

# decisionTree

March 22, 2023

## 1 DECISION TREE CLASSIFICATION USING ENTROPY AND GINI INDEX:

### 1.0.1 Dataset: Red Wine classification dataset

### 1.0.2 Contents

Input variables (based on physicochemical tests):

1. fixed acidity
2. volatile acidity
3. citric acid
4. residual sugar
5. chlorides
6. free sulfur dioxide
7. total sulfur dioxide
8. density
9. pH
10. sulphates
11. alcohol

Output variable (based on sensory data):

1. quality (score between 0 and 10)

### 1.1 1. LOAD AND EXPLORATION

```
[21]: #importing libraries

import numpy as np
import pandas as pd

import matplotlib.pyplot as plt
%matplotlib inline
```

```

import seaborn as sns
from sklearn import tree

from sklearn import metrics
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, precision_score, recall_score, \
    classification_report, confusion_matrix

from sklearn.tree import DecisionTreeClassifier

```

[22]: *#loading the data*

```

df = pd.read_csv('./winequality-red.csv')
print('The Dataset contains {} rows and {} columns '.format(df.shape[0], df.
    shape[1]))

```

The Dataset contains 1599 rows and 12 columns

[23]: df.head()

```

[23]:   fixed acidity  volatile acidity  citric acid  residual sugar  chlorides \
0           7.4             0.70         0.00           1.9       0.076
1           7.8             0.88         0.00           2.6       0.098
2           7.8             0.76         0.04           2.3       0.092
3          11.2             0.28         0.56           1.9       0.075
4           7.4             0.70         0.00           1.9       0.076

      free sulfur dioxide  total sulfur dioxide  density    pH  sulphates \
0              11.0             34.0    0.9978  3.51       0.56
1              25.0             67.0    0.9968  3.20       0.68
2              15.0             54.0    0.9970  3.26       0.65
3              17.0             60.0    0.9980  3.16       0.58
4              11.0             34.0    0.9978  3.51       0.56

      alcohol  quality
0         9.4        5
1         9.8        5
2         9.8        5
3         9.8        6
4         9.4        5

```

[24]: *#getting the statiscal information*

```

df.describe()

```

```
[24]:
```

	fixed acidity	volatile acidity	citric acid	residual sugar	\
count	1599.000000	1599.000000	1599.000000	1599.000000	
mean	8.319637	0.527821	0.270976	2.538806	
std	1.741096	0.179060	0.194801	1.409928	
min	4.600000	0.120000	0.000000	0.900000	
25%	7.100000	0.390000	0.090000	1.900000	
50%	7.900000	0.520000	0.260000	2.200000	
75%	9.200000	0.640000	0.420000	2.600000	
max	15.900000	1.580000	1.000000	15.500000	

	chlorides	free sulfur dioxide	total sulfur dioxide	density	\
count	1599.000000	1599.000000	1599.000000	1599.000000	
mean	0.087467	15.874922	46.467792	0.996747	
std	0.047065	10.460157	32.895324	0.001887	
min	0.012000	1.000000	6.000000	0.990070	
25%	0.070000	7.000000	22.000000	0.995600	
50%	0.079000	14.000000	38.000000	0.996750	
75%	0.090000	21.000000	62.000000	0.997835	
max	0.611000	72.000000	289.000000	1.003690	

	pH	sulphates	alcohol	quality
count	1599.000000	1599.000000	1599.000000	1599.000000
mean	3.311113	0.658149	10.422983	5.636023
std	0.154386	0.169507	1.065668	0.807569
min	2.740000	0.330000	8.400000	3.000000
25%	3.210000	0.550000	9.500000	5.000000
50%	3.310000	0.620000	10.200000	6.000000
75%	3.400000	0.730000	11.100000	6.000000
max	4.010000	2.000000	14.900000	8.000000

## 1.2 2. DATA CLEANING

```
[25]: #counting the frequency of each element from the 'quality'
df['quality'].value_counts().index
```

```
[25]: Int64Index([5, 6, 7, 4, 8, 3], dtype='int64')
```

So the ratings are 3,4,5,6,7 and 8 making only 6 values in quality column

```
[26]: #correlation between the columns
plt.figure(figsize=(18,10))
sns.heatmap(df.corr(), annot=True, fmt = ".1f", linewidths = .7)
```

```
[26]: <AxesSubplot:>
```



Checking for missing values:

```
[27]: df.isnull().sum()
```

```
[27]: fixed acidity      0
      volatile acidity  0
      citric acid       0
      residual sugar    0
      chlorides         0
      free sulfur dioxide 0
      total sulfur dioxide 0
      density          0
      pH              0
      sulphates        0
      alcohol          0
      quality          0
      dtype: int64
```

1.2.1 *There are no missing values in the dataset*

```
[28]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1599 entries, 0 to 1598
```

Data columns (total 12 columns):

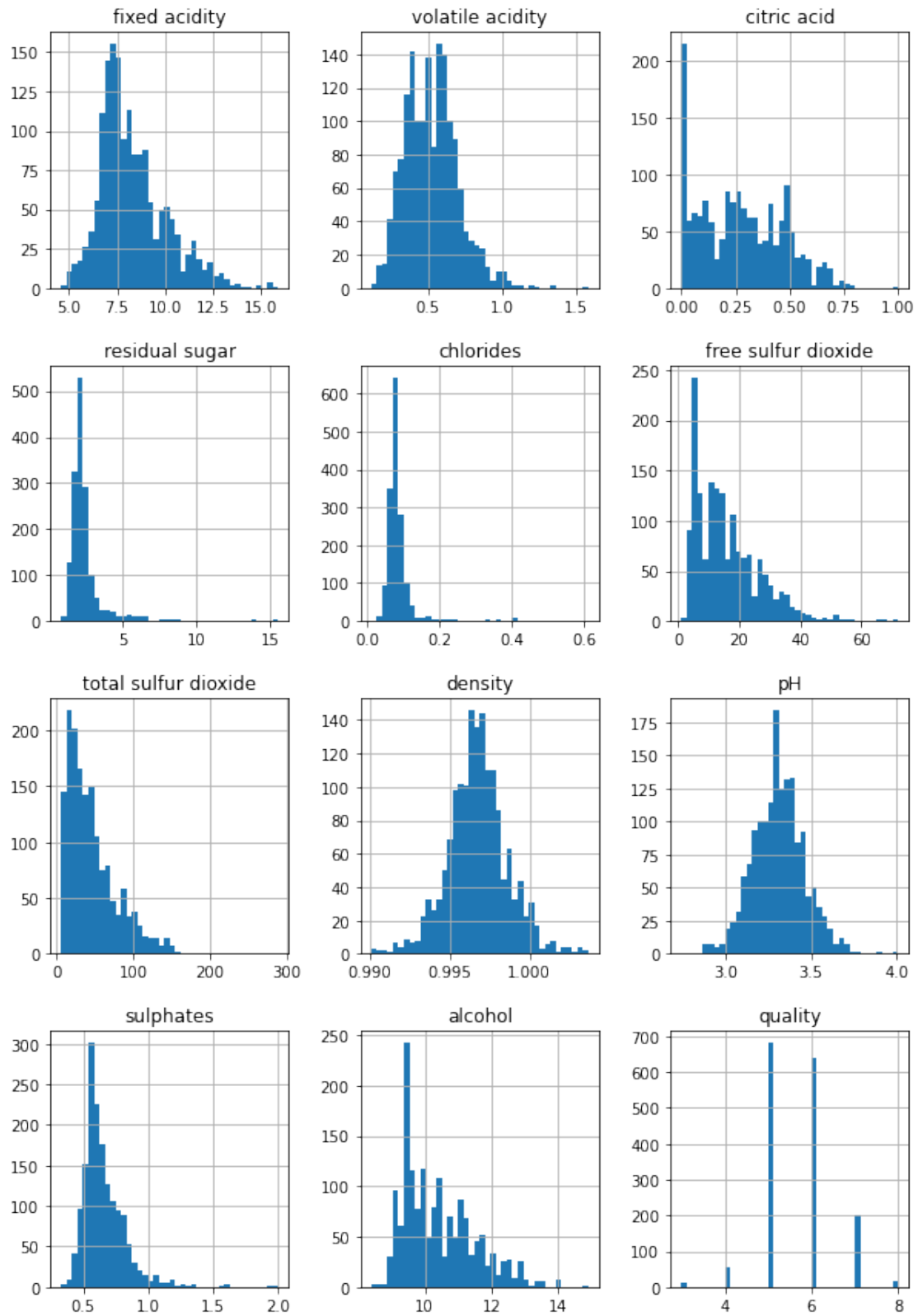
#	Column	Non-Null Count	Dtype
0	fixed acidity	1599 non-null	float64
1	volatile acidity	1599 non-null	float64
2	citric acid	1599 non-null	float64
3	residual sugar	1599 non-null	float64
4	chlorides	1599 non-null	float64
5	free sulfur dioxide	1599 non-null	float64
6	total sulfur dioxide	1599 non-null	float64
7	density	1599 non-null	float64
8	pH	1599 non-null	float64
9	sulphates	1599 non-null	float64
10	alcohol	1599 non-null	float64
11	quality	1599 non-null	int64

dtypes: float64(11), int64(1)

memory usage: 150.0 KB

### 1.2.2 Now Showing the distribution of each feature:

```
[29]: df.hist(bins=40, figsize=(10,15))  
plt.show()
```



### 1.2.3 What do we Understand?

Data distribution for attribute “alcohol” is positively skewed, for attribute “density” data quite normally distributed. Take attention to the wine quality data distribution. It’s a bimodal distribution and there are more wines with average quality than wines with ‘good’ or ‘bad’ quality.

```
[30]: #counting the frequency of each element from the 'class'
```

```
df['quality'].value_counts()
```

```
[30]: 5    681
      6    638
      7    199
      4     53
      8     18
      3     10
      Name: quality, dtype: int64
```

Human wine preferences scores varied from 3 to 8, so it’s straightforward to categorize answers into ‘bad’ or ‘good’ quality of wines. We assign for categorizes corresponding discrete values 0 or 1.

