Nutrition_Analysis_Classification

November 30, 2019

In [42]:
```
import copy
import os
import numpy as np
import pandas as pd

import matplotlib.pyplot as plt

from sklearn.utils import shuffle
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import confusion_matrix
import seaborn as sns
from sklearn.model_selection import cross_val_score,cross_validate
from sklearn.metrics import matthews_corrcoef as mcc
from sklearn.metrics import roc_curve,roc_auc_score,precision_recall_curve,classificat
#Classifiers
from sklearn.ensemble import RandomForestClassifier
from sklearn.naive_bayes import MultinomialNB,GaussianNB
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from xgboost import XGBClassifier


from sklearn.externals.six import StringIO
from IPython.display import Image
from sklearn.tree import export_graphviz
import pydotplus
import scikitplot as skplt
#classifiers End


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

1 Data Reading

In [7]:
```
data = pd.read_csv("./data/nndb_flat.csv")
```

```
In [9]: data.notnull()
        data = data.drop(columns=['CommonName','MfgName','ScientificName'])

In [10]: data.head()
```

Out[10]:

	ID	FoodGroup	ShortDescrip	Descrip	Energy_kcal	Protein_g	Fat_g	Carb_g	Sugar_g	Fiber_g	...	Folate_USRDA	Niacin_USRDA	Riboflavin_USRDA	Thiamin_USRDA	Calcium_USRDA	Copper_USRDA	Magnesium_USRDA	Phosphorus_USRDA	Selenium_USRDA	Zinc_USRDA
0	1001	Dairy and Egg Products	BUTTER,WITH SALT	Butter, salted	717.0	0.85	81.11	0.06	0.06	0.0	...	0.0075	0.002625	0.026154	0.004167	0.020000	0.000000	0.004762	0.034286	0.018182	0.008182
1	1002	Dairy and Egg Products	BUTTER,WHIPPED,WITH SALT	Butter, whipped, with salt	717.0	0.85	81.11	0.06	0.06	0.0	...	0.0075	0.002625	0.026154	0.004167	0.020000	0.000018	0.004762	0.032857	0.018182	0.004545
2	1003	Dairy and Egg Products	BUTTER OIL,ANHYDROUS	Butter oil, anhydrous	876.0	0.28	99.48	0.00	0.00	0.0	...	0.0000	0.000188	0.003846	0.000833	0.003333	0.000001	0.000000	0.004286	0.000000	0.000909
3	1004	Dairy and Egg Products	CHEESE,BLUE	Cheese, blue	353.0	21.40	28.74	2.34	0.50	0.0	...	0.0900	0.063500	0.293846	0.024167	0.440000	0.000044	0.054762	0.552857	0.263636	0.241818
4	1005	Dairy and Egg Products	CHEESE,BRICK	Cheese, brick	371.0	23.24	29.68	2.79	0.51	0.0	...	0.0500	0.007375	0.270000	0.011667	0.561667	0.000027	0.057143	0.644286	0.263636	0.236364

[5 rows x 42 columns]

2 Data Processing

```
In [11]: groups = np.array(data['FoodGroup'])
         len(set(groups))
```

```
Out[11]: 25
```

```
In [39]: set(groups)
```

```
Out[39]: {'American Indian/Alaska Native Foods',
          'Baby Foods',
          'Baked Products',
          'Beef Products',
          'Beverages',
          'Breakfast Cereals',
          'Cereal Grains and Pasta',
          'Dairy and Egg Products',
          'Fast Foods',
          'Fats and Oils',
          'Finfish and Shellfish Products',
          'Fruits and Fruit Juices',
          'Lamb, Veal, and Game Products',
          'Legumes and Legume Products',
          'Meals, Entrees, and Side Dishes',
          'Nut and Seed Products',
          'Pork Products',
          'Poultry Products',
          'Restaurant Foods',
          'Sausages and Luncheon Meats',
          'Snacks',
          'Soups, Sauces, and Gravies',
          'Spices and Herbs',
          'Sweets',
          'Vegetables and Vegetable Products'}
```

```
In [14]: nonveg = [
          'American Indian/Alaska Native Foods',
          'Beef Products',
          'Dairy and Egg Products',
          'Finfish and Shellfish Products',
          'Lamb, Veal, and Game Products',
          'Pork Products',
          'Poultry Products',
          'Sausages and Luncheon Meats',]
         remove = ['Restaurant Foods','Meals, Entrees, and Side Dishes', 'Fast Foods', 'Baked
```

```
In [15]: len(remove)
```

```
Out[15]: 4
```

```
In [16]: newlabels = []
         index = []
         j = 0
         for i in groups:
             if(i in nonveg):
                 newlabels.append('Non-Veg')
```

```
            elif(i in remove):
                newlabels.append('Remove')
                index.append(j)
            else:
                newlabels.append('Veg')
            j+=1
```

```
In [18]: len(index)
```

```
Out[18]: 1389
```

```
In [19]: from collections import Counter
```

```
In [20]: Counter(newlabels)
```

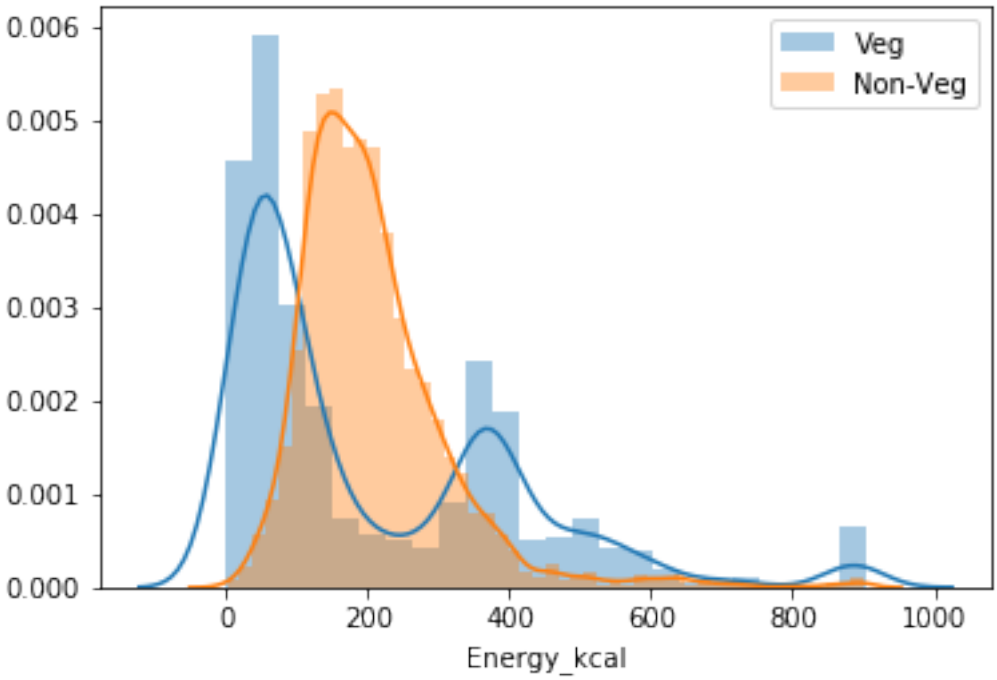
```
Out[20]: Counter({'Non-Veg': 3057, 'Veg': 4172, 'Remove': 1389})
```

