Supervised machine learning algorithms application on dataset with binomial outcome

In [45]:
```
import warnings
warnings.filterwarnings("ignore")
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.model_selection import KFold
from sklearn.ensemble import RandomForestClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn import svm
from sklearn import metrics
from sklearn import linear_model
```

Loading data called data.csv and call it data, while data_m_b was created only for plotting purpose

In [3]:
```
data = pd.read_csv("data.csv",header=0)
data_m_b=pd.read_csv("data.csv",header=0)
```

Getting first info about data

In [5]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 569 entries, 0 to 568
Data columns (total 31 columns):
diagnosis                  569 non-null object
radius_mean                569 non-null float64
texture_mean               569 non-null float64
perimeter_mean             569 non-null float64
area_mean                  569 non-null float64
smoothness_mean            569 non-null float64
compactness_mean           569 non-null float64
concavity_mean             569 non-null float64
concave points_mean        569 non-null float64
symmetry_mean              569 non-null float64
fractal_dimension_mean     569 non-null float64
radius_se                  569 non-null float64
texture_se                 569 non-null float64
perimeter_se               569 non-null float64
area_se                    569 non-null float64
smoothness_se              569 non-null float64
compactness_se             569 non-null float64
concavity_se               569 non-null float64
concave points_se          569 non-null float64
symmetry_se                569 non-null float64
fractal_dimension_se       569 non-null float64
radius_worst               569 non-null float64
texture_worst              569 non-null float64
perimeter_worst            569 non-null float64
area_worst                 569 non-null float64
smoothness_worst           569 non-null float64
compactness_worst          569 non-null float64
concavity_worst            569 non-null float64
concave points_worst       569 non-null float64
symmetry_worst             569 non-null float64
fractal_dimension_worst    569 non-null float64
dtypes: float64(30), object(1)
memory usage: 135.6+ KB
```

Name of parameters of the dataset

In [6]:
```
data.columns
```

Out[6]:
```