### 1.2.4 Good - 1, Bad - 0

```
[31]: # Dividing wine as good and bad by giving the limit for the quality
```

```
bins = (2, 6, 8)
group_names = ['bad', 'good']
df['quality'] = pd.cut(df['quality'], bins = bins, labels = group_names)
```

```
[32]: print(df['quality'].value_counts())
```

```
bad      1382
good       217
      Name: quality, dtype: int64
```

```
[33]: # assign labels to our quality variable
```

```
label_quality = LabelEncoder()

# Bad becomes 0 and good becomes 1

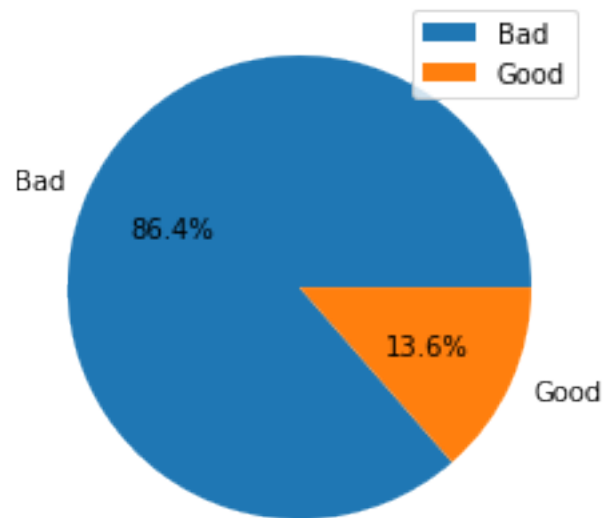
df['quality'] = label_quality.fit_transform(df['quality'])
```

```
[34]: df['quality'].value_counts()
```

```
[34]: 0    1382  
      1     217  
      Name: quality, dtype: int64
```

```
[35]: #proportion of different elements of the class
```

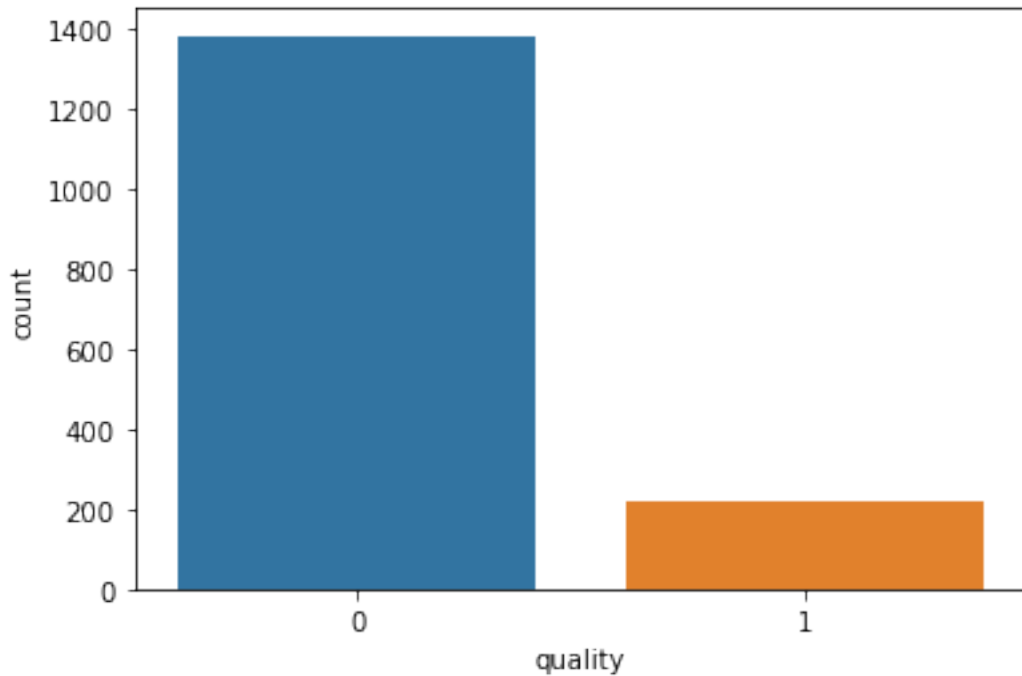
```
plt.pie(df['quality'].value_counts(),autopct="%1.1f%%",labels=['Bad','Good'])  
plt.legend();
```



```
[36]: #plot to show count of labels
```

```
sns.countplot(x=df['quality'])  
plt.show()
```





[37]: *#Filter the dataset for input and output*

```
x = df.drop(['quality'], axis=1)
y = df['quality']
```

[38]: *#splitting the processed dataset into train and test dataset*

```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.25,
↳ random_state = 50)
```

## 2 A) ALGORITHM FOR DECISION TREE IMPLEMENTED FROM SCRATCH

### 2.1 Entropy and GINI INDEX

[41]: *#class node for representing each node of the decision tree*

```
class Node():
    #constructor
    def __init__(self, feature_index=None, threshold=None, left=None,
↳ right=None, info_gain=None, value=None):

        # for decision node
        self.feature_index = feature_index
        self.threshold = threshold
```

```

        self.left = left
        self.right = right
        self.info_gain = info_gain

        # for leaf node
        self.value = value

class MyDecisionTreeClassifier():
    #constructor
    def __init__(self, criterion="gini", min_samples_split=2, max_depth=2):

        # initialize the root of the tree
        self.root = None

        # stopping conditions
        self.criterion = criterion
        self.min_samples_split = min_samples_split
        self.max_depth = max_depth

    #recursive function to build the tree
    def build_tree(self, dataset, curr_depth=0):

        X, Y = dataset[:, :-1], dataset[:, -1]
        num_samples, num_features = np.shape(X)

        # split until stopping conditions are met
        if num_samples >= self.min_samples_split and curr_depth <= self.max_depth:
            # find the best split
            best_split = self.get_best_split(dataset, num_samples, num_features)
            # check if information gain is positive
            if "info_gain" in best_split and best_split["info_gain"] > 0:
                # recur left
                left_subtree = self.build_tree(best_split["dataset_left"],
↳ curr_depth+1)
                # recur right
                right_subtree = self.build_tree(best_split["dataset_right"],
↳ curr_depth+1)
                # return decision node
                return Node(best_split["feature_index"],
↳ best_split["threshold"],
                            left_subtree, right_subtree,
↳ best_split["info_gain"])

            # compute leaf node
            leaf_value = self.calculate_leaf_value(Y)
            # return leaf node
            return Node(value=leaf_value)

```

```

#function to find the best split
def get_best_split(self, dataset, num_samples, num_features):

    # dictionary to store the best split
    best_split = {}
    max_info_gain = -float("inf")

    # loop over all the features
    for feature_index in range(num_features):
        feature_values = dataset[:, feature_index]
        possible_thresholds = np.unique(feature_values)
        # loop over all the feature values present in the data
        for threshold in possible_thresholds:
            # get current split
            dataset_left, dataset_right = self.split(dataset,
↪feature_index, threshold)
            # check if childs are not null
            if len(dataset_left)>0 and len(dataset_right)>0:
                y, left_y, right_y = dataset[:, -1], dataset_left[:, -1],
↪dataset_right[:, -1]
                # compute information gain
                curr_info_gain = self.information_gain(y, left_y, right_y,
↪self.criterion)
                # update the best split if needed
                if curr_info_gain>max_info_gain:
                    best_split["feature_index"] = feature_index
                    best_split["threshold"] = threshold
                    best_split["dataset_left"] = dataset_left
                    best_split["dataset_right"] = dataset_right
                    best_split["info_gain"] = curr_info_gain
                    max_info_gain = curr_info_gain

    # return best split
    return best_split

#function to split the data
def split(self, dataset, feature_index, threshold):

    dataset_left = np.array([row for row in dataset if
↪row[feature_index]<=threshold])
    dataset_right = np.array([row for row in dataset if
↪row[feature_index]>threshold])
    return dataset_left, dataset_right

#function to compute information gain
def information_gain(self, parent, l_child, r_child, mode="gini"):

```

```

        weight_l = len(l_child) / len(parent)
        weight_r = len(r_child) / len(parent)
        if mode=="gini":
            gain = self.gini_index(parent) - (weight_l*self.gini_index(l_child) +
↪ weight_r*self.gini_index(r_child))
        else:
            gain = self.entropy(parent) - (weight_l*self.entropy(l_child) +
↪ weight_r*self.entropy(r_child))
        return gain

#function to compute entropy
def entropy(self, y):

    class_labels = np.unique(y)
    entropy = 0
    for cls in class_labels:
        p_cls = len(y[y == cls]) / len(y)
        entropy += -p_cls * np.log2(p_cls)
    return entropy

#function to compute gini index
def gini_index(self, y):

    class_labels = np.unique(y)
    gini = 0
    for cls in class_labels:
        p_cls = len(y[y == cls]) / len(y)
        gini += p_cls**2
    return 1 - gini

#function to compute leaf node
def calculate_leaf_value(self, Y):

    Y = list(Y)
    return max(Y, key=Y.count)

#function to print the tree
def print_tree(self, tree=None, indent="  "):

    if not tree:
        tree = self.root

    if tree.value is not None:
        print(tree.value)

    else:

```

```

        print("X_"+str(tree.feature_index), "<=", tree.threshold, "?", tree.
↳info_gain)
        print("%sleft:" % (indent), end="")
        self.print_tree(tree.left, indent+indent)
        print("%sright:" % (indent), end="")
        self.print_tree(tree.right, indent+indent)

#function to train the tree
def fit(self, X, Y):

    dataset = np.concatenate((X, Y), axis=1)
    self.root = self.build_tree(dataset)

#function to predict new dataset
def predict(self, X):

    predictions = [self.make_prediction(x, self.root) for x in X]
    return predictions

#function to predict a single data point
def make_prediction(self, x, tree):

    if tree.value!=None: return tree.value
    feature_val = x[tree.feature_index]
    if feature_val<=tree.threshold:
        return self.make_prediction(x, tree.left)
    else:
        return self.make_prediction(x, tree.right)

```

```

[42]: x = df.iloc[:, :-1].values
      y = df.iloc[:, -1].values.reshape(-1,1)

```

```

[44]: #split train and test samples

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.25,↳
↳random_state = 50)

```

## 2.2 4. TRAIN THE MODEL

### 2.2.1 A) DECISION TREE IMPLEMENTED FROM SCRATCH

#### 2.2.2 USING ENTROPY

```
[45]: myClassifier_entropy = MyDecisionTreeClassifier(criterion="entropy",  
↳max_depth=50)  
myClassifier_entropy.fit(x_train, y_train)  
myClassifier_entropy.print_tree()
```

```
X_10 <= 10.4 ? 0.09345652303969632  
left:X_9 <= 0.61 ? 0.02742215521756683  
left:X_9 <= 0.56 ? 0.008250172890607414  
left:0.0  
right:X_5 <= 10.0 ? 0.024400785009314543  
left:X_5 <= 8.0 ? 0.09575537889326563  
left:0.0  
right:X_2 <= 0.02 ? 0.25767880510333147  
left:1.0  
right:X_4 <= 0.078 ? 0.1935068433729344  
left:0.0  
right:X_8 <=  
3.24 ? 0.9182958340544896  
left:1.0  
right:0.0  
right:0.0  
right:X_10 <= 9.6 ? 0.0412359652963899  
left:X_0 <= 14.3 ? 0.04638979071433067  
left:X_9 <= 0.62 ? 0.021314443909423664  
left:X_6 <= 35.0 ? 0.15649412347457692  
left:X_5 <= 7.0 ? 0.9182958340544896  
left:0.0  
right:1.0  
right:0.0  
right:0.0  
right:1.0  
right:X_2 <= 0.08 ? 0.039542966228935605  
left:0.0  
right:X_6 <= 67.0 ? 0.045874225349620046  
left:X_4 <= 0.074 ? 0.04112938525068455  
left:X_7 <= 0.99769 ? 0.10911003076268089  
left:X_4 <=  
0.069 ? 0.17404892546009187  
left:X_1 <= 0.3 ?  
0.16251125329718275  
left:0.0  
right:X_8 <= 3.23 ? 0.2621549647380449  
left:1.0
```

```

right:X_4 <= 0.059 ? 0.3435794213678428
left:0.0
right:X_1 <=
0.48 ? 0.46956521111470695
left:X_5 <= 31.0 ?
0.7219280948873623
left:1.0
right:0.0
right:0.0
right:1.0
right:X_0 <=
12.5 ? 0.4394969869215134
left:0.0
right:1.0
right:X_4 <= 0.081 ? 0.08363242229665335
left:0.0
right:X_6 <=
11.0 ? 0.1075414071369365
left:1.0
right:X_1 <= 0.89 ?
0.061704192549288606
left:X_4 <= 0.096 ? 0.08986867817719413
left:X_2 <= 0.52 ? 0.08556114743657839
left:X_8 <= 3.51
? 0.13824095117944724
left:X_4 <= 0.091 ?
0.1648677151048581
left:0.0
right:X_0 <= 9.5 ? 0.46956521111470695
left:0.0
right:X_0 <= 10.1 ? 0.9182958340544896
left:1.0
right:0.0
right:1.0
right:X_0 <=
12.5 ? 0.4591479170272448
left:1.0
right:X_1 <= 0.415 ?
0.8112781244591328
left:0.0
right:1.0
right:0.0
right:1.0
right:0.0
right:X_9 <= 0.68 ? 0.06912096376765586
left:X_1 <= 0.38 ? 0.06103333983734327
left:X_0 <= 6.4 ? 0.06198490656686273
left:0.0

```

```

right:X_0 <= 6.8 ? 0.08252524785132997
    left:1.0
    right:X_3 <= 2.9 ? 0.0880316723464829
        left:X_9 <= 0.54 ? 0.10862163149277804
            left:0.0
            right:X_8 <=
3.26 ? 0.13822251414224762
                                left:X_6 <= 16.0 ?
0.21906026991893968
    left:X_2 <= 0.34 ? 0.5032583347756457
        left:0.0
        right:1.0
    right:X_5 <= 20.0 ? 0.31668908831502096
        left:X_3 <= 1.7 ? 0.3828503397420074
            left:1.0
            right:X_2 <=
0.34 ? 0.2373974097831018
                                left:X_0 <= 10.1 ? 1.0
    left:1.0
    right:0.0
                                right:0.0
                                right:1.0
                                right:X_4 <= 0.05799999999999999
? 0.3502090290998975
    left:X_0 <= 7.1 ? 0.9182958340544896
        left:0.0
        right:1.0
    right:0.0
                                right:X_10 <= 11.0 ? 0.7642045065086203
                                    left:0.0
                                    right:1.0
    right:X_6 <= 19.0 ? 0.033748229932452856
        left:X_1 <= 0.66 ? 0.18220283362606426
            left:X_4 <= 0.086 ? 0.2655234166823892
                left:X_9 <= 0.58 ? 0.25620623685627303
                    left:0.0
                    right:X_5 <= 5.0
? 0.5216406363433185
                                left:0.0
                                right:X_4 <= 0.043 ?
0.8112781244591328
    left:0.0
    right:1.0
                                right:X_4 <= 0.10099999999999999 ?
0.6052891061068587
                                    left:1.0
                                    right:X_2 <=
0.49 ? 0.7219280948873623

```



```

left:0.0
right:1.0
right:0.0
right:X_8 <= 2.92 ? 0.028044537047481777
left:1.0
right:X_4 <= 0.065 ? 0.03593861065895981
left:X_4 <= 0.053 ? 0.13061142961974004
left:0.0
right:X_5 <=
31.0 ? 0.22625794497561413
left:X_3 <= 1.7 ?
0.2025070034547547
left:X_1 <= 0.47 ? 0.9182958340544896
left:0.0
right:1.0
right:X_1 <= 0.4 ? 0.22002600168808803
left:X_0 <= 5.9 ? 1.0
left:0.0
right:1.0
right:0.0
right:1.0
right:X_1 <= 0.42 ? 0.04560409401861014
left:X_4 <= 0.09
? 0.22994744641573744
left:0.0
right:X_5 <= 9.0 ?
0.4199730940219749
left:0.0
right:X_2 <= 0.66 ? 0.9182958340544896
left:1.0
right:0.0
right:0.0
right:X_10 <= 11.6 ? 0.10044876766219746
left:X_1 <= 0.4 ? 0.07567434015082874
left:X_9 <= 0.75 ? 0.08277568191155193
left:X_10 <= 11.0 ? 0.2777196685025808
left:0.0
right:X_1 <= 0.34 ? 0.9910760598382222
left:0.0
right:1.0
right:X_7 <= 0.9974 ? 0.09849899432197895
left:X_7 <= 0.99572 ? 0.20972714405924964
left:X_6 <= 44.0
? 0.5297257989969673
left:1.0
right:X_0 <= 9.0 ?
0.8112781244591328
left:0.0

```

```

right:1.0
0.38 ? 0.27621156854915635
0.4040097573248599
left:X_9 <= 0.78 ? 0.8112781244591328
left:1.0
right:0.0
right:1.0
right:0.0
right:X_4 <= 0.075 ? 0.2651749506101608
left:X_2 <= 0.47
? 0.5216406363433185
left:1.0
right:X_2 <= 0.49 ?
0.8112781244591328
left:0.0
right:1.0
right:1.0
right:X_10 <= 11.4 ? 0.10523421790669629
left:X_2 <= 0.16 ? 0.13666642690501452
left:X_0 <= 6.3 ? 0.23193334876682492
left:0.0
right:X_2 <=
0.06 ? 0.3435794213678428
left:0.0
right:X_10 <= 10.8 ?
0.5487949406953987
left:1.0
right:X_0 <= 6.4 ? 0.8112781244591328
left:1.0
right:0.0
right:0.0
right:X_3 <= 3.1 ? 0.31127812445913283
left:X_4 <= 0.062 ? 0.45810589515712374
left:1.0
right:X_2 <=
0.56 ? 0.3059584928680418
left:0.0
right:X_0 <= 9.9 ? 1.0
left:1.0
right:0.0
right:1.0
right:X_5 <= 18.0 ? 0.13723548885905645
left:X_7 <= 0.99468 ? 0.13755617370705508
left:1.0
right:X_7 <= 0.9948 ? 0.15375242402031997
left:0.0