```
In [21]: data['FoodGroup'] = newlabels
```

```
In [22]: data.head()
```

```
Out[22]:      ID FoodGroup             ShortDescrip                    Descrip  \
         0  1001   Non-Veg          BUTTER,WITH SALT              Butter, salted
         1  1002   Non-Veg  BUTTER,WHIPPED,WITH SALT  Butter, whipped, with salt
         2  1003   Non-Veg      BUTTER OIL,ANHYDROUS       Butter oil, anhydrous
         3  1004   Non-Veg             CHEESE,BLUE               Cheese, blue
         4  1005   Non-Veg             CHEESE,BRICK              Cheese, brick

            Energy_kcal  Protein_g  Fat_g  Carb_g  Sugar_g  Fiber_g  ...  Folate_USRDA  \
         0        717.0       0.85  81.11    0.06     0.06      0.0  ...        0.0075
         1        717.0       0.85  81.11    0.06     0.06      0.0  ...        0.0075
         2        876.0       0.28  99.48    0.00     0.00      0.0  ...        0.0000
         3        353.0      21.40  28.74    2.34     0.50      0.0  ...        0.0900
         4        371.0      23.24  29.68    2.79     0.51      0.0  ...        0.0500

            Niacin_USRDA  Riboflavin_USRDA  Thiamin_USRDA  Calcium_USRDA  Copper_USRDA  \
         0      0.002625          0.026154       0.004167       0.020000      0.000000
         1      0.002625          0.026154       0.004167       0.020000      0.000018
         2      0.000188          0.003846       0.000833       0.003333      0.000001
         3      0.063500          0.293846       0.024167       0.440000      0.000044
         4      0.007375          0.270000       0.011667       0.561667      0.000027

            Magnesium_USRDA  Phosphorus_USRDA  Selenium_USRDA  Zinc_USRDA
         0         0.004762          0.034286        0.018182    0.008182
         1         0.004762          0.032857        0.018182    0.004545
         2         0.000000          0.004286        0.000000    0.000909
         3         0.054762          0.552857        0.263636    0.241818
         4         0.057143          0.644286        0.263636    0.236364

         [5 rows x 42 columns]
```

```
In [23]: datacopy = copy.deepcopy(data)

In [52]: vegdata = datacopy.loc[datacopy['FoodGroup'] == 'Veg']
         nonveg = datacopy.loc[datacopy['FoodGroup'] == 'Non-Veg']

In [53]: sns.distplot(vegdata['Energy_kcal'])
         sns.distplot(nonveg['Energy_kcal'])
         plt.legend(['Veg','Non-Veg'])

Out[53]: <matplotlib.legend.Legend at 0x7fd1adb59518>
```




```
In [24]: data = data.loc[data['FoodGroup'] != 'Remove']

In [25]: len(data)

Out[25]: 7229

In [26]: data = data.drop(columns=['ShortDescrip','Descrip','ID'])

In [27]: energy = data['Energy_kcal']
         label = data['FoodGroup']

In [28]: data = data.drop(columns=['Energy_kcal','FoodGroup'])

In [29]: data.head()
```

Out[29]:

	Protein_g	Fat_g	Carb_g	Sugar_g	Fiber_g	VitA_mcg	VitB6_mg	VitB12_mcg	\
0	0.85	81.11	0.06	0.06	0.0	684.0	0.003	0.17	
1	0.85	81.11	0.06	0.06	0.0	684.0	0.003	0.13	
2	0.28	99.48	0.00	0.00	0.0	840.0	0.001	0.01	
3	21.40	28.74	2.34	0.50	0.0	198.0	0.166	1.22	
4	23.24	29.68	2.79	0.51	0.0	292.0	0.065	1.26	

	VitC_mg	VitE_mg	...	Folate_USRDA	Niacin_USRDA	Riboflavin_USRDA	\
0	0.0	2.32	...	0.0075	0.002625	0.026154	
1	0.0	2.32	...	0.0075	0.002625	0.026154	
2	0.0	2.80	...	0.0000	0.000188	0.003846	
3	0.0	0.25	...	0.0900	0.063500	0.293846	
4	0.0	0.26	...	0.0500	0.007375	0.270000	

	Thiamin_USRDA	Calcium_USRDA	Copper_USRDA	Magnesium_USRDA	\
0	0.004167	0.020000	0.000000	0.004762	
1	0.004167	0.020000	0.000018	0.004762	
2	0.000833	0.003333	0.000001	0.000000	
3	0.024167	0.440000	0.000044	0.054762	
4	0.011667	0.561667	0.000027	0.057143	

	Phosphorus_USRDA	Selenium_USRDA	Zinc_USRDA
0	0.034286	0.018182	0.008182
1	0.032857	0.018182	0.004545
2	0.004286	0.000000	0.000909
3	0.552857	0.263636	0.241818
4	0.644286	0.263636	0.236364

[5 rows x 37 columns]

3 Methods for Computations

In [30]:
```
def r_o_c(true_labels,scores):
#     true_labels = np.array(true_labels)
    true_labels= true_labels.replace('Veg',1)
    true_labels= true_labels.replace('Non-Veg',0)
    plt.figure()
    fpr, tpr, thresholds = roc_curve(true_labels, scores)
    plt.plot(fpr, tpr)

    plt.ylabel('True Positive Rate')
    plt.xlabel('False Positive Rate')

    plt.title('ROC Curve')
    plt.show()
```

```
def reports(classifier,train_data,train_labels,test_data,test_labels,name='',tree_flag
    print ("================================================================================
    print (name)
    print ("================================================================================
#     kf = KFold(n_splits=5)
#     kf.get_n_splits(train_data)
#     print(kf)
    scores = []
    best_train = []
    best_train_labels = []
    maxscore = 0
    scores = cross_validate(classifier, train_data, train_labels, cv=5,scoring=('f1_ma
    scores = pd.DataFrame(data=scores)
    scores = scores.drop(columns=['fit_time','score_time'])
    print (scores)

    train_x = train_data
    train_y = train_labels

    test_x = test_data
    test_y = test_labels

    classifier.fit(train_x,train_y)
    predicted = classifier.predict(test_x)
    print ("Test Data Results:")
    print ("Test Accuracy: ",accuracy_score(predicted,test_y))
    X = classification_report(test_y,predicted,output_dict=True)
    skplt.metrics.plot_confusion_matrix(test_y, predicted)
    plt.figure()
    #print (X.keys())
    print (classification_report(test_y,predicted))
    print ("Sensitivity: ", X['Non-Veg']['recall'])
    print ("Specificity: ", X['Veg']['recall'])
    print ("MCC: ",mcc(test_y,predicted))
    print ("________________________________________________________________________
    prob_scores = classifier.predict_proba(test_x)
    print ("ROC AUC",roc_auc_score(y_true=test_labels,y_score=prob_scores[:,1]))
    r_o_c(test_labels,prob_scores[:,1])

