Statistics and Machine Learning 1 Coursework: EDA & Regression

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I. Introduction

In healthcare and medical research, understanding and predicting the onset of diabetes has been a crucial and ever-evolving challenge. Diabetes, a chronic metabolic disorder, affects millions of individuals worldwide, contributing to significant health burdens and economic costs. To address this challenge, this report delves into an exploration of a dataset derived from the USA's National Institute of Diabetes and Digestive and Kidney Diseases, presenting a fundamental analysis of the data.

II. Data Description

The dataset under investigation, known as PimaDiabetes.csv, originates from the National Institute of Diabetes and Digestive and Kidney Diseases in the USA. It comprises diagnostic measures from 750 women, including factors like the number of pregnancies, plasma glucose concentration, diastolic blood pressure, triceps skin fold thickness, insulin concentration, body mass index (BMI), a diabetes pedigree score, and age. The outcome variable, denoted as 'Outcome,' indicates whether the individual tested positive (1) or negative (0) for diabetes.

III. Data Preprocessing

From observations, it became evident that the indicators 'Glucose,' 'BloodPressure,' 'SkinThickness,' 'Insulin,' and 'BMI' should not have zero values. Consequently, zero values were treated as missing data.

In order to ensure the dataset's completeness and reliability, missing values in 'Glucose,' 'BloodPressure,' 'SkinThickness,' 'Insulin,' and 'BMI' were imputed with their respective means, segregated by diabetes outcome (positive or negative).

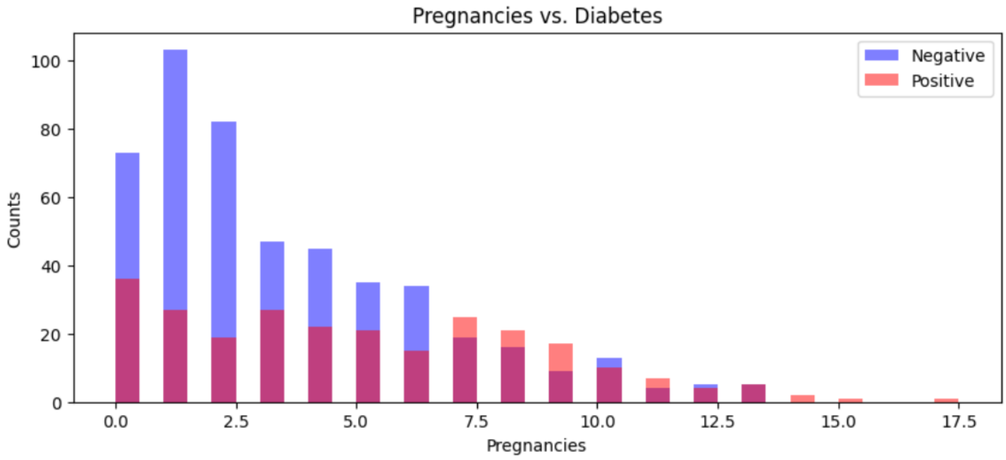
IV. Exploratory Data Analysis

Pregnancies

```
Postive:
Q1 (25th percentile): 2.0
Q2 (50th percentile - Median): 4.0
Q3 (75th percentile): 8.0
Negative:
Q1 (25th percentile): 1.0
Q2 (50th percentile - Median): 2.0
Q3 (75th percentile): 5.0
```

Plot 1: Interquartile range of Pregnancies - Diabetes Positive vs. Diabetes Negative

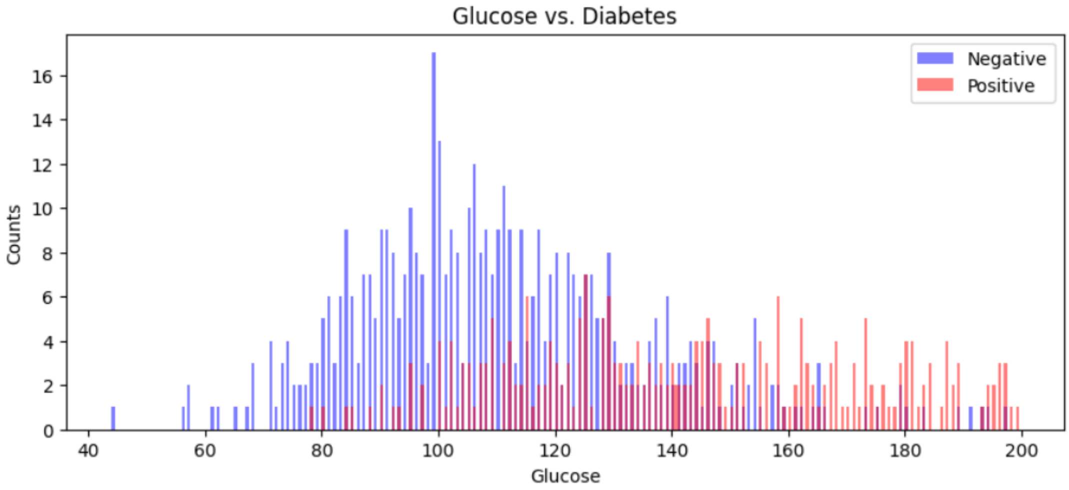
- From Plot 1, the interquartile analysis reveals that the majority of diabetes patients have a pregnancy history of 2 to 8 times, notably higher than non-diabetic individuals who typically have 1 to 5 pregnancies.



Plot 2: Histogram of "Pregnancies" vs. Diabetes

- Notably, when 'Pregnancies' are greater than or equal to 7, the proportion of individuals with diabetes significantly exceeds 50%.

Glucose



Plot 3: Histogram of "Glucose" vs. Diabetes

```
Postive:
Q1 (25th percentile): 119.0
Q2 (50th percentile - Median): 140.47884615384615
Q3 (75th percentile): 166.25
Negative:
Q1 (25th percentile): 93.25
Q2 (50th percentile - Median): 107.5
Q3 (75th percentile): 125.0
```

Plot 4: Interquartile range of "Glucose" - Diabetes Positive vs. Diabetes Negative

- From Plot 4, in two-hour oral glucose tolerance tests, patients with diabetes generally exhibit higher plasma glucose concentration (mg/dl) levels when compared to those without diabetes. Most patients with diabetes have plasma glucose concentrations ranging from 119 to 166.25, while samples from those without diabetes typically range from 93.25 to 125.

- Furthermore, when the plasma glucose concentration exceeds 120, the likelihood of diabetes is approximately 50%.

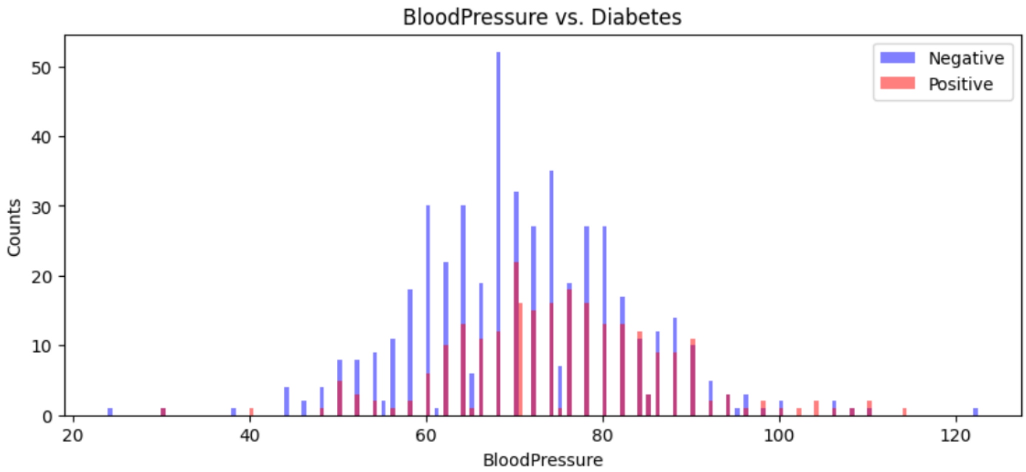
Blood Pressure

```
Negative:
Q1 (25th percentile): 64.0
Q2 (50th percentile - Median): 70.0
Q3 (75th percentile): 78.0
```

Plot 5: Interquartile range of BloodPressure - Diabetes Negative

```
count     750.000000
mean       72.214711
std        12.159133
min        24.000000
25%        64.000000
50%        72.000000
75%        80.000000
max       122.000000
Name: BloodPressure, dtype: float64
```

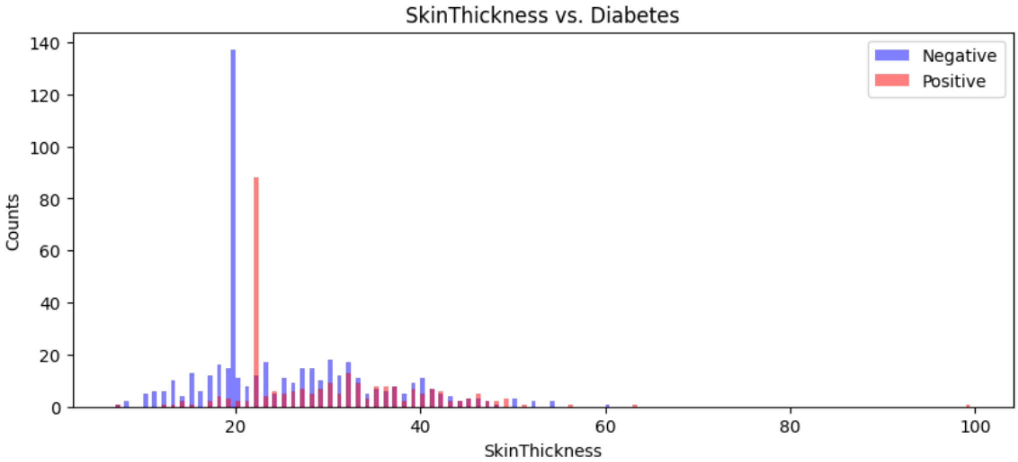
Plot 6: Interquartile range of BloodPressure



Plot 7: Histogram of "BloodPressure" vs. Diabetes

- Most individuals with diabetes have blood pressure levels between 68 and 82. However, it's important that the majority of participants fall within the standard range of 64 to 80. As a result, diabetes negative has a slightly lower blood pressure than diabetes positive.

