coursework1_template

November 3, 2020

1 Coursework 1 - Decision Trees Learning

1.0.1 Enter your candidate number here: 700041488

1.1 Summary

In this coursework, your task is to develop a machine learning classifier for predicting female patients that at high risk of Diabetes. Your model is to support clinicians in identifying patients who are likely to have "Diabetes". The dataset has 9 attributes in total including the "target/label" attribute. The full dataset is available on ELE under assessment coursework 1. The dataset consists of the following:

1.2 Dataset

1. preg: Number of times pregnant
2. plas: Plasma glucose concentration a 2 hours in an oral glucose tolerance test
3. pres: Diastolic blood pressure (mm Hg)
4. skin: Triceps skin fold thickness (mm)
5. insu: 2-Hour serum insulin (mu U/ml)
6. mass: Body mass index (weight in kg/(height in m)^2)
7. pedi: Diabetes pedigree function
8. age: Age (years)
9. class: Class variable (0 or 1)

[163]:
```
from matplotlib import pyplot as plt
from sklearn.utils import shuffle
import pandas as pd
import os
%matplotlib inline

pd.set_option('mode.chained_assignment', None)
dia_all = pd.read_csv("diabetes.txt") # This loads the full dataset # In the
↪file, attributes are separated by ,
```

[164]:
```
dia_all.head(5)
```

[164]:

	preg	plas	pres	skin	insu	mass	pedi	age	class
0	6	148	72	35	0	33.6	0.627	50	tested_positive
1	1	85	66	29	0	26.6	0.351	31	tested_negative
2	8	183	64	0	0	23.3	0.672	32	tested_positive
3	1	89	66	23	94	28.1	0.167	21	tested_negative
4	0	137	40	35	168	43.1	2.288	33	tested_positive

1.3 Seperate the inpout (attributes) from target (label)

[165]:
```
dia_all = shuffle(dia_all)
dia_all['class'] = dia_all['class'].apply(lambda x: 1 if x == 'tested_positive'␣
↪else 0)
sourcevars = dia_all.iloc[:,:-1].astype(float) #all rows + all columns except␣
↪the last one
targetvar = dia_all.iloc[:,-1:] #all rows + only the last column
```

2 Your answers

Please clearly highlight each task.

2.1 Task1 [Exploratory data analysis]

2.2 Taks 1.a [Data Processing, Statistic Analysis, Cleaning and Correlation Matrix]

Helper Functions

[21]:
```
def calculate_stats(df, col_name):
    '''
        Returns array of mean and mode of given column
        Arguments:
        df -- pandas dataframe
        col_name -- valid column name of dataframe
    '''
    try:
        mean = df[col_name].mean()
        mode = df[col_name].mode()
    except Exception as err:
        print('Column not found: %s'%col_name)
    mm_array = [mean,mode]
    return mm_array
```

Zero Replacement

[22]:
```
df = pd.DataFrame()

for col in sourcevars.columns:
    sourcevars[col] = sourcevars[col].mask(sourcevars[col] ==␣
↪0,calculate_stats(sourcevars, col)[0])
```

