Healthcare

Week 1

Data Exploration:

1. Perform descriptive analysis.

In [266]:
```
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
```

In [267]:
```
df.describe()
```

Out[267]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	
count	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	7
mean	3.845052	120.894531	69.105469	20.536458	79.799479	31.992578	0.471876	33.240885	
std	3.369578	31.972618	19.355807	15.952218	115.244002	7.884160	0.331329	11.760232	
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.078000	21.000000	
25%	1.000000	99.000000	62.000000	0.000000	0.000000	27.300000	0.243750	24.000000	
50%	3.000000	117.000000	72.000000	23.000000	30.500000	32.000000	0.372500	29.000000	
75%	6.000000	140.250000	80.000000	32.000000	127.250000	36.600000	0.626250	41.000000	
max	17.000000	199.000000	122.000000	99.000000	846.000000	67.100000	2.420000	81.000000	

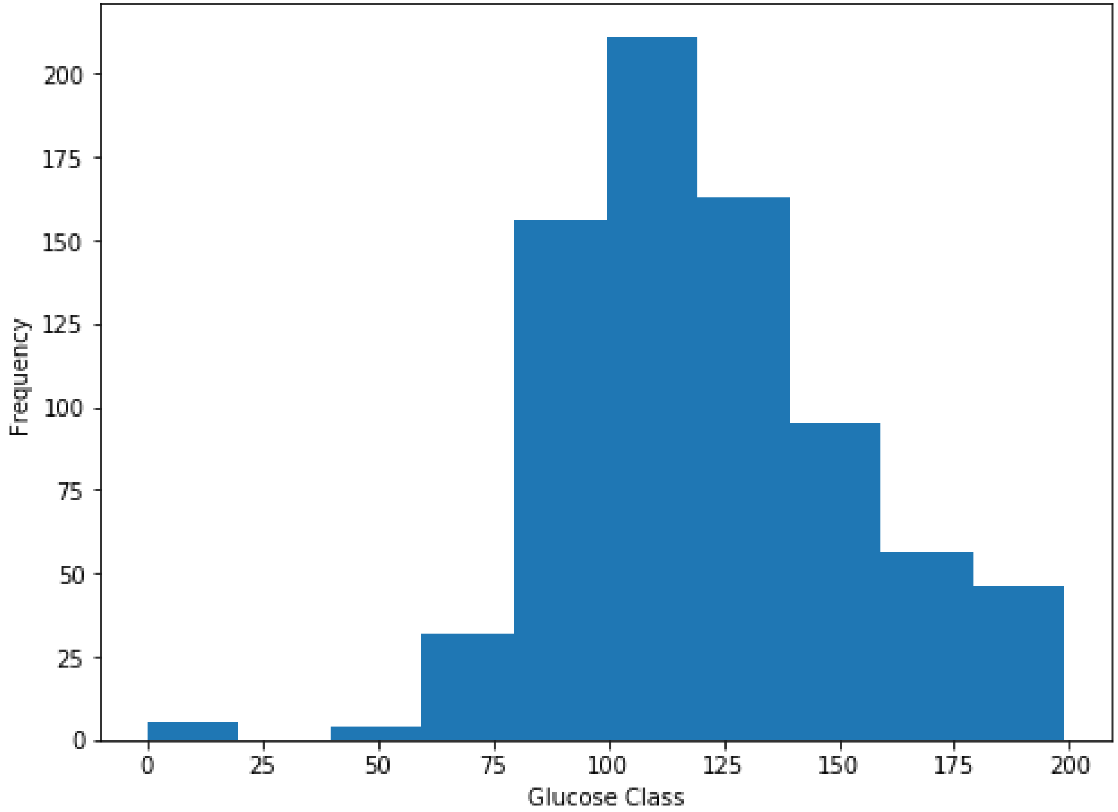
```
There are 768 entries and 9 variables
Independent variables - Pregnancies, Glucose, Blood Pressure, Insulin, BMI and Diabetes Pedigree
Function.
Outcome Variable - Age
Mean(Avg) of independent variables are
Pregnancies = 3.845052
Glucose = 120.894531
BloodPressure = 69.105469
SkinThickness=20.536458
Insulin = 79.799479
BMI = 31.992578
DiabetesPedigreeFunction = 0.471876
Mean(Avg) Age of Patients is 33.24
```

2. Visually explore these variables using histograms. Treat the missing

values accordingly.

In [268]:
```
plt.figure(figsize=(8,6))
plt.xlabel('Glucose Class')
df['Glucose'].plot.hist()
print("Mean of Glucose level is :-", df['Glucose'].mean())
```

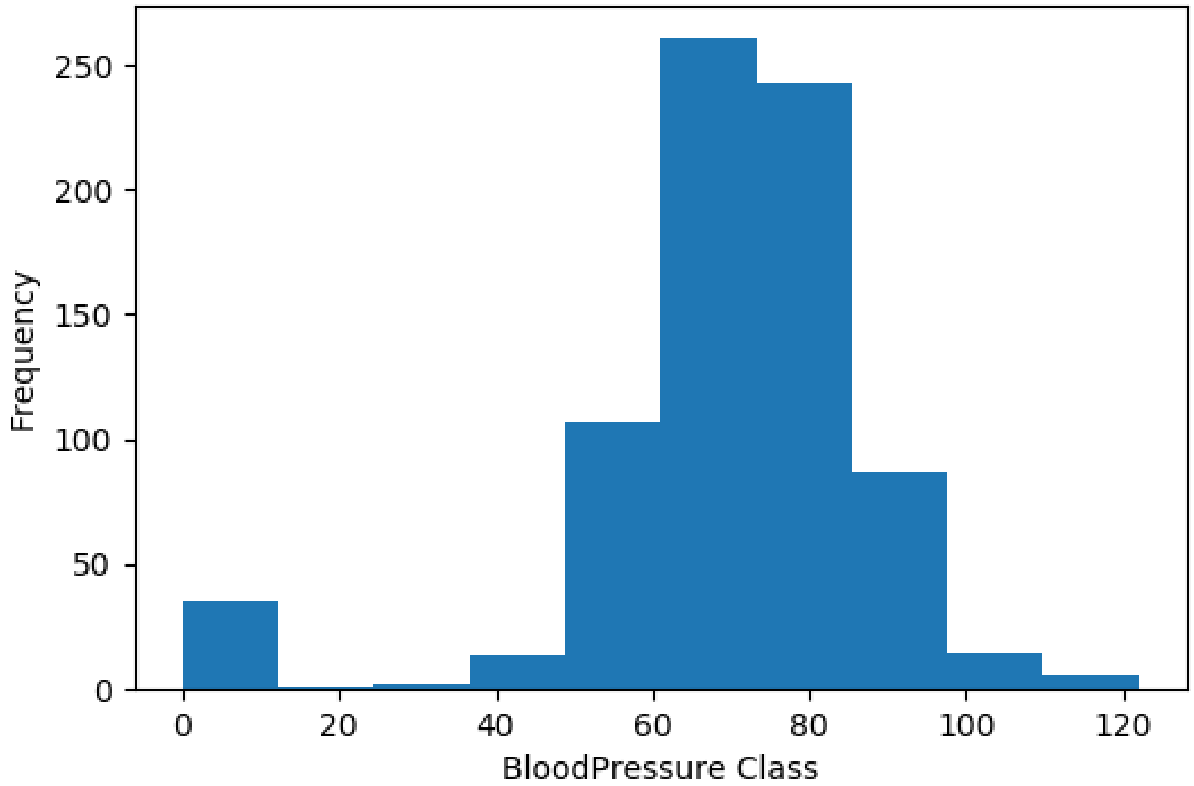
```
Mean of Glucose level is :- 120.89453125
```



In [269]:
```
df['Glucose']=df['Glucose'].replace(0,df['Glucose'].mean())
```

In [270]:
```
plt.figure(figsize=(6,4),dpi=100)
plt.xlabel('BloodPressure Class')
df['BloodPressure'].plot.hist()
print("Mean of BloodPressure level is :-", df['BloodPressure'].mean())
```

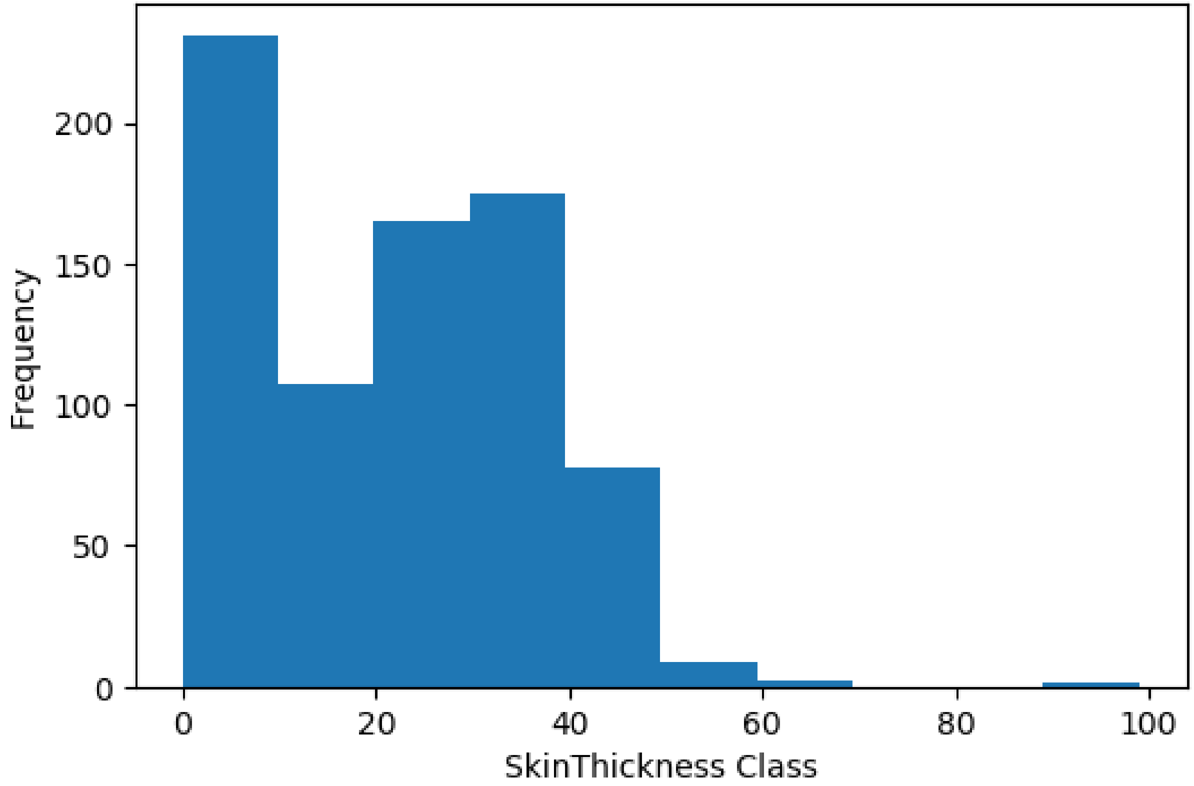
```
Mean of BloodPressure level is :- 69.10546875
```



In [271]:
```
df['BloodPressure']=df['BloodPressure'].replace(0,df['BloodPressure'].mean())
```

In [272]:
```
plt.figure(figsize=(6,4),dpi=100)
plt.xlabel('SkinThickness Class')
df['SkinThickness'].plot.hist()
print("Mean of SkinThickness is :-", df['SkinThickness'].mean())
```

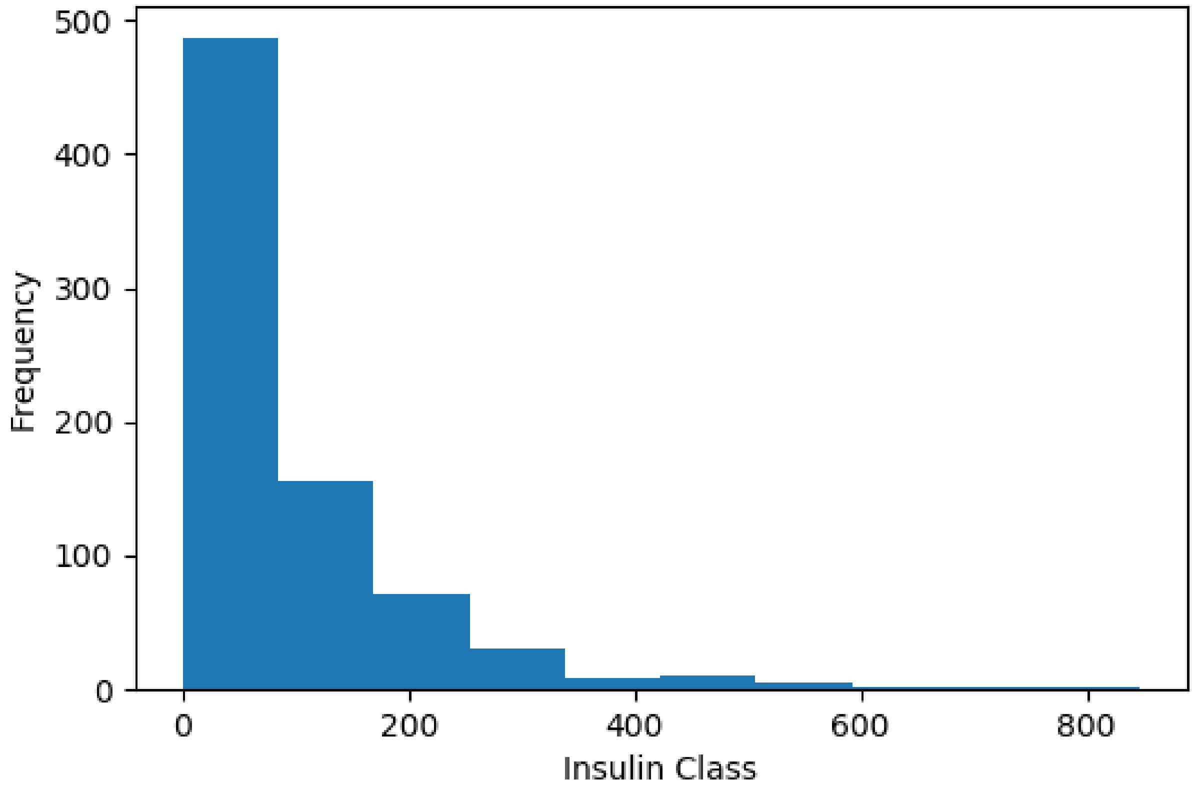
```
Mean of SkinThickness is :- 20.536458333333332
```



In [273]:
```
df['SkinThickness']=df['SkinThickness'].replace(0,df['SkinThickness'].mean())
```

In [274]:
```
plt.figure(figsize=(6,4),dpi=100)
plt.xlabel('Insulin Class')
df['Insulin'].plot.hist()
print("Mean of Insulin is :-", df['Insulin'].mean())
```

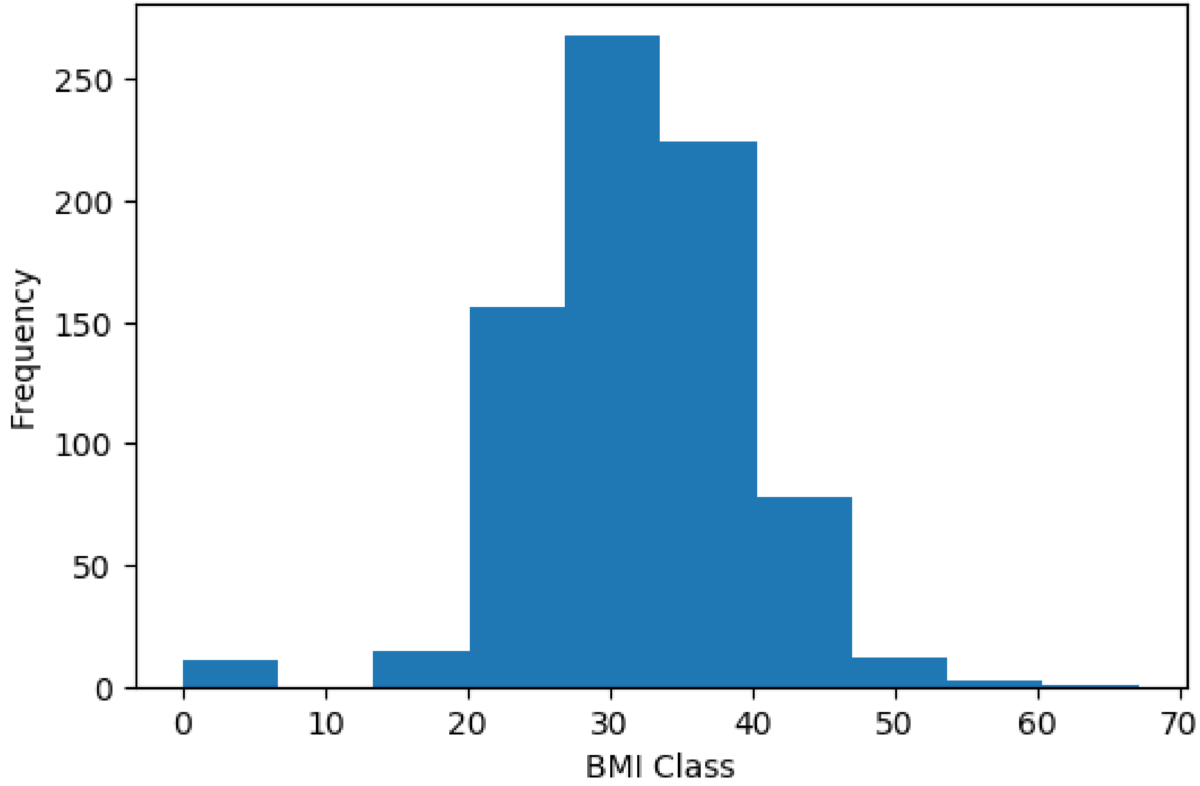
Mean of Insulin is :- 79.79947916666667



In [275]:
```
df['Insulin']=df['Insulin'].replace(0,df['Insulin'].mean())
```

In [276]:
```
plt.figure(figsize=(6,4),dpi=100)
plt.xlabel('BMI Class')
df['BMI'].plot.hist()
print("Mean of BMI is :-", df['BMI'].mean())
```

```
Mean of BMI is :- 31.992578124999977
```



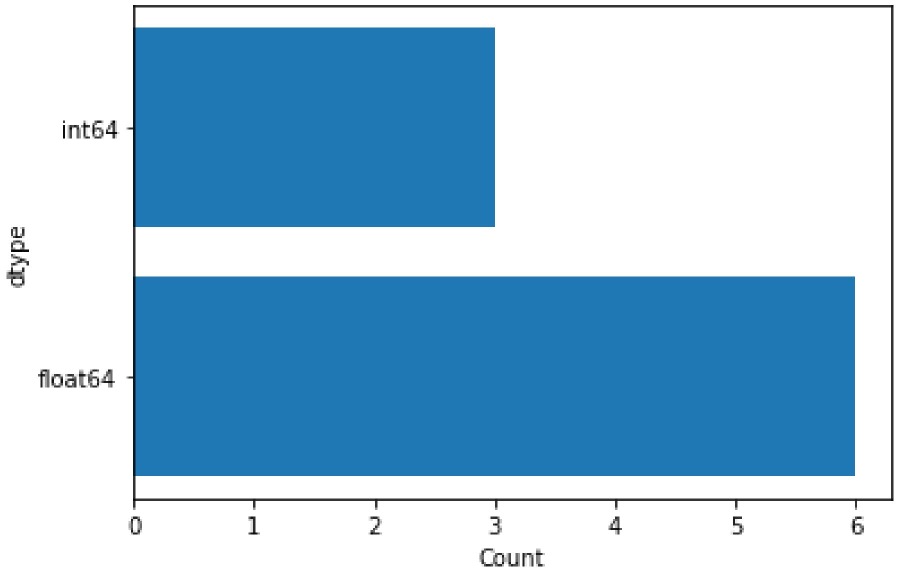
In [277]:
```
df['BMI']=df['BMI'].replace(0,df['BMI'].mean())
```

3. There are integer and float data type variables in this dataset. Create a

count (frequency) plot describing the data types and the count of variables.

In [278]:
```
df1=pd.DataFrame(df.dtypes.value_counts(),columns = ['Count'])
df1.reset_index(level=0, inplace=True)
l=(str(df1['index'][0]),str(df1['index'][1]))
yy=df1['Count']
plt.barh(l,yy)
plt.xlabel('Count')
plt.ylabel('dtype')
```

Out[278]:
```
Text(0, 0.5, 'dtype')
```



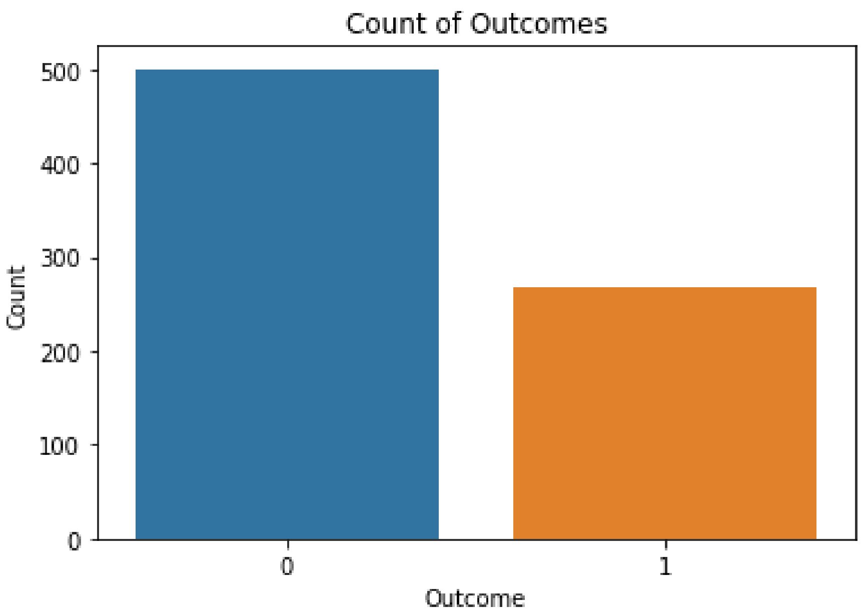
Week 2

Data Exploration:

1. Check the balance of the data by plotting the count of outcomes by their value. Describe your findings and plan future course of action.

In [284]:
```
sns.countplot(df['Outcome'])
plt.title("Count of Outcomes")
plt.xlabel('Outcome')
plt.ylabel("Count")
df['Outcome'].value_counts()
```

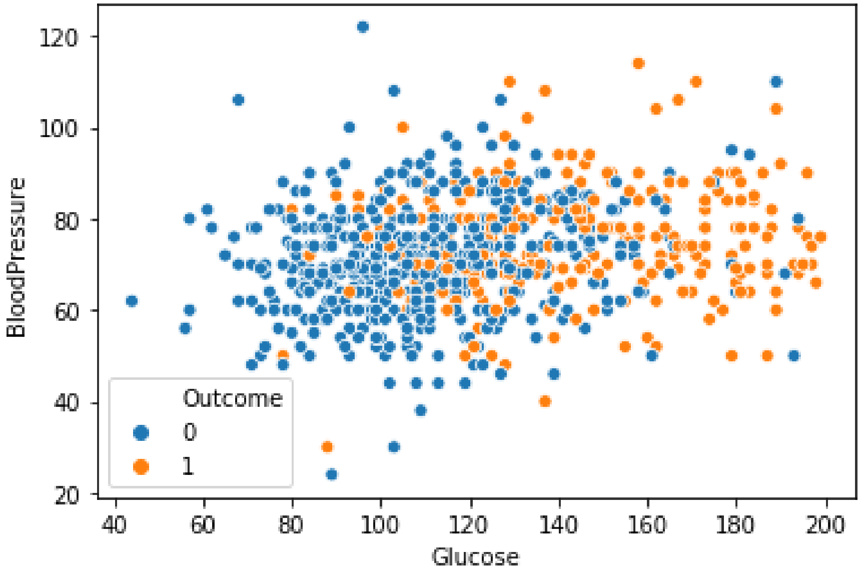
Out[284]:
```
0    500
1    268
Name: Outcome, dtype: int64
```



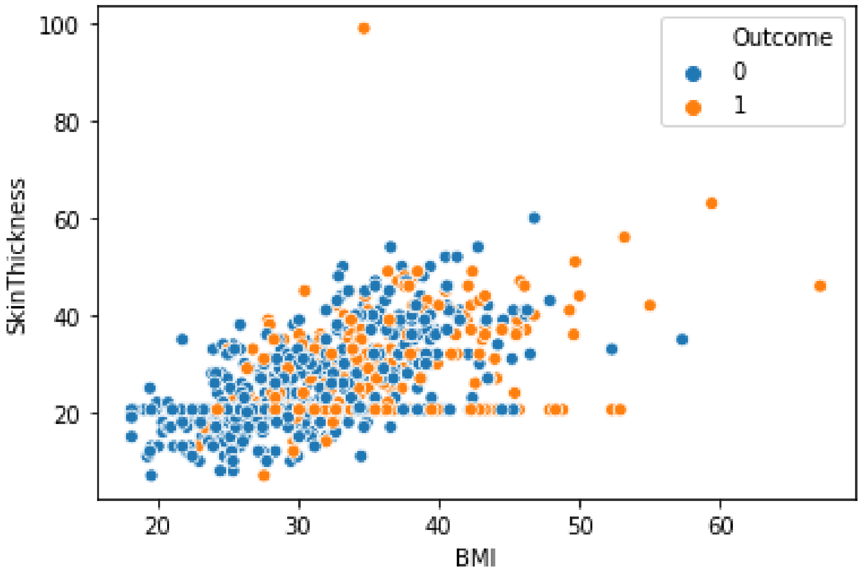

```
The outcome is observed to be in balance, it doesnt have huge difference, so no sampling needs to be
performed. We can use this data to build a model by using as train and test data. So this data can be
used for training and testing. It also helps Model Validation and ROC Curve.
```

2. Create scatter charts between the pair of variables to understand the relationships. Describe your findings.

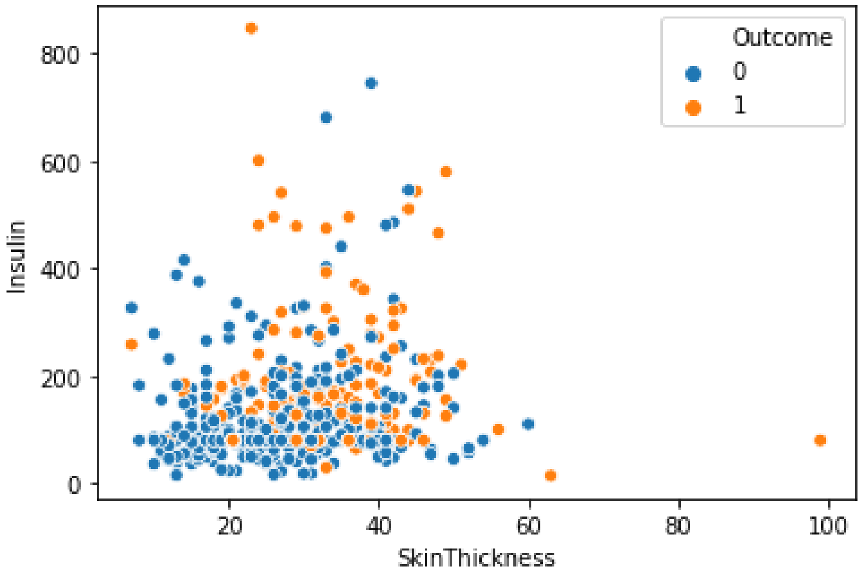
In [286]:
```
sns.scatterplot(x= "Glucose" ,y= "BloodPressure",hue="Outcome",data=df);
```



In [287]:
```
sns.scatterplot(x= "BMI" ,y= "SkinThickness",hue="Outcome",data=df);
```

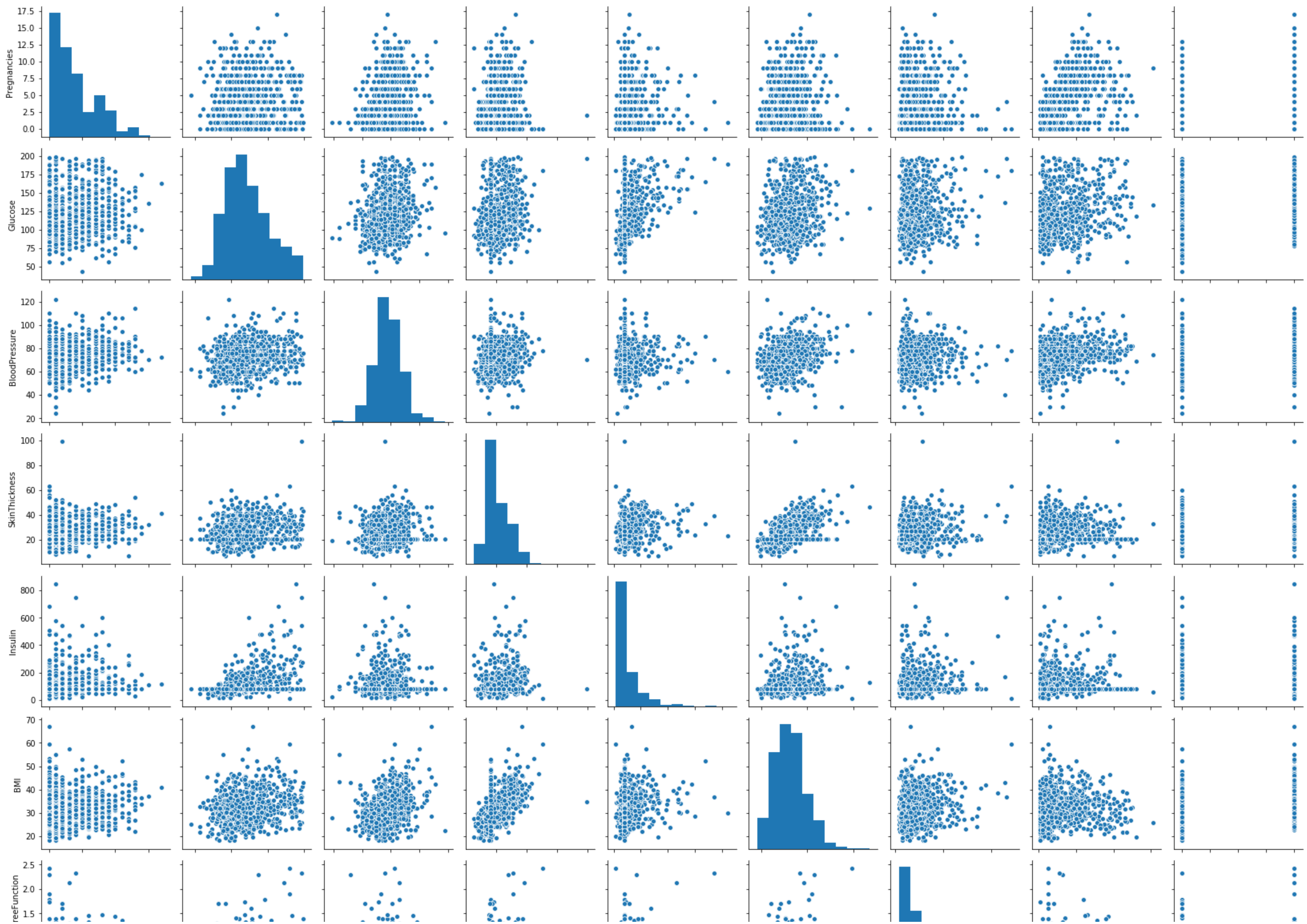


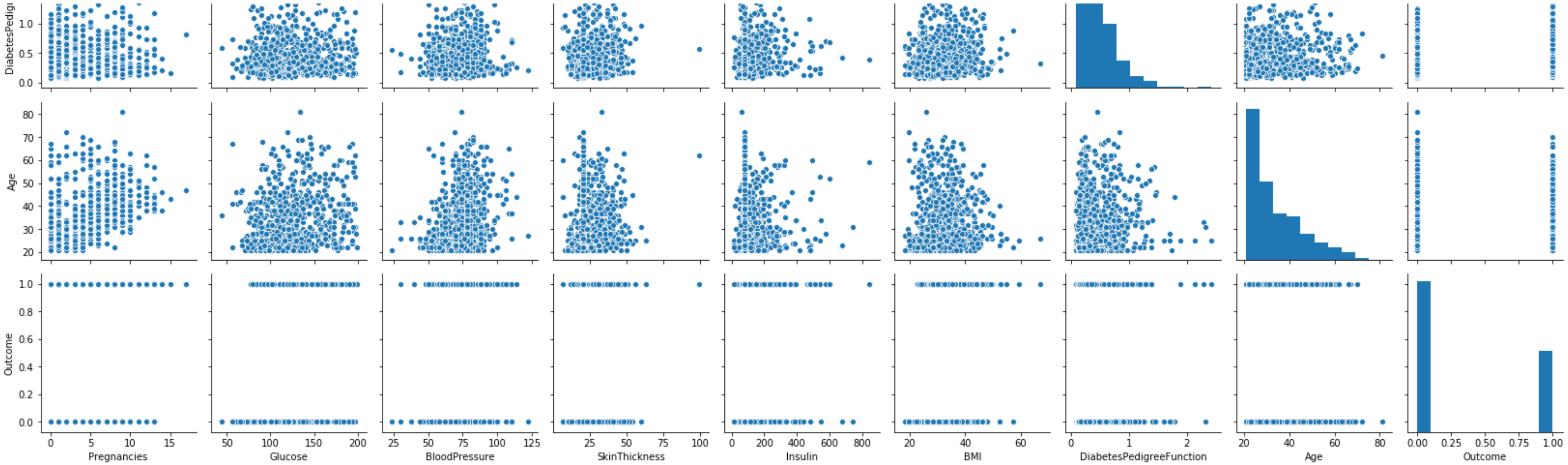
In [288]:
```
sns.scatterplot(x= "SkinThickness" ,y= "Insulin",hue="Outcome",data=df);
```



In [289]:
```
sns.pairplot(df)
```

Out[289]: <seaborn.axisgrid.PairGrid at 0xa46a42f1c8>






```
We can observe from scatter plot that there is not much correlation between variables, more can be
found out while performing correlation analysis
```

3. Perform correlation analysis. Visually explore it using a heat map.

In [290]:
```
df.corr()
```

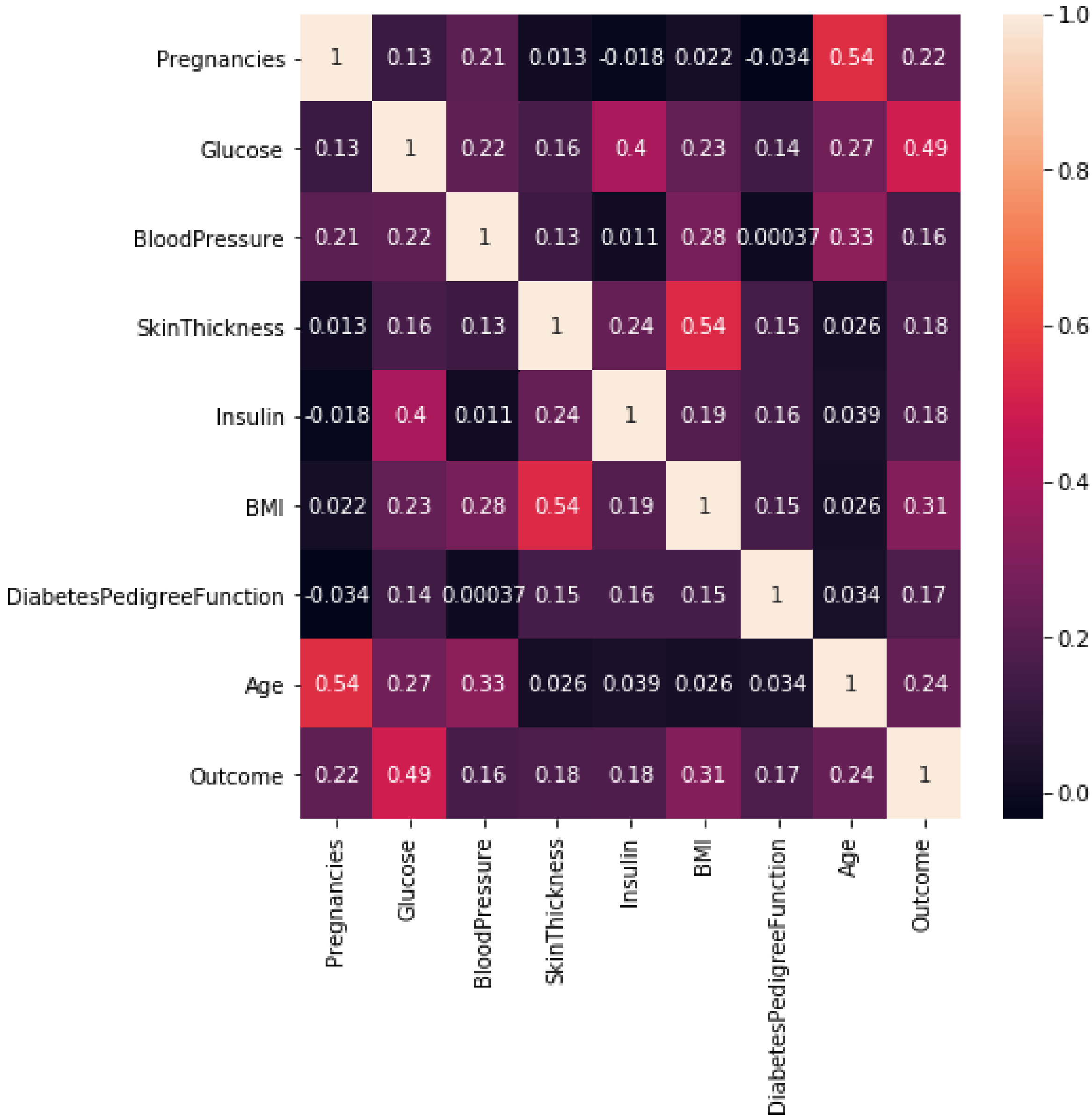
Out[290]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction
Pregnancies	1.000000	0.127964	0.208984	0.013376	-0.018082	0.021546	-0.033523
Glucose	0.127964	1.000000	0.219666	0.160766	0.396597	0.231478	0.137106
BloodPressure	0.208984	0.219666	1.000000	0.134155	0.010926	0.281231	0.000371
SkinThickness	0.013376	0.160766	0.134155	1.000000	0.240361	0.535703	0.154961
Insulin	-0.018082	0.396597	0.010926	0.240361	1.000000	0.189856	0.157806
BMI	0.021546	0.231478	0.281231	0.535703	0.189856	1.000000	0.153508
DiabetesPedigreeFunction	-0.033523	0.137106	0.000371	0.154961	0.157806	0.153508	1.000000
Age	0.544341	0.266600	0.326740	0.026423	0.038652	0.025748	0.033561
Outcome	0.221898	0.492908	0.162986	0.175026	0.179185	0.312254	0.173844

In [292]:

```
plt.subplots(figsize=(7,7))
sns.heatmap(df.corr(),annot=True)
```

Out[292]: <matplotlib.axes._subplots.AxesSubplot at 0xa46da4d788>



We can observe few variable pairs have strong positive correlation like

Pregnancies - Age

Glucose - Insulin

BloodPressure - Age

SkinThickness - BMI

Glucose - Age

Week 3

1. Devise strategies for model building. It is important to decide the right validation framework. Express your thought process.

2. Apply an appropriate classification algorithm to build a model. Compare various models with the results from KNN algorithm.

```
Outcome variable is a categorical variable, hence KNN, Logistic Regression, Random Forest is best suited model for this data.
We can apply Logistic Regression, Random Forest and compare the results with KNN.
```

Data Preprocessing

In [295]:
```python
x=df.iloc[:,:-1].values
y=df.iloc[:,-1].values
```

In [296]:
```python
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.20,random_state=0)
```

In [298]:
```python
from sklearn.preprocessing import StandardScaler
```

In [299]:
```python
Scale=StandardScaler()
x_train_std=Scale.fit_transform(x_train)
x_test_std=Scale.transform(x_test)
```

Project Task: Week 4

Data Modeling:

1. Create a classification report by analyzing sensitivity, specificity, AUC (ROC curve), etc. Please be descriptive to explain what values of these parameter you have used.

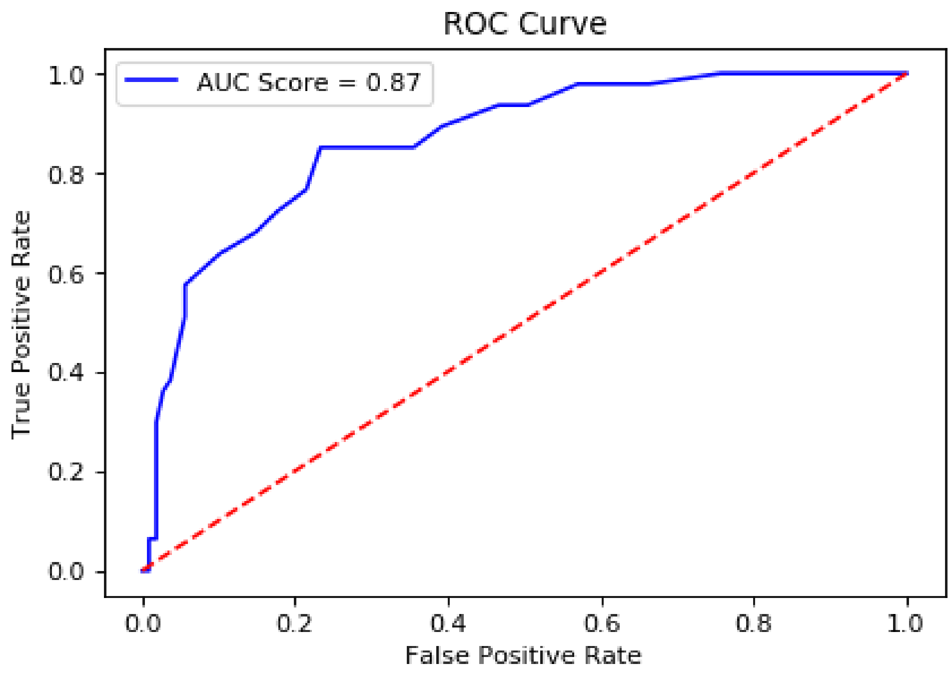
KNN

In [305]:
```
from sklearn.neighbors import KNeighborsClassifier
knn_model = KNeighborsClassifier(n_neighbors=25)
knn_model.fit(x_train_std,y_train)
knn_pred=knn_model.predict(x_test_std)
```

In [306]:
```
print("Model Validation ==>\n")
print("Accuracy Score of KNN Model::")
print(metrics.accuracy_score(y_test,knn_pred))
print("\n","Classification Report::")
print(metrics.classification_report(y_test,knn_pred),'\n')
print("\n","ROC Curve")
knn_prob=knn_model.predict_proba(x_test_std)
knn_prob1=knn_prob[:,1]
fpr,tpr,thresh=metrics.roc_curve(y_test,knn_prob1)
roc_auc_knn=metrics.auc(fpr,tpr)
plt.figure(dpi=80)
plt.title("ROC Curve")
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.plot(fpr,tpr,'b',label='AUC Score = %0.2f'%roc_auc_knn)
plt.plot(fpr,fpr,'r--',color='red')
plt.legend()
```

```
Model Validation ==>

Accuracy Score of KNN Model::
0.8181818181818182

 Classification Report::
              precision    recall  f1-score   support

           0       0.85      0.90      0.87       107
           1       0.73      0.64      0.68        47

    accuracy                           0.82       154
   macro avg       0.79      0.77      0.78       154
weighted avg       0.81      0.82      0.81       154



 ROC Curve
```

Out[306]: <matplotlib.legend.Legend at 0xa46f15d5c8>



The KNN Model has an accuracy of 81.81%, AUC score of 87% and f1 score of 82%, by using n_neighbors parameter as 25, optimal value used to get good accuracy.
These metrics can be used to find the better model

Logistic Regression

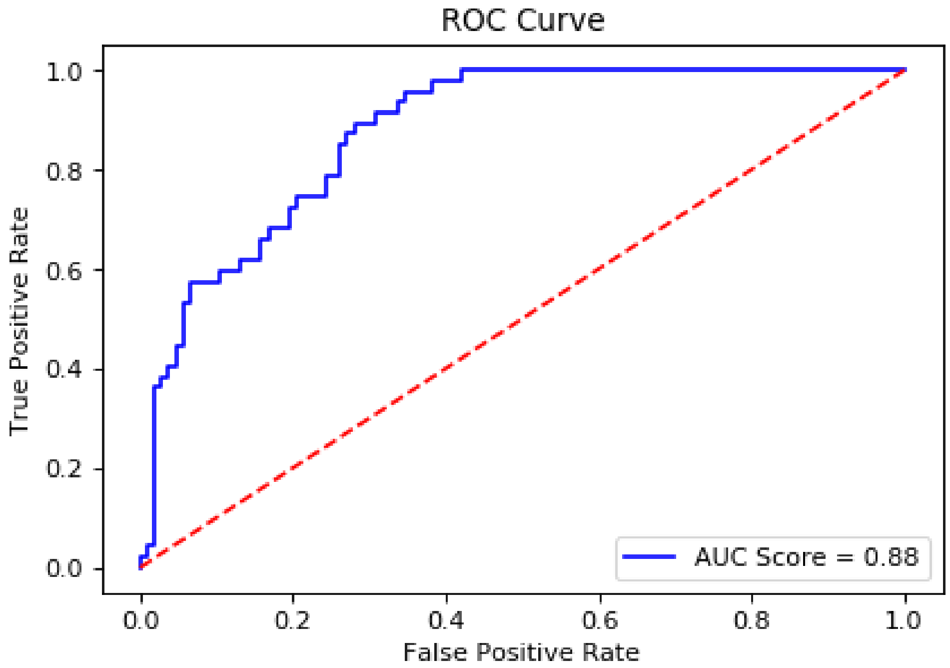
In [307]:
```
from sklearn.linear_model import LogisticRegression
lr_model = LogisticRegression(C=0.01)
lr_model.fit(x_train_std,y_train)
lr_pred=lr_model.predict(x_test_std)
```

In [308]:

```
print("Model Validation ==>\n")
print("Accuracy Score of Logistic Regression Model::")
print(metrics.accuracy_score(y_test,lr_pred))
print("\n","Classification Report::")
print(metrics.classification_report(y_test,lr_pred),'\n')
print("\n","ROC Curve")
lr_prob=lr_model.predict_proba(x_test_std)
lr_prob1=lr_prob[:,1]
fpr,tpr,thresh=metrics.roc_curve(y_test,lr_prob1)
roc_auc_lr=metrics.auc(fpr,tpr)
plt.figure(dpi=80)
plt.title("ROC Curve")
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.plot(fpr,tpr,'b',label='AUC Score = %0.2f'%roc_auc_lr)
plt.plot(fpr,fpr,'r--',color='red')
plt.legend()
```

```
Model Validation ==>

Accuracy Score of Logistic Regression Model::
0.8116883116883117

 Classification Report::
              precision    recall  f1-score   support

           0       0.82      0.93      0.87       107
           1       0.78      0.53      0.63        47

    accuracy                           0.81       154
   macro avg       0.80      0.73      0.75       154
weighted avg       0.81      0.81      0.80       154



 ROC Curve
```

Out[308]: <matplotlib.legend.Legend at 0xa46fe01688>




```
The Logistic Regression has an accuracy of 81.16%, AUC score of 88% and f1 score of 81%.
```

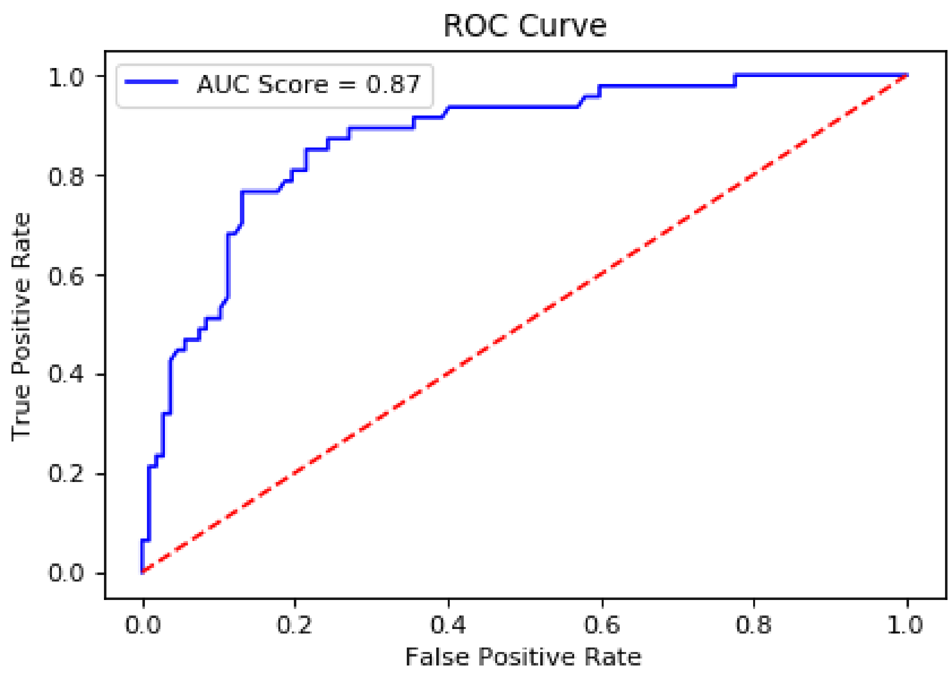
RandomForest

In [309]:
```
from sklearn.ensemble import RandomForestClassifier
rf_model = RandomForestClassifier(n_estimators=1000,random_state=0)
rf_model.fit(x_train_std,y_train)
rf_pred=rf_model.predict(x_test_std)
```

In [310]:
```
print("Model Validation ==>\n")
print("Accuracy Score of Logistic Regression Model::")
print(metrics.accuracy_score(y_test,rf_pred))
print("\n","Classification Report::")
print(metrics.classification_report(y_test,rf_pred),'\n')
print("\n","ROC Curve")
rf_prob=rf_model.predict_proba(x_test_std)
rf_prob1=rf_prob[:,1]
fpr,tpr,thresh=metrics.roc_curve(y_test,rf_prob1)
roc_auc_rf=metrics.auc(fpr,tpr)
plt.figure(dpi=80)
plt.plot(fpr,tpr,'b',label='AUC Score = %0.2f'%roc_auc_rf)
plt.title("ROC Curve")
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.plot(fpr,fpr,'r--',color='red')
plt.legend()
```

```
Model Validation ==>

Accuracy Score of Logistic Regression Model::
0.8246753246753247

 Classification Report::
              precision    recall  f1-score   support

           0       0.88      0.87      0.87       107
           1       0.71      0.72      0.72        47

    accuracy                           0.82       154
   macro avg       0.79      0.80      0.79       154
weighted avg       0.83      0.82      0.83       154



 ROC Curve
```

Out[310]: <matplotlib.legend.Legend at 0xa471009508>



The Random Forest has an accuracy of 82.46%, AUC score of 87% and f1 score of 82%. by using n_estimators parameter as 1000, which is the number of trees in the forest, more trees give more accuracy.

	Accuracy	AUC	f1
KNN	81.81%	87%	82%
LR	81.16%	88%	81%
RF	82.46%	87%	82%

So on comparison we can see that Random Forest is the best model for this data

Data Reporting:

2. Create a dashboard in tableau by choosing appropriate chart types and metrics useful for the business. The dashboard must entail the following:

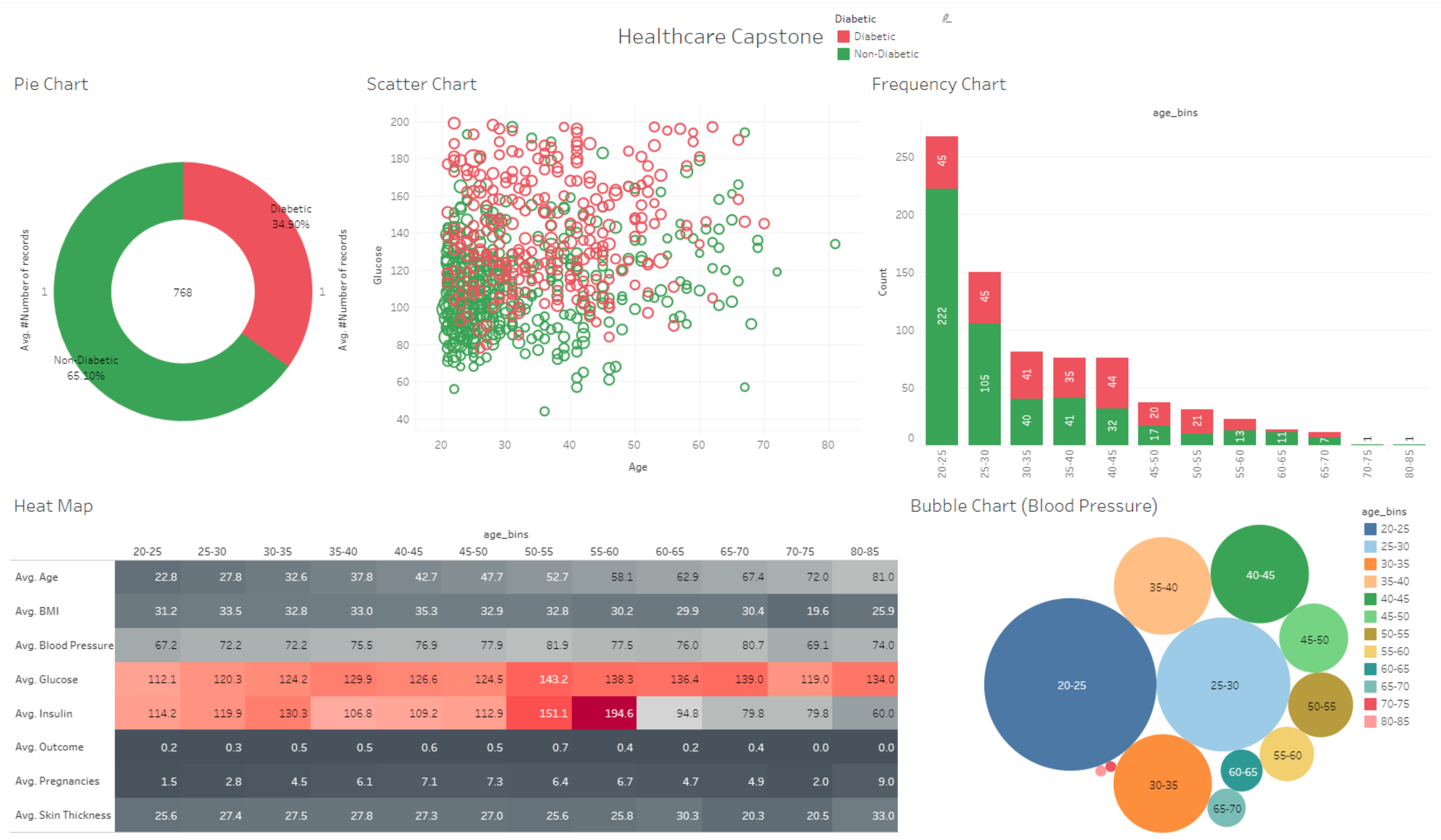
a. Pie chart to describe the diabetic or non-diabetic population

b. Scatter charts between relevant variables to analyze the relationships

c. Histogram or frequency charts to analyze the distribution of the data

d. Heatmap of correlation analysis among the relevant variables

e. Create bins of these age values: 20-25, 25-30, 30-35, etc. Analyze different variables for these age brackets using a bubble chart.



https://public.tableau.com/profile/jois.vishwesh#!/vizhome/HealthcareCapstoneVishwesh/Dashboard?publish=yes (https://public.tableau.com/profile/jois.vishwesh#!/vizhome/HealthcareCapstoneVishwesh/Dashboard?publish=yes)