Skin Thickness



Plot 8: Histogram of "SkinThickness" vs. Diabetes

```
Postive:
Q1 (25th percentile): 22.284615384615385
Q2 (50th percentile - Median): 27.0
Q3 (75th percentile): 36.0
Negative:
Q1 (25th percentile): 19.536734693877552
Q2 (50th percentile - Median): 21.0
Q3 (75th percentile): 31.0
```

Plot 9: Interquartile range of SkinThickness - Diabetes Positive vs. Diabetes Negative

- Diabetes-positive individuals generally have thicker skin, ranging from approximately 22.28 to 36.

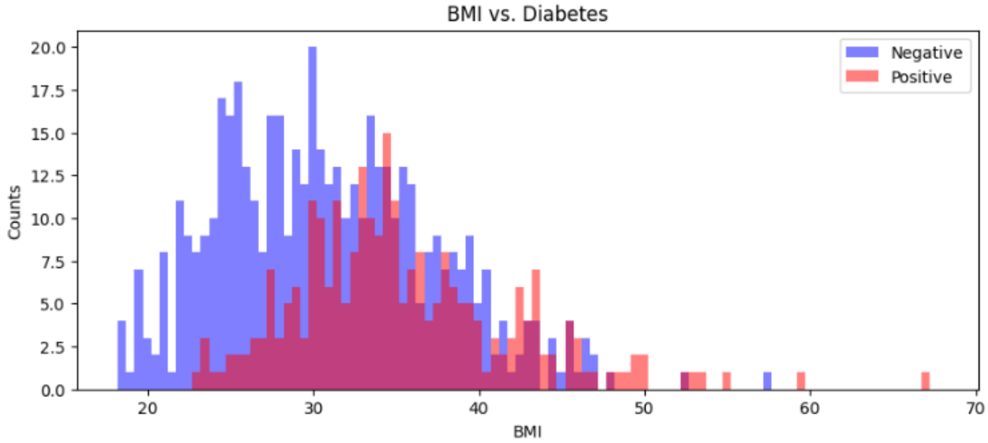
Insulin

```
Postive:
Q1 (25th percentile): 101.03846153846153
Q2 (50th percentile - Median): 101.03846153846153
Q3 (75th percentile): 168.0
Negative:
Q1 (25th percentile): 69.41632653061224
Q2 (50th percentile - Median): 69.41632653061224
Q3 (75th percentile): 105.0
```

Plot 10: Interquartile range of Insulin- Diabetes Positive vs. Diabetes Negative

- Healthy individuals tend to have an average Insulin level of around 69. However, Insulin levels exceeding 74 are often indicative of diabetes. Moreover, the majority of individuals with diabetes in the dataset exhibit an Insulin value of approximately 101.

BMI (Body Mass Index)



Plot 11: Histogram of "BMI" vs. Diabetes

```
Postive:
Q1 (25th percentile): 30.875
Q2 (50th percentile - Median): 34.3
Q3 (75th percentile): 38.775000000000006
Negative:
Q1 (25th percentile): 25.6
Q2 (50th percentile - Median): 30.2865306122449
Q3 (75th percentile): 35.275
```

Plot 12: Interquartile range of BMI- Diabetes Positive vs. Diabetes Negative

```
Prevalence:
27.2-27.7: 0.30
28.2-28.7: 0.36
29.7-30.2: 0.35
30.2-30.7: 0.42
30.7-31.2: 0.33
31.2-31.7: 0.46
31.7-32.2: 0.33
32.2-32.7: 0.40
32.7-33.2: 0.57
33.2-33.7: 0.38
33.7-34.2: 0.41
34.2-34.7: 0.54
34.7-35.2: 0.52
35.7-36.2: 0.37
36.2-36.7: 0.62
36.7-37.2: 0.33
37.2-37.7: 0.36
37.7-38.2: 0.53
38.2-38.7: 0.43
38.7-39.2: 0.42
39.2-39.7: 0.36
39.7-40.2: 0.44
40.7-41.2: 0.60
41.2-41.7: 0.33
41.7-42.2: 0.75
42.2-42.7: 0.75
42.7-43.2: 0.50
43.2-43.7: 0.64
43.7-44.2: 1.00
44.2-44.7: 0.40
45.2-45.7: 0.50
45.7-46.2: 0.75
46.7-47.2: 0.33
47.7-48.2: 0.50
48.2-48.7: 1.00
48.7-49.2: 1.00
49.2-49.7: 1.00
49.7-50.2: 1.00
52.2-52.7: 0.50
52.7-53.2: 1.00
53.2-53.7: 1.00
54.7-55.2: 1.00
59.2-59.7: 1.00
66.7-67.2: 1.00
```

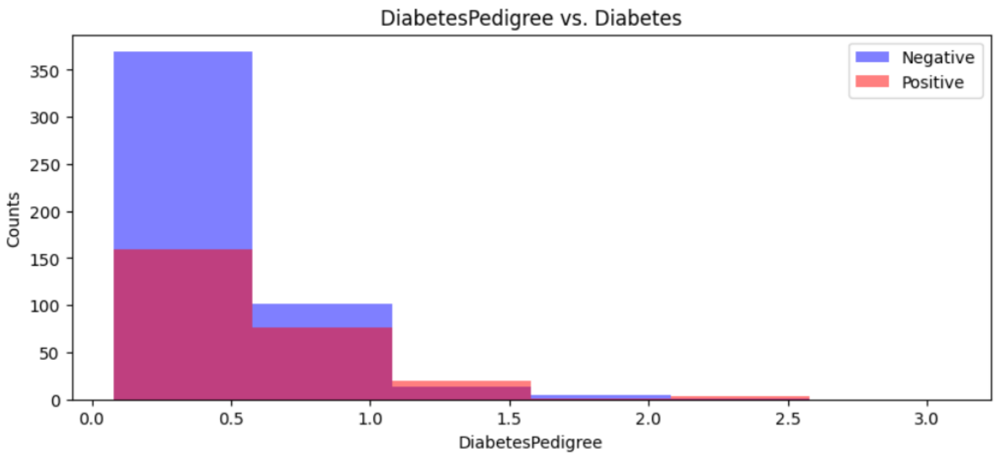
Plot 13: The prevalence of BMI

- Samples with lower BMI values are predominantly associated with non-diabetic cases. However, a BMI greater than 30 indicates over 40% likelihood of diabetes, reaching 100% for BMI greater than 48. Most diabetes patients have BMI values ranging from 30.875 to 38.775.

DiabetesPedigree

```
count     750.000000
mean        0.473544
std         0.332119
min         0.078000
25%         0.244000
50%         0.377000
75%         0.628500
max         2.420000
Name: DiabetesPedigree, dtype: float64
```

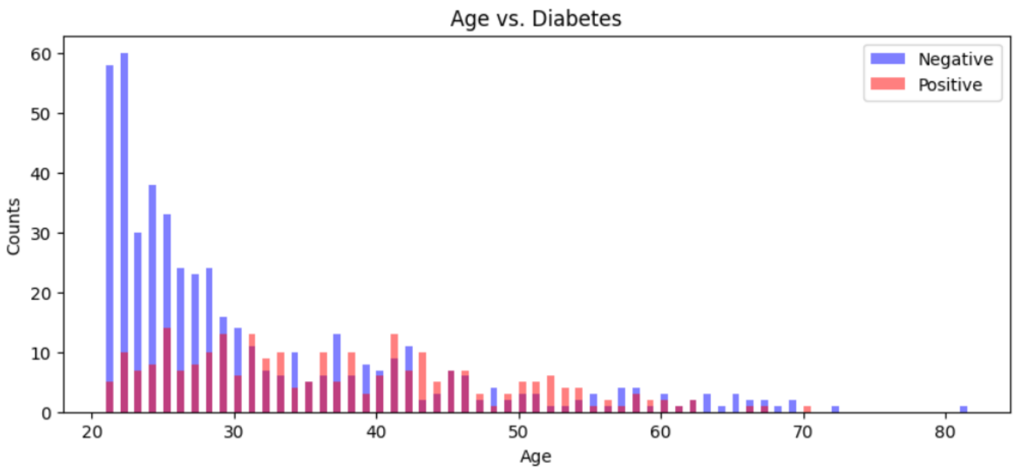
Plot 14: Interquartile range of DiabetesPedigree



Plot 15: Histogram of "DiabetesPedigree" vs. Diabetes

- Values of DiabetesPedigree are relatively small, with less distinct differences. A value greater than 0.56 indicates an extremely high diabetes prevalence.

