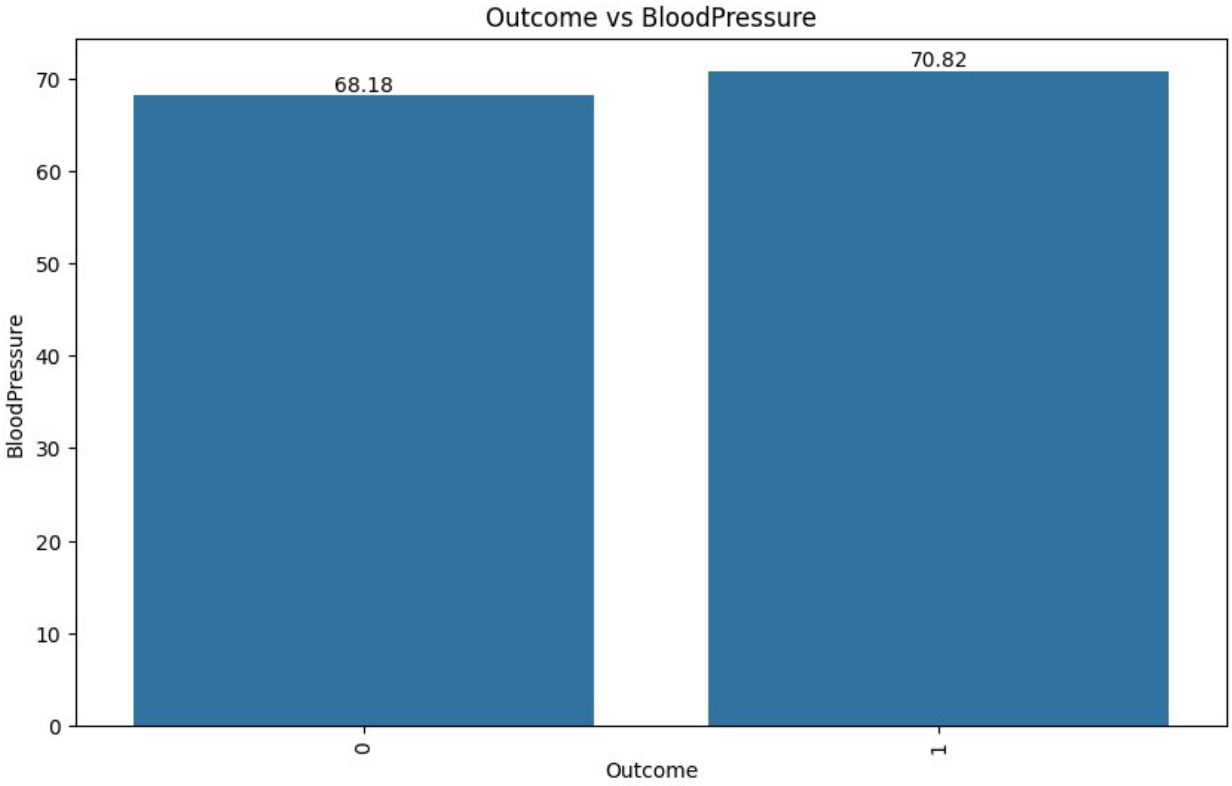

Line plot of BMI vs Age
Outcome
0
1
Age
BMI
20
30
40
50
60
70
0
10
20
30
40
50
60
70

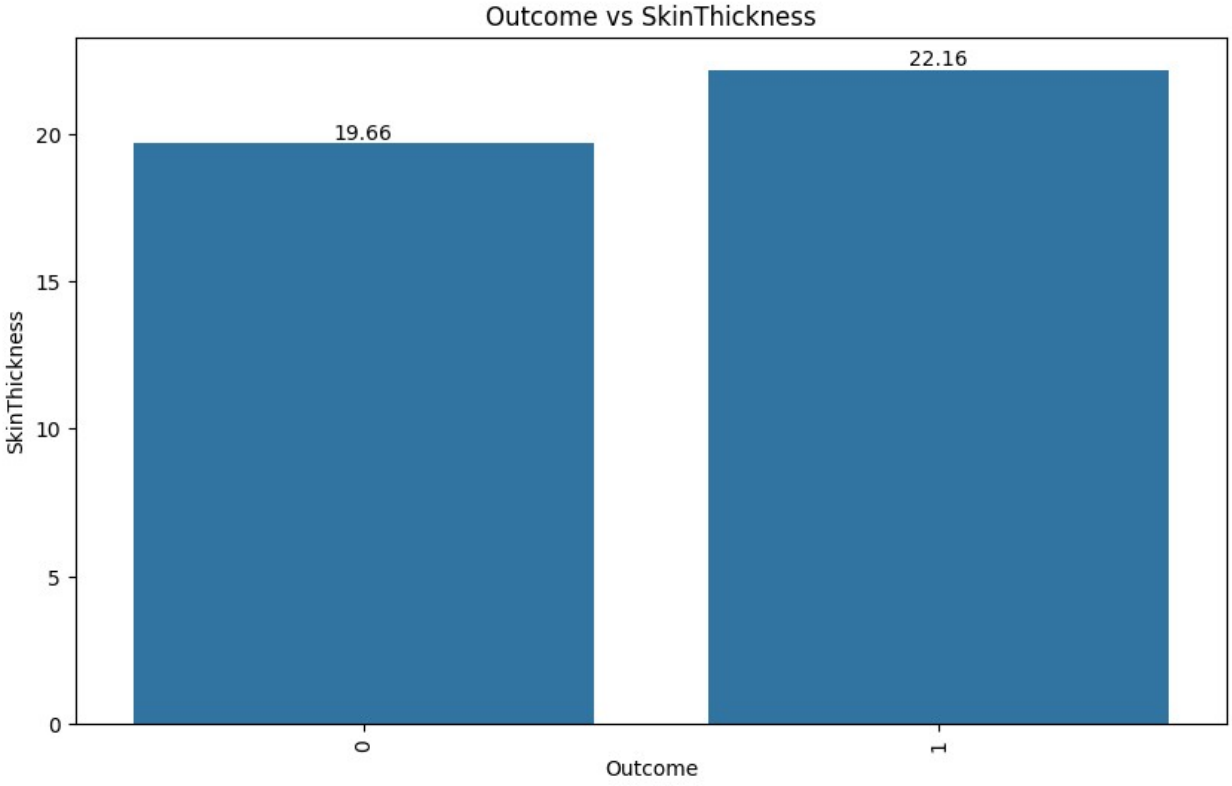


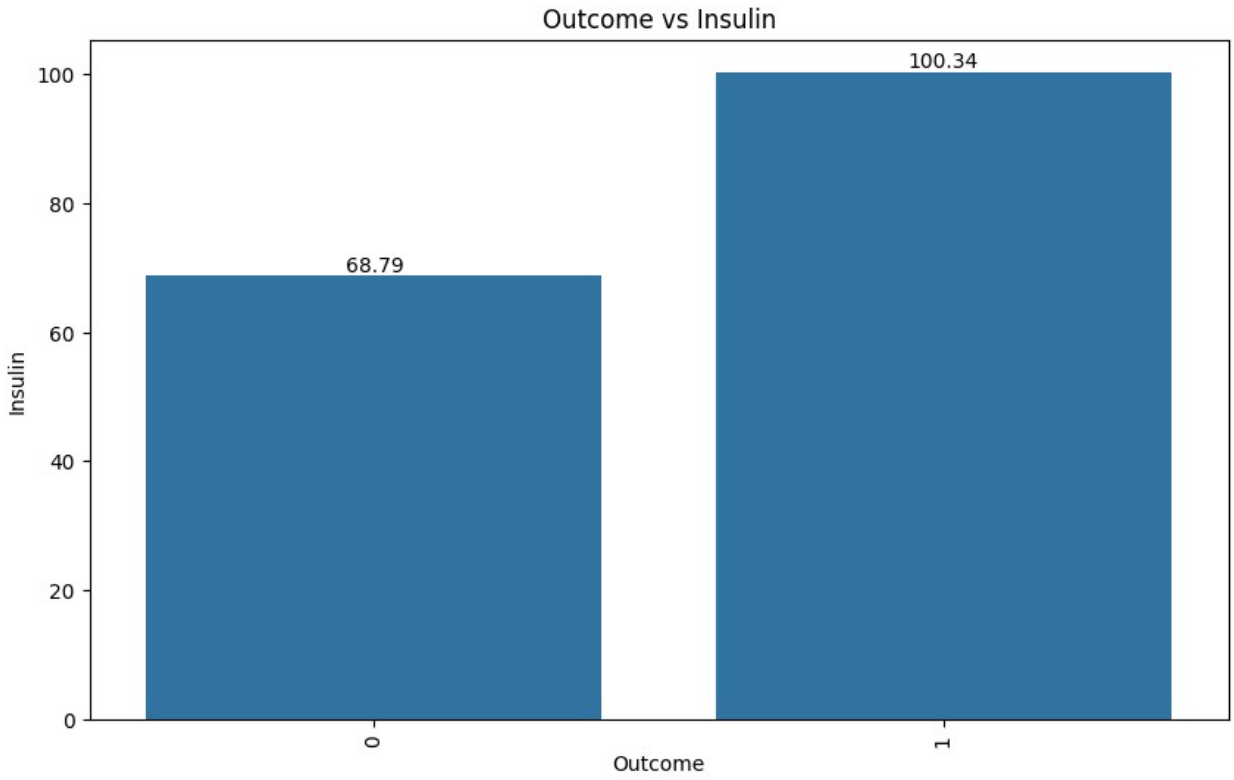

```
for dis in discrete:
    for cont in continuous:
        plt.figure(figsize=(10, 6))
        ax = sns.barplot(data=df, x=dis, y=cont, ci=None)
        plt.title(f'{dis} vs {cont}')

        for p in ax.patches:
            height = p.get_height()
            ax.annotate(f'{height:.2f}', (p.get_x() + p.get_width() /
2., height),
                        ha='center', va='bottom', fontsize=10,
color='black', rotation=0)
        plt.xticks(rotation = 90)
        plt.show()
```