```

```

right:X_7 <= 0.9962 ? 0.14157309748501146
left:X_4 <= 0.11
? 0.3095434291503252
left:1.0
right:0.0
right:X_3 <= 2.2
? 0.3814444125401065
left:0.0
right:X_5 <= 7.0 ?
0.3178113757536235
left:X_2 <= 0.5 ? 0.4591479170272448
left:0.0
right:X_4 <= 0.088 ? 0.8112781244591328
left:0.0
right:1.0
right:1.0
right:X_1 <= 0.57 ? 0.10958835569188075
left:X_5 <= 27.0 ? 0.16402047076084547
left:X_6 <= 50.0 ? 0.40590730096336636
left:X_0 <= 7.3
? 0.9709505944546686
left:1.0
right:0.0
right:0.0
right:X_5 <= 45.0 ? 0.19350684337293445
left:X_1 <= 0.42
? 0.31976006206417584
left:X_1 <= 0.33 ? 1.0
left:1.0
right:0.0
right:1.0
right:0.0
right:0.0

```

### 2.2.3 Predicting and Performance metrics of the model

```

[46]: y_pred = myClassifier_entropy.predict(x_test)
print("Accuracy = ", round(accuracy_score(y_test, y_pred)*100, 2), "%")
print("Precision = ", precision_score(y_test, y_pred))
print("Recall = ", recall_score(y_test, y_pred), "\n")

print(classification_report(y_pred, y_test))

cm = metrics.confusion_matrix(y_test, y_pred)
print("\nconfusion matrix: \n", cm)
plt.figure(figsize = (10, 7))
sns.heatmap(cm, annot=True)

```

```
print("-----")
```

```
Accuracy = 90.25 %  
Precision = 0.5434782608695652  
Recall = 0.5813953488372093
```

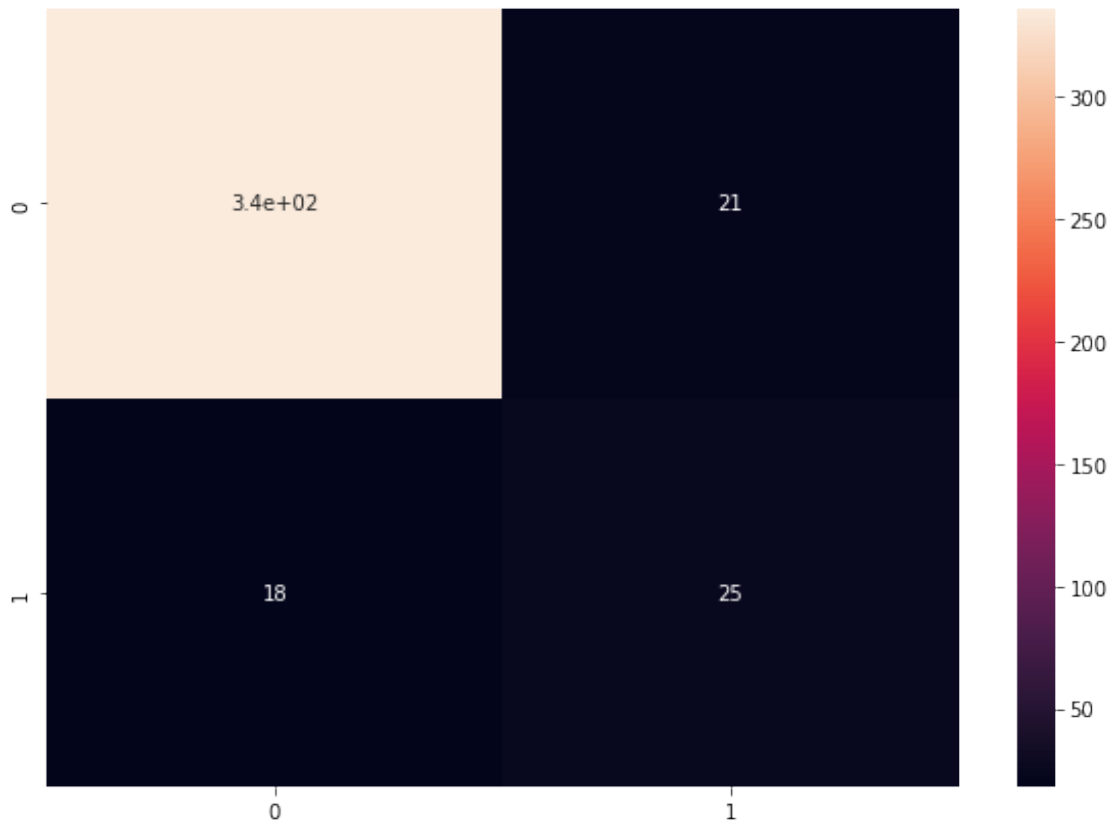
	precision	recall	f1-score	support
0.0	0.94	0.95	0.95	354
1.0	0.58	0.54	0.56	46
accuracy			0.90	400
macro avg	0.76	0.75	0.75	400
weighted avg	0.90	0.90	0.90	400

```
confusion matrix:
```

```
[[336  21]
```

```
 [ 18  25]]
```

```
-----
```



## 2.2.4 TRAINING MODEL USING DECISION TREE IMPLEMENTED FROM SCRATCH

### 2.2.5 USING GINI INDEX

```
[47]: myClassifier_gini = MyDecisionTreeClassifier(criterion="gini", max_depth=50)
myClassifier_gini.fit(x_train, y_train)
myClassifier_gini.print_tree()
```

```
X_10 <= 11.5 ? 0.03625483343863817
  left:X_1 <= 0.4 ? 0.013073495960650688
    left:X_10 <= 10.4 ? 0.03624076396118492
      left:X_9 <= 1.06 ? 0.015289095986072615
        left:X_4 <= 0.075 ? 0.015524624715379298
          left:X_0 <= 11.6 ? 0.08908202314537333
            left:X_3 <= 1.4 ? 0.04684972395295184
              left:X_0 <= 6.4
                ? 0.11111111111111111
                  left:1.0
                  right:X_0 <= 8.7 ? 0.5
                    left:0.0
                    right:1.0
                      right:X_1 <=
                        0.39 ? 0.04585610541289219
                          left:X_9 <= 0.82 ?
                            0.009307833632158063
                              left:X_2 <= 0.28 ? 0.004224058769513185
                                left:X_0 <= 7.9 ? 0.17999999999999994
                                  left:0.0
                                  right:1.0
                                    right:0.0
                                    right:X_4 <= 0.067 ? 0.375
                                      left:0.0
                                      right:1.0
                                        right:1.0
                                        right:X_2 <= 0.72 ? 0.31999999999999984
                                          left:1.0
                                          right:0.0
                                            right:X_3 <= 2.4 ? 0.0007687057248696658
                                              left:0.0
                                              right:X_2 <= 0.31 ? 0.03969754253308119
                                                left:X_0 <= 6.9
                                                  ? 0.5
                                                    left:0.0
                                                    right:1.0
                                                      right:0.0
                                                        right:X_10 <= 9.5 ? 0.5
                                                          left:0.0
```

```

        right:1.0
right:X_9 <= 0.75 ? 0.050909762825298244
    left:X_8 <= 3.28 ? 0.04692462962257682
        left:X_2 <= 0.39 ? 0.09095533865720212
            left:X_7 <= 0.99552 ? 0.3111111111111111
                left:1.0
                right:X_3 <= 2.2
? 0.31999999999999984
            left:0.0
            right:1.0
        right:X_0 <= 10.4 ? 0.08664146187775673
            left:0.0
            right:X_7 <=
0.9972 ? 0.2268518518518518
            left:1.0
            right:X_2 <= 0.65 ?
0.19753086419753085
    left:0.0
    right:X_0 <= 11.9 ? 0.4444444444444444
        left:0.0
        right:1.0
    right:X_6 <= 10.0 ? 0.05619146722164431
        left:X_1 <= 0.31 ? 0.5
            left:1.0
            right:0.0
                right:0.0
    right:X_7 <= 0.9974 ? 0.06347146701817968
        left:X_7 <= 0.99572 ? 0.1371485657199944
            left:X_6 <= 44.0 ? 0.2396449704142011
                left:1.0
                right:X_0 <= 9.0
? 0.375
            left:0.0
            right:1.0
        right:X_8 <= 3.38 ? 0.12144168962350785
            left:X_3 <= 1.6
? 0.12345679012345678
            left:X_0 <= 8.0 ?
0.4444444444444444
    left:0.0
    right:1.0
        right:0.0
            right:X_0 <= 6.1
? 0.375
            left:0.0
            right:1.0
        right:X_6 <= 21.0 ? 0.10596955128205143
            left:X_0 <= 10.6 ? 0.4444444444444444

```

```

left:0.0
right:1.0
right:X_7 <= 1.0002 ? 0.14201183431952646
left:1.0
right:0.0
right:X_10 <= 11.4 ? 0.003314260580281378
left:X_10 <= 9.8 ? 0.0011420669860130253
left:X_5 <= 12.0 ? 0.00017046813296177701
left:X_5 <= 8.0 ? 0.0008583773774161821
left:0.0
right:X_6 <= 18.0 ? 0.0073973429951689346
left:X_3 <= 1.9
? 0.4444444444444444
left:0.0
right:1.0
right:X_1 <=
0.52 ? 0.004116782188615824
left:X_1 <= 0.49 ?
0.029999999999999916
left:0.0
right:X_4 <= 0.071 ? 0.20833333333333334
left:0.0
right:X_2 <= 0.09 ? 0.4444444444444444
left:0.0
right:1.0
right:0.0
right:0.0
right:X_3 <= 5.6 ? 0.002981655912649414
left:X_9 <= 0.63 ? 0.0025556105893931313
left:X_2 <= 0.01 ? 0.0017302179614422375
left:X_1 <= 0.58
? 0.05753968253968264
left:X_2 <= 0.0 ?
0.48979591836734704
left:0.0
right:1.0
right:0.0
right:X_8 <=
3.51 ? 0.0006228373702421124
left:0.0
right:X_7 <= 0.99648 ?
0.05190311418685113
left:0.0
right:X_0 <= 7.0 ? 0.5
left:1.0
right:0.0
right:X_5 <= 3.0 ? 0.011772905933159467
left:1.0