Data Statistics

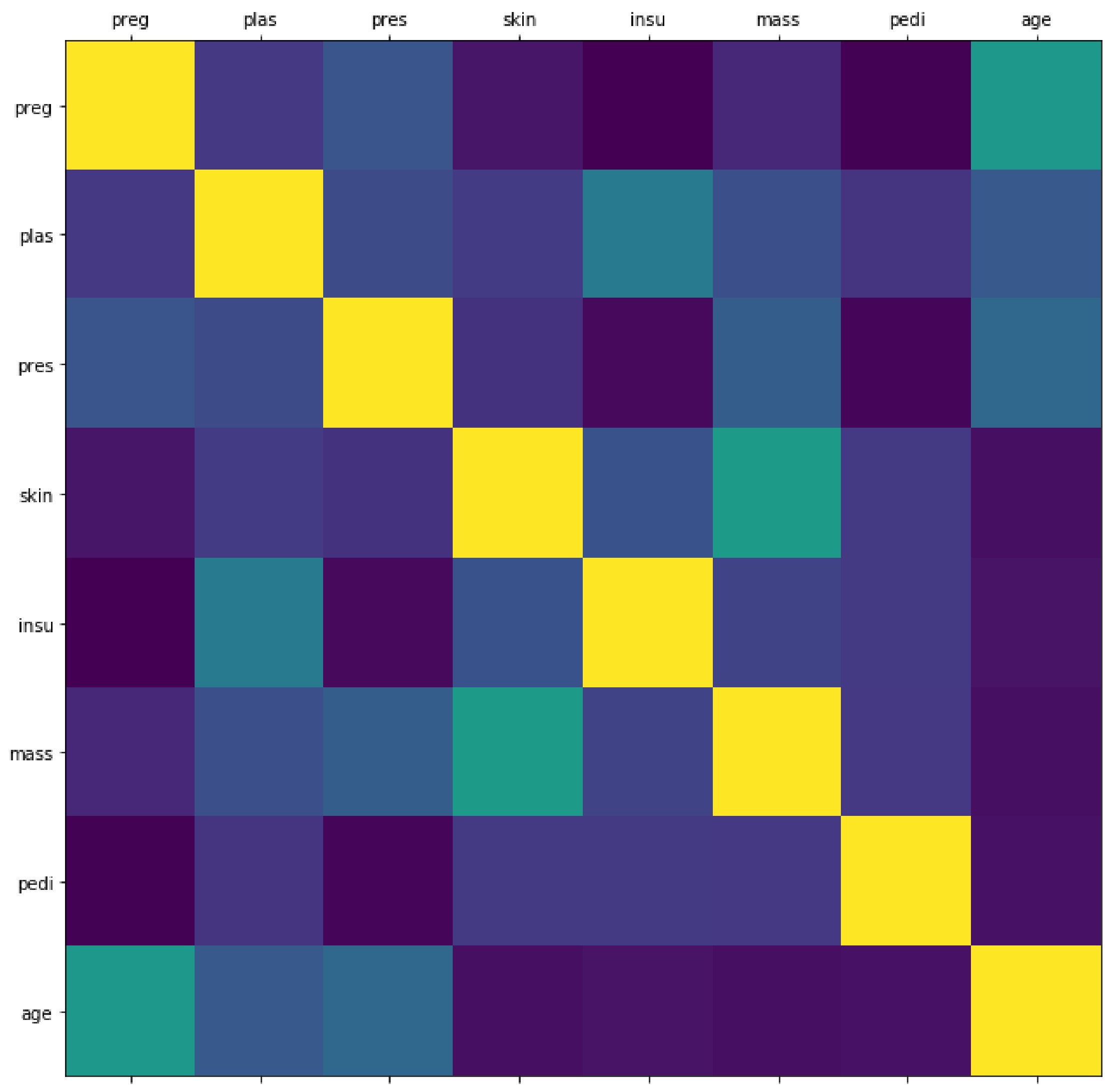
[74]:
```
dia_all.describe()
```

[74]:
```
             preg        plas        pres        skin        insu        mass  \
count  768.000000  768.000000  768.000000  768.000000  768.000000  768.000000
mean     3.845052  120.894531   69.105469   20.536458   79.799479   31.992578
std      3.369578   31.972618   19.355807   15.952218  115.244002    7.884160
min      0.000000    0.000000    0.000000    0.000000    0.000000    0.000000
25%      1.000000   99.000000   62.000000    0.000000    0.000000   27.300000
50%      3.000000  117.000000   72.000000   23.000000   30.500000   32.000000
75%      6.000000  140.250000   80.000000   32.000000  127.250000   36.600000
max     17.000000  199.000000  122.000000   99.000000  846.000000   67.100000

             pedi         age       class
count  768.000000  768.000000  768.000000
mean     0.471876   33.240885    0.348958
std      0.331329   11.760232    0.476951
min      0.078000   21.000000    0.000000
25%      0.243750   24.000000    0.000000
50%      0.372500   29.000000    0.000000
75%      0.626250   41.000000    1.000000
max      2.420000   81.000000    1.000000
```

[24]:
```
def plot_corr_matrix(data_frame, size=11):
    """
    Function plots a graphical correlation matrix for each pair of columns in␣
↪the dataframe.

    Input:
        data_frame: pandas DataFrame
        size: vertical and horizontal size of the plot

    Displays:
        Correlation Matrix.
    """

    corr = data_frame.corr()
    fig, ax = plt.subplots(figsize=(size, size))
    ax.matshow(corr)
    plt.xticks(range(len(corr.columns)), corr.columns)
```

```
    plt.yticks(range(len(corr.columns)), corr.columns)
```

[25]:
```
plot_corr_matrix(sourcevars)
```



[76]:
```
sourcevars.corr()
```

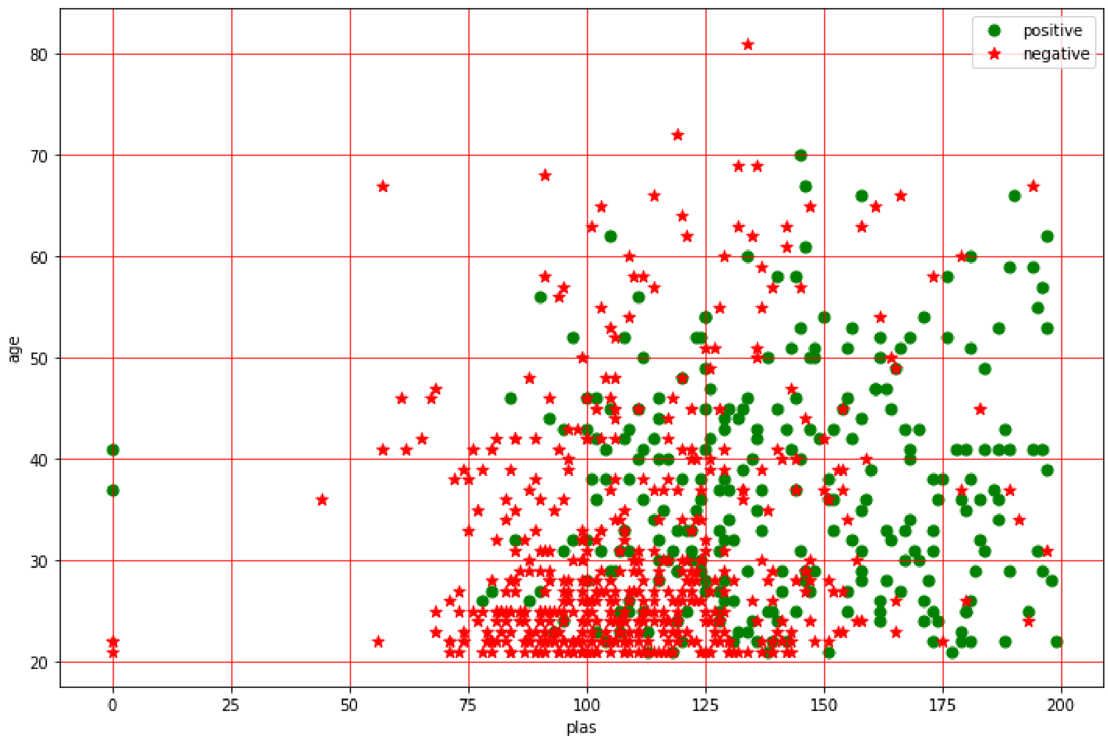
[76]:

```
          preg      plas      pres      skin      insu      mass      pedi  \
preg  1.000000  0.152568  0.253275  0.045776 -0.016738  0.097663 -0.010297
plas  0.152568  1.000000  0.219666  0.160766  0.396597  0.231478  0.137106
pres  0.253275  0.219666  1.000000  0.134155  0.010926  0.281231  0.000371
skin  0.045776  0.160766  0.134155  1.000000  0.240361  0.535703  0.154961
insu -0.016738  0.396597  0.010926  0.240361  1.000000  0.189856  0.157806
mass  0.097663  0.231478  0.281231  0.535703  0.189856  1.000000  0.153508
pedi -0.010297  0.137106  0.000371  0.154961  0.157806  0.153508  1.000000
```