    if(tree_flag):
        return classifier
```

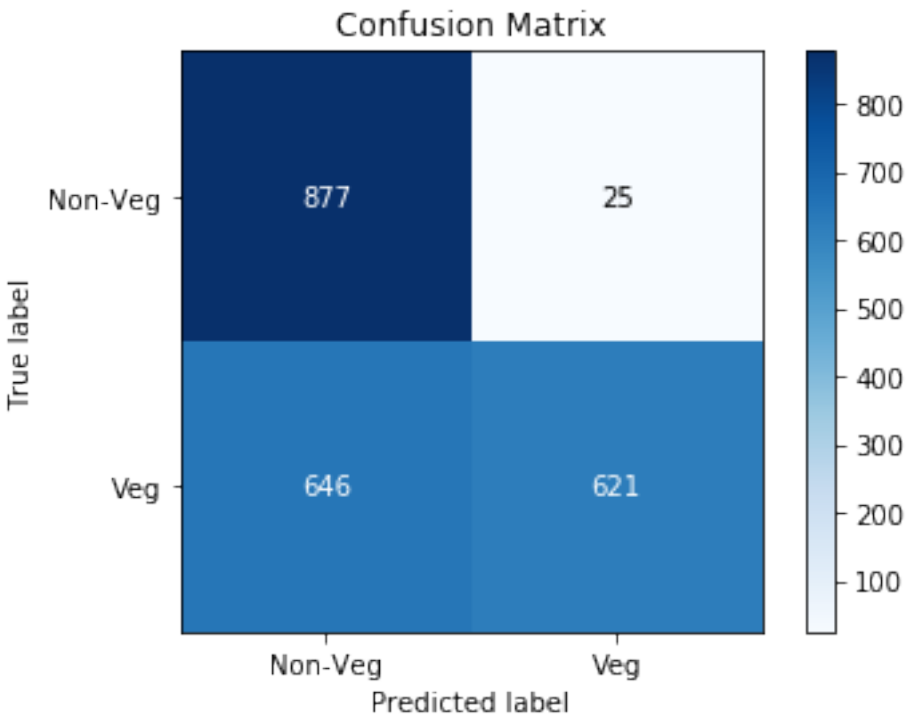
4 Train Test Split

In [31]:
```
data,label = shuffle(data,label)
X_train, X_test, y_train, y_test = train_test_split(data, label, test_size=0.30)
```

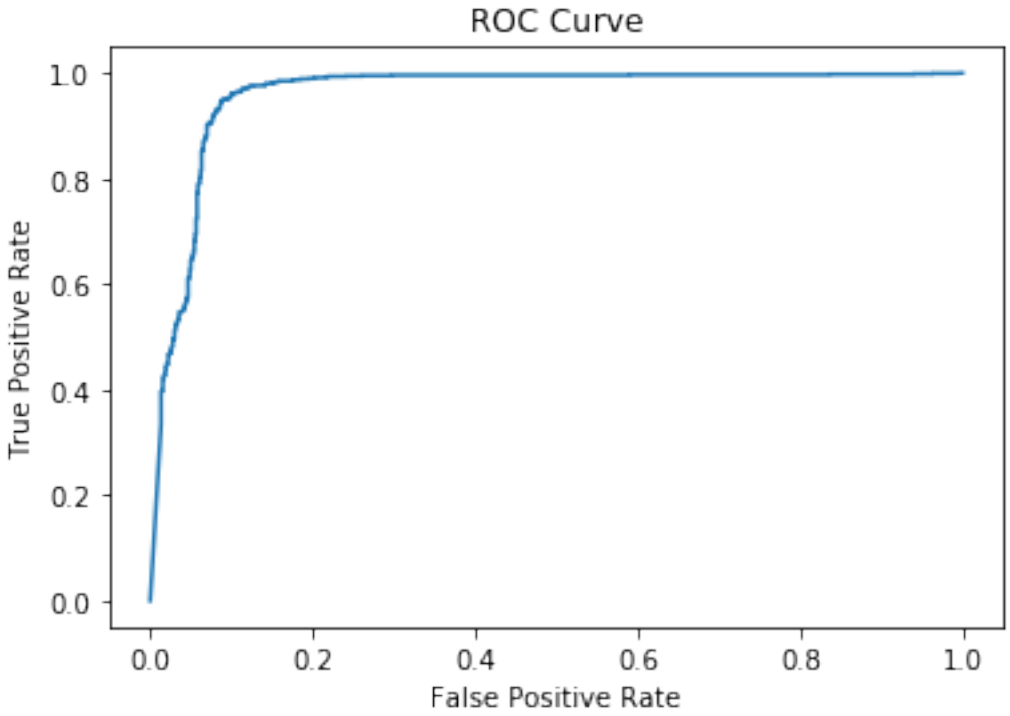
5 Gaussian Naive Bayes

```
In [32]: clf_gnb = GaussianNB()
         reports(name = 'Gaussian Naive Bayes',classifier=clf_gnb,train_data=X_train,test_data=
```

```
================================================================================
Gaussian Naive Bayes
================================================================================
   test_f1_macro  test_accuracy  test_roc_auc
0       0.687000       0.691700      0.944064
1       0.678975       0.683794      0.934348
2       0.687927       0.692688      0.954223
3       0.736847       0.738142      0.951025
4       0.724796       0.727273      0.961859
Test Data Results:
Test Accuracy:  0.6906408483171969
              precision    recall  f1-score   support

     Non-Veg       0.58      0.97      0.72       902
         Veg       0.96      0.49      0.65      1267

    accuracy                           0.69      2169
   macro avg       0.77      0.73      0.69      2169
weighted avg       0.80      0.69      0.68      2169