```

```

right:X_3 <= 1.5
? 0.010096038415366354
left:X_2 <= 0.43 ? 0.5
left:0.0
right:1.0
right:X_9 <= 0.71 ?
0.005737763813556396
left:X_10 <= 10.0 ? 0.025417106623011776
left:X_1 <= 0.48 ? 0.5
left:1.0
right:0.0
right:X_4 <= 0.118 ? 0.03122447464171685
left:X_8 <= 3.57
? 0.015176005747126589
left:X_3 <= 1.7 ?
0.015479021572957177
left:X_0 <= 7.0 ? 0.5
left:1.0
right:0.0
right:X_3 <= 5.1 ? 0.011267006802721108
left:0.0
right:X_0 <= 7.1 ? 0.4444444444444444
left:0.0
right:1.0
right:X_9 <= 0.68 ?
0.4444444444444444
left:0.0
right:1.0
right:X_1 <=
0.53 ? 0.4444444444444444
left:0.0
right:1.0
right:X_2 <= 0.09 ? 0.0017636684303352149
left:X_0 <= 8.1 ? 0.13265306122448983
left:0.0
right:1.0
right:0.0
right:X_3 <= 6.0 ? 0.2603305785123967
left:X_1 <= 0.45 ? 0.375
left:0.0
right:1.0
right:0.0
right:X_2 <= 0.29 ? 0.15052083333333338
left:X_4 <= 0.088 ? 0.07999999999999993
left:0.0
right:X_0 <= 6.5 ? 0.5
left:0.0
right:1.0

```



```

right:X_0 <= 9.8 ? 0.2222222222222222
    left:1.0
    right:X_1 <= 0.5 ? 0.4444444444444444
        left:0.0
        right:1.0
right:X_9 <= 0.68 ? 0.08000739820667302
left:X_6 <= 15.0 ? 0.04634753181112827
    left:X_9 <= 0.58 ? 0.21566162731442162
        left:X_3 <= 1.8 ? 0.11999999999999983
            left:X_4 <= 0.063 ? 0.5
                left:0.0
                right:1.0
                    right:0.0
right:X_6 <= 8.0 ? 0.24489795918367352
    left:0.0
    right:1.0
right:X_5 <= 31.0 ? 0.07255173079087426
    left:X_8 <= 3.27 ? 0.024997095879298714
        left:X_0 <= 11.9 ? 0.10741138560687441
            left:X_0 <= 10.0 ? 0.15195884447962002
                left:X_1 <= 0.31
? 0.27551020408163274
                    left:1.0
                    right:X_0 <= 9.4 ? 0.375
                        left:0.0
                        right:1.0
                            right:0.0
                                right:1.0
right:X_6 <= 99.0 ? 0.016759854529209375
    left:X_4 <= 0.086 ? 0.012302960399846262
        left:0.0
        right:X_0 <= 5.4
? 0.4444444444444444
            left:1.0
            right:0.0
                right:X_0 <= 4.7 ? 0.5
                    left:0.0
                    right:1.0
                        right:X_1 <= 0.21 ? 0.375
                            left:0.0
                            right:1.0
right:X_5 <= 18.0 ? 0.07739488813292295
    left:X_7 <= 0.99468 ? 0.043660719823041705
        left:1.0
        right:X_7 <= 0.9948 ? 0.10955198647506342
            left:0.0
            right:X_5 <= 5.0 ? 0.07213358070500941
                left:0.0

```

```

right:X_4 <= 0.128 ? 0.041838842975206514
left:X_7 <=
0.9962 ? 0.055338541666666685
left:1.0
right:X_3 <= 2.2 ?
0.22222222222222227
left:0.0
right:X_9 <= 0.86 ? 0.166666666666666657
left:1.0
right:X_5 <= 7.0 ? 0.44444444444444444
left:0.0
right:1.0
right:0.0
right:X_5 <= 27.0 ? 0.08498959417273677
left:X_6 <= 50.0 ? 0.1171875
left:X_4 <= 0.068 ? 0.5
left:1.0
right:0.0
right:0.0
right:X_1 <= 0.58 ? 0.17999999999999994
left:X_5 <= 38.0 ? 0.11574074074074076
left:X_1 <= 0.42 ? 0.08641975308641975
left:X_0 <= 8.2
? 0.5
left:1.0
right:0.0
right:1.0
right:X_0 <= 8.2 ? 0.44444444444444444
left:0.0
right:1.0
right:0.0

```

## 2.2.6 Predicting and Performance metrics of the model

```

[48]: y_pred = myClassifier_gini.predict(x_test)
print("Accuracy = ", round(accuracy_score(y_test, y_pred)*100, 2), "%")
print("Precision = ", precision_score(y_test, y_pred))
print("Recall = ", recall_score(y_test, y_pred), "\n")

print(classification_report(y_pred, y_test))

cm=metrics.confusion_matrix(y_test, y_pred)
print("\nconfusion matrix: \n", cm)
plt.figure(figsize = (10,7))
sns.heatmap(cm, annot=True)
print("-----")

```

Accuracy = 90.25 %

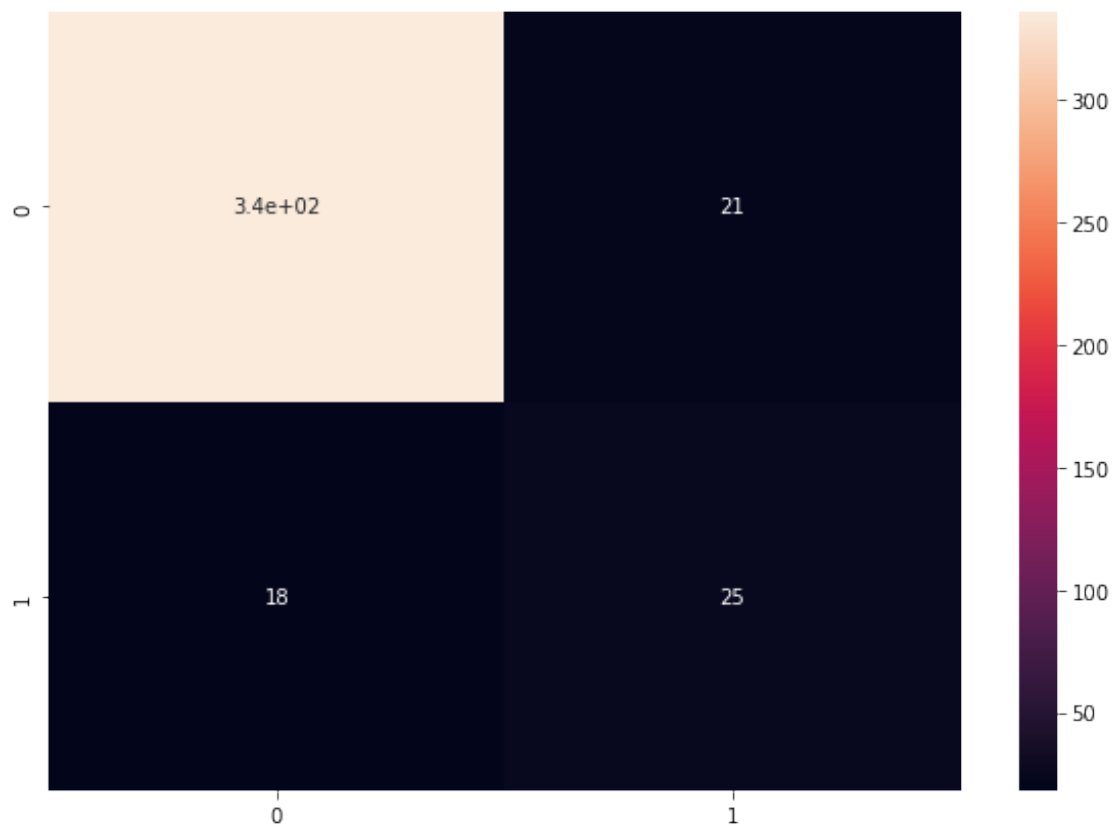
Precision = 0.5434782608695652  
Recall = 0.5813953488372093

	precision	recall	f1-score	support
0.0	0.94	0.95	0.95	354
1.0	0.58	0.54	0.56	46
accuracy			0.90	400
macro avg	0.76	0.75	0.75	400
weighted avg	0.90	0.90	0.90	400

confusion matrix:

```
[[336  21]
 [ 18  25]]
```

---



## 2.3 B) DECISION TREE from SKLEARN library ( Inbuilt modules )

### 2.4 3. TRAIN THE MODEL

#### 2.4.1 Entropy

```
[66]: x = df.drop(['quality'], axis=1)
      y = df['quality']
```

```
[61]: #splitting the processed dataset into train and test dataset

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.25,
↳random_state = 50)
```

```
[62]: builtInClassifier_entropy =
↳DecisionTreeClassifier(criterion="entropy",max_depth=50)
builtInClassifier_entropy.fit(x_train, y_train)
preds = builtInClassifier_entropy.predict(x_test)
```