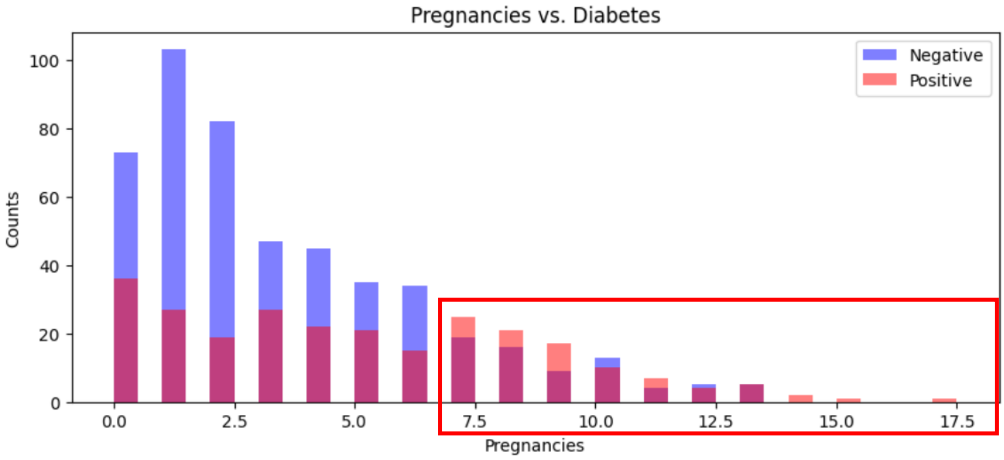
Age



Plot 16: Histogram of "DiabetesPedigree" vs. Diabetes

- The dataset primarily consists of participants aged between 20 and 30, suggesting a non-uniform age distribution. Nonetheless, a consistent number of diabetes cases are observed across different age groups, with the majority aged 28 to 44.

V. Logistic Regression based on "SevenOrMorePregnancies"



Plot 17: Histogram of "Pregnancies" vs. Diabetes

Incorporating the variable "SevenOrMorePregnancies" into our dataset and applying logistic regression was crucial. In Exploratory Data Analysis and Plot 17, I highlighted the significance of the number seven as a threshold for diabetes risk. Logistic regression allowed us to quantify the relationship between pregnancy history and diabetes risk, providing practical probabilities for diabetes development.

The logistic regression is to confirm that the number seven is a critical factor in diabetes risk. If a woman has **seven or more pregnancies**, there's a high **0.58 probability** of developing diabetes. In contrast, those with **six or fewer pregnancies** have a much lower **0.29 probability**. This stark difference highlights how important the number seven is as a dividing point in diabetes risk.

VI. Predictive Models for Diabetes Likelihood

I selected four distinct machine learning algorithms: Logistic Regression, Decision Tree Classifier, Random Forest Classifier, and KNN Classifier to predict the outcome of diabetes. The reason for choosing these algorithms is because each of them offers a unique approach to building predictive models for diabetes.

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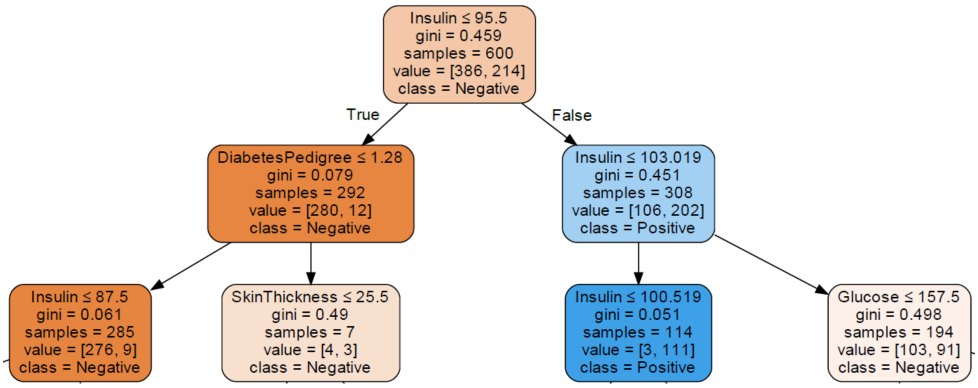
Logistic Regression

It is a well-suited choice for binary classification tasks like predicting diabetes, because of simplicity and interpretability. However, its simplicity makes it sensitive to outliers. The accuracy score of this model is approximately 0.77.

Decision Tree Classifier

It is selected for its ability to handle non-linear relationships within the data and provide a transparent decision-making process. The accuracy score of this training model is around **0.87**.

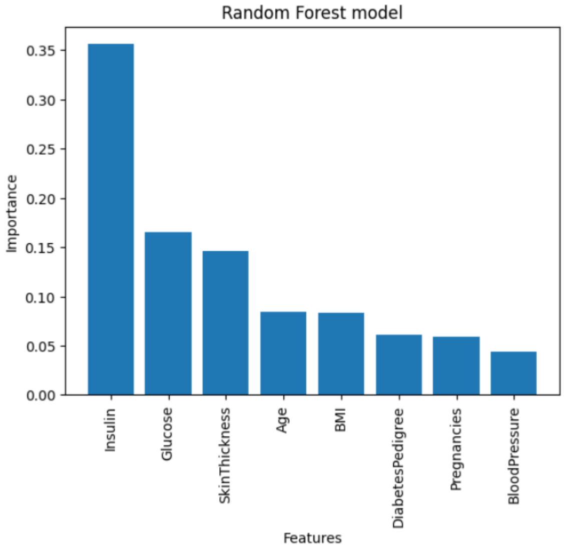


Plot 18: The top three levels of Decision Tree Model

Based on Plot 18, a crucial feature in this model is "Insulin," and a clear decision boundary can be established. Specifically, when the Insulin level is less than or equal to 95.5, approximately 386 samples are classified as Negative.

Random Forest Classifier

It is known for its robustness and ability to handle complex datasets by aggregating multiple decision trees. The accuracy score of this training model is around **0.85**.



Plot 19: The importance of each feature in Random Forest Classifier

Plot 19 clearly highlights the pivotal role of Insulin in the Random Forest Classifier, with an impressive 35% importance.

KNN Classifier

It is chosen for its simplicity and effectiveness in classifying data points based on their proximity to other data points. The accuracy score of this training model is around **0.88**.

VII. Conclusion

In this coursework, I applied diabetes prediction by using both traditional statistical methods and machine learning algorithms. The significance of features like the number of pregnancies and insulin levels has been established through exploratory data analysis and regression models. Logistic regression highlighted the pivotal role of seven or more pregnancies in diabetes risk, with a distinct probability threshold. Machine learning models, including Decision Tree, Random Forest, and KNN, demonstrated commendable accuracy in predicting diabetes outcomes. Notably, Insulin emerged as a critical factor across models.

Moreover, I make predictions on the ToPredict.csv dataset by using all models. The outcomes revealed distinct patterns:
Logistic Regression predicted [0 0 0 1 1]
Decision Tree Classifier Accuracy: [1 0 0 1 0]
Random Forest Classifier: [0 0 0 1 0]
KNN Classifier: [0 0 0 1 0]

Clearly, from these results, it's evident that both the Random Forest Classifier and KNN Classifier, two highly accurate classifiers, have arrived at the same conclusion. Therefore, I conclude that [0 0 0 1 0] represents the optimal prediction outcome.

For a visual representation of the final results, please refer to Plot 20.