Sensitivity:  0.9722838137472284
Specificity:  0.49013417521704816
MCC:  0.4983794037717869
--------------------------------------------------------------------------------
ROC AUC 0.9594175532054525
```



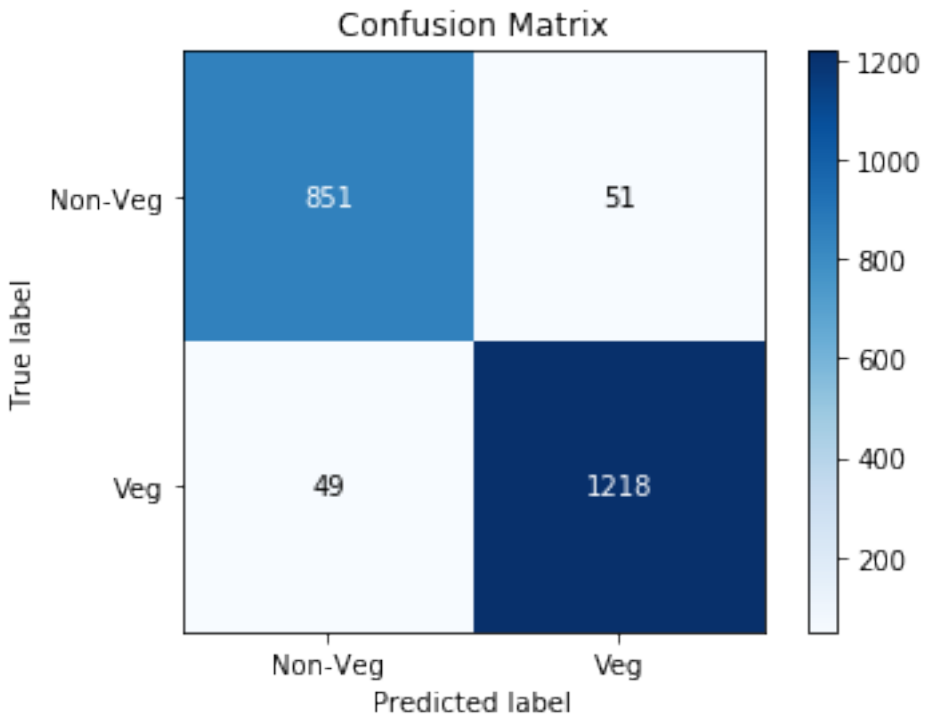
<Figure size 432x288 with 0 Axes>



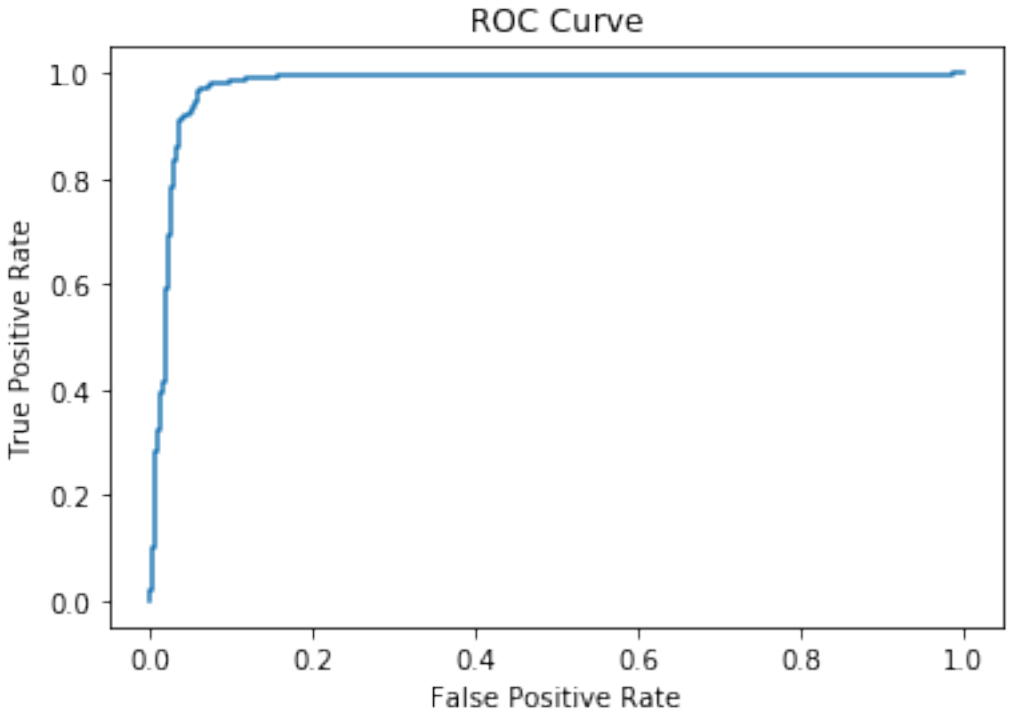
6 Logistic Regression

```
In [33]: clf_logistic = LogisticRegression(random_state=0# Gaussian Naive Bayes, solver='lbfgs
         reports(name = 'Logistic Regression',classifier=clf_logistic,train_data=X_train,test_
```

```
================================================================================
Logistic Regression
================================================================================
   test_f1_macro  test_accuracy  test_roc_auc
0       0.955349       0.956522      0.969782
1       0.937165       0.938735      0.973170
2       0.966587       0.967391      0.974518
3       0.942393       0.943676      0.978415
4       0.950226       0.951581      0.972070
Test Data Results:
Test Accuracy:  0.9538958045182112
              precision    recall  f1-score   support

     Non-Veg       0.95      0.94      0.94       902
         Veg       0.96      0.96      0.96      1267

    accuracy                           0.95      2169
   macro avg       0.95      0.95      0.95      2169
weighted avg       0.95      0.95      0.95      2169

Sensitivity:  0.9434589800443459
Specificity:  0.9613259668508287
MCC:  0.9050756418794569
--------------------------------------------------------------------------------
ROC AUC 0.9752107480176474
```



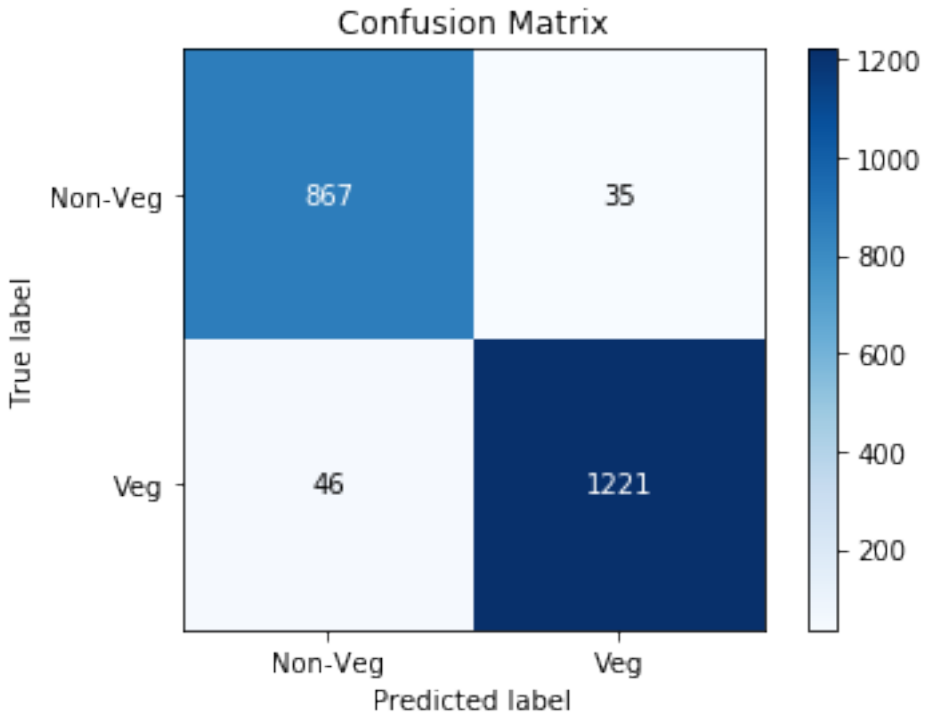
<Figure size 432x288 with 0 Axes>



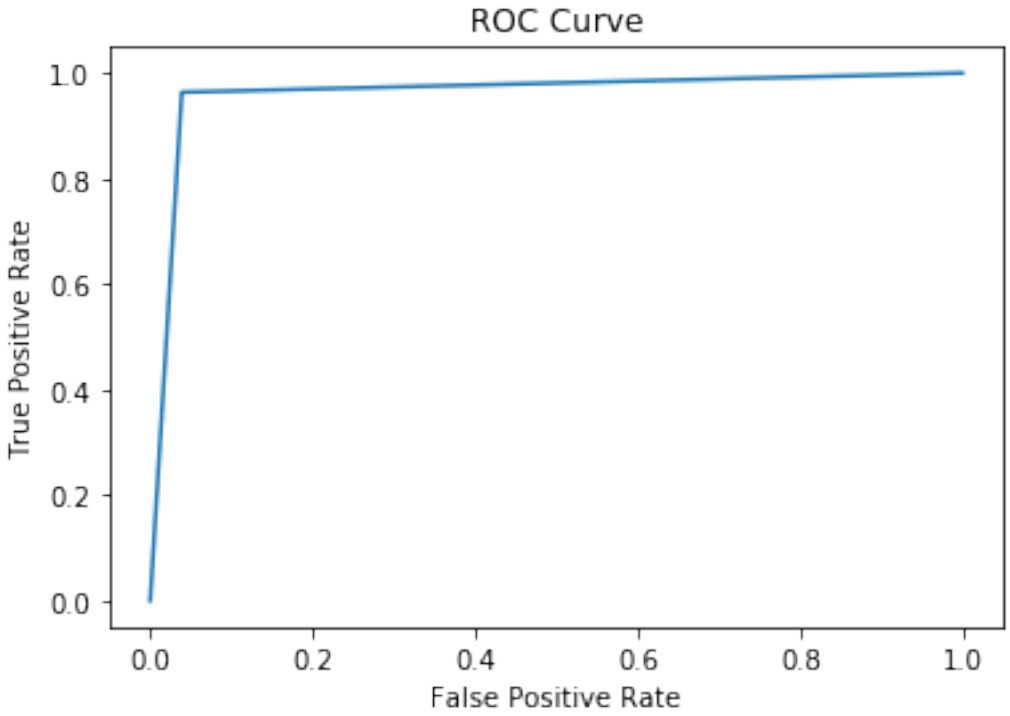
7 Decision Tree