#### 2.4.2 Predicting and Performance metrics of the model

```
[63]: y_pred = builtInClassifier_entropy.predict(x_test)
print("Accuracy = ", round(accuracy_score(y_test, y_pred)*100, 2), "%")
print("Precision = ",precision_score(y_test, y_pred))
print("Recall = ",recall_score(y_test, y_pred),"\n")

print(classification_report(y_pred,y_test))

cm=metrics.confusion_matrix(y_test,y_pred)
print("\nconfusion matrix: \n",cm)
print("-----")
```

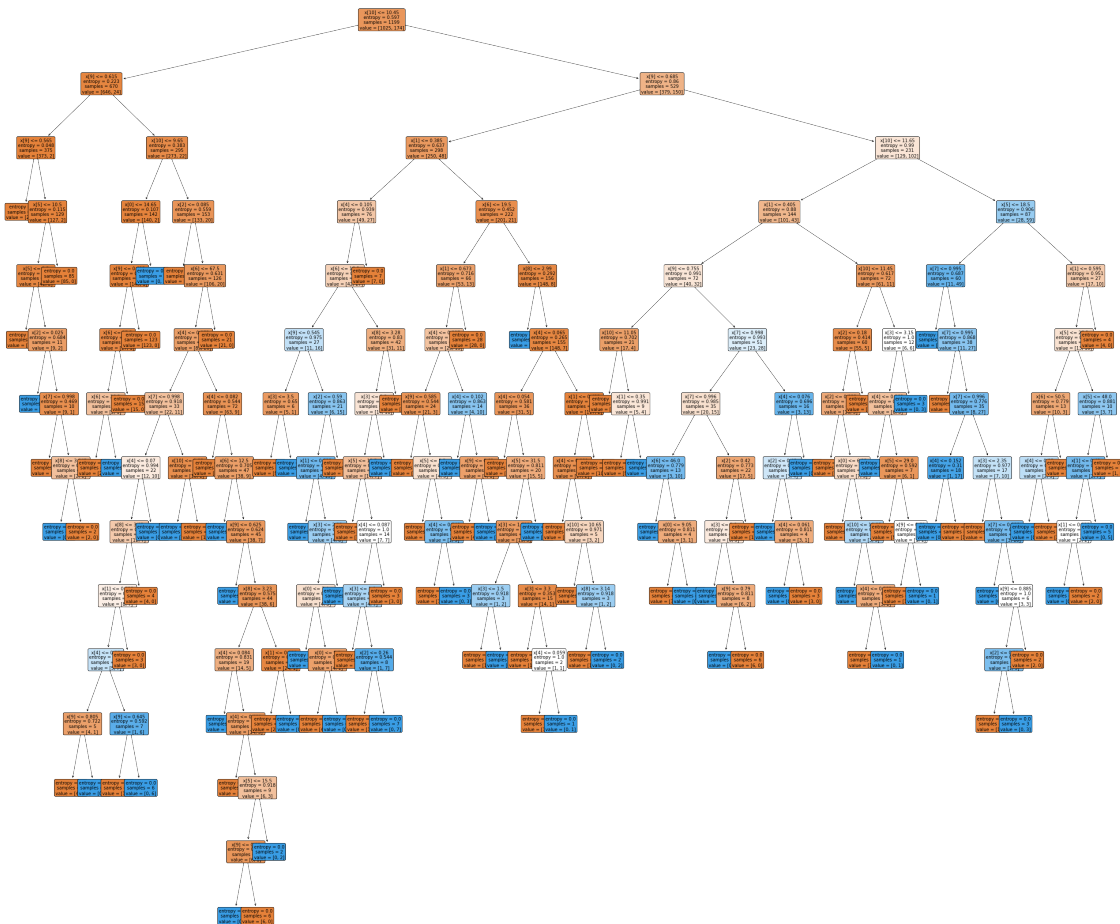
```
Accuracy = 93.25 %
Precision = 0.6904761904761905
Recall = 0.6744186046511628
```

	precision	recall	f1-score	support
0	0.96	0.96	0.96	358
1	0.67	0.69	0.68	42
accuracy			0.93	400
macro avg	0.82	0.83	0.82	400
weighted avg	0.93	0.93	0.93	400

```
confusion matrix:
[[344 13]
```

```
[ 14 29]]
```

```
[64]: fig = plt.figure(figsize=(45,40))
tree.plot_tree(builtInClassifier_entropy, filled=True, rounded=True,
↳ fontsize=10)
plt.show()
```



```
[67]: print(tree.export_text(builtInClassifier_entropy, feature_names = x.columns.
↳ tolist()))
```

```
|--- alcohol <= 10.45
|   |--- sulphates <= 0.62
|   |   |--- sulphates <= 0.56
|   |   |   |--- class: 0
|   |   |   |--- sulphates > 0.56
|   |   |       |--- free sulfur dioxide <= 10.50
|   |   |       |--- free sulfur dioxide <= 8.50
```

```
| | | | |--- class: 0
| | | | |--- free sulfur dioxide > 8.50
| | | | |--- citric acid <= 0.02
| | | | |--- class: 1
| | | | |--- citric acid > 0.02
| | | | |--- density <= 1.00
| | | | |--- class: 0
| | | | |--- density > 1.00
| | | | |--- pH <= 3.25
| | | | |--- class: 1
| | | | |--- pH > 3.25
| | | | |--- class: 0
| | | |--- free sulfur dioxide > 10.50
| | | |--- class: 0
|--- sulphates > 0.62
| |--- alcohol <= 9.65
| | |--- fixed acidity <= 14.65
| | | |--- sulphates <= 0.62
| | | |--- total sulfur dioxide <= 37.50
| | | |--- total sulfur dioxide <= 26.50
| | | |--- class: 0
| | | |--- total sulfur dioxide > 26.50
| | | |--- class: 1
| | | |--- total sulfur dioxide > 37.50
| | | |--- class: 0
| | | |--- sulphates > 0.62
| | | |--- class: 0
| | | |--- fixed acidity > 14.65
| | | |--- class: 1
| |--- alcohol > 9.65
| | |--- citric acid <= 0.09
| | | |--- class: 0
| | |--- citric acid > 0.09
| | | |--- total sulfur dioxide <= 67.50
| | | |--- chlorides <= 0.07
| | | |--- density <= 1.00
| | | |--- chlorides <= 0.07
| | | |--- pH <= 3.43
| | | |--- volatile acidity <= 0.53
| | | |--- chlorides <= 0.06
| | | |--- truncated branch of depth 2
| | | |--- chlorides > 0.06
| | | |--- truncated branch of depth 2
| | | |--- volatile acidity > 0.53
| | | |--- class: 0
| | | |--- pH > 3.43
| | | |--- class: 0
| | | |--- chlorides > 0.07
```



```
| | | | | | | | | | | | |--- class: 0  
| | | | | | | | | | | | |--- fixed acidity > 9.80  
| | | | | | | | | | | | |--- class: 1  
| | | | | | | | | | | | |--- residual sugar > 2.35  
| | | | | | | | | | | | |--- class: 1  
| | | | | | | | | | | | |--- citric acid > 0.59  
| | | | | | | | | | | | |--- class: 0  
| | | | | | | |--- total sulfur dioxide > 17.50  
| | | | | | | |--- pH ≤ 3.28  
| | | | | | | |--- residual sugar ≤ 3.30  
| | | | | | | |--- free sulfur dioxide ≤ 12.50  
| | | | | | | |--- class: 0  
| | | | | | | |--- free sulfur dioxide > 12.50  
| | | | | | | |--- chlorides ≤ 0.09  
| | | | | | | |--- residual sugar ≤ 1.60  
| | | | | | | |--- class: 0  
| | | | | | | |--- residual sugar > 1.60  
| | | | | | | |--- citric acid ≤ 0.26  
| | | | | | | |--- class: 0  
| | | | | | | |--- citric acid > 0.26  
| | | | | | | |--- class: 1  
| | | | | | | |--- chlorides > 0.09  
| | | | | | | |--- class: 0  
| | | | | | | |--- residual sugar > 3.30  
| | | | | | | |--- class: 1  
| | | | | | | |--- pH > 3.28  
| | | | | | | |--- class: 0  
| | | | | | | |--- chlorides > 0.11  
| | | | | | | |--- class: 0  
| | | |--- volatile acidity > 0.38  
| | | |--- total sulfur dioxide ≤ 19.50  
| | | |--- volatile acidity ≤ 0.67  
| | | |--- chlorides ≤ 0.09  
| | | |--- sulphates ≤ 0.58  
| | | |--- class: 0  
| | | |--- sulphates > 0.58  
| | | |--- free sulfur dioxide ≤ 5.50  
| | | |--- class: 0  
| | | |--- free sulfur dioxide > 5.50  
| | | |--- chlorides ≤ 0.05  
| | | |--- class: 0  
| | | |--- chlorides > 0.05  
| | | |--- class: 1  
| | | |--- chlorides > 0.09  
| | | |--- chlorides ≤ 0.10  
| | | |--- class: 1  
| | | |--- chlorides > 0.10  
| | | |--- sulphates ≤ 0.62
```



```

| | | | | | | | | |--- class: 0
| | | | | | | | | |--- sulphates > 0.62
| | | | | | | | | |--- class: 1
| | | | | | | | | |--- volatile acidity > 0.67
| | | | | | | | | |--- class: 0
| | | | |--- total sulfur dioxide > 19.50
| | | | |--- pH <= 2.99
| | | | |--- class: 1
| | | | |--- pH > 2.99
| | | | |--- chlorides <= 0.07
| | | | | | |--- chlorides <= 0.05
| | | | | | |--- class: 0
| | | | | | |--- chlorides > 0.05
| | | | | | |--- free sulfur dioxide <= 31.50
| | | | | | |--- residual sugar <= 1.73
| | | | | | |--- residual sugar <= 1.50
| | | | | | |--- class: 0
| | | | | | |--- residual sugar > 1.50
| | | | | | |--- class: 1
| | | | | | |--- residual sugar > 1.73
| | | | | | |--- residual sugar <= 3.30
| | | | | | |--- class: 0
| | | | | | |--- residual sugar > 3.30
| | | | | | |--- chlorides <= 0.06
| | | | | | |--- class: 0
| | | | | | |--- chlorides > 0.06
| | | | | | |--- class: 1
| | | | | | |--- free sulfur dioxide > 31.50
| | | | | | |--- class: 1
| | | | |--- chlorides > 0.07
| | | | | | |--- volatile acidity <= 0.42
| | | | | | |--- chlorides <= 0.09
| | | | | | |--- class: 0
| | | | | | |--- chlorides > 0.09
| | | | | | |--- alcohol <= 10.65
| | | | | | |--- class: 0
| | | | | | |--- alcohol > 10.65
| | | | | | |--- pH <= 3.14
| | | | | | |--- class: 0
| | | | | | |--- pH > 3.14
| | | | | | |--- class: 1
| | | | | | |--- volatile acidity > 0.42
| | | | | | |--- class: 0
| |--- sulphates > 0.69
| | |--- alcohol <= 11.65
| | |--- volatile acidity <= 0.41
| | |--- sulphates <= 0.75
| | |--- alcohol <= 11.05

```

```
| | | | |--- class: 0  
| | | | |--- alcohol > 11.05  
| | | | |--- volatile acidity <= 0.35  
| | | | |--- class: 0  
| | | | |--- volatile acidity > 0.35  
| | | | |--- class: 1  
| | | |--- sulphates > 0.75  
| | | |--- density <= 1.00  
| | | |--- density <= 1.00  
| | | |--- total sulfur dioxide <= 46.00  
| | | |--- class: 1  
| | | |--- total sulfur dioxide > 46.00  
| | | |--- fixed acidity <= 9.05  
| | | |--- class: 0  
| | | |--- fixed acidity > 9.05  
| | | |--- class: 1  
| | | |--- density > 1.00  
| | | |--- citric acid <= 0.42  
| | | |--- residual sugar <= 2.00  
| | | |--- class: 1  
| | | |--- residual sugar > 2.00  
| | | |--- sulphates <= 0.79  
| | | |--- class: 1  
| | | |--- sulphates > 0.79  
| | | |--- class: 0  
| | | |--- citric acid > 0.42  
| | | |--- class: 0  
| | | |--- density > 1.00  
| | | |--- chlorides <= 0.08  
| | | |--- citric acid <= 0.48  
| | | |--- class: 1  
| | | |--- citric acid > 0.48  
| | | |--- chlorides <= 0.06  
| | | |--- class: 1  
| | | |--- chlorides > 0.06  
| | | |--- class: 0  
| | | |--- chlorides > 0.08  
| | | |--- class: 1  
| | |--- volatile acidity > 0.41  
| | |--- alcohol <= 11.45  
| | |--- citric acid <= 0.18  
| | |--- citric acid <= 0.09  
| | |--- class: 0  
| | |--- citric acid > 0.09  
| | |--- fixed acidity <= 6.35  
| | |--- class: 0  
| | |--- fixed acidity > 6.35  
| | |--- alcohol <= 10.85
```

```
| | | | | | | | | |--- class: 1  
| | | | | | | | | |--- alcohol > 10.85  
| | | | | | | | | |--- chlorides <= 0.10  
| | | | | | | | | |--- class: 0  
| | | | | | | | | |--- chlorides > 0.10  
| | | | | | | | | |--- class: 1  
| | | | | | | | |--- citric acid > 0.18  
| | | | | | | | |--- class: 0  
| | | | | | | |--- alcohol > 11.45  
| | | | | | | |--- residual sugar <= 3.15  
| | | | | | | |--- chlorides <= 0.07  
| | | | | | | |--- class: 1  
| | | | | | | |--- chlorides > 0.07  
| | | | | | | |--- free sulfur dioxide <= 29.00  
| | | | | | | |--- class: 0  
| | | | | | | |--- free sulfur dioxide > 29.00  
| | | | | | | |--- sulphates <= 0.73  
| | | | | | | |--- class: 0  
| | | | | | | |--- sulphates > 0.73  
| | | | | | | |--- class: 1  
| | | | | | | |--- residual sugar > 3.15  
| | | | | | | |--- class: 1  
| | | | | | | |--- alcohol > 11.65  
| | | | | | | |--- free sulfur dioxide <= 18.50  
| | | | | | | |--- density <= 0.99  
| | | | | | | |--- class: 1  
| | | | | | | |--- density > 0.99  
| | | | | | | |--- density <= 0.99  
| | | | | | | |--- class: 0  
| | | | | | | |--- density > 0.99  
| | | | | | | |--- density <= 1.00  
| | | | | | | |--- chlorides <= 0.15  
| | | | | | | |--- class: 1  
| | | | | | | |--- chlorides > 0.15  
| | | | | | | |--- class: 0  
| | | | | | | |--- density > 1.00  
| | | | | | | |--- residual sugar <= 2.35  
| | | | | | | |--- class: 0  
| | | | | | | |--- residual sugar > 2.35  
| | | | | | | |--- density <= 1.00  
| | | | | | | |--- class: 1  
| | | | | | | |--- density > 1.00  
| | | | | | | |--- sulphates <= 0.88  
| | | | | | | |--- citric acid <= 0.51  
| | | | | | | |--- class: 0  
| | | | | | | |--- citric acid > 0.51  
| | | | | | | |--- class: 1  
| | | | | | | |--- sulphates > 0.88
```

```
| | | | | | |--- class: 0  
| | | |--- free sulfur dioxide > 18.50  
| | | | |--- volatile acidity <= 0.59  
| | | | | |--- free sulfur dioxide <= 27.50  
| | | | | | |--- total sulfur dioxide <= 50.50  
| | | | | | | |--- chlorides <= 0.07  
| | | | | | | |--- class: 1  
| | | | | | | |--- chlorides > 0.07  
| | | | | | | |--- class: 0  
| | | | | | |--- total sulfur dioxide > 50.50  
| | | | | | | |--- class: 0  
| | | | | | |--- free sulfur dioxide > 27.50  
| | | | | | |--- free sulfur dioxide <= 48.00  
| | | | | | | |--- volatile acidity <= 0.43  
| | | | | | | |--- volatile acidity <= 0.34  
| | | | | | | |--- class: 1  
| | | | | | | |--- volatile acidity > 0.34  
| | | | | | | |--- class: 0  
| | | | | | |--- volatile acidity > 0.43  
| | | | | | | |--- class: 1  
| | | | | | |--- free sulfur dioxide > 48.00  
| | | | | | | |--- class: 0  
| | | | |--- volatile acidity > 0.59  
| | | | |--- class: 0
```

### 2.4.3 DECISION TREE from SKLEARN library ( Inbuilt modules )

#### 2.4.4 GINI INDEX

```
[68]: builtInClassifier_gini = DecisionTreeClassifier(criterion="gini",max_depth=50)
builtInClassifier_gini.fit(x_train, y_train)
preds = builtInClassifier_gini.predict(x_test)
score = builtInClassifier_gini.score(x_test, y_test)
score
```

[68]: 0.9175

#### 2.4.5 Predicting and Performance metrics of the model

```
[69]: y_pred = builtInClassifier_gini.predict(x_test)
print("Accuracy = ", round(accuracy_score(y_test, y_pred)*100, 2), "%")
print("Precision = ", precision_score(y_test, y_pred))
print("Recall = ", recall_score(y_test, y_pred), "\n")

print(classification_report(y_pred, y_test))

cm=metrics.confusion_matrix(y_test, y_pred)
```