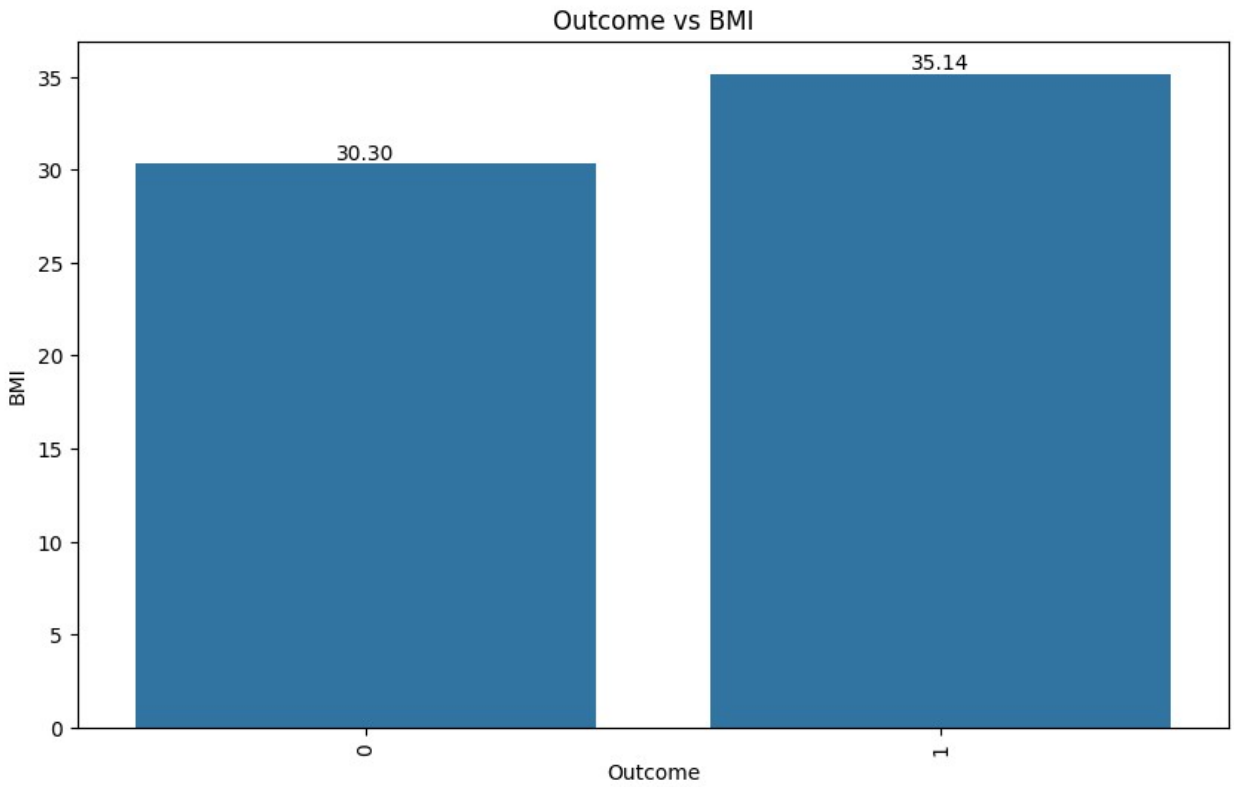

Outcome vs Pregnancies
Pregnancies
Outcome
0
1
2
3
4
5
3.30
4.87
0
1

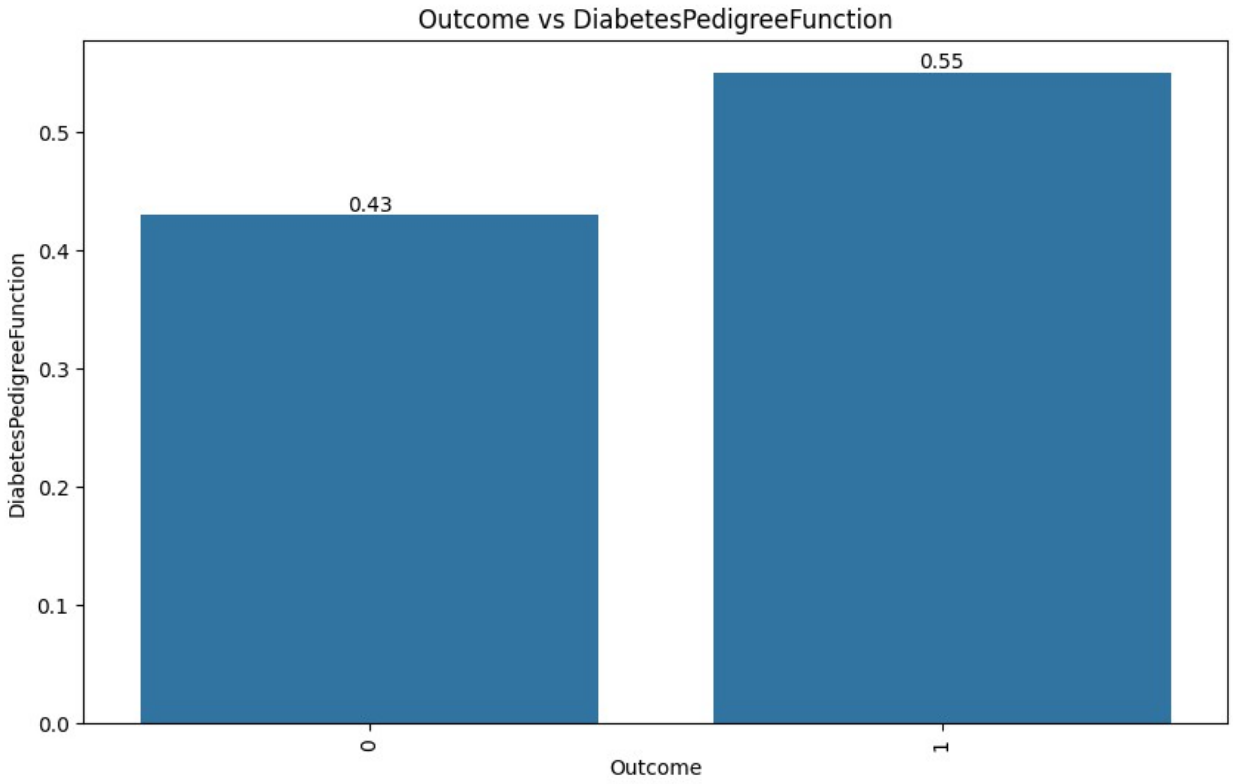

Outcome vs Glucose
Glucose
Outcome
0
20
40
60
80
100
120
140
109.98
141.26
0
1

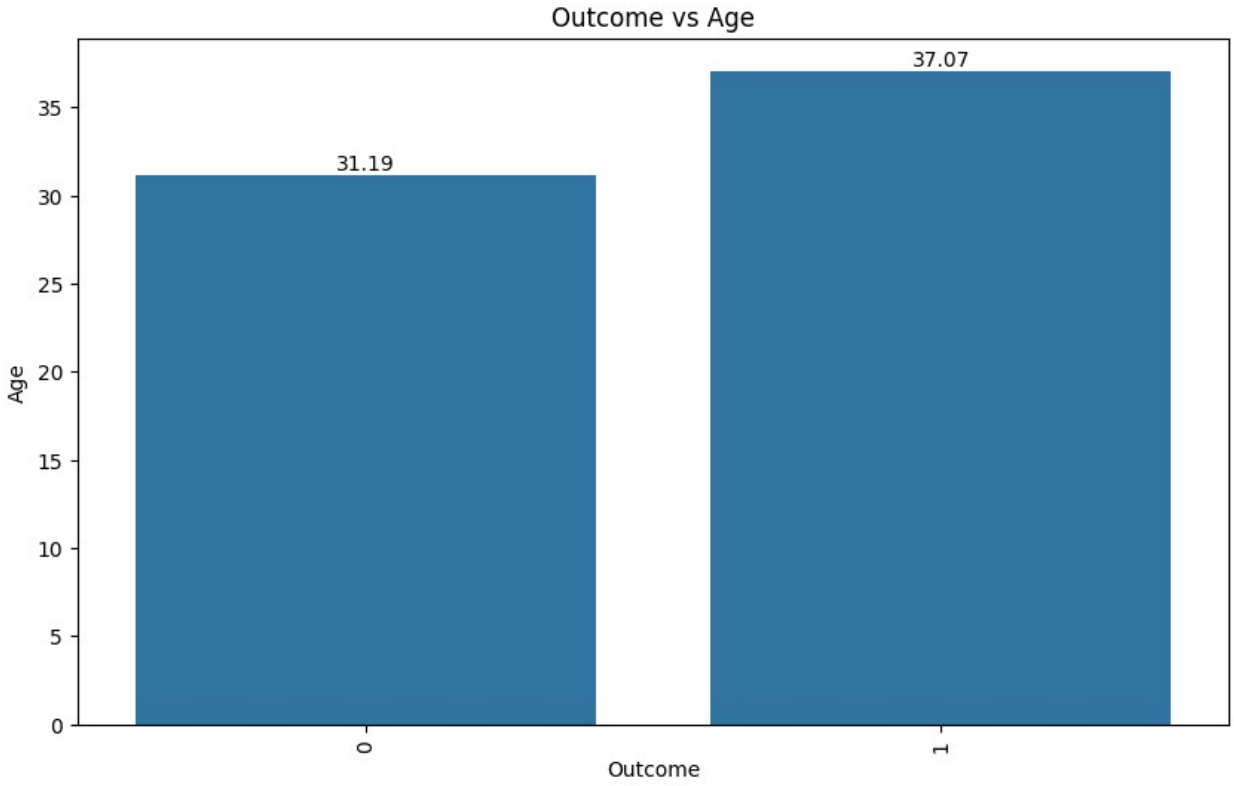

Outcome vs BloodPressure
70.82
68.18
70
60
50
40
30
20
10
0
BloodPressure
0
1
Outcome


Outcome vs SkinThickness
22.16
19.66
20
15
10
5
0
SkinThickness
0
1
Outcome

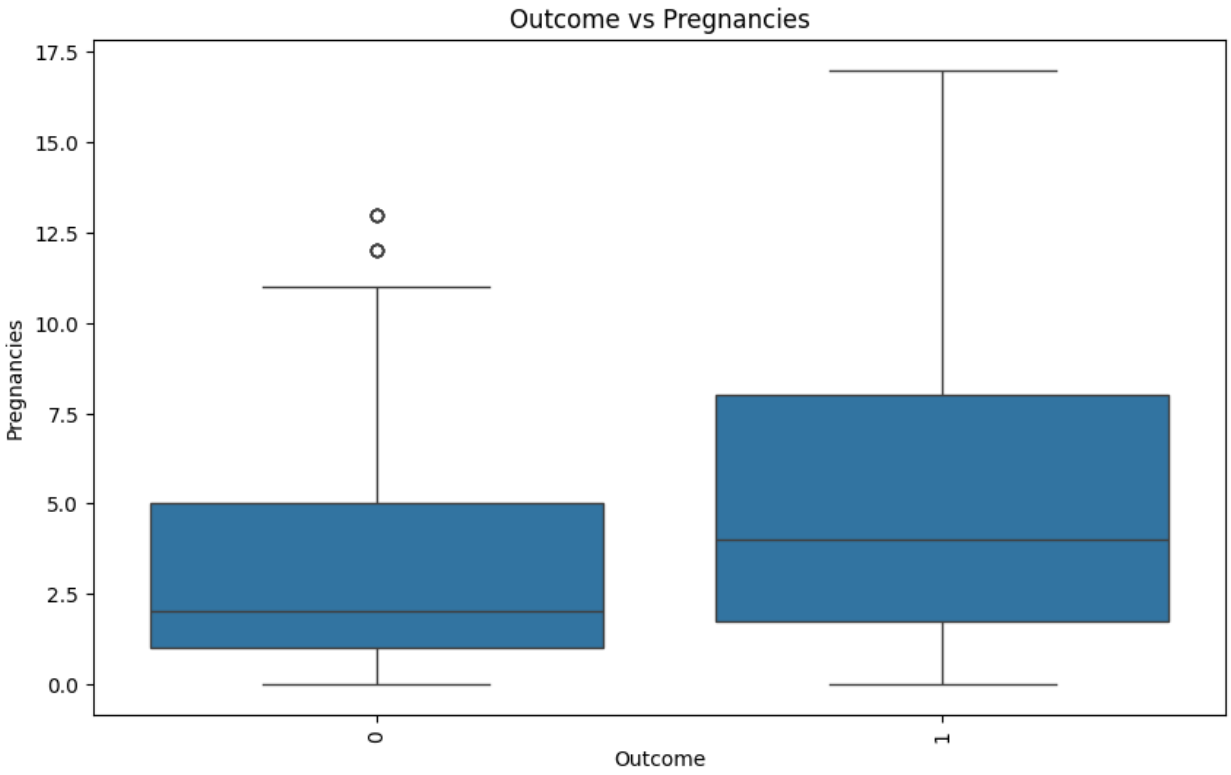

Outcome vs Insulin
100.34
68.79
Insulin
0
20
40
60
80
100
0
1
Outcome

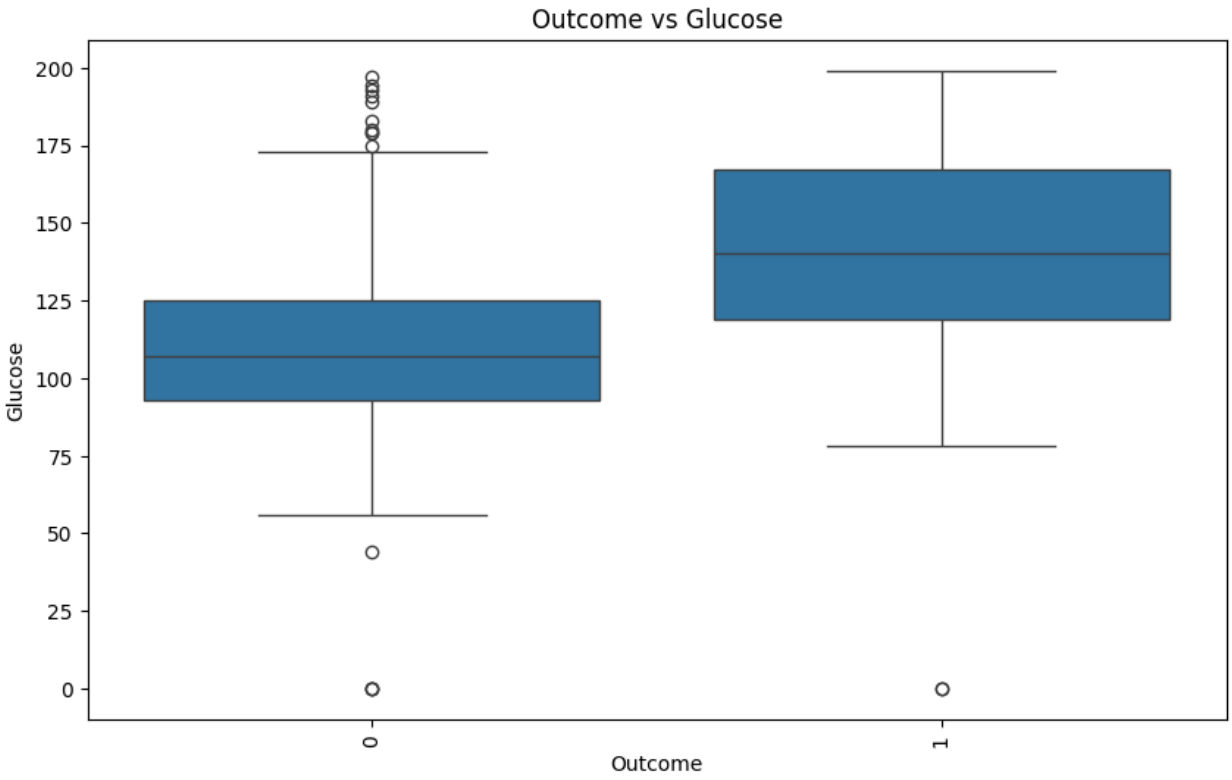

Outcome vs BMI
35.14
30.30
BMI
0
5
10
15
20
25
30
35
0
1
Outcome

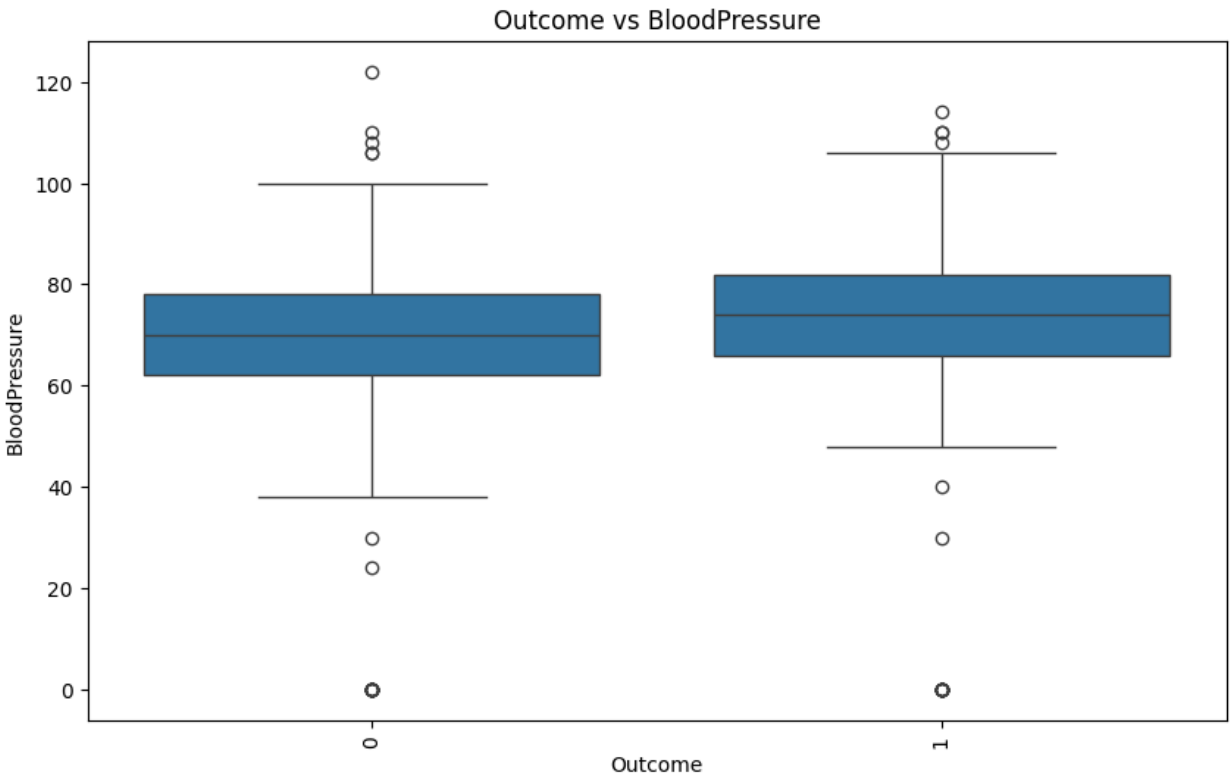

Outcome vs DiabetesPedigreeFunction
DiabetesPedigreeFunction
0.0
0.1
0.2
0.3
0.4
0.5
0.43
0.55
0
1
Outcome