```
In [34]: clf_decision_tree = DecisionTreeClassifier(random_state=0)

         image = reports(name = 'Decision Tree',classifier=clf_decision_tree,train_data=X_trai
         dot_data = StringIO()
         export_graphviz(image, out_file=dot_data,
                filled=True, rounded=True,
                special_characters=True)
         graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
         #         img= graph.create_jpeg()
         Image(graph.create_jpeg())
         #         plt.imshow(img)
```

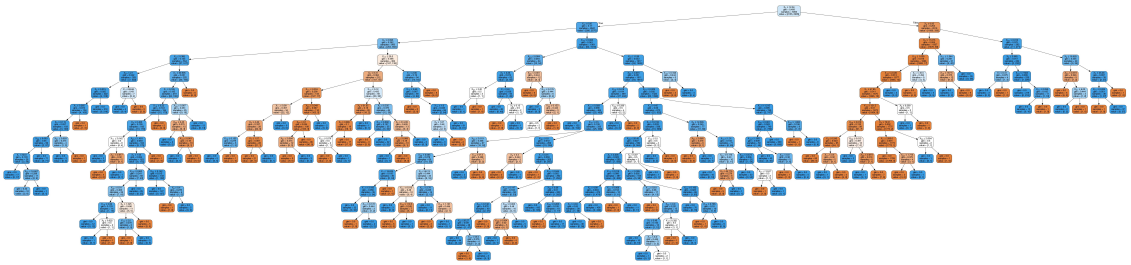
```
================================================================================
Decision Tree
================================================================================
   test_f1_macro  test_accuracy  test_roc_auc
0       0.951322       0.952569      0.953614
1       0.964690       0.965415      0.965387
2       0.958730       0.959486      0.960495
3       0.951533       0.952569      0.951620
4       0.949422       0.950593      0.949583
Test Data Results:
Test Accuracy:  0.9626556016597511
              precision    recall  f1-score   support

     Non-Veg       0.95      0.96      0.96       902
         Veg       0.97      0.96      0.97      1267

    accuracy                           0.96      2169
   macro avg       0.96      0.96      0.96      2169
weighted avg       0.96      0.96      0.96      2169

Sensitivity:  0.9611973392461197
Specificity:  0.9636937647987371
MCC:  0.9233194198134717
--------------------------------------------------------------------------------
ROC AUC 0.9623996135921752
```




```
<Figure size 432x288 with 0 Axes>
```



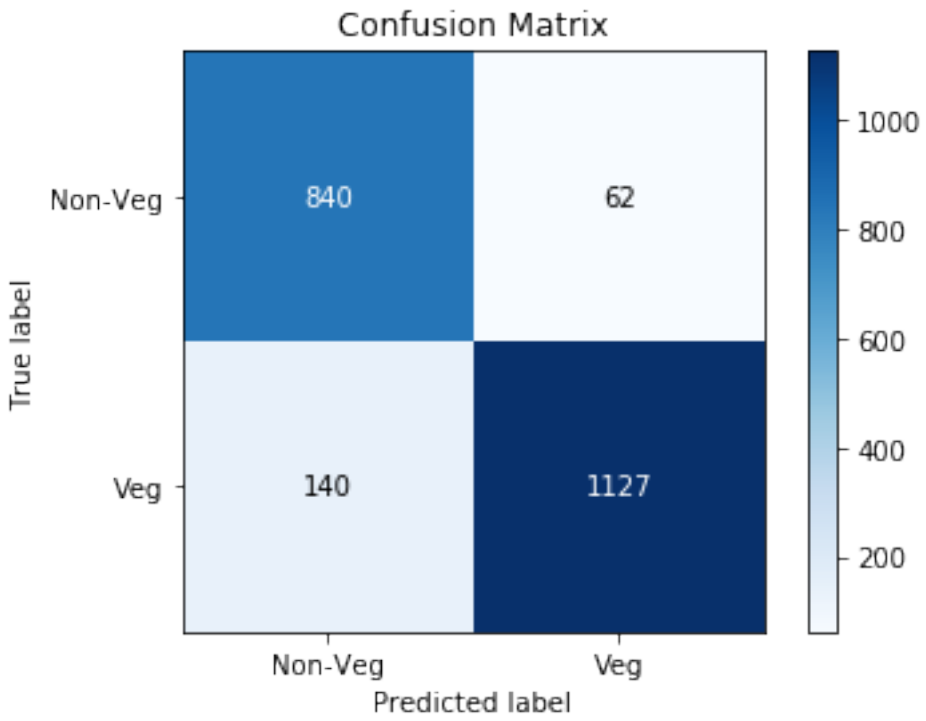
Out[34]:



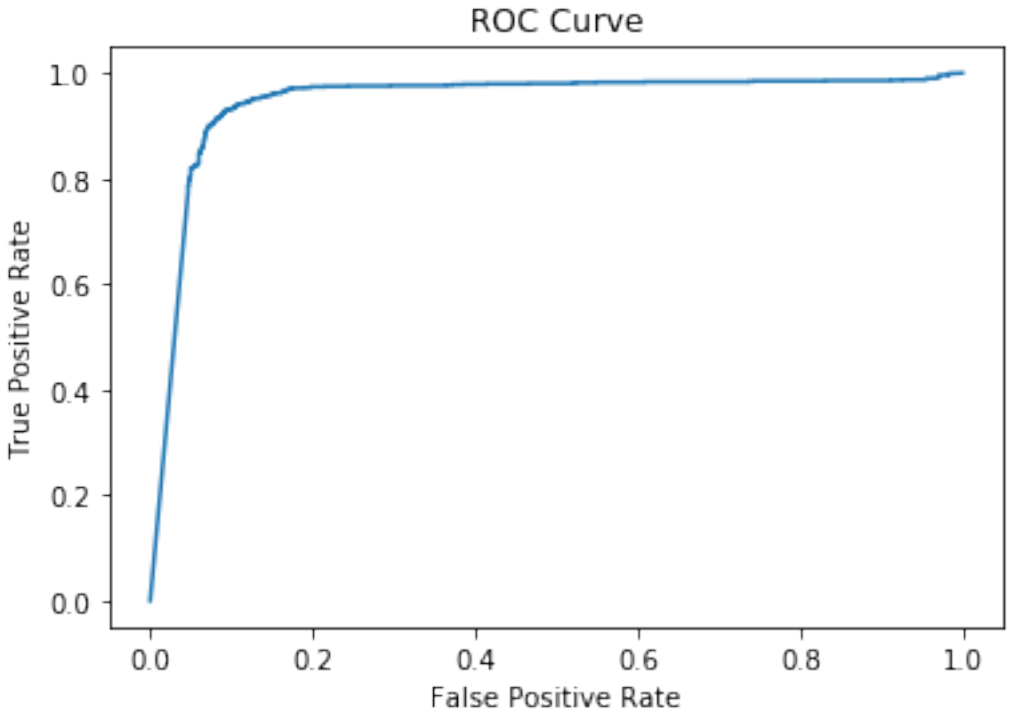
8 Multinomial Naive Bayes