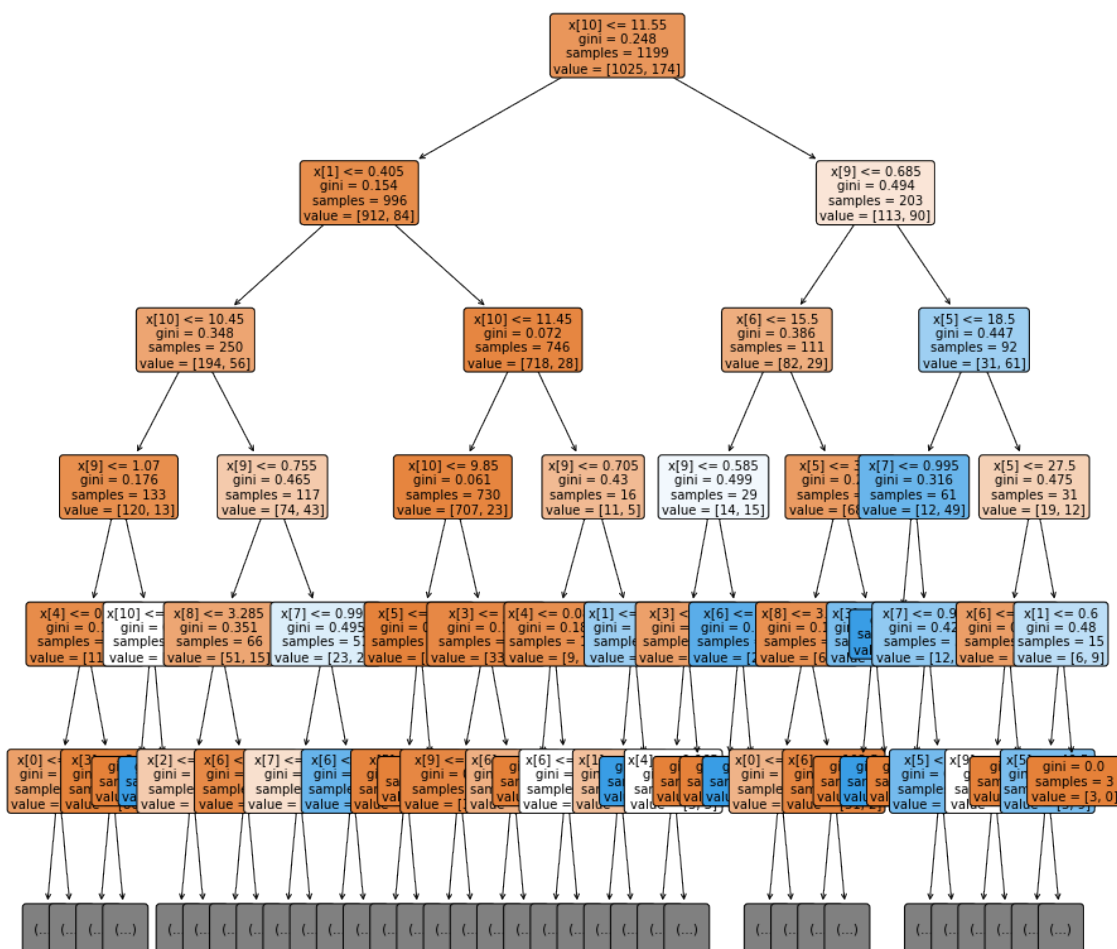
```
print("\nconfusion matrix: \n",cm)
print("-----")
```

```
Accuracy = 91.75 %
Precision = 0.6190476190476191
Recall = 0.6046511627906976
```

	precision	recall	f1-score	support
0	0.96	0.95	0.95	358
1	0.60	0.62	0.61	42
accuracy			0.92	400
macro avg	0.78	0.79	0.78	400
weighted avg	0.92	0.92	0.92	400

```
confusion matrix:
[[341  16]
 [ 17  26]]
-----
```

```
[70]: fig = plt.figure(figsize=(15,15))
tree.plot_tree(builtInClassifier_gini, filled=True, rounded=True, max_depth=5,
↳fontsize=10)
plt.show()
```



```
[71]: print(tree.export_text(builtInClassifier_gini, feature_names = x.columns.
    ↪tolist()))
```

```
|--- alcohol <= 11.55
|   |--- volatile acidity <= 0.41
|   |   |--- alcohol <= 10.45
|   |   |   |--- sulphates <= 1.07
|   |   |   |   |--- chlorides <= 0.08
|   |   |   |   |   |--- fixed acidity <= 11.70
|   |   |   |   |   |   |--- residual sugar <= 1.45
|   |   |   |   |   |   |   |--- density <= 1.00
|   |   |   |   |   |   |   |   |--- class: 1
|   |   |   |   |   |   |   |   |--- density > 1.00
|   |   |   |   |   |   |   |   |--- fixed acidity <= 9.15
|   |   |   |   |   |   |   |   |--- class: 0
```



[illegible]



```

| | | | | | | | |--- class: 1
| | | | |--- density > 1.00
| | | | |--- total sulfur dioxide <= 21.50
| | | | |--- pH <= 3.28
| | | | |--- class: 0
| | | | |--- pH > 3.28
| | | | |--- class: 1
| | | | |--- total sulfur dioxide > 21.50
| | | | |--- density <= 1.00
| | | | |--- class: 1
| | | | |--- density > 1.00
| | | | |--- class: 0
| |--- volatile acidity > 0.41
| | |--- alcohol <= 11.45
| | | |--- alcohol <= 9.85
| | | |--- free sulfur dioxide <= 12.50
| | | |--- free sulfur dioxide <= 8.50
| | | |--- class: 0
| | | |--- free sulfur dioxide > 8.50
| | | |--- total sulfur dioxide <= 18.50
| | | |--- sulphates <= 0.61
| | | |--- class: 1
| | | |--- sulphates > 0.61
| | | |--- class: 0
| | | |--- total sulfur dioxide > 18.50
| | | |--- volatile acidity <= 0.52
| | | |--- volatile acidity <= 0.50
| | | |--- class: 0
| | | |--- volatile acidity > 0.50
| | | |--- chlorides <= 0.08
| | | |--- class: 0
| | | |--- chlorides > 0.08
| | | |--- citric acid <= 0.12
| | | |--- class: 0
| | | |--- citric acid > 0.12
| | | |--- class: 1
| | | |--- volatile acidity > 0.52
| | | |--- class: 0
| | | |--- free sulfur dioxide > 12.50
| | | |--- class: 0
| | | |--- alcohol > 9.85
| | | |--- residual sugar <= 5.70
| | | |--- sulphates <= 0.63
| | | |--- citric acid <= 0.01
| | | |--- volatile acidity <= 0.58
| | | |--- citric acid <= 0.00
| | | |--- class: 0
| | | |--- citric acid > 0.00

```

[illegible]

[illegible]



```
| | | | | | |--- total sulfur dioxide > 39.50  
| | | | | | |--- class: 0  
| | |--- free sulfur dioxide > 18.50  
| | | |--- free sulfur dioxide <= 27.50  
| | | | |--- total sulfur dioxide <= 50.50  
| | | | | |--- sulphates <= 0.77  
| | | | | | |--- class: 1  
| | | | | | |--- sulphates > 0.77  
| | | | | | |--- class: 0  
| | | | |--- total sulfur dioxide > 50.50  
| | | | |--- class: 0  
| | | |--- free sulfur dioxide > 27.50  
| | | | |--- volatile acidity <= 0.60  
| | | | | |--- free sulfur dioxide <= 40.50  
| | | | | | |--- volatile acidity <= 0.43  
| | | | | | | |--- volatile acidity <= 0.38  
| | | | | | | | |--- class: 1  
| | | | | | | | |--- volatile acidity > 0.38  
| | | | | | | | |--- class: 0  
| | | | | | |--- volatile acidity > 0.43  
| | | | | | | |--- class: 1  
| | | | | | |--- free sulfur dioxide > 40.50  
| | | | | | |--- density <= 0.99  
| | | | | | |--- class: 0  
| | | | | | |--- density > 0.99  
| | | | | | |--- class: 1  
| | | | |--- volatile acidity > 0.60  
| | | | |--- class: 0
```

### 2.4.6 Checking the best suited depth of decision tree for the dataset ( this time inbuilt module is used !!)

```
[74]: Ks = 100
mean_acc = np.zeros((Ks-1))
for n in range(1,Ks):

    #Train Model and Predict
    builtInClassifier = DecisionTreeClassifier(max_depth = n).
    fit(x_train,y_train)
    yhat=builtInClassifier.predict(x_test)
    mean_acc[n-1] = metrics.accuracy_score(y_test, yhat)

print(mean_acc)
```

0.8925	0.9075	0.9125	0.905	0.915	0.9175	0.9075	0.9125	0.9125	0.9025
0.8925	0.9025	0.8925	0.915	0.915	0.9025	0.9025	0.8975	0.905	0.9
0.9025	0.9	0.9	0.905	0.9075	0.895	0.9	0.91	0.9	0.9125

```

0.89    0.9025 0.9075 0.9    0.91    0.915    0.9025 0.905    0.9125 0.8975
0.9125 0.91    0.9    0.91    0.915    0.9    0.9125 0.9025 0.9075 0.9125
0.9075 0.915    0.895    0.905    0.915    0.9075 0.905    0.905    0.9075 0.9
0.9125 0.9075 0.9025 0.915    0.9075 0.905    0.8975 0.9075 0.9075 0.9025
0.9125 0.8975 0.9    0.9075 0.895    0.9025 0.905    0.92    0.9075 0.91
0.9    0.905    0.8975 0.91    0.895    0.9025 0.91    0.9    0.9125 0.9125
0.9    0.9025 0.905    0.9025 0.905    0.9025 0.9025 0.905    0.905    ]

```

```

[75]: print( "The best accuracy was with", mean_acc.max(), "with depth =", mean_acc.
      ↪ argmax()+1)

```

The best accuracy was with 0.92 with depth = 78

The best accuracy was with 0.9225 with depth = 6

## 2.5 4. EVALUATE THE PERFORMANCE OF THE ALGORITHMS:

### 2.6 COMPARISON OF PERFORMANCE OF BOTH IMPLEMENTATION:

#### 2.6.1 (i) DECISION TREE from scratch:

##### Entropy:

1. Accuracy = 90.25 %
2. Precision = 0.5434782608695652
3. Recall = 0.5813953488372093

##### Gini:

1. Accuracy = 90.25 %
2. Precision = 0.5434782608695652
3. Recall = 0.5813953488372093

#### 2.6.2 (ii) DECISION TREE using SKlearn module:

##### Entropy:

1. Accuracy = 91.5 %
2. Precision = 0.6097560975609756
3. Recall = 0.5813953488372093

##### Gini:

1. Accuracy = 90.25 %
2. Precision = 0.5434782608695652
3. Recall = 0.5813953488372093

```
[ ]:
```

```
[ ]:
```