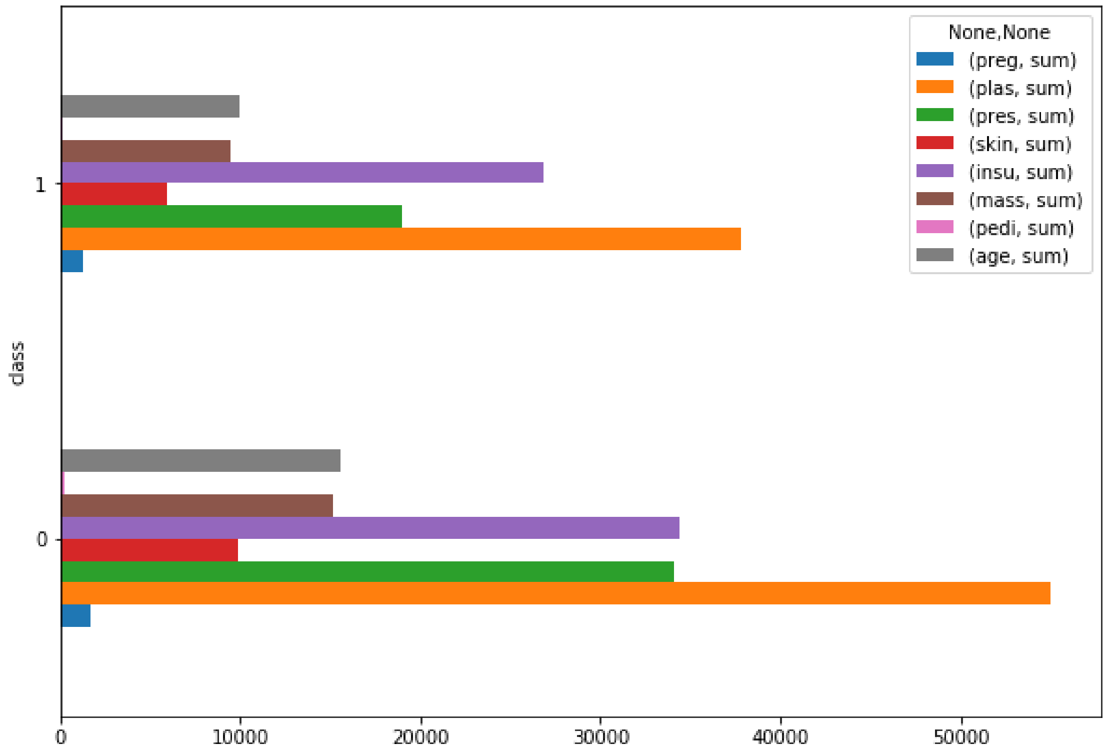
```
age   0.525261  0.266600  0.326740  0.026423  0.038652  0.025748  0.033561

           age
preg  0.525261
plas  0.266600
pres  0.326740
skin  0.026423
insu  0.038652
mass  0.025748
pedi  0.033561
age   1.000000
```

2.3 Task 1.b [Understand data using grouping and Class Distribution]

[179]:
```
ax = dia_all[dia_all['class']==1].plot.scatter(x='plas', y='age', marker='o',␣
↪color='green', s=50, label='positive', figsize=(12,8))
dia_all[dia_all['class']==0].plot.scatter(x='plas', y='age', marker='*',␣
↪color='red', s=60, label='negative', ax=ax)
plt.grid(True, linewidth=0.7, color='#ff0000', linestyle='-')
```



[183]:
```
df2 = dia_all.groupby(['class']).agg(['sum'])
df2.plot(kind='barh', stacked=False, figsize=(10,7));
```



Check for distribution of true and false cases

[28]:
```
num_obs = len(dia_all)
num_true = len(targetvar.loc[targetvar['class'] == 1])
num_false = len(targetvar.loc[targetvar['class'] == 0])

print("Number of True cases:  {0} ({1:2.2f}%)".format(num_true, ((1.00 *␣
↪num_true)/(1.0 * num_obs)) * 100))
print('_________________________________________________')
print("Number of False cases: {0} ({1:2.2f}%)".format(num_false, (( 1.0 *␣
↪num_false)/(1.0 * num_obs)) * 100))
```

```
Number of True cases:  268 (34.90%)
_________________________________________________
Number of False cases: 500 (65.10%)
```

2.4 Task 2.a [Classification]

2.5 2.a.1 Decision Tree (DT) classifier

[29]:
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import GridSearchCV
from sklearn import metrics
import numpy as np
```

General normalization function

[136]:
```
def standardize(X):
    """ Standardize the dataset X """
    X_std = X
    mean = X.mean(axis=0)
    std = X.std(axis=0)
    X_std = (X - X.mean(axis=0)) / X.std(axis=0)
    return X_std
```

[79]:
```
def split_data(split_test_size = 0.30):
    X = sourcevars
    y = targetvar
    X_train, X_test, y_train, y_test =␣
 ↪train_test_split(X,targetvar,test_size=split_test_size, random_state = 0)
    sc = StandardScaler()
    X_train = sc.fit_transform(X_train)
    X_test = sc.transform(X_test)
    return X_train, X_test, y_train, y_test
```

Find optimum parameters using Grid Search technique

[32]:
```
# Parameter evaluation
treeclf = DecisionTreeClassifier(random_state=42)

parameters = {'max_depth': [6, 7, 8, 9],
              'min_samples_split': [2, 3, 4, 5],
              'max_features': [1, 2, 3, 4]
}

gridsearch=GridSearchCV(treeclf, parameters, cv=100, scoring='roc_auc')
gridsearch.fit(sourcevars,targetvar)

print(gridsearch.best_params_)
print(gridsearch.best_score_)
```

```
{'max_depth': 6, 'max_features': 4, 'min_samples_split': 3}
0.7736666666666666
```

[84]:
```
X_train, X_test, y_train, y_test = split_data()

tree = DecisionTreeClassifier(max_depth=6,max_features = 4, min_samples_split =␣
 ↪3, random_state = 0)
tree.fit(X_train,y_train)

print("Accuracy on training set: {:.3f}".format(tree.score(X_train,y_train)))
print("Accuracy on test set: {:.3f}".format(tree.score(X_test,y_test)))
```

```
Accuracy on training set: 0.872
Accuracy on test set: 0.766
```

[85]:
```
prediction_from_test_data = tree.predict(X_test)
accuracy = metrics.accuracy_score(y_test, prediction_from_test_data)

print ("Accuracy of Decision Tree is: {0:0.4f}".format(accuracy))
```

```
Accuracy of Decision Tree is: 0.7662
```

[86]:
```
print ("Confusion Matrix")
print ("{0}".format(metrics.confusion_matrix(y_test, prediction_from_test_data,␣
 ↪labels=[1, 0])))
```

```
Confusion Matrix
[[ 52  25]
 [ 29 125]]
```

[87]:
```
print ("Classification Report")
print('_________________________________________________________')
print ("{0}".format(metrics.classification_report(y_test,␣
 ↪prediction_from_test_data, labels=[1, 0])))
```

```
Classification Report
_________________________________________________________
              precision    recall  f1-score   support

           1       0.64      0.68      0.66        77
           0       0.83      0.81      0.82       154

    accuracy                           0.77       231
   macro avg       0.74      0.74      0.74       231
weighted avg       0.77      0.77      0.77       231
```

[88]:
```
# Making the Confusion Matrix
from sklearn.metrics import classification_report, confusion_matrix

y_pred = tree.predict(X_test)
cm = confusion_matrix(y_test, y_pred)

print('TP - True Negative {}'.format(cm[0,0]))
print('FP - False Positive {}'.format(cm[0,1]))
print('FN - False Negative {}'.format(cm[1,0]))
print('TP - True Positive {}'.format(cm[1,1]))
print('__________________________________________________')
print('Accuracy Rate: {}'.format(np.divide(np.sum([cm[0,0],cm[1,1]]),np.
 ↪sum(cm))))
print('Misclassification Rate: {}'.format(np.divide(np.
 ↪sum([cm[0,1],cm[1,0]]),np.sum(cm))))

round(metrics.roc_auc_score(y_test,y_pred),5)
print('__________________________________________________')
print ("Confusion Matrix")
print(cm)
```

```
TP - True Negative 125
FP - False Positive 29
FN - False Negative 25
TP - True Positive 52
__________________________________________________
Accuracy Rate: 0.7662337662337663
Misclassification Rate: 0.23376623376623376
__________________________________________________
Confusion Matrix
[[125  29]
 [ 25  52]]
```

2.6 2.a.2 - Repeat(2.a.1) the experiment 10 times (General function for multiple iterations)

[89]:
```
MSE = []
ACCURACY = []
TN, FP, FN, TP = [],[],[],[]
PRECISION = []

for i in range(10):
    random_train_test_split = round(np.random.uniform(0,1),2)
    X_train, X_test, y_train, y_test = split_data(random_train_test_split)
    model = DecisionTreeClassifier(max_depth=7,max_features = 3,␣
 ↪min_samples_split = 5, random_state = 0)
```

```
    model.fit(X_train,y_train)

    prediction_from_test_data = model.predict(X_test)
    accuracy = metrics.accuracy_score(y_test, prediction_from_test_data)
    MSE.append(metrics.mean_squared_error(y_test, prediction_from_test_data))
    cm = confusion_matrix(y_test, prediction_from_test_data)
    precision = metrics.precision_score(prediction_from_test_data, y_test,␣
 ↪average='micro')

    TN.append(cm[0,0]); FP.append(cm[0,1]); FN.append(cm[1,0]); TP.
 ↪append(cm[1,1])
    PRECISION.append(precision); ACCURACY.append(accuracy)

    print('Running cyle: %s'%str(i))
    print('_________________________________________________________________')
    print('Random Split {}'.format(random_train_test_split))
    print('TN - True Negative {}'.format(cm[0,0]))
    print('FP - False Positive {}'.format(cm[0,1]))
    print('FN - False Negative {}'.format(cm[1,0]))
    print('TP - True Positive {}'.format(cm[1,1]))
    print('Precision of Decision Tree {0:0.4f}'.format(precision))
    print ("Accuracy of Decision Tree {0:0.4f}".format(accuracy))
    print("Test set MSE for {} cycle:{}".format(i+1,MSE[i]))
    print('_________________________________________________________________')


print("Mean MSE for {}-random split cross validation : {}".format(len(MSE), np.
 ↪mean(MSE)))
print("Mean Accuracy for {}-random split cross validation : {}".
 ↪format(len(ACCURACY), np.mean(ACCURACY)))
print("Mean Precision for {}-random split cross validation : {}".
 ↪format(len(PRECISION), np.mean(PRECISION)))
print("Mean True Negative for {}-random split cross validation : {}".
 ↪format(len(TN), np.mean(TN)))
print("Mean False Positive for {}-random split cross validation : {}".
 ↪format(len(FP), np.mean(FP)))
print("Mean False Negative for {}-random split cross validation : {}".
 ↪format(len(FN), np.mean(FN)))
print("Mean True Positive for {}-random split cross validation : {}".
 ↪format(len(TP), np.mean(TP)))
```

```
Running cyle: 0
_________________________________________________________________
Random Split 0.99
TN - True Negative 404
FP - False Positive 90
FN - False Negative 112
```

```
TP - True Positive 155
Precision of Decision Tree 0.7346
Accuracy of Decision Tree 0.7346
Test set MSE for 1 cycle:0.26544021024967146
-------------------------------------------------------------------
Running cyle: 1
-------------------------------------------------------------------
Random Split 0.16
TN - True Negative 61
FP - False Positive 21
FN - False Negative 10
TP - True Positive 31
Precision of Decision Tree 0.7480
Accuracy of Decision Tree 0.7480
Test set MSE for 2 cycle:0.25203252032520324
-------------------------------------------------------------------
Running cyle: 2
-------------------------------------------------------------------
Random Split 0.31
TN - True Negative 128
FP - False Positive 32
FN - False Negative 37
TP - True Positive 42
Precision of Decision Tree 0.7113
Accuracy of Decision Tree 0.7113
Test set MSE for 3 cycle:0.28870292887029286
-------------------------------------------------------------------
Running cyle: 3
-------------------------------------------------------------------
Random Split 0.42
TN - True Negative 161
FP - False Positive 59
FN - False Negative 37
TP - True Positive 66
Precision of Decision Tree 0.7028
Accuracy of Decision Tree 0.7028
Test set MSE for 4 cycle:0.29721362229102166
-------------------------------------------------------------------
Running cyle: 4
-------------------------------------------------------------------
Random Split 0.36
TN - True Negative 145
FP - False Positive 44
FN - False Negative 36
TP - True Positive 52
Precision of Decision Tree 0.7112
Accuracy of Decision Tree 0.7112
Test set MSE for 5 cycle:0.2888086642599278
```

```
---------------------------------------------------------------------
Running cyle: 5
---------------------------------------------------------------------
Random Split 0.51
TN - True Negative 202
FP - False Positive 64
FN - False Negative 49
TP - True Positive 77
Precision of Decision Tree 0.7117
Accuracy of Decision Tree 0.7117
Test set MSE for 6 cycle:0.288265306122449
---------------------------------------------------------------------
Running cyle: 6
---------------------------------------------------------------------
Random Split 0.7
TN - True Negative 276
FP - False Positive 79
FN - False Negative 82
TP - True Positive 101
Precision of Decision Tree 0.7007
Accuracy of Decision Tree 0.7007
Test set MSE for 7 cycle:0.2992565055762082
---------------------------------------------------------------------
Running cyle: 7
---------------------------------------------------------------------
Random Split 0.58
TN - True Negative 214
FP - False Positive 85
FN - False Negative 54
TP - True Positive 93
Precision of Decision Tree 0.6883
Accuracy of Decision Tree 0.6883
Test set MSE for 8 cycle:0.3116591928251121
---------------------------------------------------------------------
Running cyle: 8
---------------------------------------------------------------------
Random Split 0.95
TN - True Negative 311
FP - False Positive 162
FN - False Negative 77
TP - True Positive 180
Precision of Decision Tree 0.6726
Accuracy of Decision Tree 0.6726
Test set MSE for 9 cycle:0.3273972602739726
---------------------------------------------------------------------
Running cyle: 9
---------------------------------------------------------------------
Random Split 0.36
```

```
TN - True Negative 145
FP - False Positive 44
FN - False Negative 36
TP - True Positive 52
Precision of Decision Tree 0.7112
Accuracy of Decision Tree 0.7112
Test set MSE for 10 cycle:0.2888086642599278

-----------------------------------------------------------------
Mean MSE for 10-random split cross validation : 0.2907584875053787
Mean Accuracy for 10-random split cross validation : 0.7092415124946214
Mean Precision for 10-random split cross validation : 0.7092415124946214
Mean True Negative for 10-random split cross validation : 204.7
Mean False Positive for 10-random split cross validation : 68.0
Mean False Negative for 10-random split cross validation : 53.0
Mean True Positive for 10-random split cross validation : 84.9
```

2.7 2.b.1 Peformance comparsion between Gini impurity ("gini") to information gain ("entropy")

[90]:
```
def compare_performance(criterion='gini', max_depth = 7, min_samples_split = 5):
    tree = DecisionTreeClassifier(max_depth=max_depth, max_features = 3,␣
 ↪min_samples_split = min_samples_split, random_state=0, criterion=criterion)
    tree.fit(X_train,y_train)
    return [tree.score(X_train,y_train), tree.score(X_test,y_test)]

print('Performance Check on: gini')

train_gini, test_gini = compare_performance(criterion='gini')

print('_________________________________________________')
print("Accuracy on training set: {:.3f}".format(train_gini))
print("Accuracy on test set: {:.3f}".format(test_gini))
print('_________________________________________________')
print('Performance Check on: entropy')

train_entropy, test_entropy = compare_performance(criterion='entropy')

print('_________________________________________________')
print("Accuracy on training set: {:.3f}".format(train_entropy))
print("Accuracy on test set: {:.3f}".format(test_entropy))
print('_________________________________________________')
```

```
Performance Check on: gini
_________________________________________________
Accuracy on training set: 0.868
Accuracy on test set: 0.711
```

```
------------------------------------------------
Performance Check on: entropy
------------------------------------------------
Accuracy on training set: 0.843
Accuracy on test set: 0.704
------------------------------------------------
```

2.8 2.b.2 Peformance comparsion between Gini impurity ("gini") to information gain ("entropy") on random train test split and for 10 iterations

[91]:
```
def repeat_experiment(criterion = 'gini'):
    ACCURACY = []
    for i in range(10):
        random_train_test_split = round(np.random.uniform(0,1),2)
        X_train, X_test, y_train, y_test = split_data(random_train_test_split)
        model = DecisionTreeClassifier(max_depth=7,max_features = 3,␣
 ↪min_samples_split = 5, random_state = 0)
        model.fit(X_train,y_train)

        prediction_from_test_data = model.predict(X_test)
        ACCURACY.append(metrics.accuracy_score(y_test,␣
 ↪prediction_from_test_data))
    return ACCURACY

accuracy_gini = repeat_experiment(criterion='gini')

print("Mean Accuracy gini for {}-random train test cross validation : {}".
 ↪format(len(accuracy_gini), np.mean(accuracy_gini)))
```

```
Mean Accuracy gini for 10-random train test cross validation :
0.6893745870311155
```

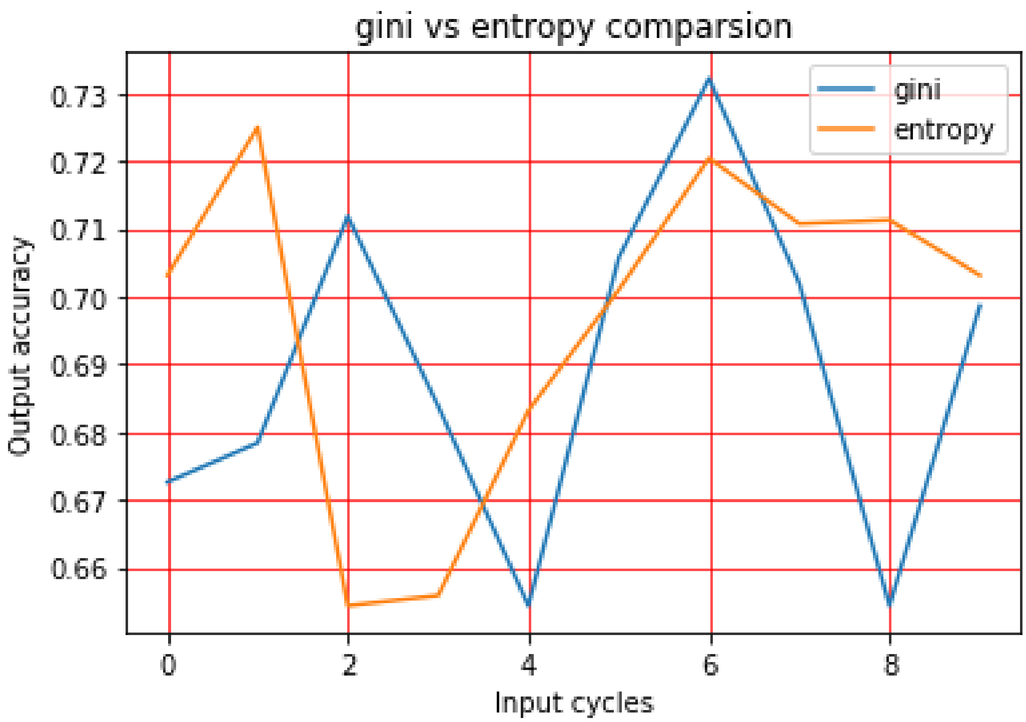
[92]:
```
accuracy_entropy = repeat_experiment(criterion='entropy')

print("Mean Accuracy entropy for {}-random train test cross validation : {}".
 ↪format(len(accuracy_entropy), np.mean(accuracy_entropy)))
```

```
Mean Accuracy entropy for 10-random train test cross validation :
0.6967989583165975
```

2.9 2.c Performance comparsion between "gini" and "entropy" using chart

[180]:
```
cycles = range(10)
plt.plot(cycles, accuracy_gini, label='gini')
plt.plot(cycles, accuracy_entropy, label='entropy')
```