```
In [35]: clf_mnb = MultinomialNB()
         reports(name = 'Multinomial Naive Bayes',classifier=clf_mnb,train_data=X_train,test_da
```

```
================================================================================
Multinomial Naive Bayes
================================================================================
   test_f1_macro  test_accuracy  test_roc_auc
0       0.881953       0.883399      0.926860
1       0.893444       0.895257      0.927643
2       0.903186       0.904150      0.953225
3       0.888725       0.890316      0.927002
4       0.907881       0.909091      0.953578
Test Data Results:
Test Accuracy:  0.9068695251267865
              precision    recall  f1-score   support

     Non-Veg       0.86      0.93      0.89       902
         Veg       0.95      0.89      0.92      1267

    accuracy                           0.91      2169
   macro avg       0.90      0.91      0.91      2169
weighted avg       0.91      0.91      0.91      2169

Sensitivity:  0.9312638580931264
Specificity:  0.8895027624309392
MCC:  0.8128441734476113
--------------------------------------------------------------------------------
ROC AUC 0.9465937310230532
```



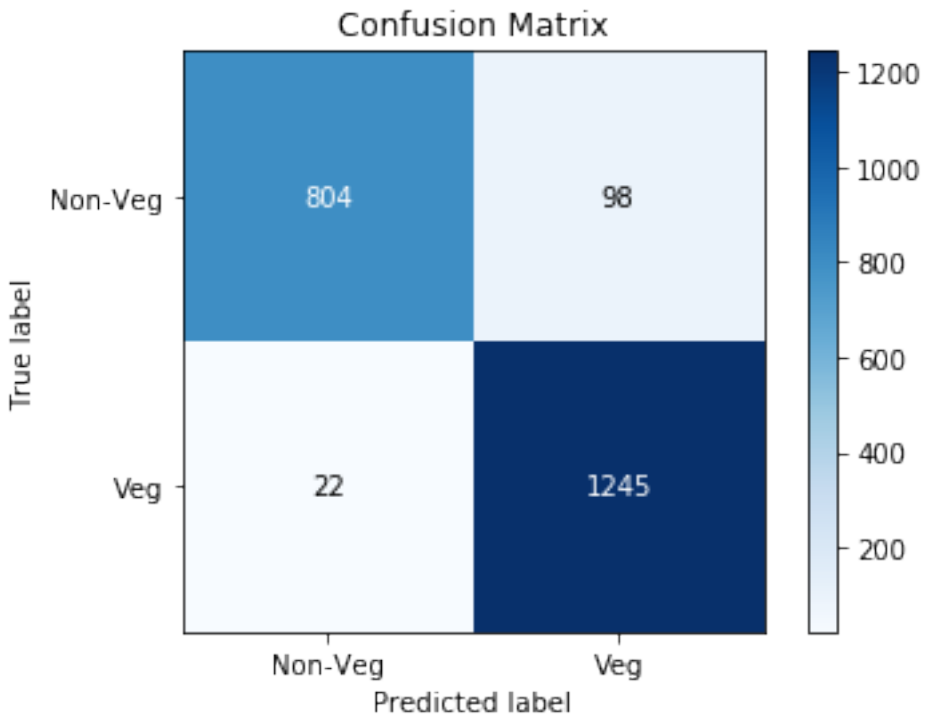

```
<Figure size 432x288 with 0 Axes>
```



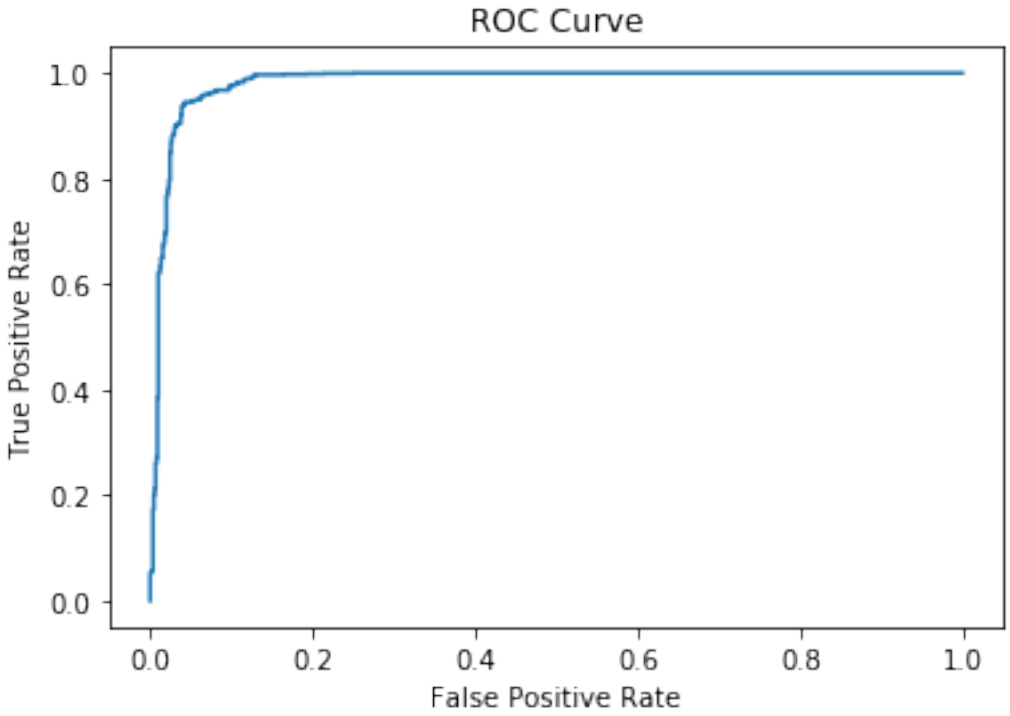
9 Random Forest

```
In [36]: clf_randomforest = RandomForestClassifier(n_estimators=200, max_depth=2,random_state=
         reports(name = 'Random Forest',classifier=clf_randomforest,train_data=X_train,test_da
```

```
================================================================================
Random Forest
================================================================================
   test_f1_macro  test_accuracy  test_roc_auc
0       0.930904       0.933794      0.974614
1       0.926840       0.929842      0.977649
2       0.944648       0.946640      0.983625
3       0.940407       0.942688      0.977066
4       0.936348       0.938735      0.972477
Test Data Results:
Test Accuracy:  0.9446749654218534
              precision    recall  f1-score   support