Index(['diagnosis', 'radius_mean', 'texture_mean', 'perimeter_mean',
       'area_mean', 'smoothness_mean', 'compactness_mean', 'concavity_mea
n',
       'concave points_mean', 'symmetry_mean', 'fractal_dimension_mean',
       'radius_se', 'texture_se', 'perimeter_se', 'area_se', 'smoothness_s
e',
       'compactness_se', 'concavity_se', 'concave points_se', 'symmetry_s
e',
       'fractal_dimension_se', 'radius_worst', 'texture_worst',
       'perimeter_worst', 'area_worst', 'smoothness_worst',
       'compactness_worst', 'concavity_worst', 'concave points_worst',
       'symmetry_worst', 'fractal_dimension_worst'],
      dtype='object')
```

Snapshot of the data

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

Out[7]:

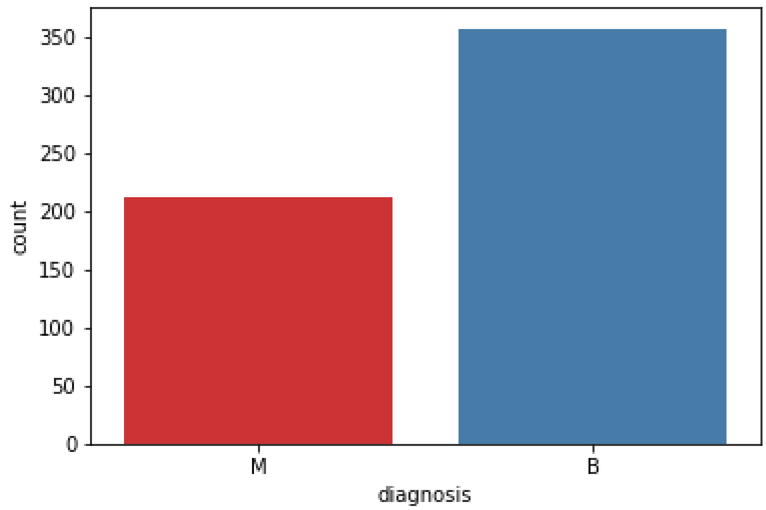
	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	coı
0	M	17.99	10.38	122.80	1001.0	0.11840	
1	M	20.57	17.77	132.90	1326.0	0.08474	
2	M	19.69	21.25	130.00	1203.0	0.10960	
3	M	11.42	20.38	77.58	386.1	0.14250	
4	M	20.29	14.34	135.10	1297.0	0.10030	

5 rows × 31 columns

Countplot of Malignant vs Benign observations

In [8]:
```
sns.countplot(x=data['diagnosis'],label="Count",palette="Set1")
```

Out[8]: <matplotlib.axes._subplots.AxesSubplot at 0x1172bb0>



Defining all predictors as variabl all_predictors that will be used later

In [9]:
```
all_predictors=['radius_mean', 'texture_mean', 'perimeter_mean',
       'area_mean', 'smoothness_mean', 'compactness_mean', 'concavity_mean',
       'concave points_mean', 'symmetry_mean', 'fractal_dimension_mean',
       'radius_se', 'texture_se', 'perimeter_se', 'area_se', 'smoothness_se',
       'compactness_se', 'concavity_se', 'concave points_se', 'symmetry_se',
       'fractal_dimension_se', 'radius_worst', 'texture_worst',
       'perimeter_worst', 'area_worst', 'smoothness_worst',
       'compactness_worst', 'concavity_worst', 'concave points_worst',
       'symmetry_worst', 'fractal_dimension_worst']
```

Chaning M and B at diagnosis column on 1 and 0

In [10]:
```
data['diagnosis']=data['diagnosis'].map({'M':1,'B':0})
```

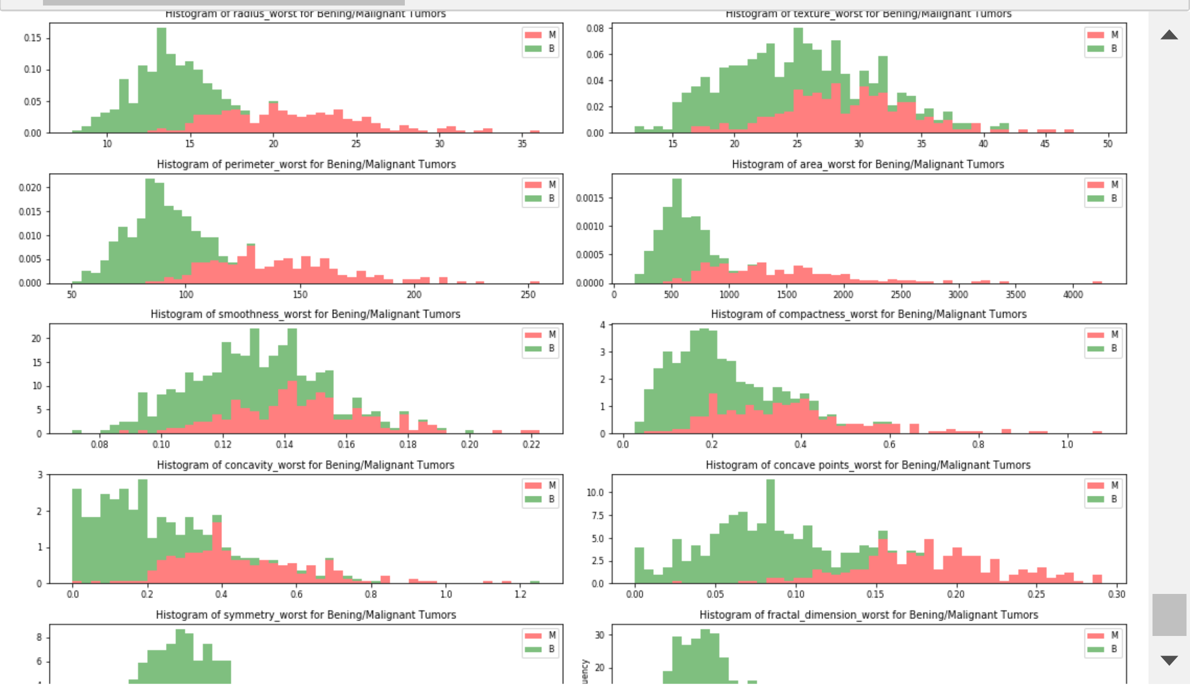
Creating variable for dependant variable

In [11]:
```
outcome_var= "diagnosis"
```

In [ ]:
```
Histogram plots for each predictor seperated by Diagnosis
```

In [17]:

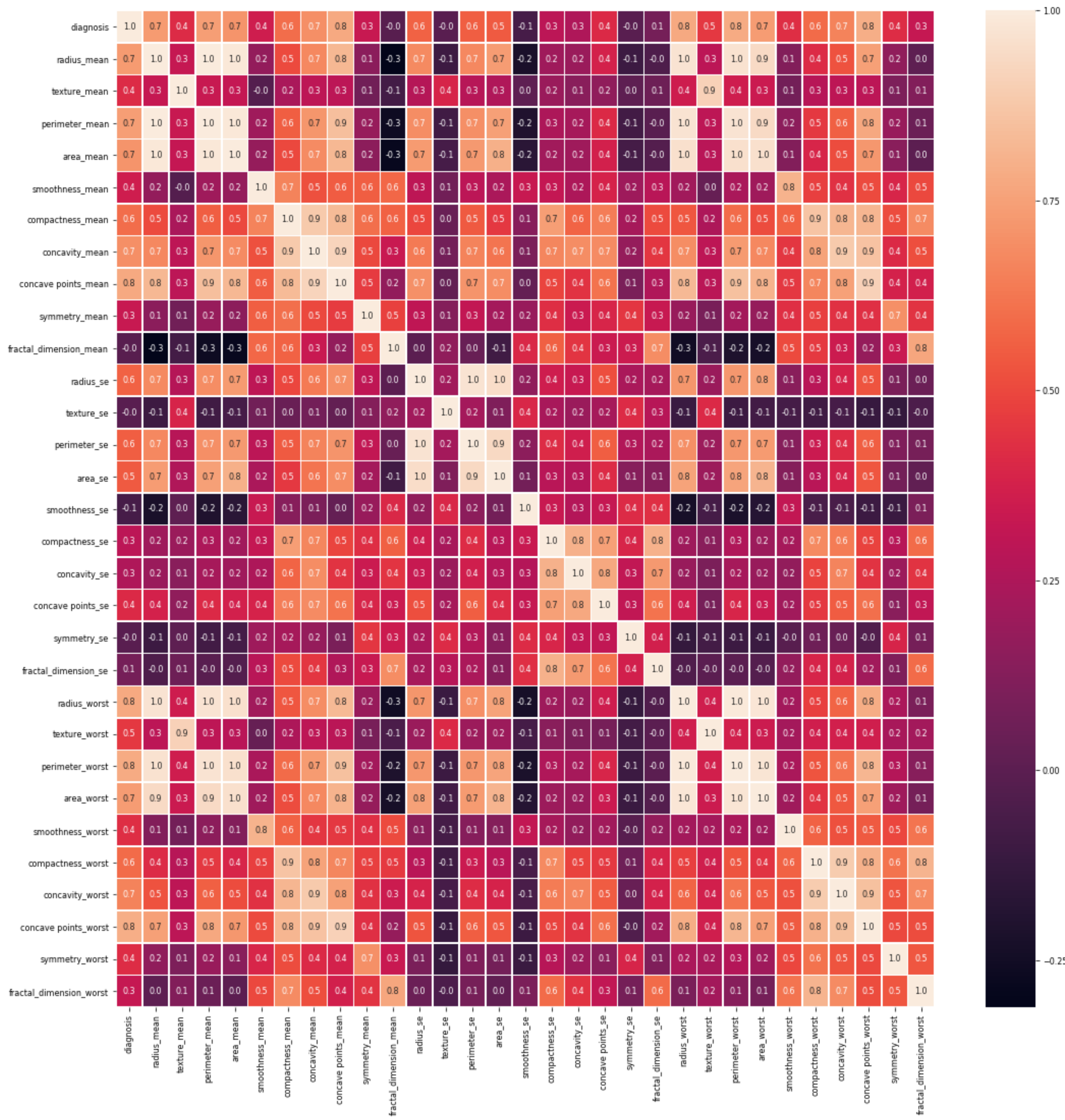
```
import matplotlib.pyplot as plt
import matplotlib.gridspec as gridspec

features_mean=list(data.columns[1:31])
dfM=data[data['diagnosis'] ==1]
dfB=data[data['diagnosis'] ==0]
plt.rcParams.update({'font.size': 8})
fig, axes = plt.subplots(nrows=15, ncols=2, figsize=(15,30))
axes = axes.ravel()
for idx,ax in enumerate(axes):
    ax.figure
    binwidth= (max(data[features_mean[idx]]) - min(data[features_mean[idx]]))
    ax.hist([dfM[features_mean[idx]],dfB[features_mean[idx]]], bins=np.arange
    ax.legend(loc='upper right')
    ax.set_title(f"Histogram of {features_mean[idx]} for Bening/Malignant Tum
    plt.ylabel("Frequency")
plt.ylabel("Frequency")
plt.tight_layout()
plt.show()
```



Correalation Heatmap for all predictors

In [18]:
```python
#correlation map
f,ax = plt.subplots(figsize=(18, 18))
sns.heatmap(data.corr(), annot=True, linewidths=.5, fmt= '.1f',ax=ax)
```

Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0xada7d90>



Defining a function that will do the same process for each algorithm. First calculated accuracy for training data, then divides data into 4 folds and gives 4-fold CV scores.

In [23]:
```
def classification_model(model,data,prediction_input,output):

    model.fit(data[prediction_input],data[output])

    predictions = model.predict(data[prediction_input])

    accuracy = metrics.accuracy_score(predictions,data[output])
    print("Accuracy : %s" % "{0:.3%}".format(accuracy))


    kf = KFold(n_splits=4,random_state=41,shuffle=True)
    print (kf)
    error = []
    for train, test in kf.split(data):
        train_X = (data[prediction_input].iloc[train,:])
        train_y = data[output].iloc[train]
        model.fit(train_X, train_y)


        test_X=data[prediction_input].iloc[test,:]
        test_y=data[output].iloc[test]
        error.append(model.score(test_X,test_y))

        print("Cross-Validation Score : %s" % "{0:.3%}".format(error[-1]))

    print(f"Average accuracy score is : %s" % "{0:.3%}".format(np.mean(error)
```

6 Most significant predictors chosen by Logitic regression with stepwise selction using SAS are defined as prediction_var

In [21]:
```
outcome_var= "diagnosis"
prediction_var = ['radius_se','area_worst','concavity_worst','compactness_se'
```

Results of Decision Tree Classifier using all predictors

In [26]:
```
model = DecisionTreeClassifier()
classification_model(model,data,all_predictors,outcome_var)
```

```
Accuracy : 100.000%
KFold(n_splits=4, random_state=41, shuffle=True)
Cross-Validation Score : 97.203%
Cross-Validation Score : 88.732%
Cross-Validation Score : 88.732%
Cross-Validation Score : 95.070%
Average accuracy score is : 92.435%
```

Results of Decision Tree Classifier using 6 predictors

In [27]:
```
model = DecisionTreeClassifier()
classification_model(model,data,prediction_var,outcome_var)
```

```
Accuracy : 100.000%
KFold(n_splits=4, random_state=41, shuffle=True)
Cross-Validation Score : 97.902%
Cross-Validation Score : 90.845%
Cross-Validation Score : 90.141%
Cross-Validation Score : 93.662%
Average accuracy score is : 93.137%
```

Results of Random Forest Classifier using 6 predictors

In [30]:
```
model = RandomForestClassifier(n_estimators=100, max_features=2)
classification_model(model, data,prediction_var,outcome_var)
```

```
Accuracy : 100.000%
KFold(n_splits=4, random_state=41, shuffle=True)
Cross-Validation Score : 99.301%
Cross-Validation Score : 95.775%
Cross-Validation Score : 92.254%
Cross-Validation Score : 96.479%
Average accuracy score is : 95.952%
```

Results of Random Forest Classifier using all predictors

In [31]:
```
model = RandomForestClassifier(n_estimators=100,max_depth=30, max_features=2)
classification_model(model, data,all_predictors,outcome_var)
```

```
Accuracy : 100.000%
KFold(n_splits=4, random_state=41, shuffle=True)
Cross-Validation Score : 98.601%
Cross-Validation Score : 93.662%
Cross-Validation Score : 89.437%
Cross-Validation Score : 98.592%
Average accuracy score is : 95.073%
```

```
Results of SVM with gaussian rbf kernel using 6 predictors
```

In [459]:
```
model = svm.SVC(kernel='rbf')
classification_model(model,data,prediction_var,outcome_var)
```

```
Accuracy : 99.473%
KFold(n_splits=4, random_state=41, shuffle=True)
Cross-Validation Score : 67.133%
Cross-Validation Score : 61.972%
Cross-Validation Score : 67.606%
Cross-Validation Score : 65.493%
[0.6713286713286714, 0.6197183098591549, 0.676056338028169, 0.6549295774647
887]
Average accuracy score is : 65.551%
```

Results of SVM with gaussian rbf kernel using all predictors

In [32]:
```
model = svm.SVC(kernel='rbf')
classification_model(model,data,all_predictors,outcome_var)
```

```
Accuracy : 100.000%
KFold(n_splits=4, random_state=41, shuffle=True)
Cross-Validation Score : 62.937%
Cross-Validation Score : 59.155%
Cross-Validation Score : 64.085%
Cross-Validation Score : 64.789%
Average accuracy score is : 62.741%
```

Results of SVM with linear kernel using 6 predictors

In [33]:
```
model = svm.SVC(kernel='linear')
classification_model(model,data,prediction_var,outcome_var)
```

```
Accuracy : 95.782%
KFold(n_splits=4, random_state=41, shuffle=True)
Cross-Validation Score : 98.601%
Cross-Validation Score : 95.070%
Cross-Validation Score : 91.549%
Cross-Validation Score : 96.479%
Average accuracy score is : 95.425%
```

Results of SVM with linear kernel using all predictors

In [34]:
```
model = svm.SVC(kernel='linear')
classification_model(model,data,all_predictors,outcome_var)
```

```
Accuracy : 96.661%
KFold(n_splits=4, random_state=41, shuffle=True)
Cross-Validation Score : 98.601%
Cross-Validation Score : 93.662%
Cross-Validation Score : 90.141%
Cross-Validation Score : 96.479%
Average accuracy score is : 94.721%
```

Results of SVM with sigmoid kernel using 6 predictors

In [463]:

```
model = svm.SVC(kernel='sigmoid')
classification_model(model,data,prediction_var,outcome_var)
```

```
Accuracy : 62.742%
KFold(n_splits=4, random_state=41, shuffle=True)
Cross-Validation Score : 62.937%
Cross-Validation Score : 59.155%
Cross-Validation Score : 64.085%
Cross-Validation Score : 64.789%
[0.6293706293706294, 0.5915492957746479, 0.6408450704225352, 0.647887323943
662]
Average accuracy score is : 62.741%
```

Results of SVM with sigmoid kernel using all predictors

In [36]:

```
model = svm.SVC(kernel='sigmoid')
classification_model(model,data,all_predictors,outcome_var)
```

```
Accuracy : 62.742%
KFold(n_splits=4, random_state=41, shuffle=True)
Cross-Validation Score : 62.937%
Cross-Validation Score : 59.155%
Cross-Validation Score : 64.085%
Cross-Validation Score : 64.789%
Average accuracy score is : 62.741%
```

Results of Kneigbors classifier using Euclidean distances using 6 predictors

In [37]:

```
model = KNeighborsClassifier()
classification_model(model,data,prediction_var,outcome_var)
```

```
Accuracy : 93.497%
KFold(n_splits=4, random_state=41, shuffle=True)
Cross-Validation Score : 93.007%
Cross-Validation Score : 88.028%
Cross-Validation Score : 90.141%
Cross-Validation Score : 97.183%
Average accuracy score is : 92.090%
```

Results of Kneigbors classifier using Euclidean distances using all predictors

In [467]:
```
model = KNeighborsClassifier()
classification_model(model,data,all_predictors,outcome_var)
```

```
Accuracy : 94.728%
KFold(n_splits=4, random_state=41, shuffle=True)
Cross-Validation Score : 93.007%
Cross-Validation Score : 92.254%
Cross-Validation Score : 91.549%
Cross-Validation Score : 95.070%
[0.9300699300699301, 0.9225352112676056, 0.9154929577464789, 0.950704225352
1126]
Average accuracy score is : 92.970%
```

Results of Kneigbors classifier using Manhattan distances using 6 predictors

In [466]:
```
model = KNeighborsClassifier(p=1)
classification_model(model,data,prediction_var,outcome_var)
```

```
Accuracy : 94.376%
KFold(n_splits=4, random_state=41, shuffle=True)
Cross-Validation Score : 94.406%
Cross-Validation Score : 88.732%
Cross-Validation Score : 90.141%
Cross-Validation Score : 95.775%
[0.9440559440559441, 0.8873239436619719, 0.9014084507042254, 0.957746478873
2394]
Average accuracy score is : 92.263%
```

Results of Kneighbors classifier using Manhattan distances using all predictors

In [468]:
```
model = KNeighborsClassifier(p=1)
classification_model(model,data,all_predictors,outcome_var)
```

```
Accuracy : 95.431%
KFold(n_splits=4, random_state=41, shuffle=True)
Cross-Validation Score : 94.406%
Cross-Validation Score : 91.549%
Cross-Validation Score : 92.254%
Cross-Validation Score : 95.775%
[0.9440559440559441, 0.9154929577464789, 0.9225352112676056, 0.957746478873
2394]
Average accuracy score is : 93.496%
```

Results of Kneighbors classifier using Minkowski p=3 distances using all predictors

In [469]:
```
model = KNeighborsClassifier(p=3)
classification_model(model,data,all_predictors,outcome_var)
```

```
Accuracy : 94.552%
KFold(n_splits=4, random_state=41, shuffle=True)
Cross-Validation Score : 93.706%
Cross-Validation Score : 92.254%
Cross-Validation Score : 91.549%
Cross-Validation Score : 95.070%
[0.9370629370629371, 0.9225352112676056, 0.9154929577464789, 0.950704225352
1126]
Average accuracy score is : 93.145%
```

Results of Kneighbors classifier using Minkowski p=3 distances using 6 predictors

In [40]:
```
model = KNeighborsClassifier(p=3)
classification_model(model,data,prediction_var,outcome_var)
```

```
Accuracy : 93.322%
KFold(n_splits=4, random_state=41, shuffle=True)
Cross-Validation Score : 93.007%
Cross-Validation Score : 88.028%
Cross-Validation Score : 90.845%
Cross-Validation Score : 97.183%
Average accuracy score is : 92.266%
```

Unfortunately my computer coulndt run polynomial kernel of SVM

In [41]:
```
#model = svm.SVC(kernel='poly')
#classification_model(model,X,prediction_var2,outcome_var2)
```

Results of Logistic Regression with ridge penalty using 6 predictors

In [42]:
```
model=LogisticRegression()
classification_model(model,data,prediction_var,outcome_var)
model.coef_
```

```
Accuracy : 94.903%
KFold(n_splits=4, random_state=41, shuffle=True)
Cross-Validation Score : 96.503%
Cross-Validation Score : 88.732%
Cross-Validation Score : 90.141%
Cross-Validation Score : 95.775%
Average accuracy score is : 92.788%
```

Out[42]:
```
array([[0.64156833, 0.00555452, 2.72633102, 0.02941559, 0.02380858,
        0.84950026]])
```

Results of Logistic Regression with ridge penalty using 6 predictors

In [483]:
```
model=LogisticRegression(penalty='l2')
classification_model(model,data,all_predictors,outcome_var)
```

```
Accuracy : 95.958%
KFold(n_splits=4, random_state=41, shuffle=True)
Cross-Validation Score : 97.902%
Cross-Validation Score : 92.254%
Cross-Validation Score : 92.958%
Cross-Validation Score : 95.775%
[0.9790209790209791, 0.9225352112676056, 0.9295774647887324, 0.957746478873
2394]
Average accuracy score is : 94.722%
```

Results of Logistic Regression with lasso penalty using 6 predictors and coefficients of predictors

In [43]:
```
model=LogisticRegression(penalty='l1')
classification_model(model,data,prediction_var,outcome_var)
model.coef_
```

```
Accuracy : 95.431%
KFold(n_splits=4, random_state=41, shuffle=True)
Cross-Validation Score : 98.601%
Cross-Validation Score : 95.070%
Cross-Validation Score : 90.845%
Cross-Validation Score : 97.183%
Average accuracy score is : 95.425%
```

Out[43]:
```
array([[2.10321532, 0.00892396, 5.16799515, 0.        , 0.15701974,
        0.        ]])
```

Results of Logistic Regression with lasso penalty using all predictors and coefficients of predictors

In [46]:
```
model=LogisticRegression(penalty='l1')
classification_model(model,data,all_predictors,outcome_var)
model.coef_
```

```
Accuracy : 95.958%
KFold(n_splits=4, random_state=41, shuffle=True)
Cross-Validation Score : 98.601%
Cross-Validation Score : 92.958%
Cross-Validation Score : 92.254%
Cross-Validation Score : 95.775%
Average accuracy score is : 94.897%
```

Out[46]:
```
array([[-4.0958732 , -0.06593394,  0.09680937,  0.01957743,  0.        ,
         0.        ,  0.        ,  0.        ,  0.        ,  0.        ,
         0.        , -0.93429995, -0.1148191 ,  0.11208174,  0.        ,
         0.        ,  0.        ,  0.        ,  0.        ,  0.        ,
        -0.19824339,  0.30622498,  0.18648275,  0.01283658,  0.        ,
         0.        ,  2.7244296 ,  0.        ,  0.        ,  0.        ]])
```

Decision Tree and Random forest plots

In [47]:
```
y=data_m_b['diagnosis']
x=data_m_b.iloc[:,1:]
```

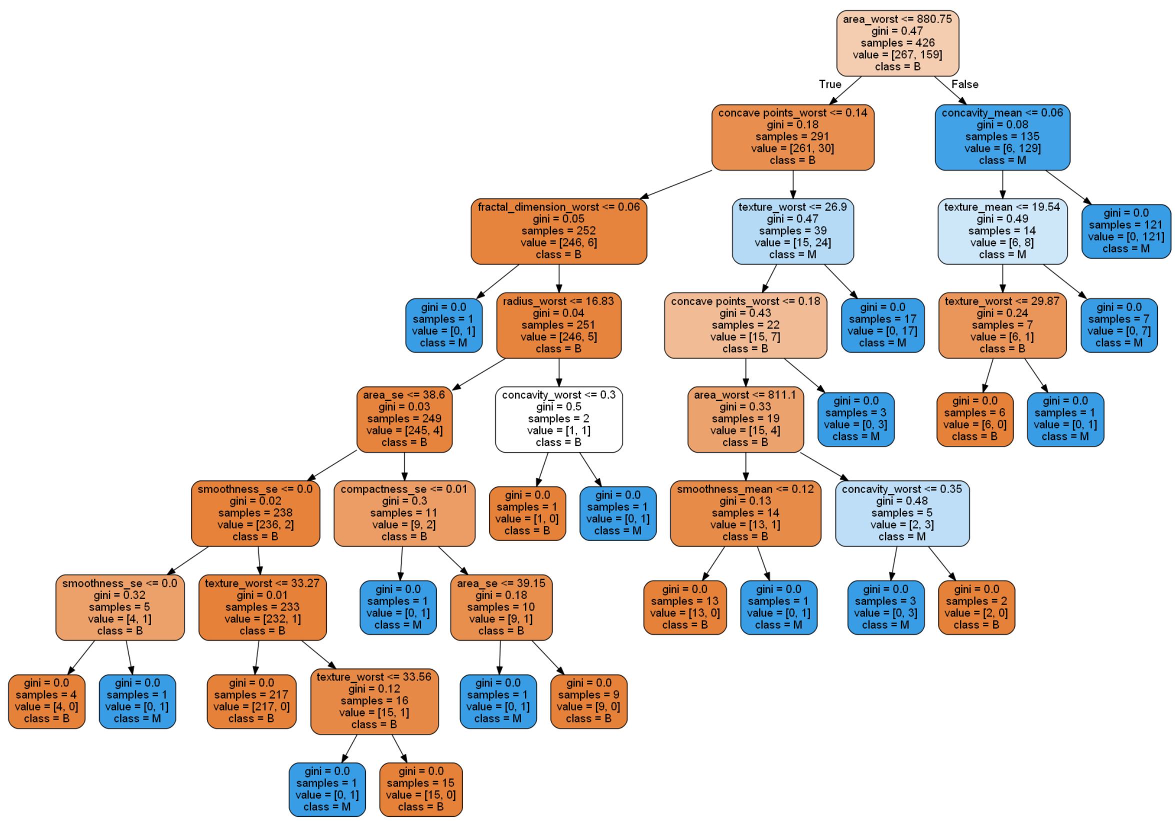
In [48]:
```
import pydotplus
from sklearn import tree
import graphviz
from IPython.display import Image
x_train, x_test, y_train, y_test = train_test_split(data_m_b[all_predictors],
```

In [49]:

```
model = DecisionTreeClassifier()
model.fit(x_train,y_train)
predictions = model.predict(data_m_b[all_predictors])
accuracy = metrics.accuracy_score(predictions,data_m_b[outcome_var])
print("Accuracy : %s" % "{0:.3%}".format(accuracy))
error=[]
error.append(model.score(x_test,y_test))
print(error)
dot_data = tree.export_graphviz(model, out_file=None,
                feature_names = x.columns,class_names = model.classes_, round
                precision = 2, filled = True)
graph = graphviz.Source(dot_data)
graph = pydotplus.graph_from_dot_data(dot_data)

# Show graph
Image(graph.create_png())
# Create PDF
```

```
Accuracy : 99.473%
[0.9790209790209791]
```

Out[49]:



In [50]:

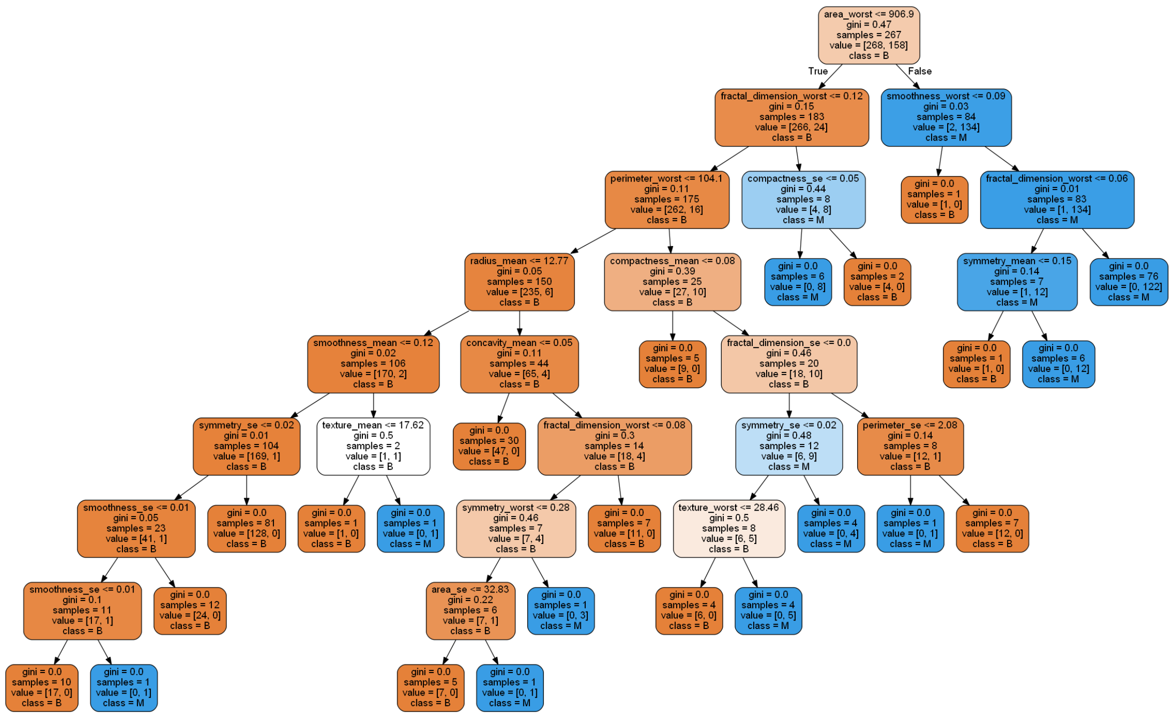
```
graph.write_pdf("decision_tree.pdf")

# Create PNG
graph.write_png("decision_tree.png")
graph
```

Out[50]: <pydotplus.graphviz.Dot at 0xe27c470>

In [51]:

```
model1 = RandomForestClassifier(n_estimators=100, max_features=2)
model1.fit(x_train,y_train)
# Extract single tree
estimator = model1.estimators_[42]

dot_data = tree.export_graphviz(estimator, out_file=None,
                feature_names = x.columns,class_names = model1.classes_, rour
                precision = 2, filled = True)
graph = graphviz.Source(dot_data)
graph = pydotplus.graph_from_dot_data(dot_data)

# Show graph
Image(graph.create_png())
```

Out[51]:



In [52]:

```
# Create PDF
graph.write_pdf("random_forest2.pdf")

# Create PNG
graph.write_png("random_forest2.png")
```

Out[52]: True