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigree	Age	Outcome
0	4	136	70	0	0	31.2	1.182	22	0
1	1	121	78	39	74	39.0	0.261	28	0
2	3	108	62	24	0	26.0	0.223	25	0
3	0	181	88	44	510	43.3	0.222	26	1
4	8	154	78	32	0	32.4	0.443	45	0

Plot 20: ToPredict.csv and Predicted Outcome

VIII. Code and Figures

student #:11356590

In [4]:
```
import pandas as pd
```

In [5]:
```
data = pd.read_csv("PimaDiabetes.csv")
data.head(5)
```

Out[5]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigree	Age	Outcome
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0
2	8	183	64	0	0	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.167	21	0
4	0	137	40	35	168	43.1	2.288	33	1

In [6]:
```
print(data.columns.to_list())
```

```
['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin', 'BMI', 'DiabetesPedigree', 'Age',
'Outcome']
```

In [7]:
```
data.describe()
```

Out[7]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigree	Age	Outcom
count	750.000000	750.000000	750.000000	750.000000	750.000000	750.000000	750.000000	750.000000	750.00000
mean	3.844000	120.737333	68.982667	20.489333	80.378667	31.959067	0.473544	33.166667	0.34666
std	3.370085	32.019671	19.508814	15.918828	115.019198	7.927399	0.332119	11.708872	0.47622
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.078000	21.000000	0.00000
25%	1.000000	99.000000	62.000000	0.000000	0.000000	27.300000	0.244000	24.000000	0.00000
50%	3.000000	117.000000	72.000000	23.000000	36.500000	32.000000	0.377000	29.000000	0.00000
75%	6.000000	140.750000	80.000000	32.000000	129.750000	36.575000	0.628500	40.750000	1.00000
max	17.000000	199.000000	122.000000	99.000000	846.000000	67.100000	2.420000	81.000000	1.00000

The indicators 'Glucose,' 'BloodPressure,' 'SkinThickness,' 'Insulin,' and 'BMI' must not be zero, which leads me to suspect that this dataset has been filled with zeros to handle missing data.

In [8]:
```
# function to fill in missing data
def fill_in_missing_value(data, col_name):

    # Create a boolean mask to identify missing values in the specified column
    missing_value = (data[col_name] == 0)
    # Create a boolean mask to identify positive outcome cases
    positive = (data['Outcome'] == 1)
    # Create a boolean mask to identify negative outcome cases
    negative = (data['Outcome'] == 0)

    # Find the indices of missing values where outcome is positive
    o_index = data[positive & missing_value].index
    # Find the indices of missing values where outcome is negative
    x_index = data[negative & missing_value].index

    # Calculate the mean of positive outcome cases
    o_mean = data.loc[positive, col_name].mean()
    # Calculate the mean of negative outcome cases
    x_mean = data.loc[negative, col_name].mean()

    # Fill in missing values for positive outcome cases with the mean
    data.loc[o_index, col_name] = o_mean
    # Fill in missing values for negative outcome cases with the mean
    data.loc[x_index, col_name] = x_mean
```

```
    return data
```

In [9]:
```
# fill in missing data
data = fill_in_missing_value(data, "Glucose")
data = fill_in_missing_value(data, "BloodPressure")
data = fill_in_missing_value(data, "SkinThickness")
data = fill_in_missing_value(data, "Insulin")
data = fill_in_missing_value(data, "BMI")
```

In [10]:
```
# to check the existence of missing value
# if min != 0, then we suceed to fill in.
data.min()
```

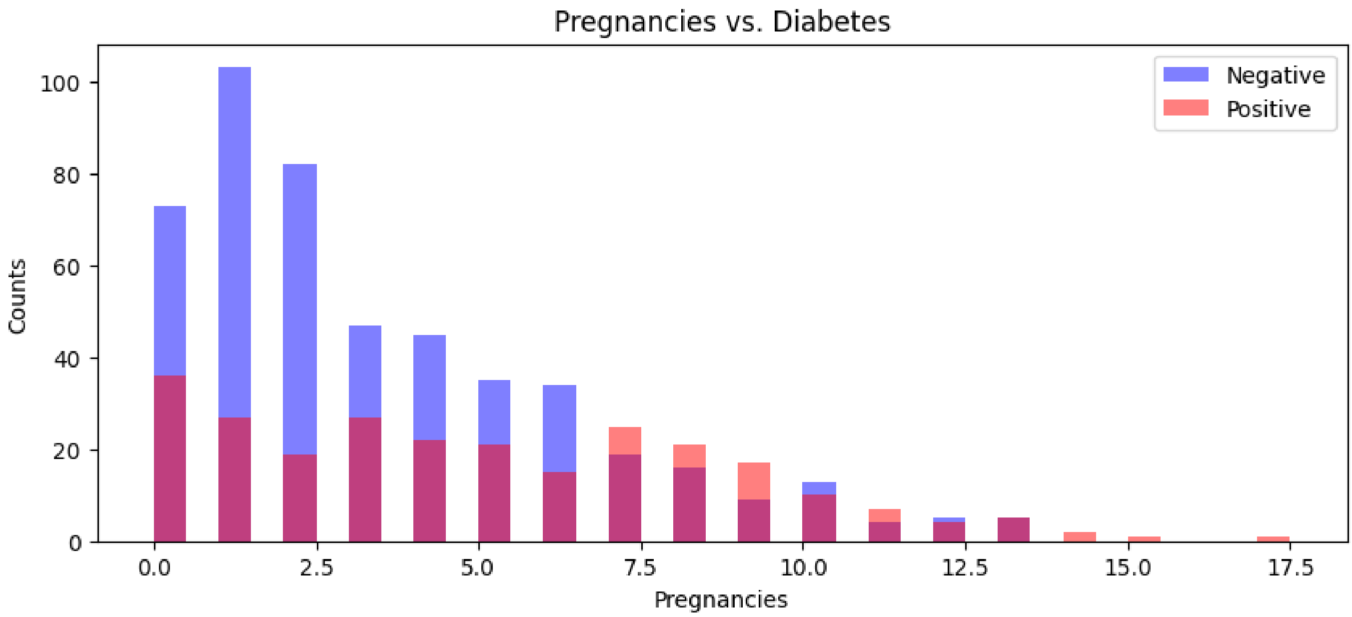
Out[10]:
```
Pregnancies           0.000
Glucose              44.000
BloodPressure        24.000
SkinThickness         7.000
Insulin              14.000
BMI                  18.200
DiabetesPedigree      0.078
Age                  21.000
Outcome               0.000
dtype: float64
```

In [11]:
```
# EDA function
import matplotlib.pyplot as plt
import numpy as np

def IQR(num):
    q1 = np.percentile(num, 25)
    q2 = np.percentile(num, 50)
    q3 = np.percentile(num, 75)
    print("Q1 (25th percentile):", q1)
    print("Q2 (50th percentile - Median):", q2)
    print("Q3 (75th percentile):", q3)

def eda(data, col_name):

    print(data[col_name].describe())

    # Sample data
    col = data[col_name].values  # Ensure col is a NumPy array
    outcome = data['Outcome']


    # Calculate the distribution of "Outcome" for each "Pregnancies" category
    o_num = col[outcome == 1]
    x_num = col[outcome == 0]

    # Create separate bar charts for Outcome 0 and 1
    plt.figure(figsize=(10, 4))

    # Plot histograms for Negative and Positive
    plt.hist(x_num, bins=np.arange(min(col), max(col) + 1, 0.5), alpha=0.5, label='Negative', color='blue')
    plt.hist(o_num, bins=np.arange(min(col), max(col) + 1, 0.5), alpha=0.5, label='Positive', color='red')

    # Add labels and title
    plt.xlabel(col_name)
    plt.ylabel('Counts')
    plt.title('{} vs. Diabetes'.format(col_name))
    plt.legend()

    plt.show()

    # Print IQR
    print("Postive:")
    IQR(o_num)
    print("Negative:")
    IQR(x_num)

#     # Calculate and print prevalences
#     print("\nPrevalence:")
#     for bin_edge in np.arange(min(col), max(col) + 1, 0.5):
```

```python
#         bin_start = bin_edge
#         bin_end = bin_edge + 0.5
#         o_count = len(o_num[(o_num >= bin_start) & (o_num < bin_end)])
#         x_count = len(x_num[(x_num >= bin_start) & (x_num < bin_end)])
#         total_count = o_count + x_count
#         if total_count == 0:
#             pre = 0
#         else:
#             pre = o_count / total_count
#         # only print bigger number in "Prevalence"
#         if pre > 0.3:
#             print("{bin_start}-{bin_end}: {pre:.2f}".format(bin_start=bin_start, bin_end=bin_end, pre=pre
```

In [12]:
```python
eda(data, "Pregnancies")
```

```
count    750.000000
mean       3.844000
std        3.370085
min        0.000000
25%        1.000000
50%        3.000000
75%        6.000000
max       17.000000
Name: Pregnancies, dtype: float64
```