     Non-Veg       0.97      0.89      0.93       902
         Veg       0.93      0.98      0.95      1267

    accuracy                           0.94      2169
   macro avg       0.95      0.94      0.94      2169
weighted avg       0.95      0.94      0.94      2169

Sensitivity:  0.8913525498891353
Specificity:  0.9826361483820047
MCC:  0.887093430317214
--------------------------------------------------------------------------------
ROC AUC 0.9826396484528811
```



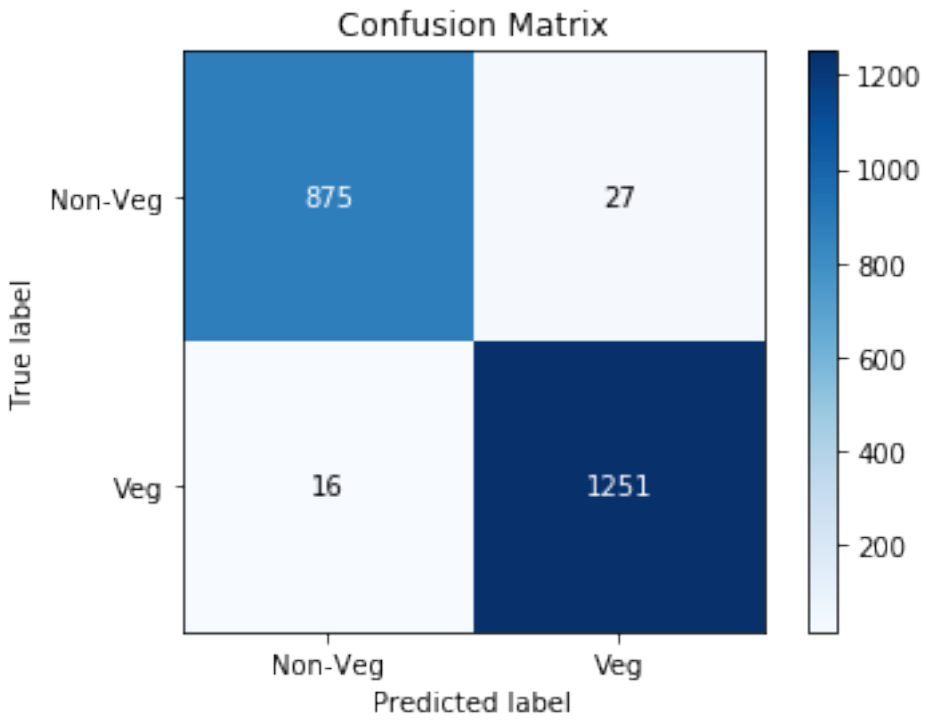

```
<Figure size 432x288 with 0 Axes>
```



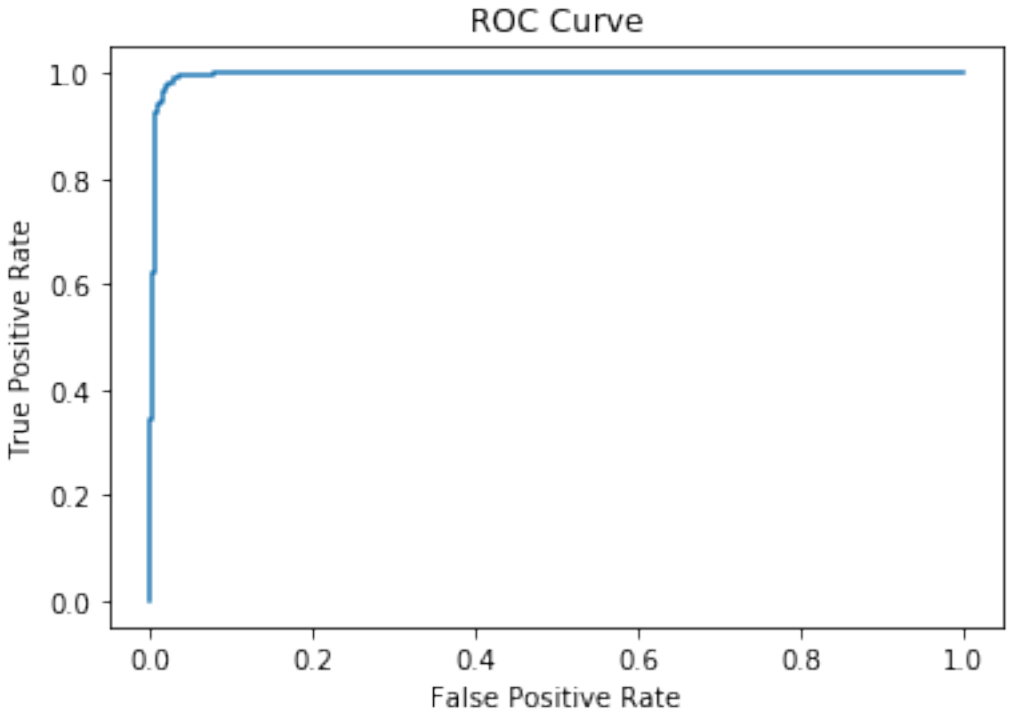
10 XG Boost

```
In [37]: clf_xgb = XGBClassifier(learning_rate=0.1, n_estimators=150, max_depth=10,
                                 min_child_weight=3, gamma=0.2, subsample=0.6, colsample_bytre
                                 objective='binary:logistic', nthread=4, scale_pos_weight=1, s
         reports(name = 'XG Boost',classifier=clf_xgb,train_data=X_train,test_data=X_test,trai
```

```
================================================================================
XG Boost
================================================================================
   test_f1_macro  test_accuracy  test_roc_auc
0       0.970600       0.971344      0.994461
1       0.969556       0.970356      0.995126
2       0.979756       0.980237      0.998211
3       0.980725       0.981225      0.997169
4       0.975661       0.976285      0.997161
Test Data Results:
Test Accuracy:  0.9801751959428308
              precision    recall  f1-score   support

     Non-Veg       0.98      0.97      0.98       902
         Veg       0.98      0.99      0.98      1267

    accuracy                           0.98      2169
   macro avg       0.98      0.98      0.98      2169
weighted avg       0.98      0.98      0.98      2169