```
plt.title('gini vs entropy comparsion')
plt.xlabel('Input cycles')
plt.ylabel('Output accuracy')
plt.grid(True, linewidth=0.7, color='#ff0000', linestyle='-')
plt.legend()
plt.show()
```



2.10 2.d why standardizing helps in improving performance

Standardizing a dataset in machine learning helps with making the data comparable across tasks and algorithms.There are many data preprocessing steps that could be applied to a dataset, such as data normalization, feature selection, data transformations, and so on. In the given dataset there were some zero values which are kind of outliers in data and hence removing zeros before applying DT algorithm definitely improved the performance. Also when I tried to standardize the dataset using formula

standardized_data $= \frac{data-\mu}{\sigma}$

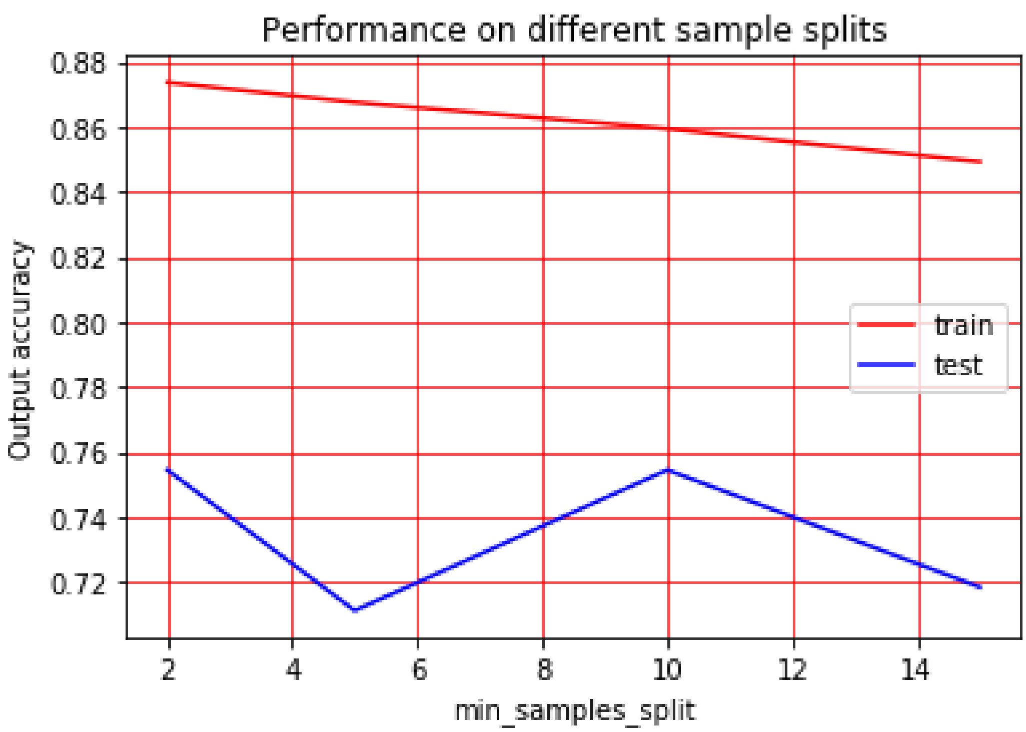
There was no change in the performance of the model. The reason for that is because the data is highly correlated and is standardized.

2.11 Task 3[Classification parameters DT]

2.12 Task 3.a min_samples_split effect on performance of algorithm

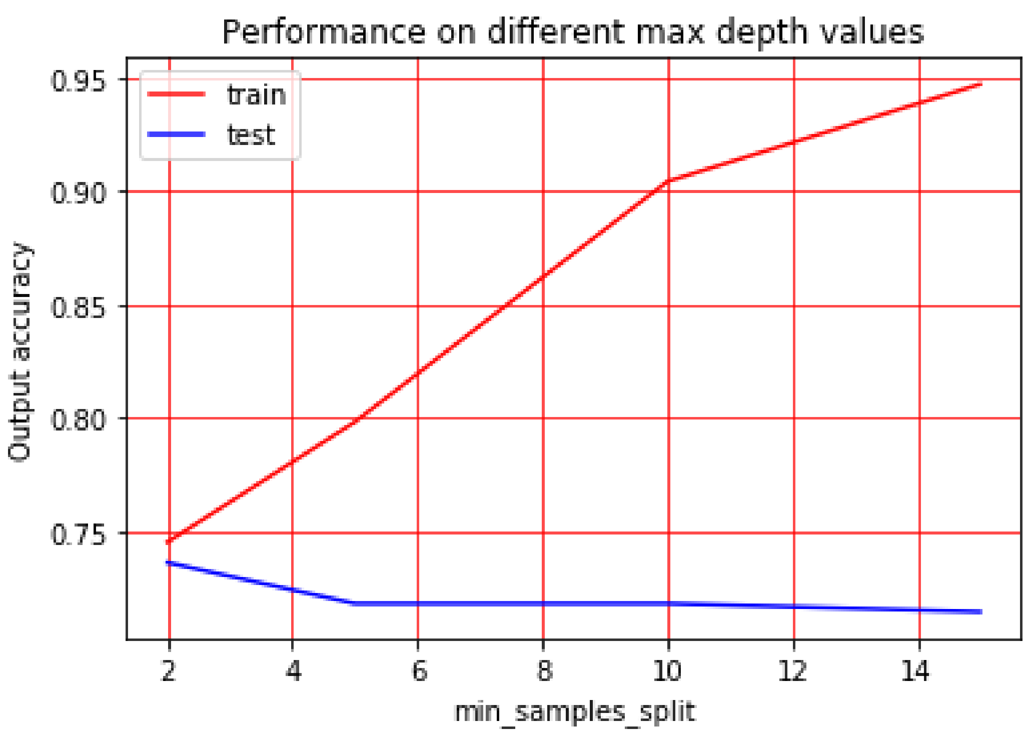
[181]:

```
min_samples_split = [2, 5, 10, 15]
acc_comparsion_train = []
acc_comparsion_test = []

for sample in min_samples_split:
    acc_comparsion_train.append(compare_performance(min_samples_split =␣
 ↪sample)[0])
    acc_comparsion_test.append(compare_performance(min_samples_split =␣
 ↪sample)[1])

plt.plot(min_samples_split, acc_comparsion_train, label='train', color='r')
plt.plot(min_samples_split, acc_comparsion_test, label='test', color='b')
plt.title('Performance on different sample splits')
plt.grid(True, linewidth=0.7, color='#ff0000', linestyle='-')
plt.xlabel('min_samples_split')
plt.ylabel('Output accuracy')
plt.legend()
plt.show()
```



2.13 Task 3.b max_depth effect on performance of algorithm

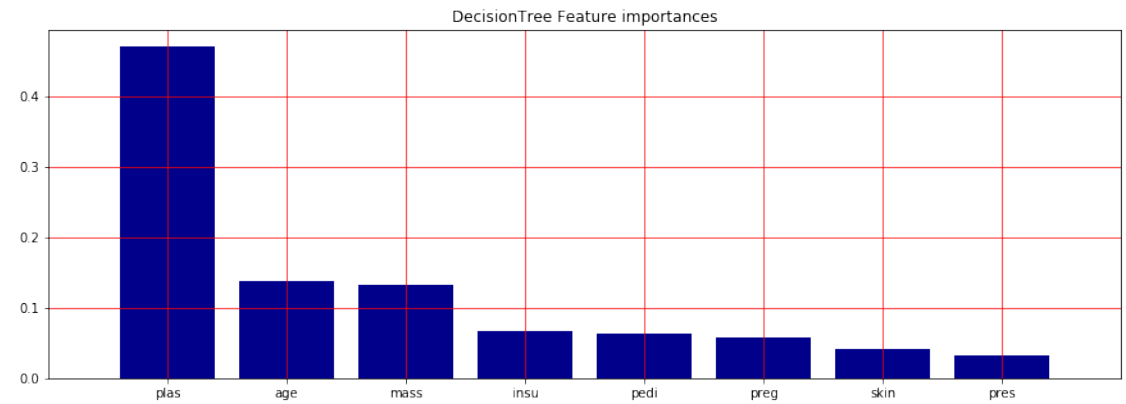
[182]:
```
max_depth = [3, 4, 5, 6]
acc_comparsion_train = []
acc_comparsion_test = []

for sample in min_samples_split:
    acc_comparsion_train.append(compare_performance(max_depth = sample)[0])
    acc_comparsion_test.append(compare_performance(max_depth = sample)[1])

plt.plot(min_samples_split, acc_comparsion_train, label='train', color='r')
plt.plot(min_samples_split, acc_comparsion_test, label='test', color='b')
plt.title('Performance on different max depth values')
plt.grid(True, linewidth=0.7, color='#ff0000', linestyle='-')
plt.xlabel('min_samples_split')
plt.ylabel('Output accuracy')
plt.legend()
plt.show()
```



2.14 Task 4[Decision Tree Boundaries] - Implemented this part to understand decision tree better

[96]:
```
#Feature Importance DecisionTreeClassifier

importance = tree.feature_importances_
indices = np.argsort(importance)[::-1]
feature = X_train
feat_names = sourcevars.columns

print("DecisionTree Feature ranking:")
print('_________________________________________________')

for f in range(feature.shape[1]):
    print("%d. feature %s (%f)" % (f + 1, feat_names[indices[f]],␣
↪importance[indices[f]]))

print('_________________________________________________')

plt.figure(figsize=(15,5))
plt.title("DecisionTree Feature importances")
plt.bar(range(feature.shape[1]), importance[indices], color='#00008B',␣
↪align="center")
plt.xticks(range(feature.shape[1]), list(feat_names[indices]))
plt.xlim([-1, feature.shape[1]])
plt.grid(True, linewidth=0.7, color='#ff0000', linestyle='-')
plt.show()
```

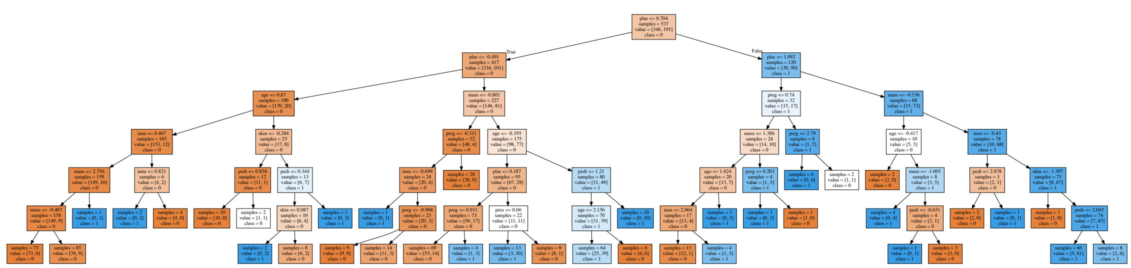
```
DecisionTree Feature ranking:
_________________________________________________
1. feature plas (0.470215)
2. feature age (0.136975)
3. feature mass (0.131788)
4. feature insu (0.066243)
5. feature pedi (0.063821)
6. feature preg (0.057307)
7. feature skin (0.041671)
8. feature pres (0.031980)
_________________________________________________
```



[97]:

```
from sklearn.tree import export_graphviz
import graphviz

importance = tree.feature_importances_
indices = np.argsort(importance)[::-1]

export_graphviz(tree,out_file="diabetes_tree.dot",class_names=["0","1"],
feature_names=sourcevars.columns,impurity=False,filled=True)

with open("diabetes_tree.dot") as f:
    dot_graph = f.read()
graphviz.Source(dot_graph)
```

[97]:



[98]:

```
#Evaluation DecisionTreeClassifier

from sklearn.metrics import roc_curve, auc
import random

y_pred = model.predict(X_test)
fpr,tpr,thres = roc_curve(y_test, y_pred)
roc_auc = auc(fpr, tpr)
```

```
plt.title('DecisionTreeClassifier-Receiver Operating Characteristic Test Data')
plt.plot(fpr, tpr, color='green', lw=2, label='DecisionTree ROC curve (area =␣
 ↪%0.2f)' % roc_auc)
plt.legend(loc='lower right')

plt.plot([0,1],[0,1],'r--')
plt.xlim([-0.1,1.2])
plt.ylim([-0.1,1.2])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.grid(True, linewidth=0.7, color='black', linestyle='-')
plt.show()
```