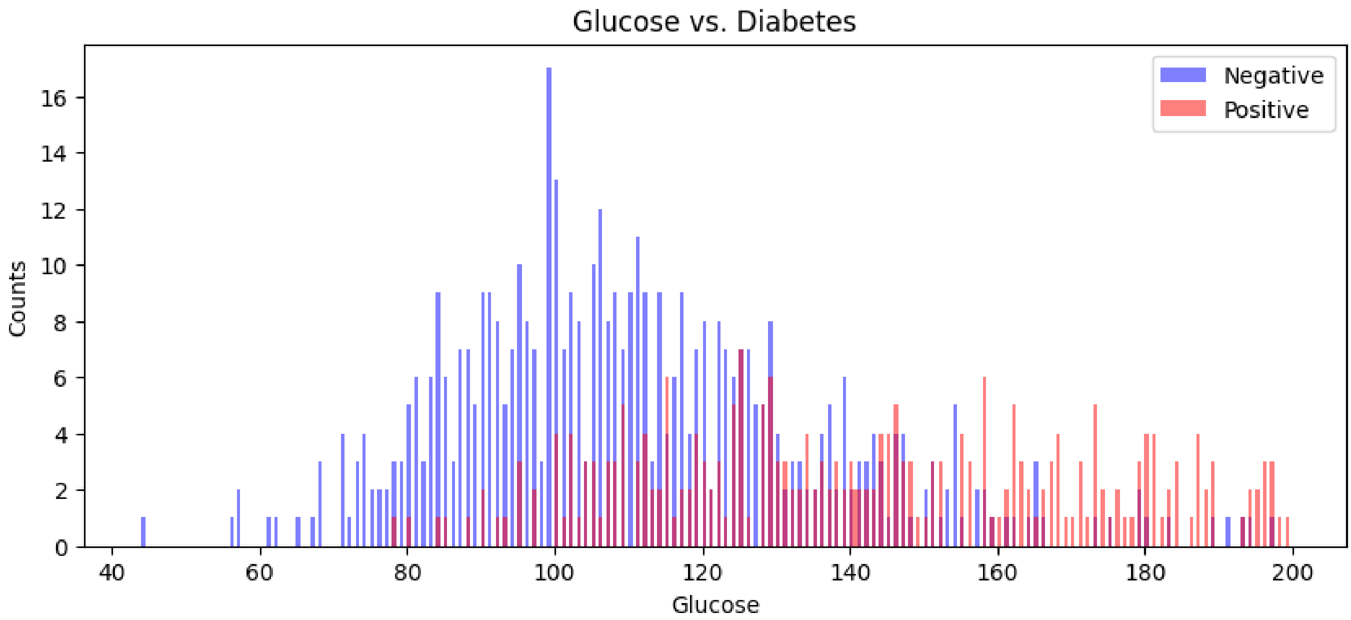

```
Postive:
Q1 (25th percentile): 2.0
Q2 (50th percentile - Median): 4.0
Q3 (75th percentile): 8.0
Negative:
Q1 (25th percentile): 1.0
Q2 (50th percentile - Median): 2.0
Q3 (75th percentile): 5.0
```

From the quartile analysis, it can be observed that the majority of diabetes patients have a pregnancy history ranging from 2 to 8 times, which is notably higher compared to those without the condition, who typically have a history of one to five pregnancies.

Additionally, when 'Pregnancies' is greater than or equal to 7, the proportion of individuals with diabetes is significantly higher than those without the condition, often exceeding 50%.

In [13]:
```python
eda(data, "Glucose")
```

```
count    750.000000
mean     121.553253
std       30.476753
min       44.000000
25%       99.000000
50%      117.000000
75%      140.989423
max      199.000000
Name: Glucose, dtype: float64
```



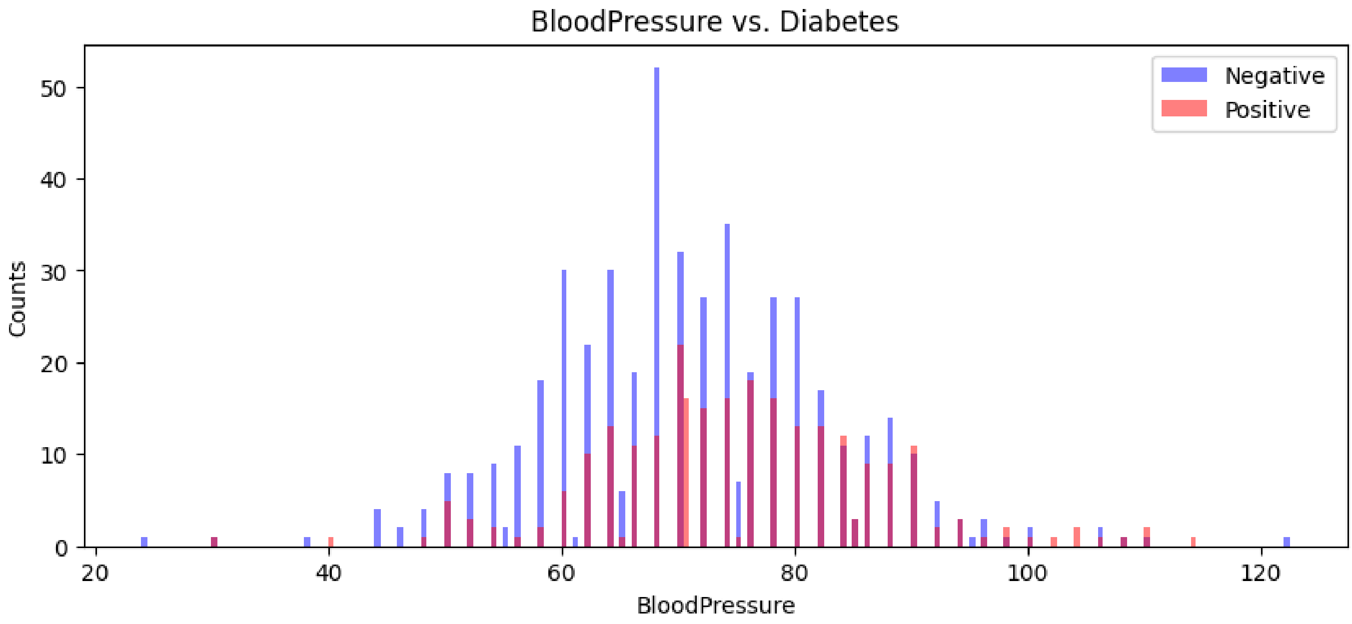

```
Postive:
Q1 (25th percentile): 119.0
Q2 (50th percentile - Median): 140.47884615384615
Q3 (75th percentile): 166.25
Negative:
Q1 (25th percentile): 93.25
Q2 (50th percentile - Median): 107.5
Q3 (75th percentile): 125.0
```

From the quartile results of the samples among individuals with diabetes and those without, it becomes evident that following a two-hour oral glucose tolerance test, patients with diabetes generally exhibit notably higher plasma glucose concentration (mg/dl) levels when compared to those without diabetes. The majority of patients with diabetes have plasma glucose concentrations ranging from 119 to 166.25, while samples from those without diabetes typically range from 93.25 to 125.

Furthermore, it is worth noting that when the plasma glucose concentration exceeds 120, the likelihood of diabetes is approximately 50%.

In [14]:
```
eda(data, "BloodPressure")
```

```
count    750.000000
mean      72.214711
std       12.159133
min       24.000000
25%       64.000000
50%       72.000000
75%       80.000000
max      122.000000
Name: BloodPressure, dtype: float64
```

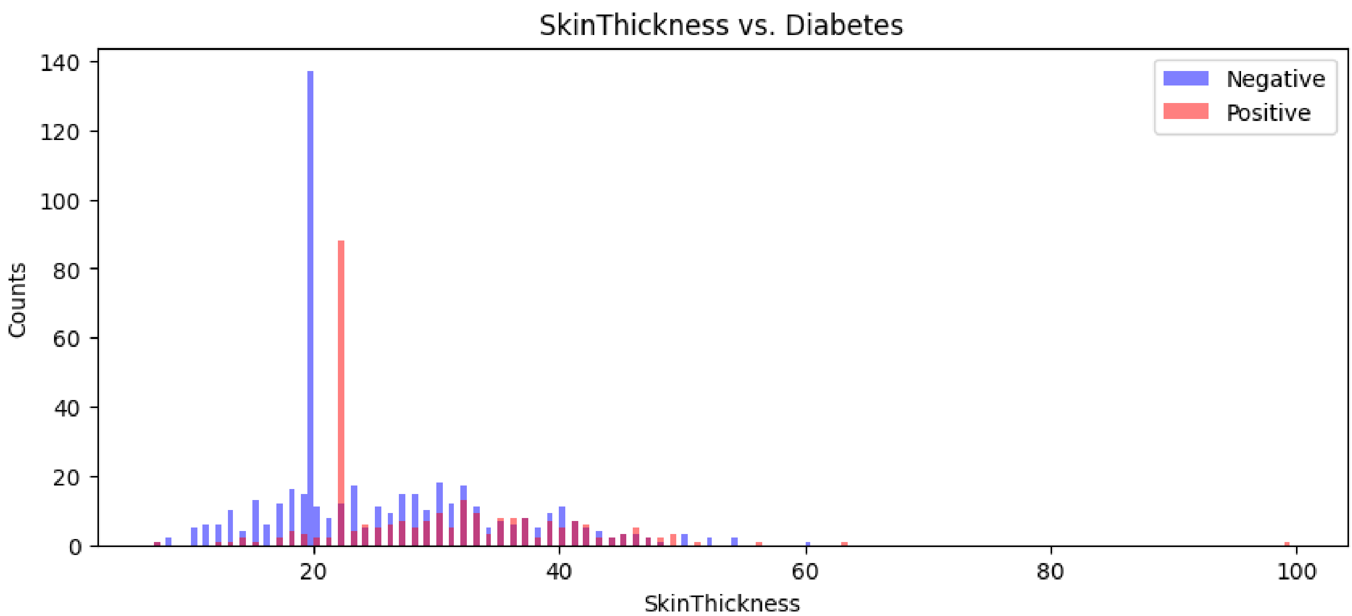



```
Postive:
Q1 (25th percentile): 68.0
Q2 (50th percentile - Median): 74.0
Q3 (75th percentile): 82.0
Negative:
Q1 (25th percentile): 64.0
Q2 (50th percentile - Median): 70.0
Q3 (75th percentile): 78.0
```

Regarding blood pressure, most individuals with diabetes have blood pressure levels between 68 and 82. While the quartile comparison shows slightly higher blood pressure in those with diabetes, it's important to note that the majority of participants fall within the standard range of 64 to 80. As a result, it's visually challenging to establish a clear link between blood pressure and diabetes.