Sensitivity:  0.9700665188470067
Specificity:  0.9873717442778216
MCC:  0.9591754995596457
--------------------------------------------------------------------------------
ROC AUC 0.9963153003848328
```



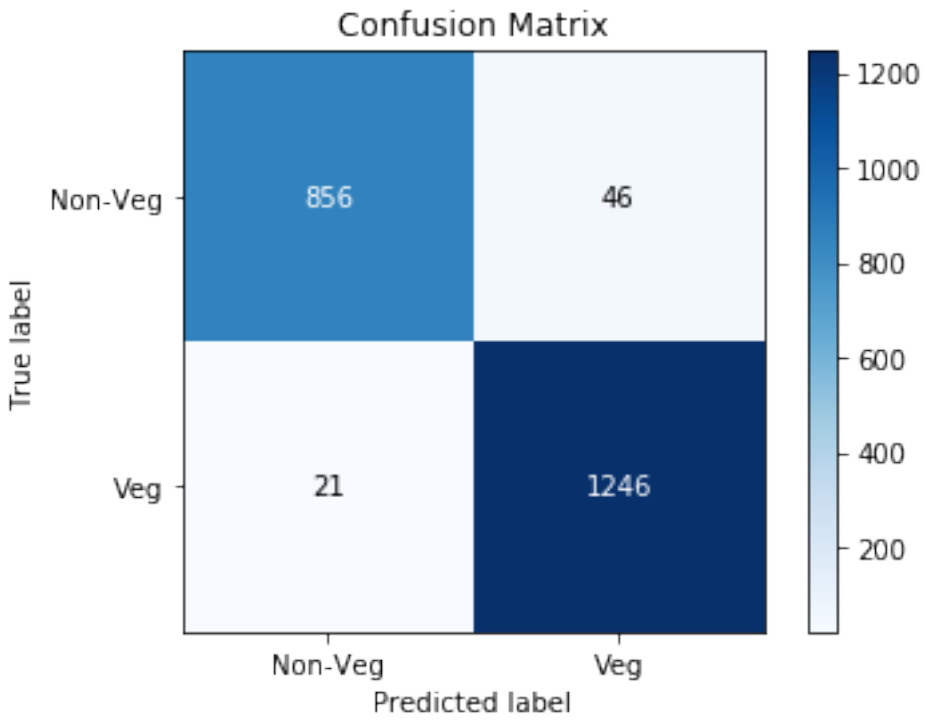
<Figure size 432x288 with 0 Axes>



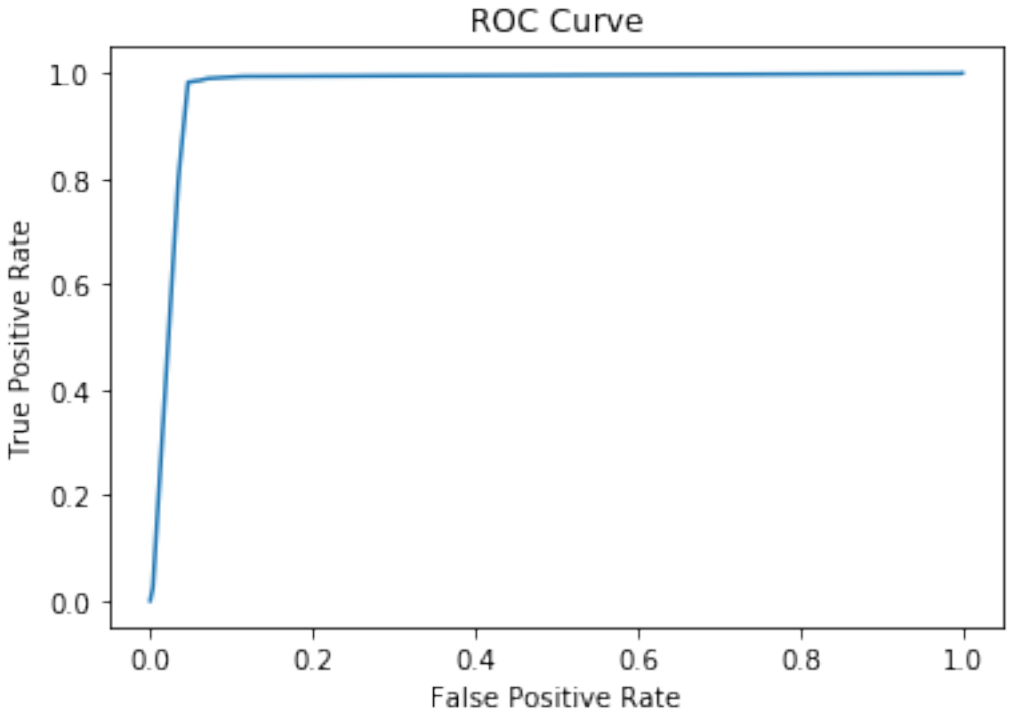
11 Decision Tree

```
In [40]: clf_decision_tree_mod = DecisionTreeClassifier(random_state=0,max_depth=10,max_leaf_n

         image = reports(name = 'Decision Tree Mod',classifier=clf_decision_tree_mod,train_data
         dot_data = StringIO()
         export_graphviz(image, out_file=dot_data,
                filled=True, rounded=True,
                special_characters=True)
         graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
         Image(graph.create_jpeg())
```

```
================================================================================
Decision Tree Mod
================================================================================
   test_f1_macro  test_accuracy  test_roc_auc
0       0.959299       0.960474      0.961825
1       0.959435       0.960474      0.970297
2       0.968531       0.969368      0.974947
3       0.957264       0.958498      0.964628
4       0.958117       0.959486      0.962450
Test Data Results:
Test Accuracy:  0.9691101890272015
              precision    recall  f1-score   support

     Non-Veg       0.98      0.95      0.96       902
         Veg       0.96      0.98      0.97      1267

    accuracy                           0.97      2169
   macro avg       0.97      0.97      0.97      2169
weighted avg       0.97      0.97      0.97      2169

Sensitivity:  0.9490022172949002
Specificity:  0.9834254143646409
MCC:  0.9364307312089986
--------------------------------------------------------------------------------
ROC AUC 0.9731723942409832
```



<Figure size 432x288 with 0 Axes>



Out[40]:


X0 ≤ 12.04
gini = 0.489
samples = 5060
value = [2155, 2905]
True
False
X4 ≤ 0.05
gini = 0.17
samples = 2841
value = [266, 2575]
X4 ≤ 0.95
gini = 0.253
samples = 2219
value = [1889, 330]
X0 ≤ 2.995
gini = 0.362
samples = 860
value = [204, 656]
gini = 0.061
samples = 1981
value = [62, 1919]
X2 ≤ 17.075
gini = 0.059
samples = 1937
value = [1878, 59]
gini = 0.075
samples = 282
value = [11, 271]
gini = 0.125
samples = 554
value = [37, 517]
X17 ≤ 29.5
gini = 0.496
samples = 306
value = [167, 139]
X18 ≤ 1.039
gini = 0.018
samples = 1886
value = [1869, 17]
X28 ≤ 0.084
gini = 0.291
samples = 51
value = [9, 42]
X2 ≤ 8.31
gini = 0.384
samples = 212
value = [157, 55]
X24 ≤ 0.858
gini = 0.19
samples = 94
value = [10, 84]
gini = 0.013
samples = 1877
value = [1865, 12]
gini = 0.494
samples = 9
value = [4, 5]
gini = 0.375
samples = 12
value = [9, 3]
gini = 0.0
samples = 39
value = [0, 39]
X30 ≤ 0.013
gini = 0.208
samples = 144
value = [127, 17]
X16 ≤ 0.12
gini = 0.493
samples = 68
value = [30, 38]
gini = 0.087
samples = 88
value = [4, 84]
gini = 0.0
samples = 6
value = [6, 0]
gini = 0.457
samples = 34
value = [22, 12]
gini = 0.087
samples = 110
value = [105, 5]
gini = 0.18
samples = 20
value = [18, 2]
X0 ≤ 6.535
gini = 0.375
samples = 48
value = [12, 36]
X13 ≤ 0.002
gini = 0.157
samples = 35
value = [3, 32]
gini = 0.426
samples = 13
value = [9, 4]
gini = 0.0
samples = 3
value = [3, 0]
gini = 0.0
samples = 32
value = [0, 32]

In [ ]: