In [15]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import os
from sklearn import datasets, metrics, linear_model, tree
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import GaussianNB
from sklearn.preprocessing import MinMaxScaler
from sklearn.neural_network import MLPClassifier

os.chdir('D:\\Documents\\DAAN862')

df = pd.read_csv('breastcancer.csv')
display(df)
```

	Age	BMI	Glucose	Insulin	HOMA	Leptin	Adiponectin	Resistin	MCP.1	Classification
0	48	23.500000	70	2.707	0.467409	8.8071	9.702400	7.99585	417.114	1
1	83	20.690495	92	3.115	0.706897	8.8438	5.429285	4.06405	468.786	1
2	82	23.124670	91	4.498	1.009651	17.9393	22.432040	9.27715	554.697	1
3	68	21.367521	77	3.226	0.612725	9.8827	7.169560	12.76600	928.220	1
4	86	21.111111	92	3.549	0.805386	6.6994	4.819240	10.57635	773.920	1
...	...	...	...	...	...	...	...	...	...	...
111	45	26.850000	92	3.330	0.755688	54.6800	12.100000	10.96000	268.230	2
112	62	26.840000	100	4.530	1.117400	12.4500	21.420000	7.32000	330.160	2
113	65	32.050000	97	5.730	1.370998	61.4800	22.540000	10.33000	314.050	2
114	72	25.590000	82	2.820	0.570392	24.9600	33.750000	3.27000	392.460	2
115	86	27.180000	138	19.910	6.777364	90.2800	14.110000	4.35000	90.090	2

116 rows × 10 columns

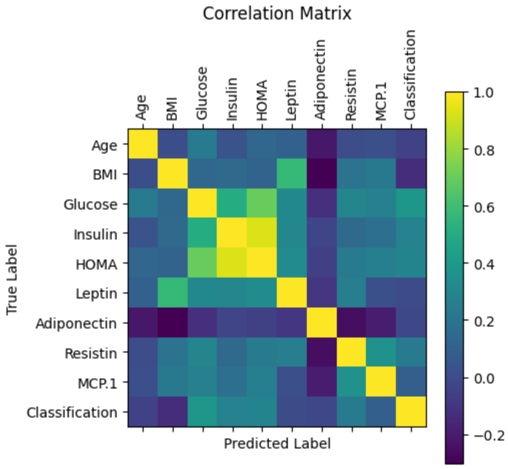
In [2]:
```python
# Question 1 - Perform exploratory data analysis
display(df.describe())
display(df.corr())
```

	Age	BMI	Glucose	Insulin	HOMA	Leptin	Adiponectin	Resistin	MCP.1	Classification
count	116.000000	116.000000	116.000000	116.000000	116.000000	116.000000	116.000000	116.000000	116.000000	116.000000
mean	57.301724	27.582111	97.793103	10.012086	2.694988	26.615080	10.180874	14.725966	534.647000	1.551724
std	16.112766	5.020136	22.525162	10.067768	3.642043	19.183294	6.843341	12.390646	345.912663	0.499475
min	24.000000	18.370000	60.000000	2.432000	0.467409	4.311000	1.656020	3.210000	45.843000	1.000000
25%	45.000000	22.973205	85.750000	4.359250	0.917966	12.313675	5.474283	6.881763	269.978250	1.000000
50%	56.000000	27.662416	92.000000	5.924500	1.380939	20.271000	8.352692	10.827740	471.322500	2.000000
75%	71.000000	31.241442	102.000000	11.189250	2.857787	37.378300	11.815970	17.755207	700.085000	2.000000
max	89.000000	38.578759	201.000000	58.460000	25.050342	90.280000	38.040000	82.100000	1698.440000	2.000000

	Age	BMI	Glucose	Insulin	HOMA	Leptin	Adiponectin	Resistin	MCP.1	Classification
Age	1.000000	0.008530	0.230106	0.032495	0.127033	0.102626	-0.219813	0.002742	0.013462	-0.043555
BMI	0.008530	1.000000	0.138845	0.145295	0.114480	0.569593	-0.302735	0.195350	0.224038	-0.132586
Glucose	0.230106	0.138845	1.000000	0.504653	0.696212	0.305080	-0.122121	0.291327	0.264879	0.384315
Insulin	0.032495	0.145295	0.504653	1.000000	0.932198	0.301462	-0.031296	0.146731	0.174356	0.276804
HOMA	0.127033	0.114480	0.696212	0.932198	1.000000	0.327210	-0.056337	0.231101	0.259529	0.284012
Leptin	0.102626	0.569593	0.305080	0.301462	0.327210	1.000000	-0.095389	0.256234	0.014009	-0.001078
Adiponectin	-0.219813	-0.302735	-0.122121	-0.031296	-0.056337	-0.095389	1.000000	-0.252363	-0.200694	-0.019490
Resistin	0.002742	0.195350	0.291327	0.146731	0.231101	0.256234	-0.252363	1.000000	0.366474	0.227310
MCP.1	0.013462	0.224038	0.264879	0.174356	0.259529	0.014009	-0.200694	0.366474	1.000000	0.091381
Classification	-0.043555	-0.132586	0.384315	0.276804	0.284012	-0.001078	-0.019490	0.227310	0.091381	1.000000

In [3]:
```python
# Question 1 Cont
plt.matshow(df.corr())
plt.title('Correlation Matrix', position = (0.5, 1.1))
plt.colorbar()
plt.xticks(range(10), list(df.columns), rotation=90)
plt.yticks(range(10), list(df.columns))
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
```

Out[3]: Text(0.5, 0, 'Predicted Label')



In [4]:
```
# Question 2 - Use 30% of data to build a logistic rgression model
X = df.iloc[:, 0:9]
y = df.Classification

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

lr = linear_model.LogisticRegression(solver='lbfgs', max_iter=1000)
lr.fit(X_train, y_train)
```

Out[4]:
```
▾ LogisticRegression
LogisticRegression(max_iter=1000)
```

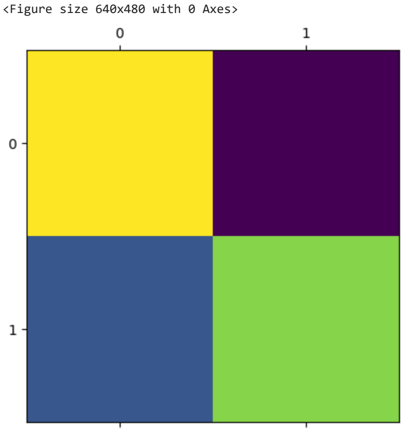
In [5]:
```
# Question 2 Cont - Predict the Labels Variable
lr_train_pred = lr.predict(X_train)
lr_test_pred = lr.predict(X_test)
print('Trained Accuracy:')
display(metrics.accuracy_score(y_train, lr_train_pred))
print('Test Accuracy:')
display(metrics.accuracy_score(y_test, lr_test_pred))
```

```
Trained Accuracy:
0.7901234567901234
Test Accuracy:
0.7428571428571429
```

In [6]:
```
# Question 2 Cont
# We can use a confusion matrix to see how each value compares
# such that 0 - 0 and 1 - 1 are all matching values and
# 1 - 0 and 0 - 1 are mismatched
test_cm = metrics.confusion_matrix(y_test, lr_test_pred)
display(test_cm)
plt.figure()
plt.matshow(test_cm)
```

```
array([[14,  3],
       [ 6, 12]], dtype=int64)
```

Out[6]:
```
<matplotlib.image.AxesImage at 0x1f021d923b0>
<Figure size 640x480 with 0 Axes>
```



In [7]:
```
# Question 3 - Build the Naive Bayes model to predict Labels
NB = GaussianNB()
NB.fit(X_train, y_train)
GaussianNB(priors=None)

NB_train_pred = NB.predict(X_train)
NB_test_pred = NB.predict(X_test)

print('Trained Accuracy:')
display(metrics.accuracy_score(y_train, NB_train_pred))
print('Test Accuracy:')
display(metrics.accuracy_score(y_test, NB_test_pred))
```

```
Trained Accuracy:
0.6049382716049383
Test Accuracy:
0.6571428571428571
```

In [20]:
```
# Question 4 - Build the Decision Tree model to predict Labels
DT = tree.DecisionTreeClassifier(max_depth = 10, min_samples_split = 5)
DT.fit(X_train, y_train)

DT_pred = DT.predict(X_test)
print('Test Accuracy:')
display(metrics.accuracy_score(DT_pred, y_test))
print(metrics.classification_report(y_test, DT_pred))
```

```
Test Accuracy:
0.8
              precision    recall  f1-score   support

           1       0.81      0.76      0.79        17
           2       0.79      0.83      0.81        18

    accuracy                           0.80        35
   macro avg       0.80      0.80      0.80        35
weighted avg       0.80      0.80      0.80        35
```

In [19]:
```
# Question 5 - Build the Neural Network to predict Labels
scaler = MinMaxScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

NN = MLPClassifier(solver = 'lbfgs', alpha = 1e-5,
                  hidden_layer_sizes = (10,4), random_state = 1)

NN.fit(X_train_scaled, y_train)

NN_pred = NN.predict(X_test_scaled)
print('Accuracy: ')
display(metrics.accuracy_score(NN_pred, y_test))
print(metrics.classification_report(y_test, NN_pred))
```

```
Accuracy:
0.7428571428571429
              precision    recall  f1-score   support

           1       0.72      0.76      0.74        17
           2       0.76      0.72      0.74        18

    accuracy                           0.74        35
   macro avg       0.74      0.74      0.74        35
weighted avg       0.74      0.74      0.74        35
```

In [22]:
```
# Question 6 - Which Model is Best?

# According to the accuracy results displayed per each model, the Decision tree model
# was the most accurate out of the models used with an accuracy of 80% for the test data.
# The logistics regression model and neural network were both second best with a tested accuracy
# of 74.29%.
# We can infer that the most accurate at predicting Label's value in this scenario is the best model to use.
```

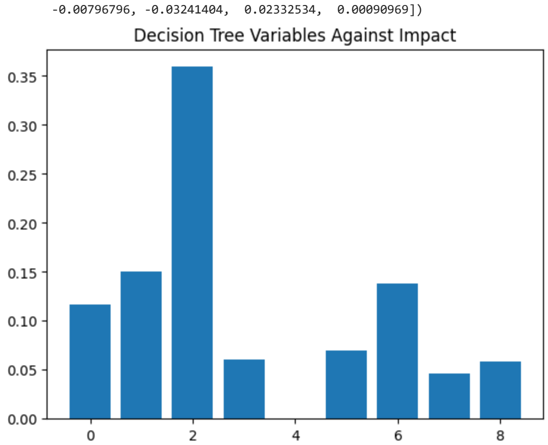
In [41]:
```
# Question 6 Cont - Which variable is most important?
# Lets use both the LR and the DT models to determine, where
# more confidence is given to the DT due to the higher accuracy

# We can use coef_ for LR and feature_importances_ for DT to get an array of weights
# that each variable has on the model
importance_lr = lr.coef_[0]
importance_dt = DT.feature_importances_

display(importance_dt)
display(importance_lr)

# Plot the DT Variables as Box plot
plt.bar([x for x in range(len(importance_dt))], importance_dt)
plt.title('Decision Tree Variables Against Impact')
plt.show()
```

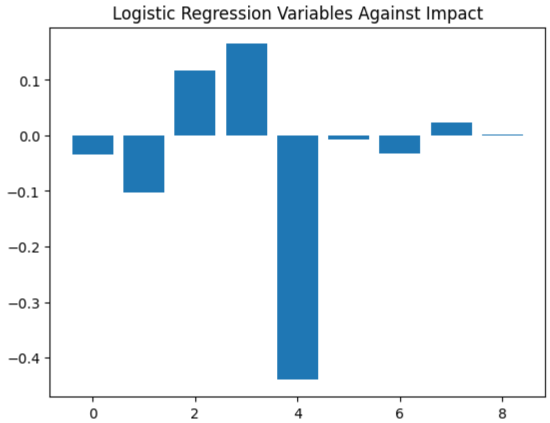
```
array([0.11629181, 0.15052565, 0.35939932, 0.06073649, 0.        ,
       0.06927582, 0.13830139, 0.04648804, 0.05898148])
array([-0.03418905, -0.102659  ,  0.11745601,  0.16455198, -0.44013788,
       -0.00796796, -0.03241404,  0.02332534,  0.00090969])
```



In [43]:
```
# Question 6 Cont - Plot the LR variables
plt.bar([x for x in range(len(importance_lr))], importance_lr)
plt.title('Logistic Regression Variables Against Impact')
plt.show()

# As shown, the DT model indicates that the 3rd variable, Glucose, has the most
# impact on whether the patient will have breast cancer or not. Alternatively,
# the LR model shows that HOMA levels have the highest correlation - which shows that
# despite each model had relatively high accuracy in predicting outcome,
```

```
# there are different weights to each variable. For this question, we will
# assume that Glucose is most important due to the fact that the DT model has higher
# accuracy.
```



In [ ]:

```
```