In [15]:
```
eda(data, "SkinThickness")
```

```
count    750.000000
mean      26.553920
std        9.655994
min        7.000000
25%       19.536735
50%       23.000000
75%       32.000000
max       99.000000
Name: SkinThickness, dtype: float64
```

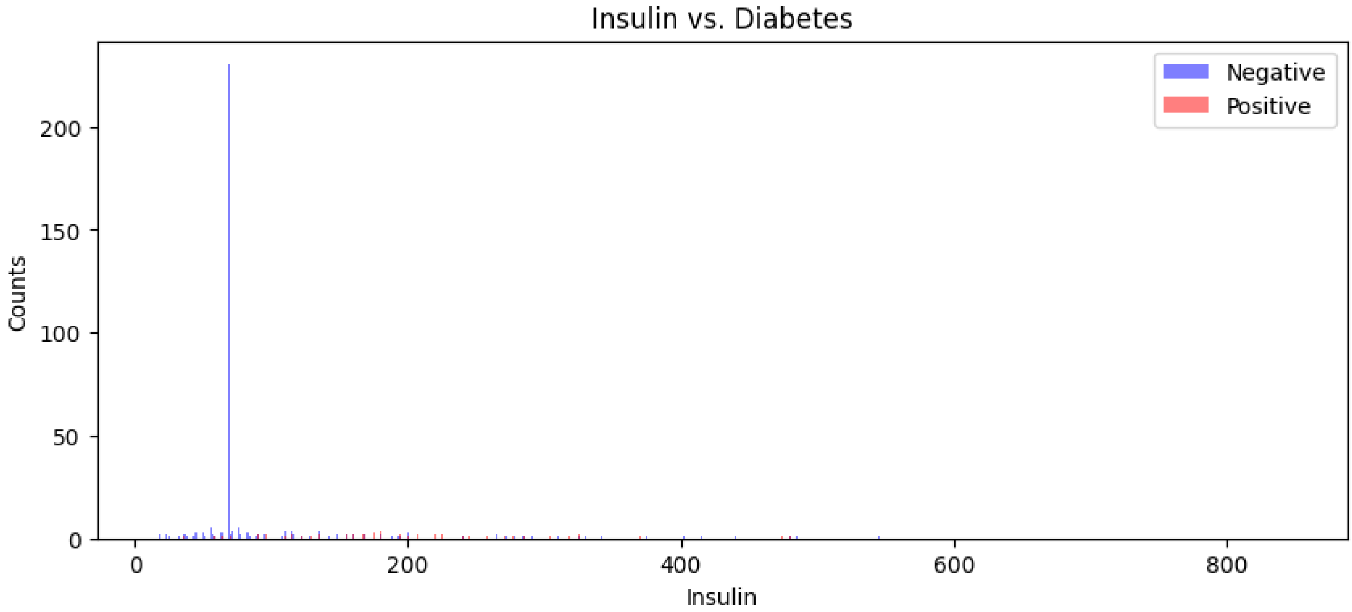


```
Postive:
Q1 (25th percentile): 22.284615384615385
Q2 (50th percentile - Median): 27.0
Q3 (75th percentile): 36.0
Negative:
Q1 (25th percentile): 19.536734693877552
Q2 (50th percentile - Median): 21.0
Q3 (75th percentile): 31.0
```

Diabetes-positive individuals generally have thicker skin than diabetes-negative ones, with skin thickness ranging from approximately 22.28 to 36.

In [16]:
```python
eda(data, "Insulin")
```

```
count    750.000000
mean     119.449109
std       93.222636
min       14.000000
25%       69.416327
50%      100.000000
75%      129.750000
max      846.000000
Name: Insulin, dtype: float64
```

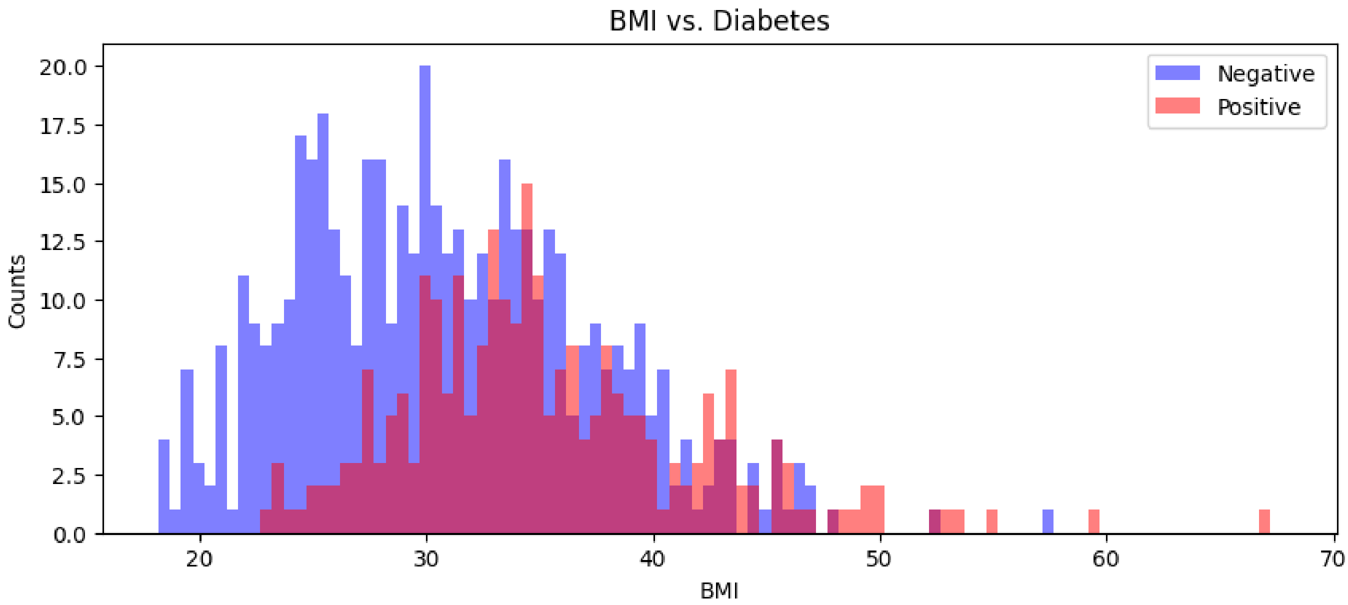



```
Postive:
Q1 (25th percentile): 101.03846153846153
Q2 (50th percentile - Median): 101.03846153846153
Q3 (75th percentile): 168.0
Negative:
Q1 (25th percentile): 69.41632653061224
Q2 (50th percentile - Median): 69.41632653061224
Q3 (75th percentile): 105.0
```

Healthy individuals have an Insulin level of around 69. Most cases with Insulin levels exceeding 74 are diabetes patients. Furthermore, the majority of individuals with diabetes have an Insulin value of approximately 101.

In [17]:
```python
eda(data, "BMI")
```

```
count    750.000000
mean      32.416135
std        6.906108
min       18.200000
25%       27.500000
50%       32.000000
75%       36.575000
max       67.100000
Name: BMI, dtype: float64
```

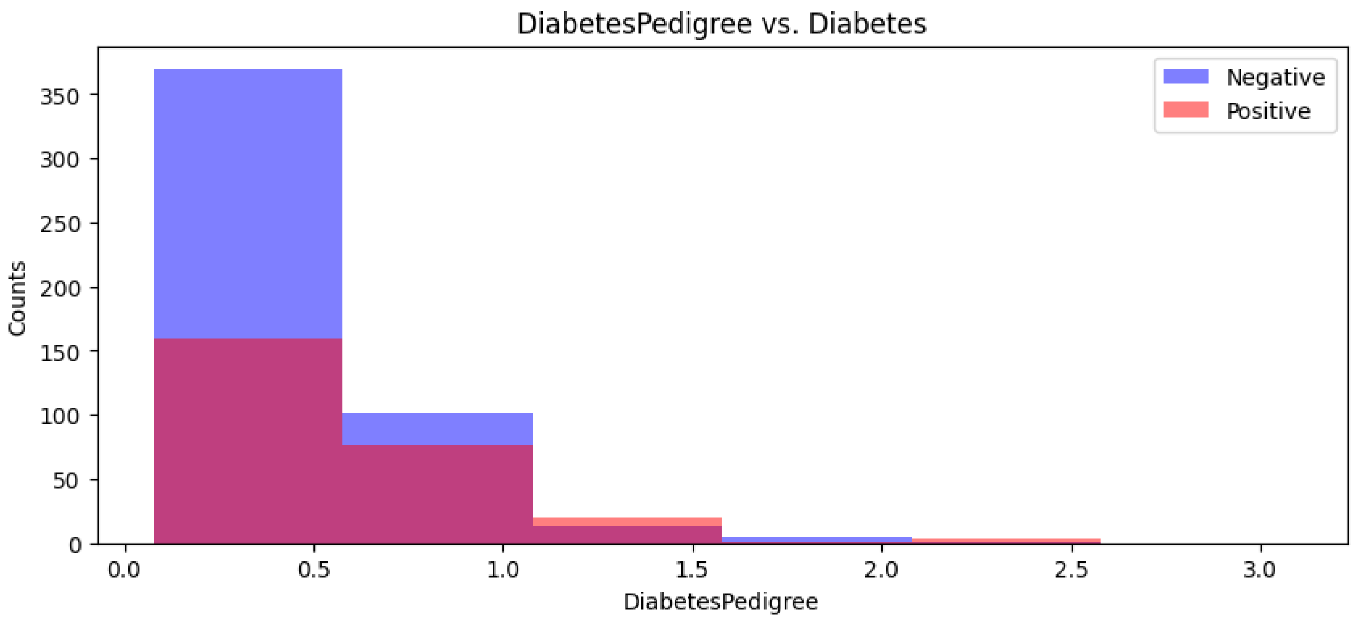



```
Postive:
Q1 (25th percentile): 30.875
Q2 (50th percentile - Median): 34.3
Q3 (75th percentile): 38.775000000000006
Negative:
Q1 (25th percentile): 25.6
Q2 (50th percentile - Median): 30.2865306122449
Q3 (75th percentile): 35.275
```

From the BMI data, it's evident that samples with lower BMI values are predominantly negative for diabetes. However, starting from a BMI greater than 30, over 40% of participants have positive diabetes test results. This proportion increases significantly for individuals with a BMI greater than 48, where all participants are diabetes patients. Moreover, most diabetes patients have BMI values ranging from 30.875 to 38.775.

In [18]:
```
eda(data, "DiabetesPedigree")
```

```
count    750.000000
mean       0.473544
std        0.332119
min        0.078000
25%        0.244000
50%        0.377000
75%        0.628500
max        2.420000
Name: DiabetesPedigree, dtype: float64
```

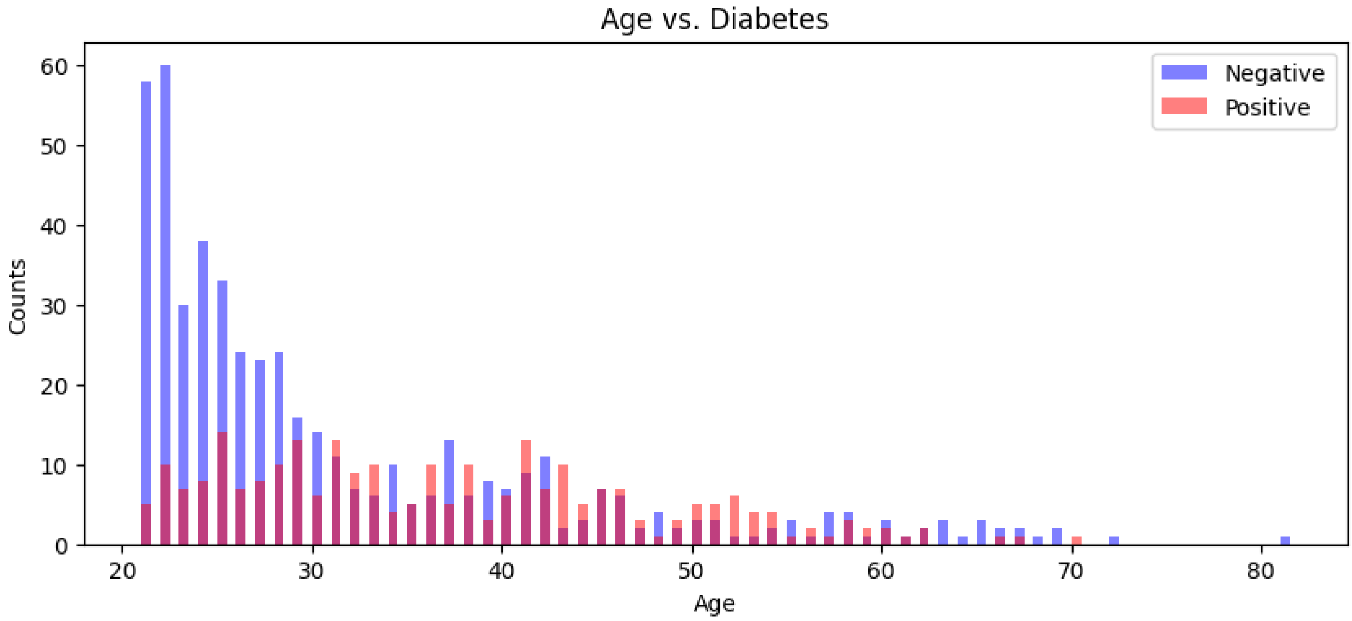


```
Postive:
Q1 (25th percentile): 0.2625
Q2 (50th percentile - Median): 0.4535
Q3 (75th percentile): 0.728
Negative:
Q1 (25th percentile): 0.231
Q2 (50th percentile - Median): 0.3375
Q3 (75th percentile): 0.5692499999999999
```

While the values of DiabetesPedigree are relatively small, differences are less apparent. Nevertheless, it's noteworthy that a value greater than 0.56 is associated with an extremely high diabetes prevalence.

In [19]:
```
eda(data, "Age")
```

```
count    750.000000
mean      33.166667
std       11.708872
min       21.000000
25%       24.000000
50%       29.000000
75%       40.750000
max       81.000000
Name: Age, dtype: float64
```




```
Postive:
Q1 (25th percentile): 28.0
Q2 (50th percentile - Median): 36.0
Q3 (75th percentile): 44.0
Negative:
Q1 (25th percentile): 23.0
Q2 (50th percentile - Median): 27.0
Q3 (75th percentile): 37.0
```

In this dataset, most participants are aged between 20 and 30 years, indicating that the age distribution isn't uniformly spread for prevalence interpretation. However, the data shows a consistent number of diabetes cases across different age groups, with the majority of diabetes patients falling between the ages of 28 and 44 years.

Summary of EDA finding

Pregnancy History:

- Most diabetes patients had pregnancies ranging from 2 to 8 times, higher than those without diabetes (1 to 5 pregnancies).
- **High Risk:** When 'Pregnancies' is greater than or equal to 7, diabetes prevalence exceeds 50%.

Plasma Glucose Concentration:

- Diabetes patients have higher plasma glucose levels (119 to 166.25) compared to non-diabetic individuals (93.25 to 125).
- **Threshold:** When plasma glucose exceeds 120, the likelihood of diabetes is around 50%.

Blood Pressure:

- Most diabetics have blood pressure between 68 and 82, but many participants fall within the standard range of 64 to 80.
- **Inconclusive:** Establishing a clear link between blood pressure and diabetes is visually challenging.

Skin Thickness:

- Diabetics generally have thicker skin (22.28 to 36).
- **High Proportion:** A significant number of diabetics have 'SkinThickness' in the 22.0 to 44.5 range.

Insulin Levels:

- Healthy individuals have an Insulin level of around 69.
- **Diabetes Indicator:** High Insulin levels (>74) often indicate diabetes.

BMI (Body Mass Index):

- Lower BMI values are mostly associated with non-diabetic cases.
- **High Risk:** BMI > 30 indicates over 40% likelihood of diabetes, increasing to 100% with BMI > 48.
- **Common Range:** Most diabetes patients have BMI between 30.875 and 38.775.

DiabetesPedigree:

- Values are relatively small and less distinct.
- **High Risk:** Values greater than 0.56 indicate an extremely high diabetes prevalence.

Age:

- Participants aged 20 to 30 dominate the dataset.
- **Consistent Diabetes Cases:** Diabetes cases are consistent across different age groups, with the majority aged 28 to 44.

In [20]:

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression

# Initialize values to 0.
data['SevenOrMorePregnancies'] = 0
# Set the value to 1 for rows when meet data['Pregnancies'] >= 7.
data.loc[data['Pregnancies'] >= 7, 'SevenOrMorePregnancies'] = 1

# Split the data into a training set and a testing set
X = data[['SevenOrMorePregnancies']]
y = data['Outcome']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Fit a logistic regression model
model = LogisticRegression()
model.fit(X_train, y_train)


# Calculate the probability of diabetes
# [0] means data['SevenOrMorePregnancies'] == 0 (< 7 children)
# Probability with 0 or 6 children
```

```
prob_0 = model.predict_proba(pd.DataFrame([0]))[0, 1]
# [1] means data['SevenOrMorePregnancies'] == 1 (>= 7 children)
# Probability with 7 or more children
prob_1 = model.predict_proba(pd.DataFrame([1]))[0, 1]

print(f"Probability of diabetes with 0 to 6 children:\t{prob_0:.2f}")
print(f"Probability of diabetes with 7 or more children:{prob_1:.2f}")
```

```
Probability of diabetes with 0 to 6 children:	0.29
Probability of diabetes with 7 or more children:0.58
```

```
D:\anaconda\envs\envs_notebook\lib\site-packages\sklearn\base.py:420: UserWarning: X does not have valid fe
ature names, but LogisticRegression was fitted with feature names
  warnings.warn(
D:\anaconda\envs\envs_notebook\lib\site-packages\sklearn\base.py:420: UserWarning: X does not have valid fe
ature names, but LogisticRegression was fitted with feature names
  warnings.warn(
```

The EDA analysis highlights 7 as a crucial threshold for diabetes outcomes. Using logistic regression, we found that the probability of diabetes with 7 or more children is 0.58, while it's only 0.29 for 0 to 6 children.

In [21]:
```
from sklearn.model_selection import train_test_split
y = data["Outcome"]
X = data.drop(["Outcome", "SevenOrMorePregnancies"] , axis=1)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

In [22]:
```
# logistic regression
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score

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

y_pred = log_model.predict(X_test)

accuracy = accuracy_score(y_test, y_pred)
print(f"Logistic Regression Accuracy : {accuracy:.2f}")
```

```
Logistic Regression Accuracy : 0.77
```

```
D:\anaconda\envs\envs_notebook\lib\site-packages\sklearn\linear_model\_logistic.py:458: ConvergenceWarning:
lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
```

Logistic Regression

- It is a well-suited choice for binary classification tasks like predicting diabetes, thanks to its simplicity and interpretability.

In [23]:
```
# Decision tree
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score

tree_model = DecisionTreeClassifier()
tree_model.fit(X_train, y_train)

y_pred = tree_model.predict(X_test)

accuracy = accuracy_score(y_test, y_pred)
print(f"Decision Tree Classifier Accuracy: {accuracy:.2f}")
```

```
Decision Tree Classifier Accuracy: 0.87
```

Decision Tree Classifier

- It is selected for its ability to handle non-linear relationships within the data and provide a transparent decision-making process.

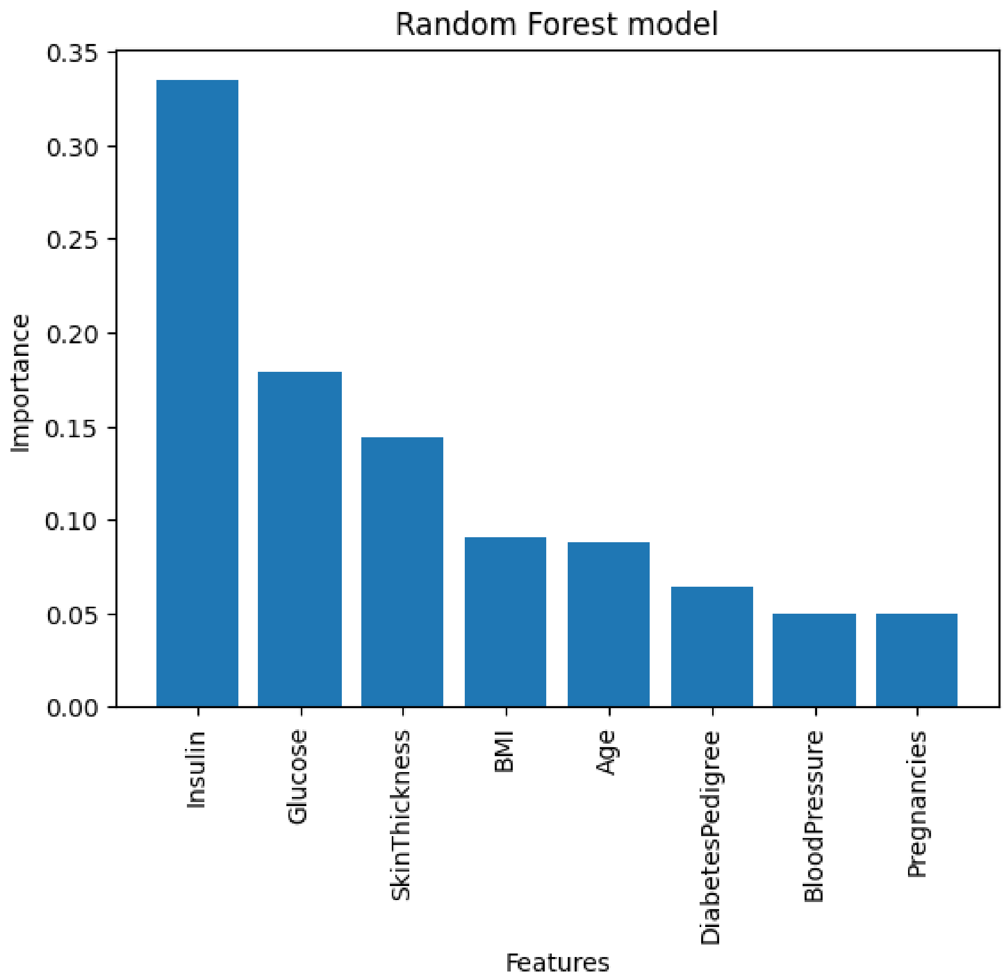
In [24]:
```python
from sklearn.tree import export_graphviz
import graphviz

dot_data = export_graphviz(tree_model, out_file=None,
                           feature_names=X.columns,
                           filled=True, rounded=True,
                           class_names=["Negative", "Positive"],
                           special_characters=True)

graph = graphviz.Source(dot_data)
graph.render("decision_tree")
graph.view()
```

Out[24]:
```
'decision_tree.pdf'
```

In [25]:
```python
# random forest
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score

forest_model = RandomForestClassifier()
forest_model.fit(X_train, y_train)

y_pred = forest_model.predict(X_test)

accuracy = accuracy_score(y_test, y_pred)
print(f"Random Forest Classifier Accuracy: {accuracy:.2f}")
```

```
Random Forest Classifier Accuracy: 0.85
```

In [26]:
```python
import matplotlib.pyplot as plt
from sklearn.ensemble import RandomForestClassifier


# Get feature importances
feature_importances = forest_model.feature_importances_

# Sort feature importances in descending order
sorted_idx = np.argsort(feature_importances)[::-1]

# Get the names of the features
feature_names = X.columns

# Plot all features
N = 8
plt.bar(range(N), feature_importances[sorted_idx][:N])
plt.xticks(range(N), [feature_names[i] for i in sorted_idx][:N], rotation=90)
plt.xlabel('Features')
plt.ylabel('Importance')
plt.title('Random Forest model'.format(N))
plt.show()
```



In [27]:
```
# KNN
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score

k = 12
KNN_model = KNeighborsClassifier(n_neighbors=k)
KNN_model.fit(X_train, y_train)

y_pred = KNN_model.predict(X_test)

accuracy = accuracy_score(y_test, y_pred)
print(f"KNN Classifier Accuracy : {accuracy:.2f}")
```

```
KNN Classifier Accuracy : 0.88
```

In [28]:
```
X_test.columns.to_list()
```

Out[28]:
```
['Pregnancies',
 'Glucose',
 'BloodPressure',
 'SkinThickness',
 'Insulin',
 'BMI',
 'DiabetesPedigree',
 'Age']
```

In [29]:
```
# load ToPredict.csv
predict_data = pd.read_csv("ToPredict.csv")
predict_data.head()
```

Out[29]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigree	Age
0	4	136	70	0	0	31.2	1.182	22
1	1	121	78	39	74	39.0	0.261	28
2	3	108	62	24	0	26.0	0.223	25
3	0	181	88	44	510	43.3	0.222	26
4	8	154	78	32	0	32.4	0.443	45

In [30]:

```
print("Logistic Regression:\t\t\t", log_model.predict(predict_data))
print("Decision Tree Classifier Accuracy : \t", tree_model.predict(predict_data))
print("Random Forest Classifier:\t\t", forest_model.predict(predict_data))
print("KNN Classifier:\t\t\t\t", KNN_model.predict(predict_data))
```

```
Logistic Regression:                    [0 0 0 1 1]
Decision Tree Classifier Accuracy :     [1 0 0 1 0]
Random Forest Classifier:               [0 0 0 1 0]
KNN Classifier:                         [0 0 0 1 0]
```

It is obvious that **[0 0 0 1 0]** is the highest probability prediction of ToPredict.csv

In [31]:

```
predict_data["Outcome"] =  KNN_model.predict(predict_data)
predict_data
```

Out[31]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigree	Age	Outcome
0	4	136	70	0	0	31.2	1.182	22	0
1	1	121	78	39	74	39.0	0.261	28	0
2	3	108	62	24	0	26.0	0.223	25	0
3	0	181	88	44	510	43.3	0.222	26	1
4	8	154	78	32	0	32.4	0.443	45	0