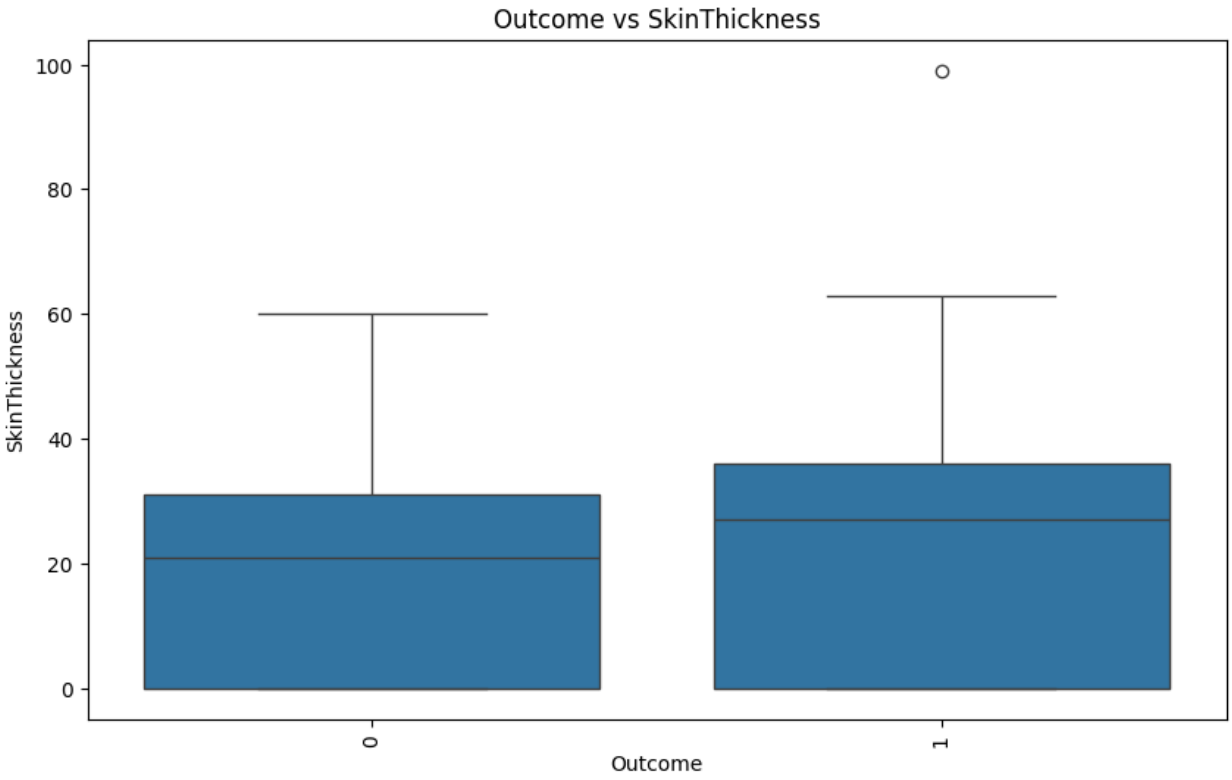

Outcome vs Age
Age
0
5
10
15
20
25
30
35
31.19
37.07
0
1
Outcome

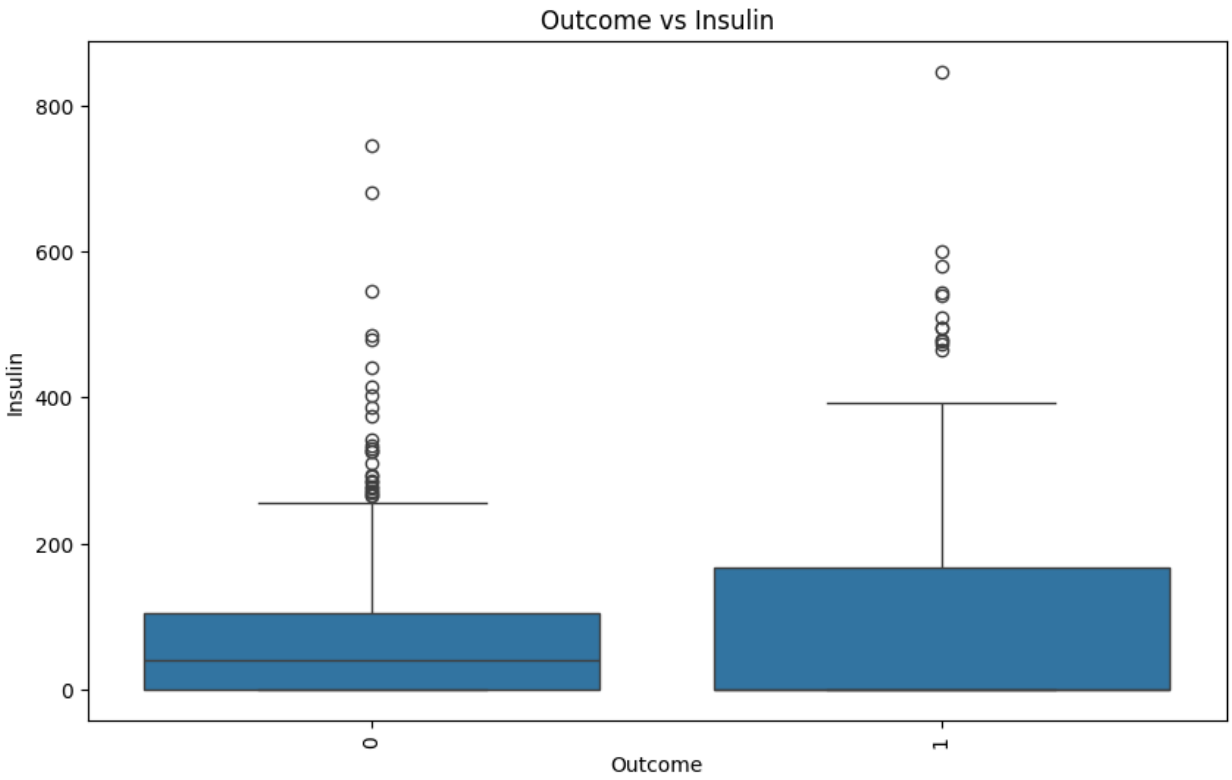
```
for dis in discrete:
    for cont in continuous:
        plt.figure(figsize=(10, 6))
        ax = sns.boxplot(data=df, x=dis, y=cont)
        plt.title(f'{dis} vs {cont}')
        plt.xticks(rotation = 90)
        plt.show()
```

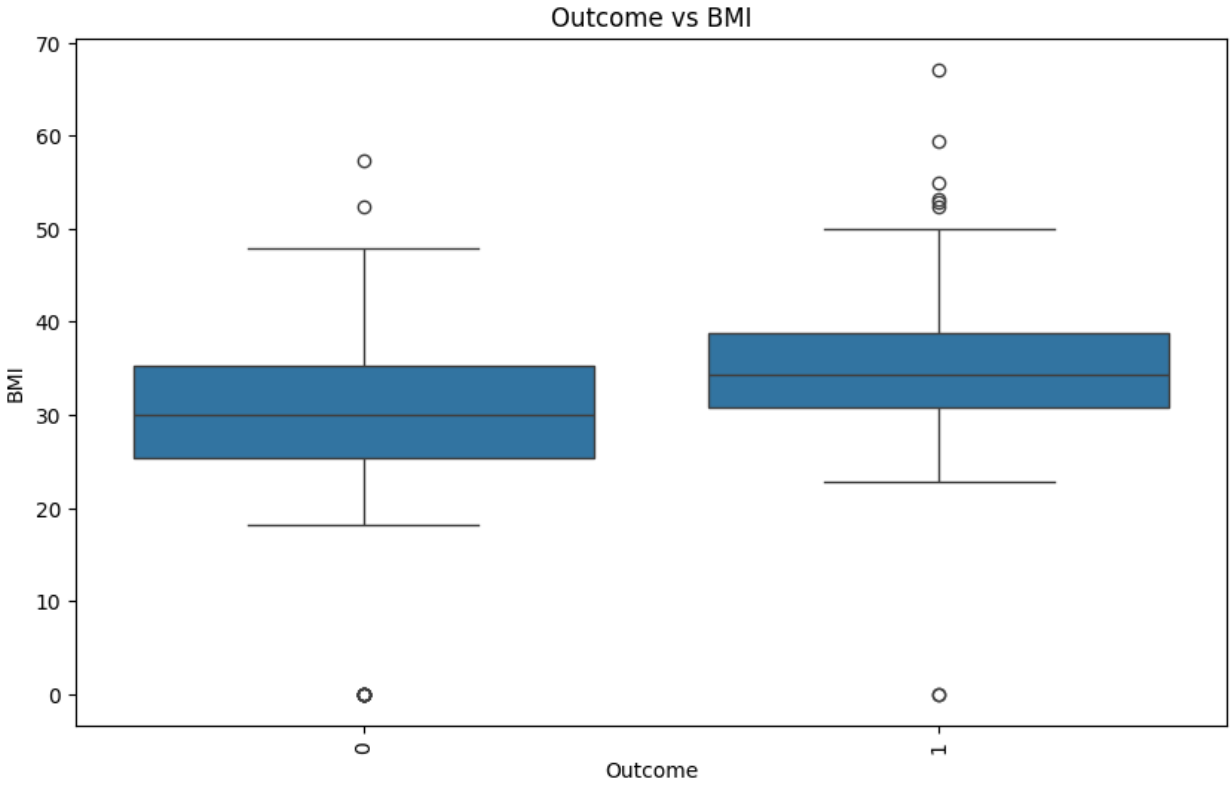


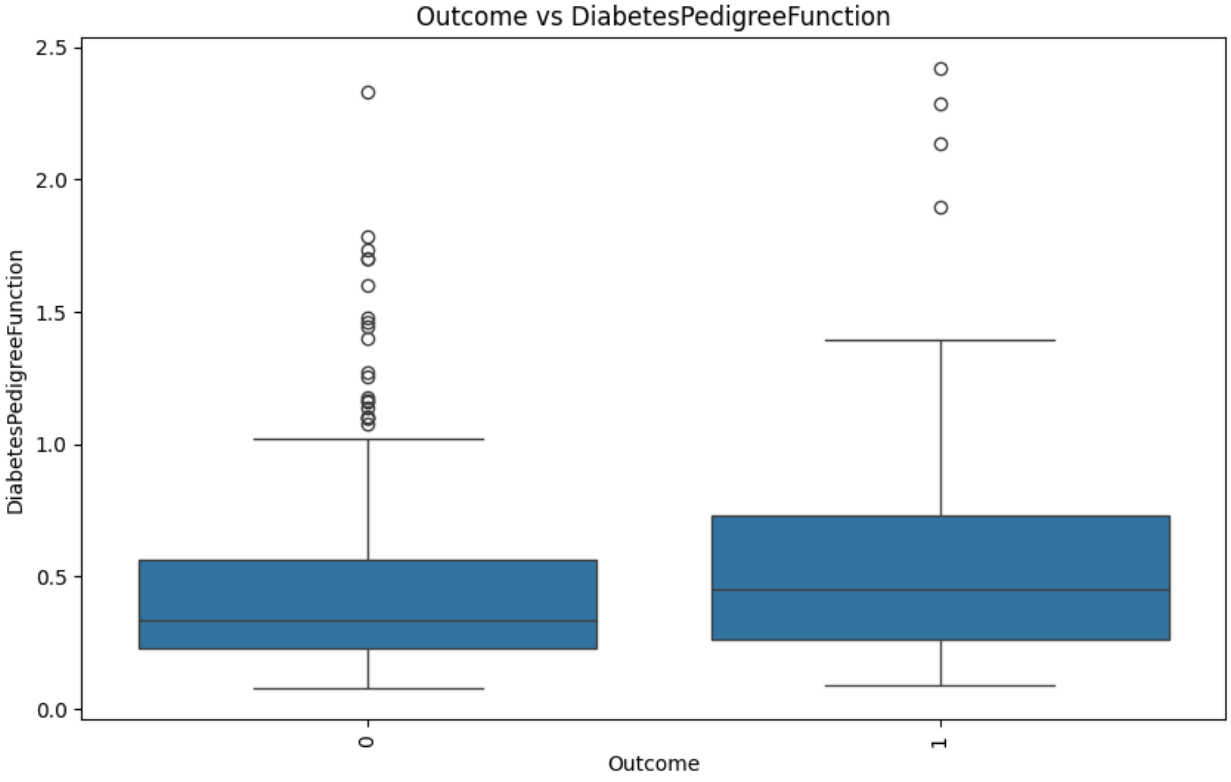

Outcome vs Glucose
Glucose
200
175
150
125
100
75
50
25
0
0
1
Outcome

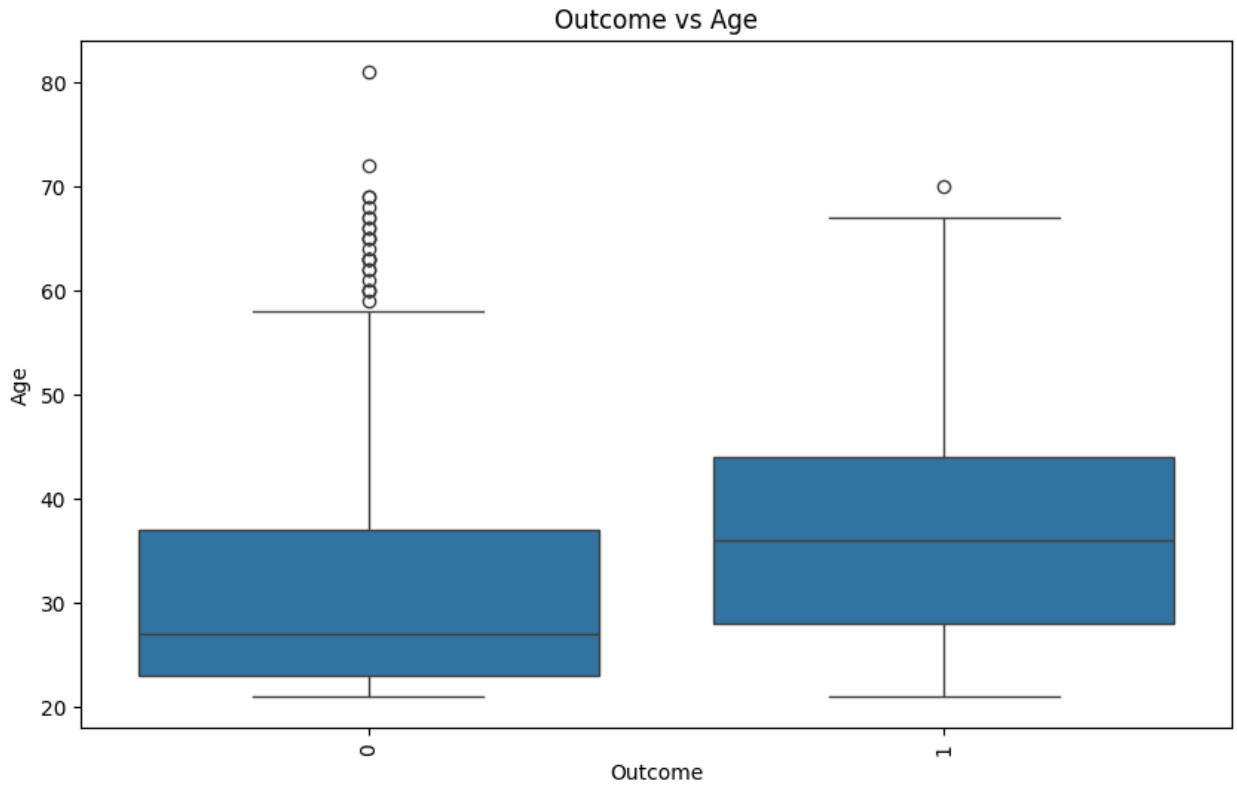

Outcome vs BloodPressure
BloodPressure
120
100
80
60
40
20
0
0
1
Outcome


Outcome vs SkinThickness
SkinThickness
100
80
60
40
20
0
0
1
Outcome

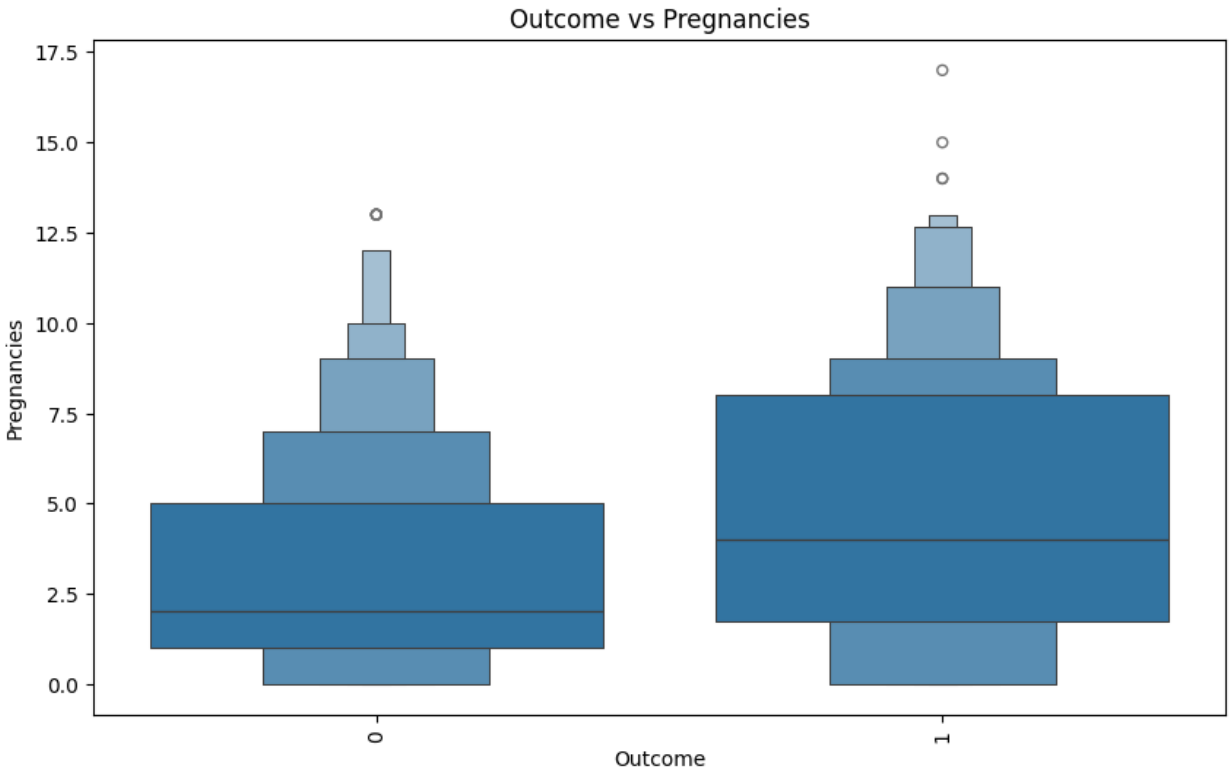

Outcome vs Insulin
Insulin
800
600
400
200
0
0
1
Outcome

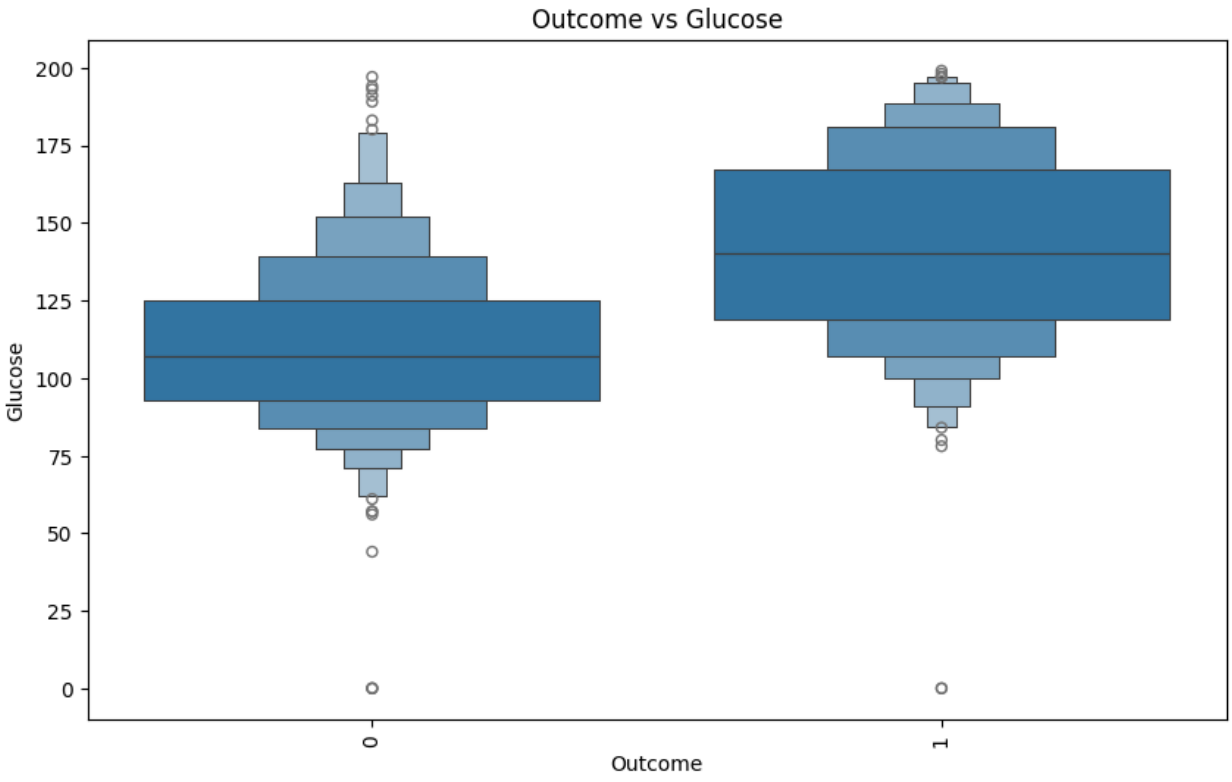

Outcome vs BMI
BMI
70
60
50
40
30
20
10
0
0
1
Outcome

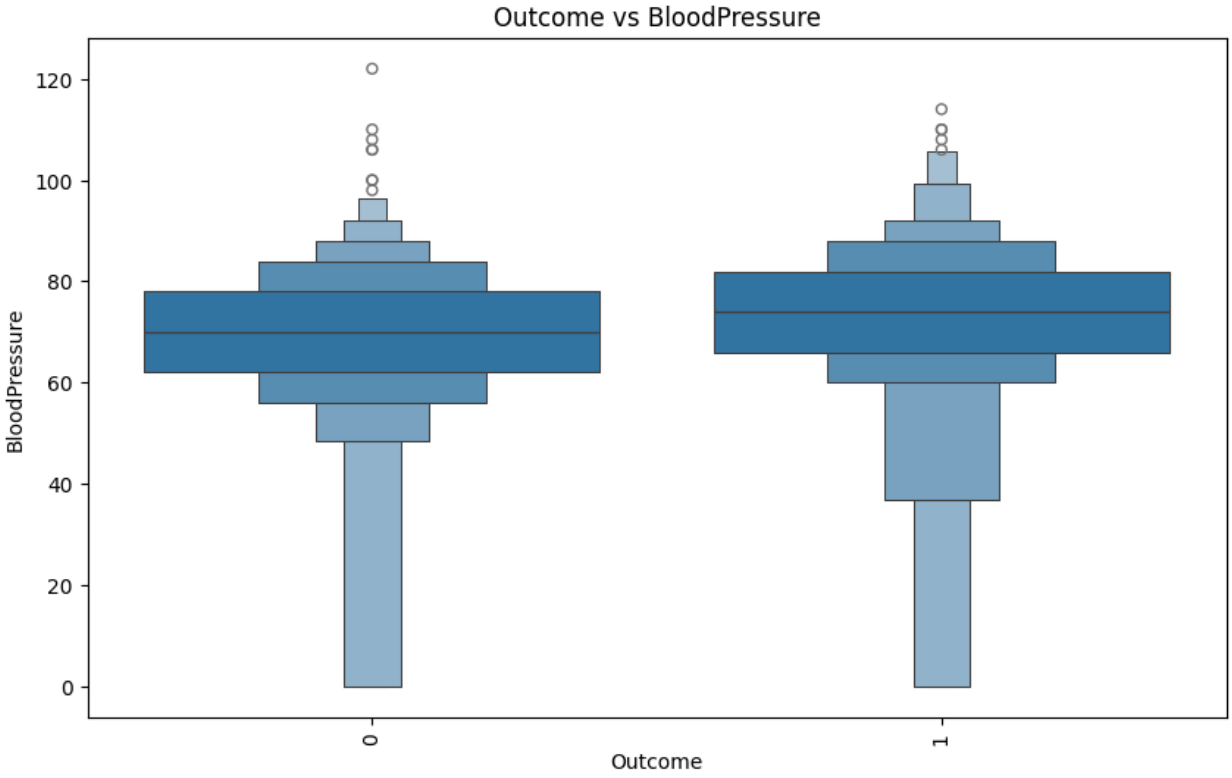

Outcome vs DiabetesPedigreeFunction
DiabetesPedigreeFunction
2.5
2.0
1.5
1.0
0.5
0.0
0
1
Outcome

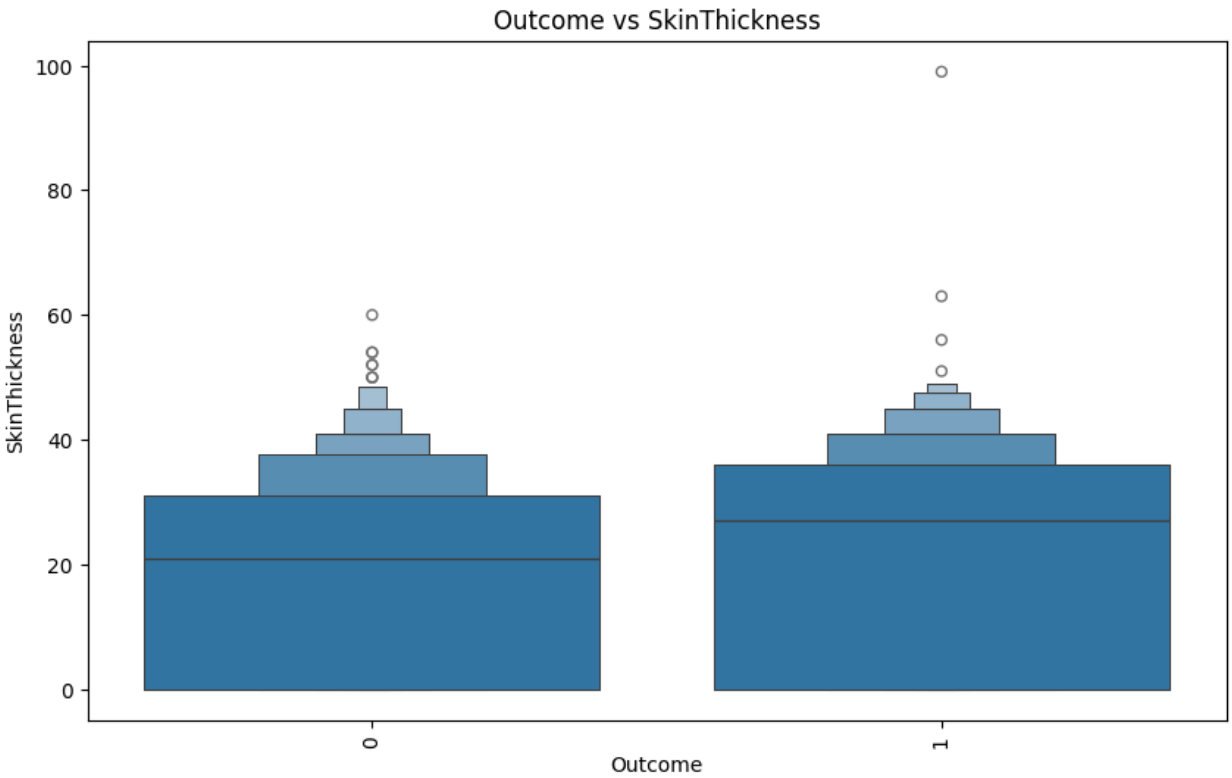


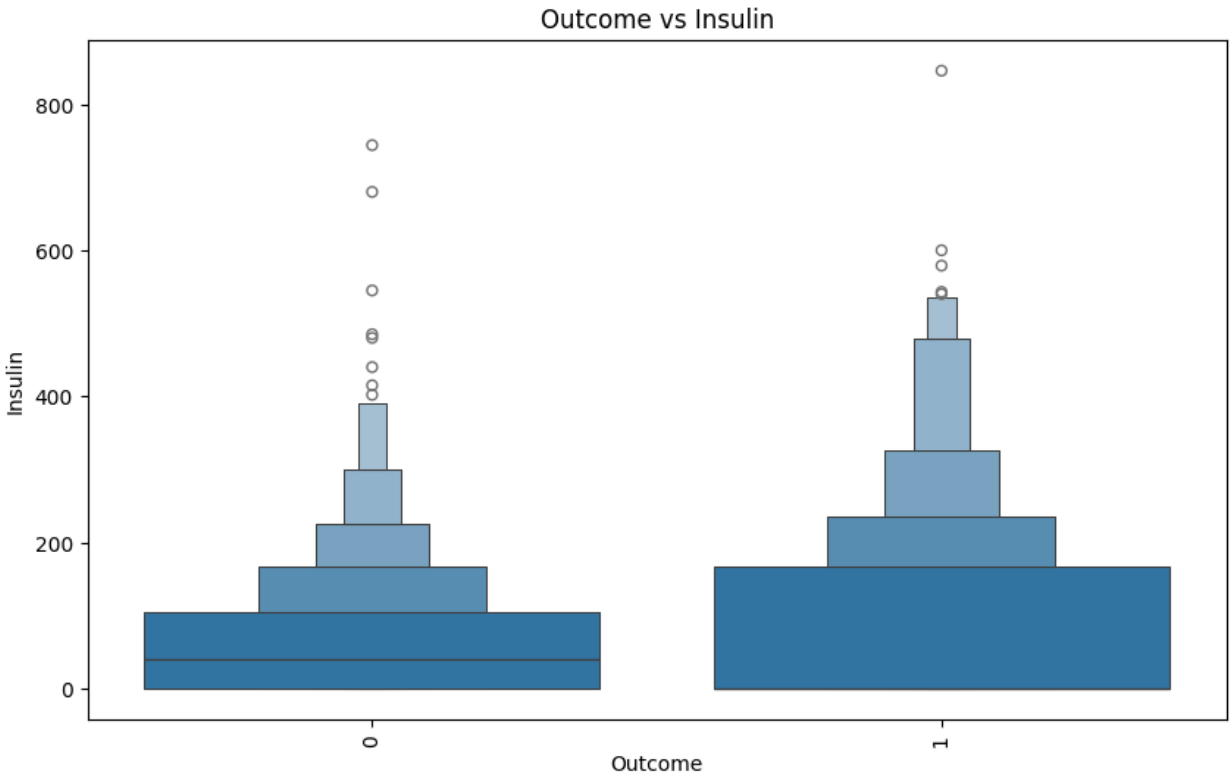

```
for dis in discrete:
    for cont in continuous:
        plt.figure(figsize=(10, 6))
        ax = sns.boxenplot(data=df, x=dis, y=cont)
        plt.title(f'{dis} vs {cont}')
        plt.xticks(rotation = 90)
        plt.show()
```

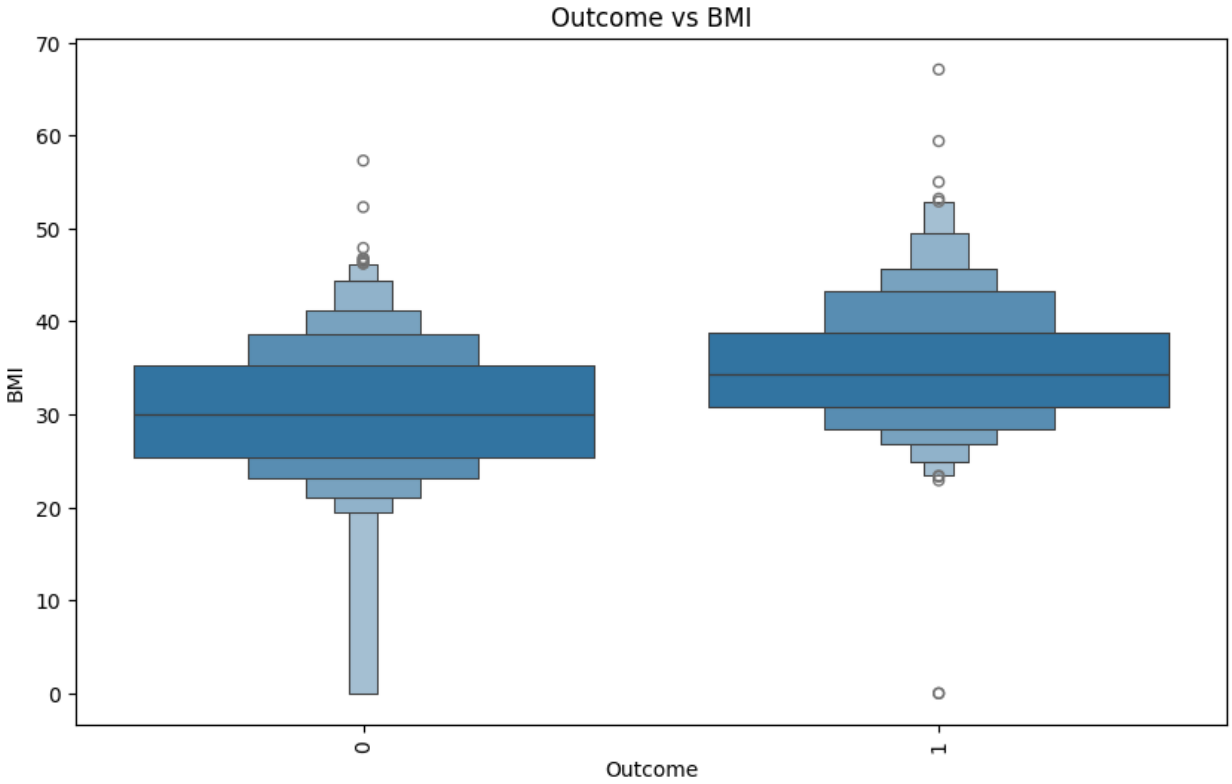

Outcome vs Pregnancies
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
Pregnancies
0
1
Outcome

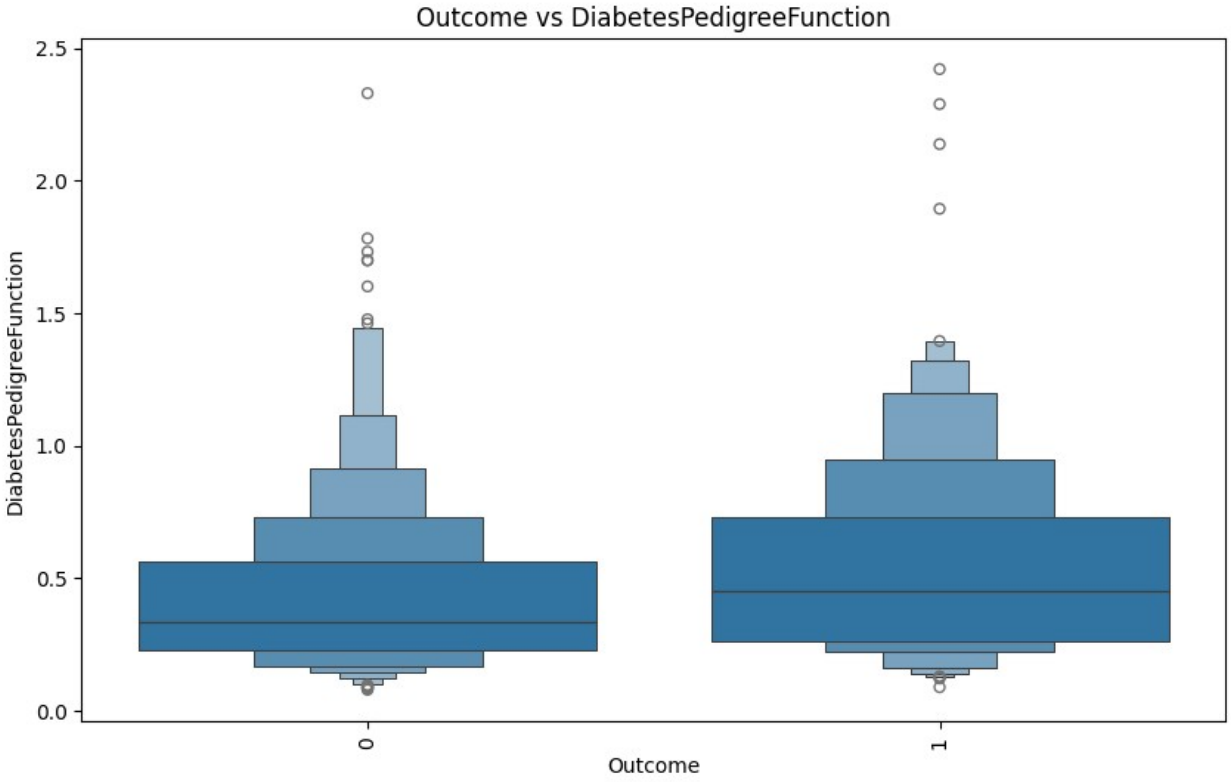

Outcome vs Glucose
200
175
150
125
100
75
50
25
0
Glucose
0
1
Outcome

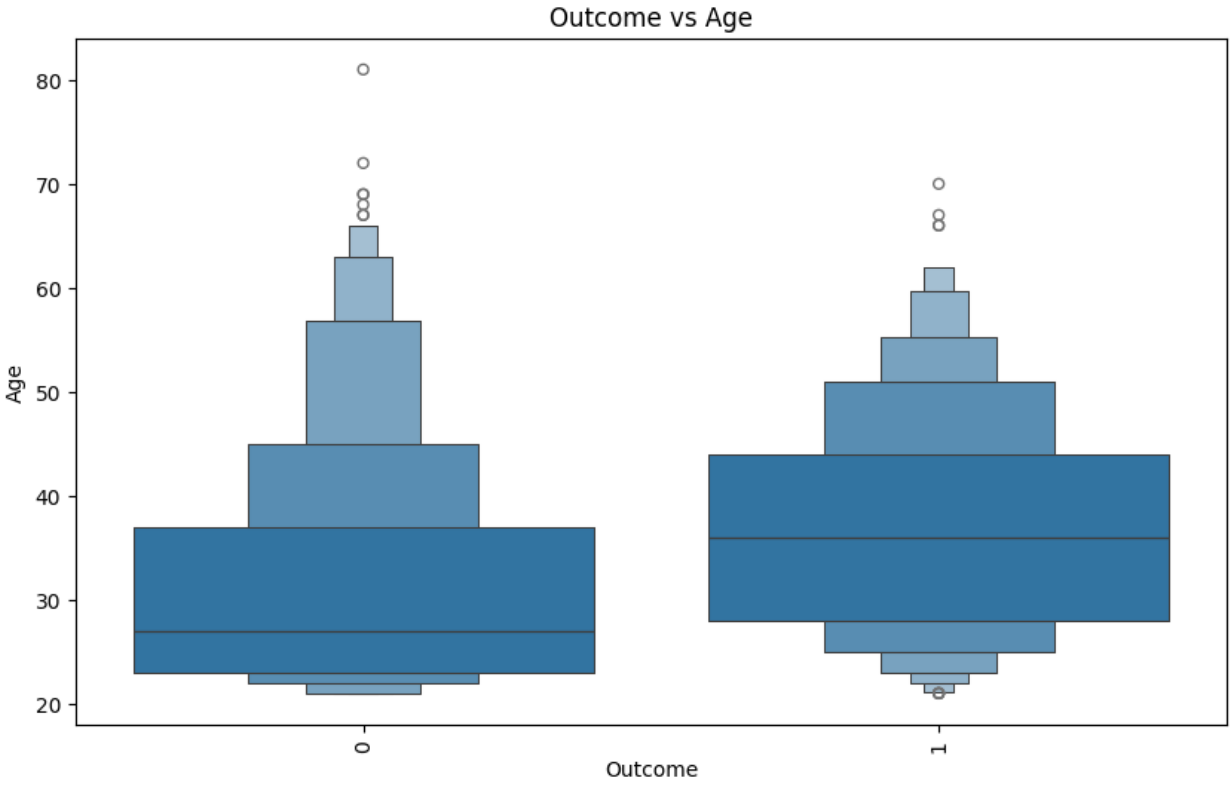

Outcome vs BloodPressure
BloodPressure
120
100
80
60
40
20
0
0
1
Outcome


Outcome vs SkinThickness
SkinThickness
100
80
60
40
20
0
0
1
Outcome

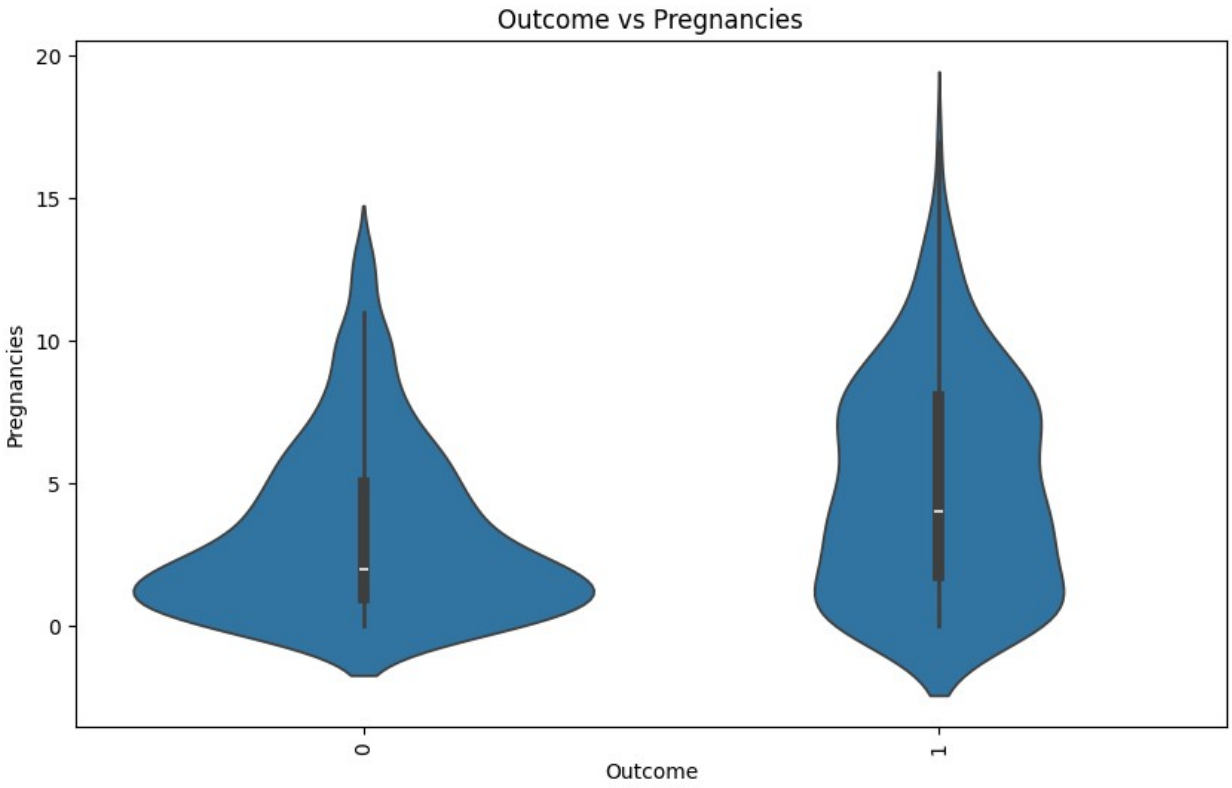

Outcome vs Insulin
Insulin
800
600
400
200
0
0
1
Outcome

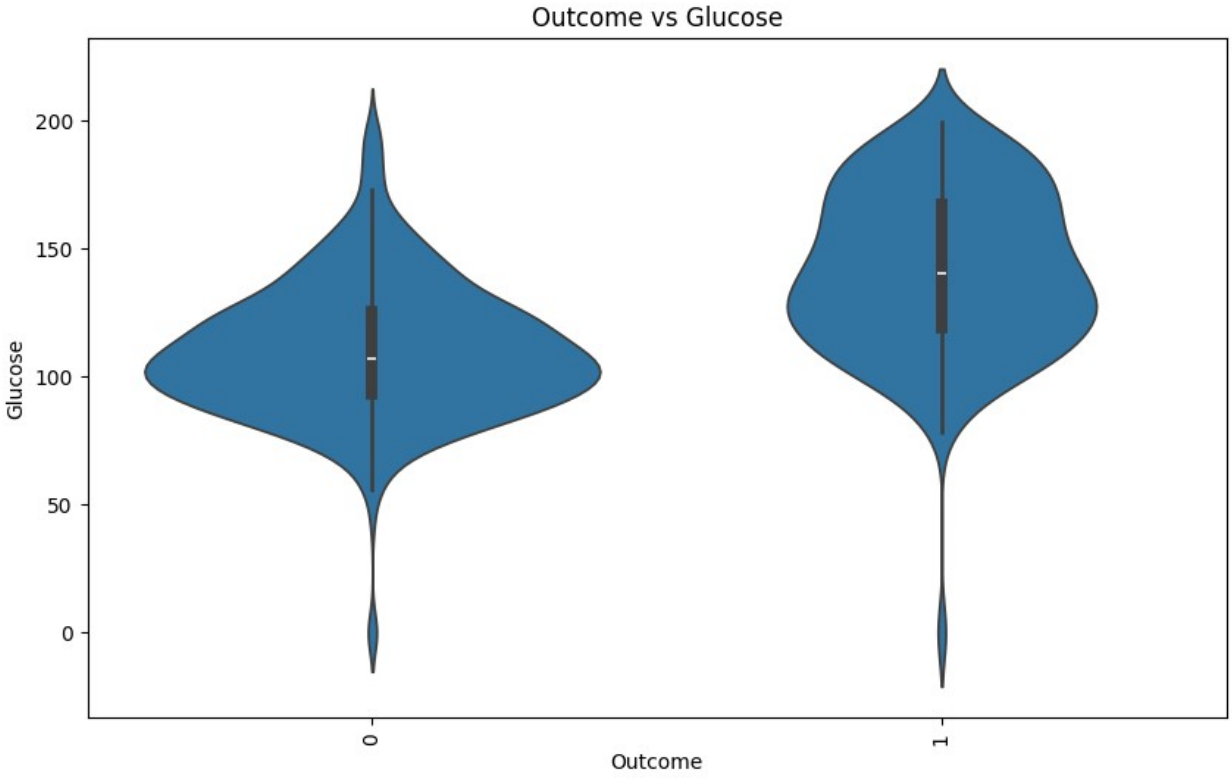

Outcome vs BMI
BMI
70
60
50
40
30
20
10
0
0
1
Outcome

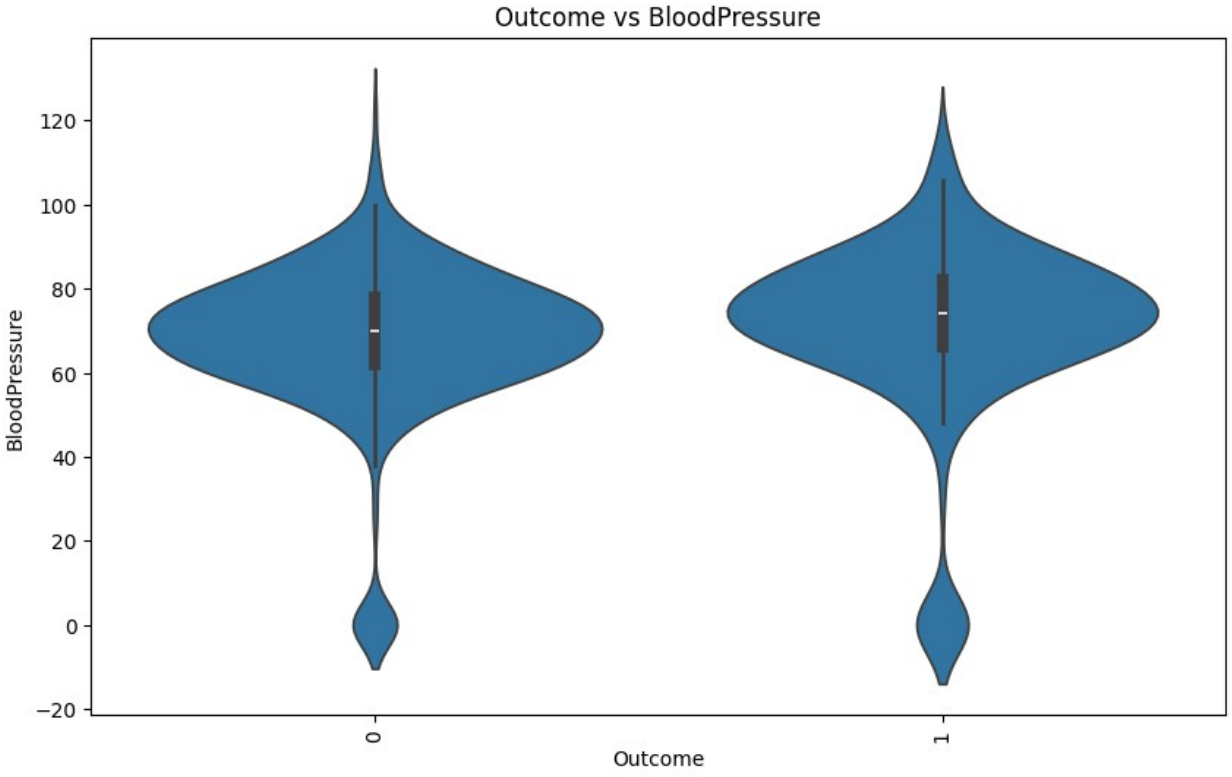

Outcome vs DiabetesPedigreeFunction
DiabetesPedigreeFunction
2.5
2.0
1.5
1.0
0.5
0.0
0
1
Outcome


Outcome vs Age
Age
80
70
60
50
40
30
20
0
1
Outcome

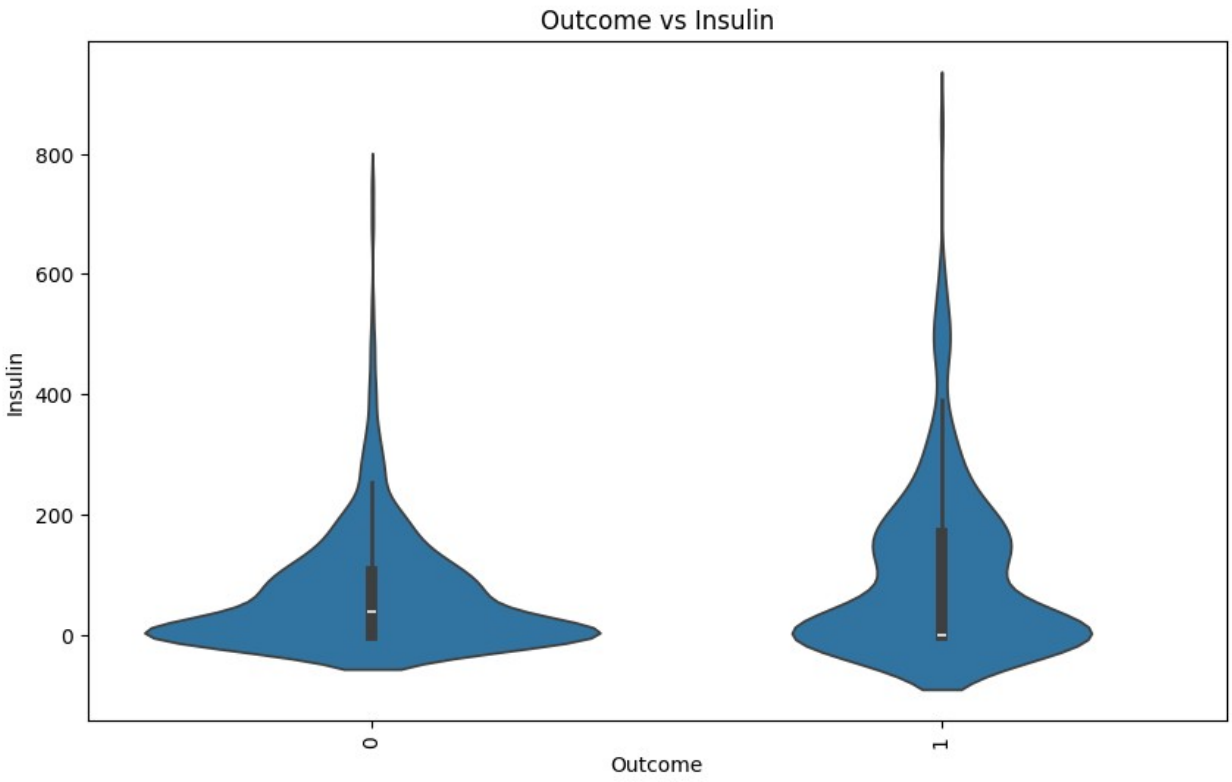
```
for dis in discrete:
    for cont in continuous:
        plt.figure(figsize=(10, 6))
        ax = sns.violinplot(data=df, x=dis, y=cont)
        plt.title(f'{dis} vs {cont}')
        plt.xticks(rotation = 90)
        plt.show()
```

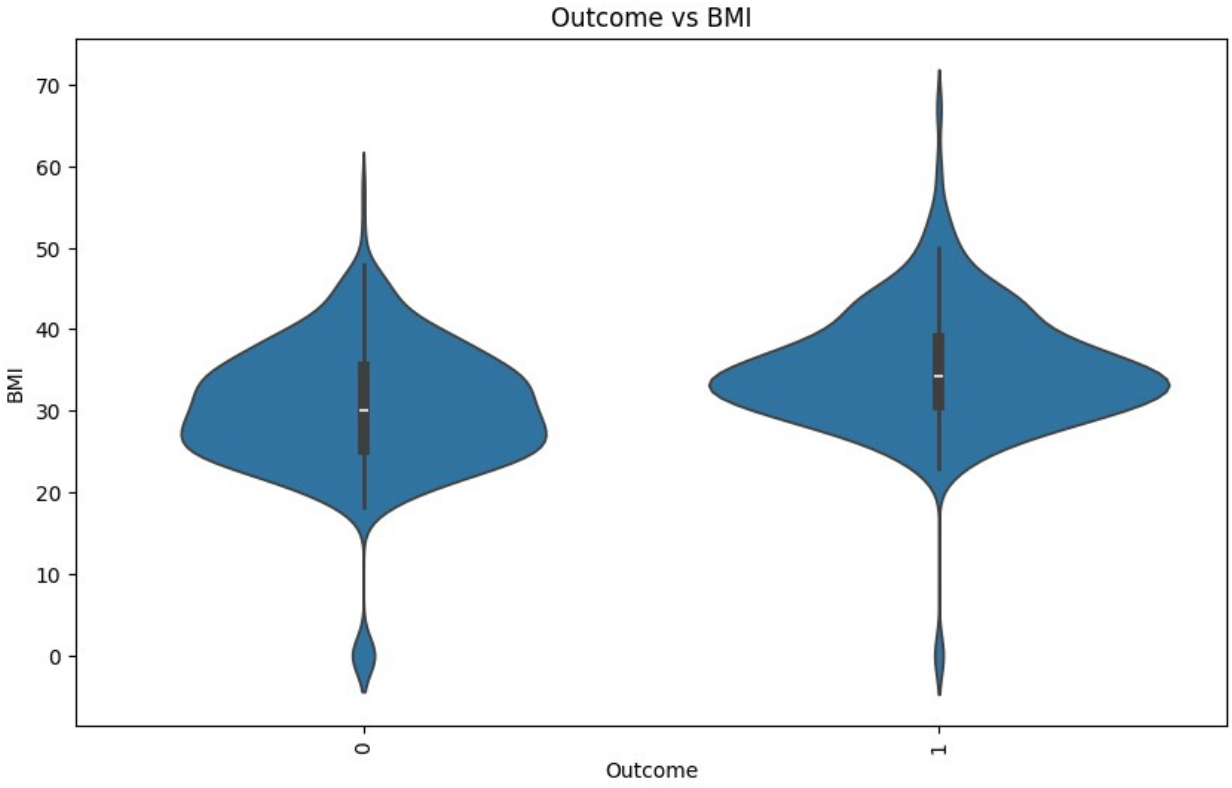


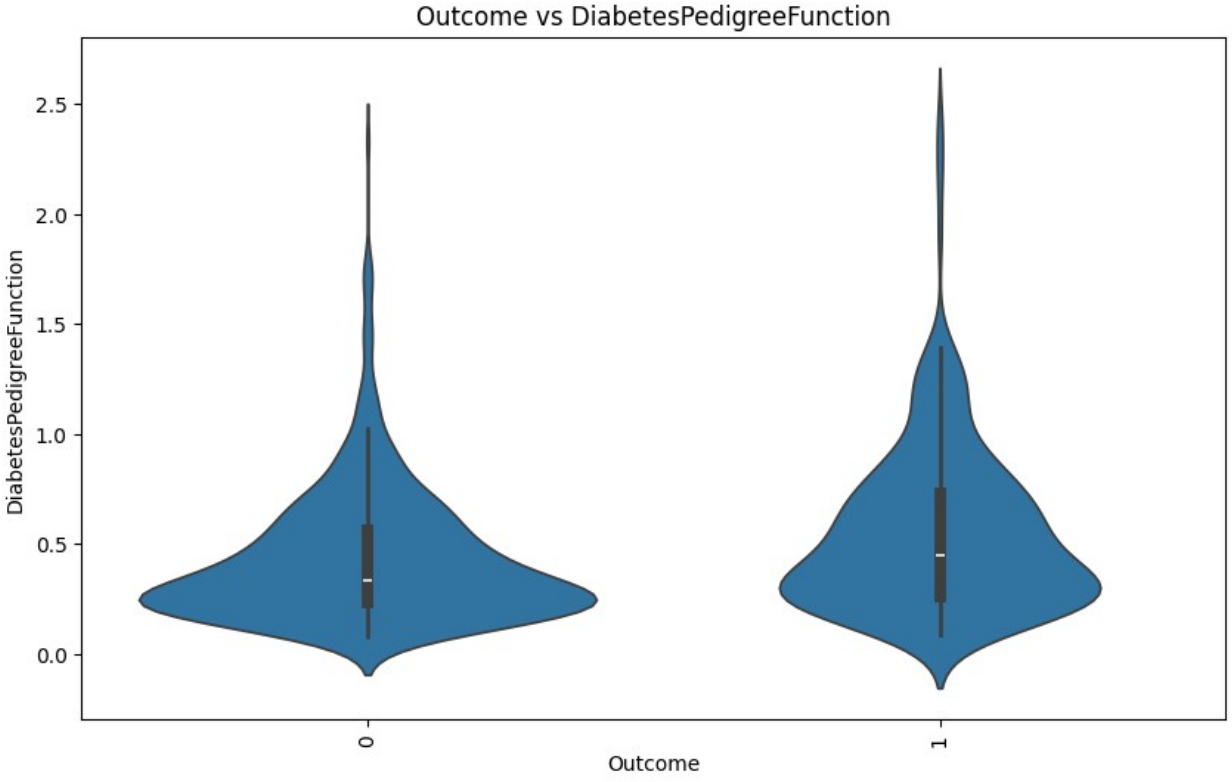

Outcome vs Glucose
Glucose
200
150
100
50
0
0
1
Outcome

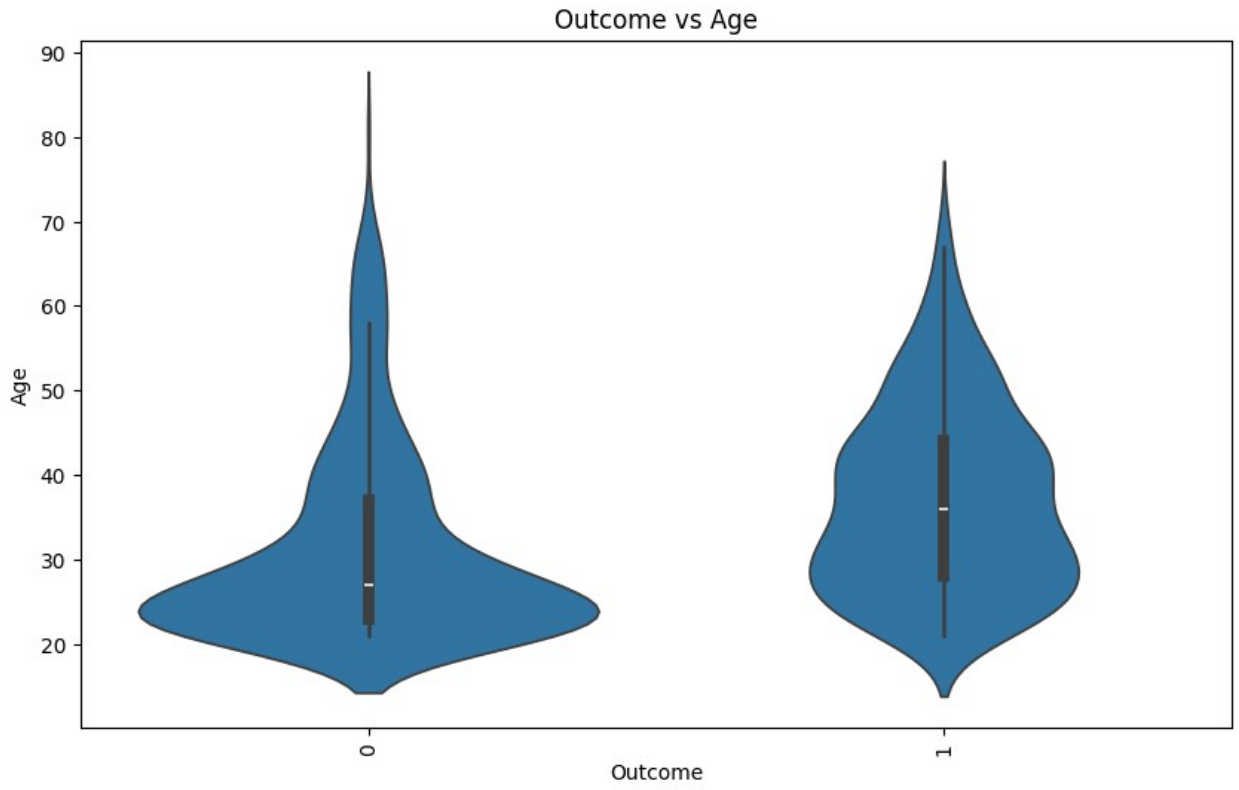

Outcome vs BloodPressure
BloodPressure
120
100
80
60
40
20
0
−20
0
1
Outcome


Outcome vs SkinThickness
SkinThickness
100
80
60
40
20
0
0
1
Outcome

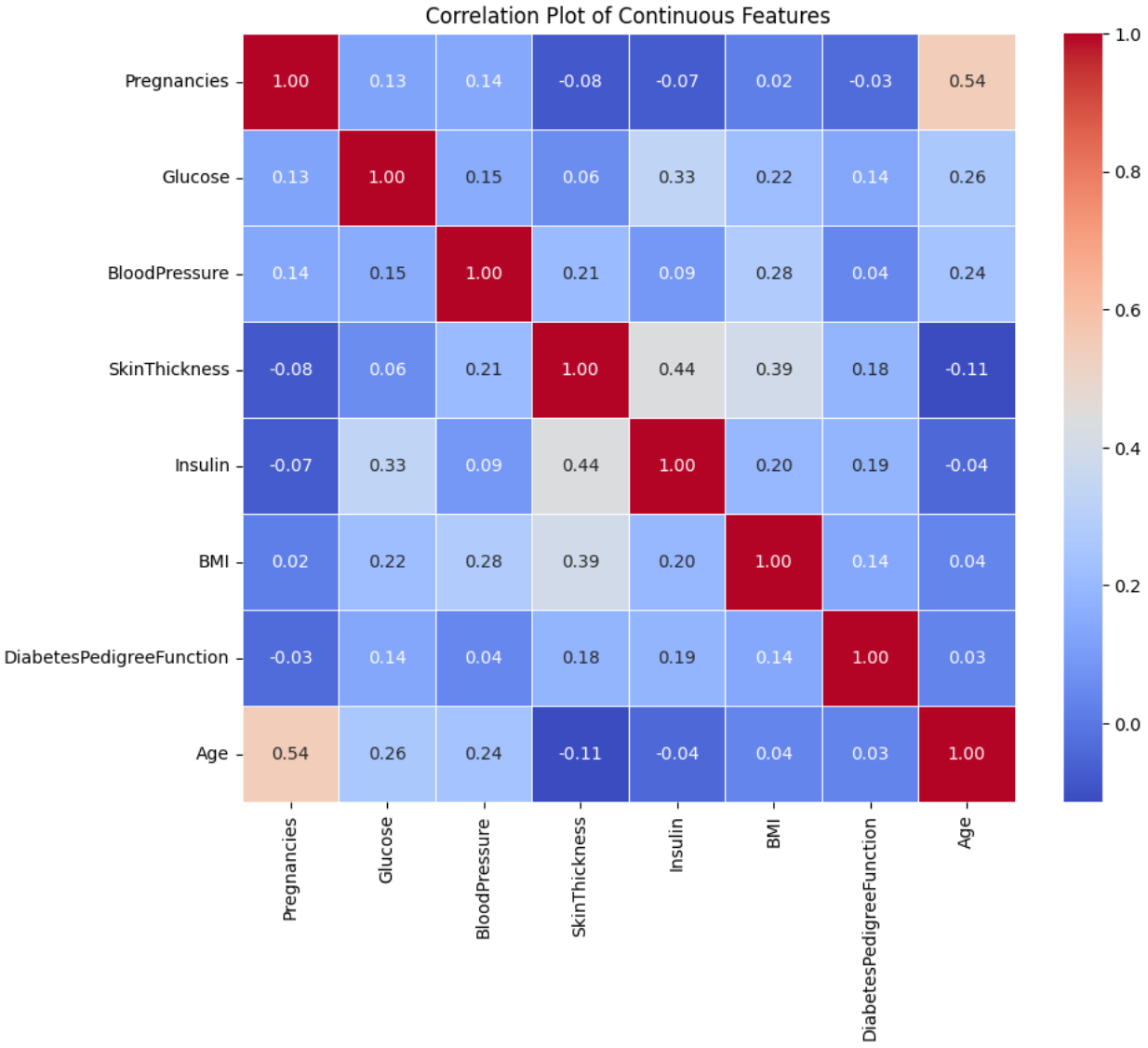

Outcome vs Insulin
Insulin
800
600
400
200
0
0
1
Outcome


Outcome vs BMI
BMI
70
60
50
40
30
20
10
0
0
1
Outcome


Outcome vs DiabetesPedigreeFunction
DiabetesPedigreeFunction
2.5
2.0
1.5
1.0
0.5
0.0
0
1
Outcome




```
corr_matrix = df[continuous].corr()

plt.figure(figsize=(10, 8))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt=".2f",
linewidths=0.5)
plt.title('Correlation Plot of Continuous Features')
plt.show()
```




```
corr_matrix

                          Pregnancies   Glucose  BloodPressure
SkinThickness  \
Pregnancies                  1.000000  0.129459       0.141282      -
0.081672
Glucose                      0.129459  1.000000       0.152590
0.057328
BloodPressure                0.141282  0.152590       1.000000
0.207371
SkinThickness               -0.081672  0.057328       0.207371
1.000000
Insulin                     -0.073535  0.331357       0.088933
0.436783
BMI                          0.017683  0.221071       0.281805
0.392573
```

```
DiabetesPedigreeFunction    -0.033523  0.137337       0.041265
0.183928
Age                          0.544341  0.263514       0.239528      -
0.113970

                            Insulin       BMI  DiabetesPedigreeFunction
\
Pregnancies               -0.073535  0.017683                 -0.033523

Glucose                    0.331357  0.221071                  0.137337

BloodPressure              0.088933  0.281805                  0.041265

SkinThickness              0.436783  0.392573                  0.183928

Insulin                    1.000000  0.197859                  0.185071

BMI                        0.197859  1.000000                  0.140647

DiabetesPedigreeFunction   0.185071  0.140647                  1.000000

Age                       -0.042163  0.036242                  0.033561


                                Age
Pregnancies                0.544341
Glucose                    0.263514
BloodPressure              0.239528
SkinThickness             -0.113970
Insulin                   -0.042163
BMI                        0.036242
DiabetesPedigreeFunction   0.033561
Age                        1.000000
```

```python
threshold = 0.7
features_to_drop = []
for i in range(len(corr_matrix.columns)):
    for j in range(i):
        if abs(corr_matrix.iloc[i, j]) > threshold:
            colname = corr_matrix.columns[i]
            if colname not in features_to_drop:
                features_to_drop.append(colname)

features_to_drop
```

```
[]
```

Feature Engineering

```
def bmi_category(bmi):
    if bmi <= 18.5:
        return 'Underweight'
    elif 18.5 < bmi <= 24.9:
        return 'Healthy'
    elif 25 <= bmi <= 29.9:
        return 'Pre-obese'
    elif 30 <= bmi <= 34.9:
        return 'Obesity class 1'
    elif 35 <= bmi <= 39.9:
        return 'Obesity class 2'
    else:
        return 'Obesity class 3'

df['BMI_Category'] = df['BMI'].apply(bmi_category)

def insulin_category(insulin):
    if insulin < 25:
        return 'Fasting or 3+ hours after glucose ingestion'
    elif 30 <= insulin <= 230:
        return '30 minutes after glucose administration'
    elif 18 <= insulin <= 276:
        return '1 hour after glucose ingestion'
    elif 16 <= insulin <= 166:
        return '2 hours after glucose ingestion'
    else:
        return 'Other'

df['Insulin_Category'] = df['Insulin'].apply(insulin_category)

df
```

```
     Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI
\
0              6      148             72             35        0  33.6

1              1       85             66             29        0  26.6

2              8      183             64              0        0  23.3

3              1       89             66             23       94  28.1

4              0      137             40             35      168  43.1

..           ...      ...            ...            ...      ...   ...

763           10      101             76             48      180  32.9

764            2      122             70             27        0  36.8
```

```
765            5      121             72             23      112  26.2

766            1      126             60              0        0  30.1

767            1       93             70             31        0  30.4


     DiabetesPedigreeFunction  Age  Outcome     BMI_Category  \
0                       0.627   50        1  Obesity class 1
1                       0.351   31        0       Pre-obese
2                       0.672   32        1         Healthy
3                       0.167   21        0       Pre-obese
4                       2.288   33        1  Obesity class 3
..                        ...  ...      ...             ...
763                     0.171   63        0  Obesity class 1
764                     0.340   27        0  Obesity class 2
765                     0.245   30        0       Pre-obese
766                     0.349   47        1  Obesity class 1
767                     0.315   23        0  Obesity class 1

                                Insulin_Category
0    Fasting or 3+ hours after glucose ingestion
1    Fasting or 3+ hours after glucose ingestion
2    Fasting or 3+ hours after glucose ingestion
3        30 minutes after glucose administration
4        30 minutes after glucose administration
..                                           ...
763      30 minutes after glucose administration
764  Fasting or 3+ hours after glucose ingestion
765      30 minutes after glucose administration
766  Fasting or 3+ hours after glucose ingestion
767  Fasting or 3+ hours after glucose ingestion

[768 rows x 11 columns]
```

```
object_columns = df.select_dtypes(include=['object']).columns
print("Object type columns:")
print(object_columns)

numerical_columns = df.select_dtypes(include=['int64',
'float64']).columns
print("\nNumerical type columns:")
print(numerical_columns)
```

```
Object type columns:
Index(['BMI_Category', 'Insulin_Category'], dtype='object')

Numerical type columns:
Index(['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness',
'Insulin',
```

```
       'BMI', 'DiabetesPedigreeFunction', 'Age', 'Outcome'],
      dtype='object')
```

```
df['Outcome']
```

```
0      1
1      0
2      1
3      0
4      1
      ..
763    0
764    0
765    0
766    1
767    0
Name: Outcome, Length: 768, dtype: int64
```

```
df_new = pd.get_dummies(df, columns=['BMI_Category',
'Insulin_Category'])

numerical_columns_1 = ['Pregnancies', 'Glucose', 'BloodPressure',
'SkinThickness', 'Insulin','BMI', 'DiabetesPedigreeFunction', 'Age']

pivot_table = pd.pivot_table(df_new, values='Glucose',
index='Outcome', aggfunc='mean')
pivot_table
```

```
            Glucose
Outcome
0        109.980000
1        141.257463
```

```
pivot_table = pd.pivot_table(df_new, values=['Glucose',
'BloodPressure', 'Insulin','BMI', 'Age'], index=['Outcome'],
aggfunc=['mean', 'max'])
pivot_table
```

```
              mean
max        \
               Age        BMI BloodPressure     Glucose     Insulin
Age   BMI
Outcome

0        31.190000  30.304200     68.184000  109.980000   68.792000
81  57.3
1        37.067164  35.142537     70.824627  141.257463  100.335821
70  67.1


        BloodPressure Glucose Insulin
```

```
Outcome
0                 122     197     744
1                 114     199     846
```

Modeling

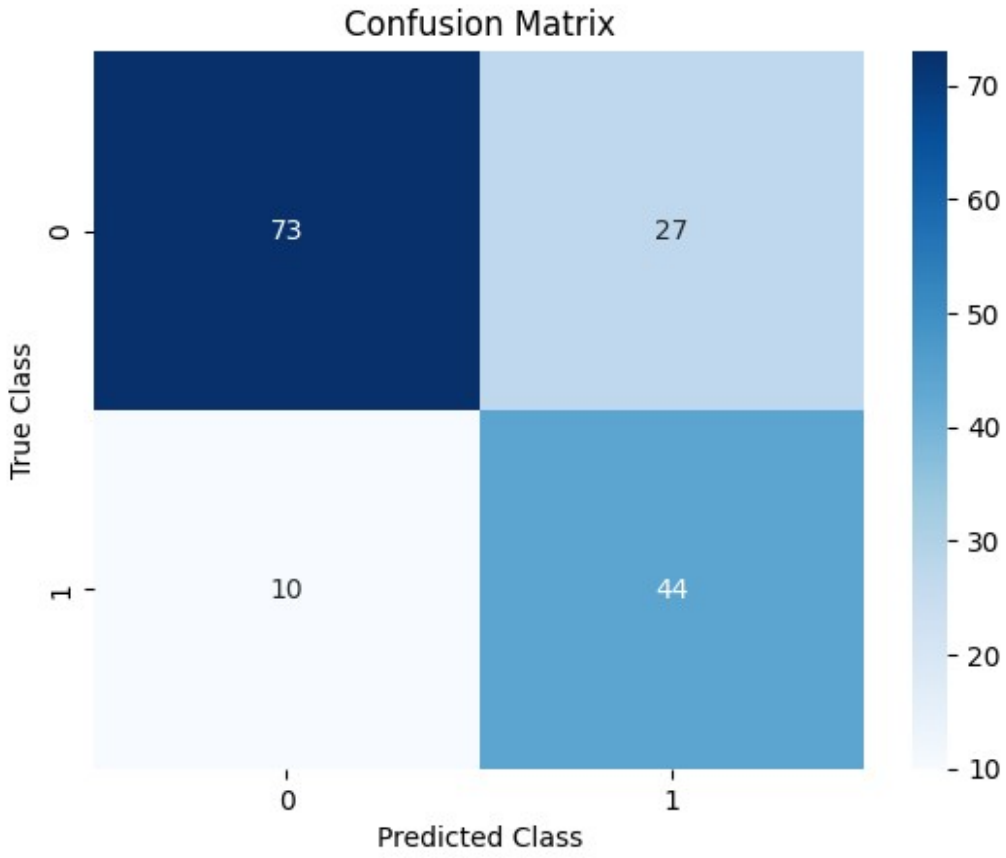
```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
df_new[numerical_columns_1] =
scaler.fit_transform(df_new[numerical_columns_1])

X = df_new.drop(['Outcome'], axis = 1)
y = df_new['Outcome']

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, stratify =
y, random_state= 42, test_size = 0.20)

from imblearn.over_sampling import SMOTE

sm = SMOTE()

X_train, y_train = sm.fit_resample(X_train, y_train)

from sklearn.linear_model import LogisticRegression

model = LogisticRegression()
model.fit(X_train, y_train)

LogisticRegression()

y_pred = model.predict(X_test)

from sklearn.metrics import accuracy_score, precision_score,
recall_score, f1_score, confusion_matrix, classification_report

accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)

print("Accuracy: {:.2f}".format(accuracy))
print("Precision: {:.2f}".format(precision))
print("Recall: {:.2f}".format(recall))
print("F1-score: {:.2f}".format(f1))

Accuracy: 0.76
Precision: 0.62
```

```
Recall: 0.81
F1-score: 0.70
```

```
cm = confusion_matrix(y_test, y_pred)
print("Confusion matrix:")
print(cm)
```

```
Confusion matrix:
[[73 27]
 [10 44]]
```

```
sns.heatmap(cm, annot=True, cmap="Blues")
plt.title("Confusion Matrix")
plt.xlabel("Predicted Class")
plt.ylabel("True Class")
plt.show()
```




```
report = classification_report(y_test, y_pred)
print("Classification report:")
print(report)
```

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

```
              0       0.88      0.73      0.80       100
              1       0.62      0.81      0.70        54

    accuracy                            0.76       154
   macro avg       0.75      0.77      0.75       154
weighted avg       0.79      0.76      0.76       154
```

```
from sklearn.tree import DecisionTreeClassifier

clf = DecisionTreeClassifier()
clf.fit(X_train, y_train)
```

```
DecisionTreeClassifier()
```

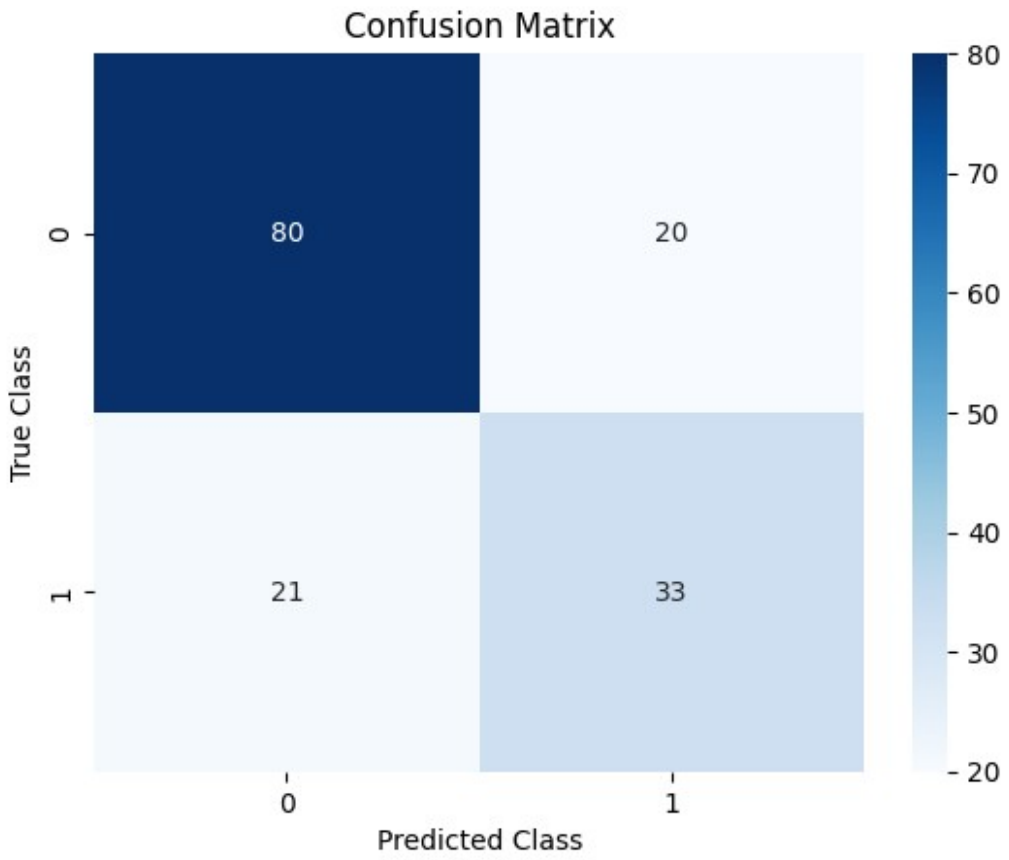
```
y_pred = clf.predict(X_test)

accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)

print("Accuracy: {:.2f}".format(accuracy))
print("Precision: {:.2f}".format(precision))
print("Recall: {:.2f}".format(recall))
print("F1-score: {:.2f}".format(f1))
```

```
Accuracy: 0.73
Precision: 0.62
Recall: 0.61
F1-score: 0.62
```

```
cm = confusion_matrix(y_test, y_pred)
print("Confusion matrix:")
print(cm)
```

```
Confusion matrix:
[[80 20]
 [21 33]]
```

```
sns.heatmap(cm, annot=True, cmap="Blues")
plt.title("Confusion Matrix")
plt.xlabel("Predicted Class")
plt.ylabel("True Class")
plt.show()
```




```
report = classification_report(y_test, y_pred)
print("Classification report:")
print(report)
```

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

           0       0.79      0.80      0.80       100
           1       0.62      0.61      0.62        54

    accuracy                           0.73       154
   macro avg       0.71      0.71      0.71       154
weighted avg       0.73      0.73      0.73       154
```

```
from sklearn.ensemble import RandomForestClassifier

rf = RandomForestClassifier(n_estimators=100)
rf.fit(X_train, y_train)
```

```
RandomForestClassifier()
```

```
y_pred = rf.predict(X_test)
```

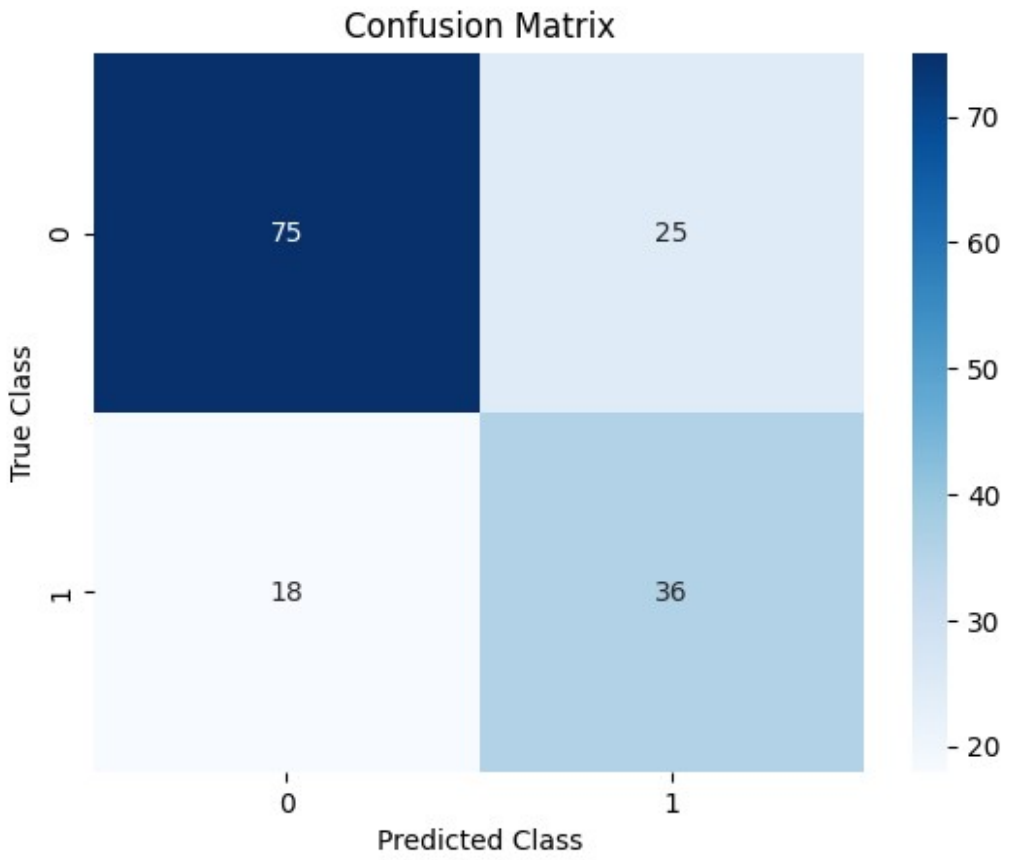
```
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)

print("Accuracy: {:.2f}".format(accuracy))
print("Precision: {:.2f}".format(precision))
print("Recall: {:.2f}".format(recall))
print("F1-score: {:.2f}".format(f1))
```

```
Accuracy: 0.72
Precision: 0.59
Recall: 0.67
F1-score: 0.63
```

```
cm = confusion_matrix(y_test, y_pred)
print("Confusion matrix:")
print(cm)
```

```
Confusion matrix:
[[75 25]
 [18 36]]
```

```
sns.heatmap(cm, annot=True, cmap="Blues")
plt.title("Confusion Matrix")
plt.xlabel("Predicted Class")
plt.ylabel("True Class")
plt.show()
```




```
report = classification_report(y_test, y_pred)
print("Classification report:")
print(report)
```

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

           0       0.81      0.75      0.78       100
           1       0.59      0.67      0.63        54

    accuracy                           0.72       154
   macro avg       0.70      0.71      0.70       154
weighted avg       0.73      0.72      0.72       154
```

```
from sklearn.svm import SVC

sv = SVC(kernel='linear')
sv.fit(X_train, y_train)
```

```
SVC(kernel='linear')
```

```
y_pred = sv.predict(X_test)
```

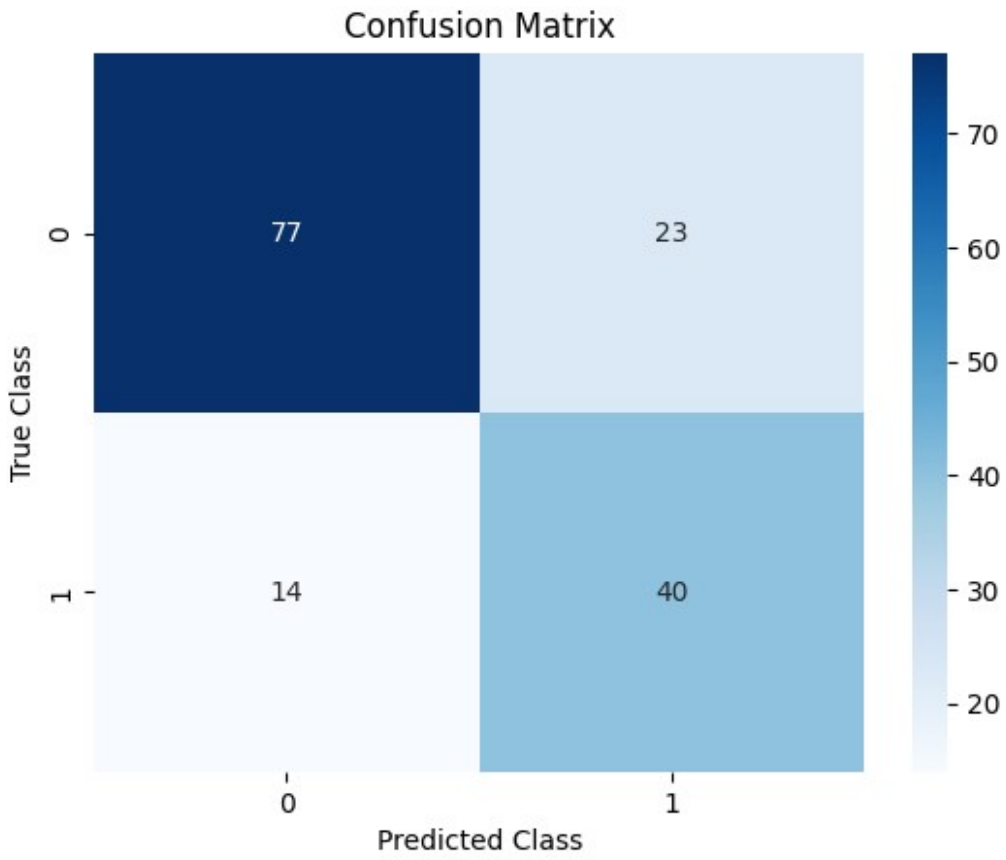
```
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)

print("Accuracy: {:.2f}".format(accuracy))
print("Precision: {:.2f}".format(precision))
print("Recall: {:.2f}".format(recall))
print("F1-score: {:.2f}".format(f1))
```

```
Accuracy: 0.76
Precision: 0.63
Recall: 0.74
F1-score: 0.68
```

```
cm = confusion_matrix(y_test, y_pred)
print("Confusion matrix:")
print(cm)
```

```
Confusion matrix:
[[77 23]
 [14 40]]
```

```
sns.heatmap(cm, annot=True, cmap="Blues")
plt.title("Confusion Matrix")
plt.xlabel("Predicted Class")
plt.ylabel("True Class")
plt.show()
```




```
report = classification_report(y_test, y_pred)
print("Classification report:")
print(report)
```

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

           0       0.85      0.77      0.81       100
           1       0.63      0.74      0.68        54

    accuracy                           0.76       154
   macro avg       0.74      0.76      0.75       154
weighted avg       0.77      0.76      0.76       154
```

```
from sklearn.ensemble import GradientBoostingClassifier

gbc = GradientBoostingClassifier()
gbc.fit(X_train, y_train)
```

```
GradientBoostingClassifier()
```

```
y_pred = gbc.predict(X_test)
```

```
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)

print("Accuracy: {:.2f}".format(accuracy))
print("Precision: {:.2f}".format(precision))
print("Recall: {:.2f}".format(recall))
print("F1-score: {:.2f}".format(f1))
```

```
Accuracy: 0.76
Precision: 0.63
Recall: 0.76
F1-score: 0.69
```

```
import pickle
```

Pickle in Python is primarily used in serializing and deserializing a Python object structure. In other words, it's the process of converting a Python object into a byte stream to store it in a file/database, maintain program state across sessions, or transport data over the network.

```
model_filename = 'svm_model_diabetes.pkl'
with open(model_filename, 'wb') as file:
    pickle.dump(sv, file)

print(f"Model saved to {model_filename}")
```

```
Model saved to svm_model_diabetes.pkl
```

Thanks !!!