```python
# Library import

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
sns.set()
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")

#Loading dataset
df = pd.read_csv('Obesity Classification.csv')
df.head()
```

	ID	Age	Gender	Height	Weight	BMI	Label
0	1	25	Male	175	80	25.3	Normal Weight
1	2	30	Female	160	60	22.5	Normal Weight
2	3	35	Male	180	90	27.3	Overweight
3	4	40	Female	150	50	20.0	Underweight
4	5	45	Male	190	100	31.2	Obese

```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 108 entries, 0 to 107
Data columns (total 7 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   ID      108 non-null    int64
 1   Age     108 non-null    int64
 2   Gender  108 non-null    object
 3   Height  108 non-null    int64
 4   Weight  108 non-null    int64
 5   BMI     108 non-null    float64
 6   Label   108 non-null    object
dtypes: float64(1), int64(4), object(2)
memory usage: 6.0+ KB
```

```python
# drop first column

#df = df.drop(['ID'], axis =1)

df.describe()
```

	ID	Age	Height	Weight	BMI
count	108.000000	108.000000	108.000000	108.000000	108.000000
mean	56.046296	46.555556	166.574074	59.490741	20.549074
std	31.917939	24.720620	27.873615	28.856233	7.583818
min	1.000000	11.000000	120.000000	10.000000	3.900000
25%	28.750000	27.000000	140.000000	35.000000	16.700000

```
50%     56.500000   42.500000  175.000000   55.000000   21.200000
75%     83.250000   59.250000  190.000000   85.000000   26.100000
max    110.000000  112.000000  210.000000  120.000000   37.200000
```

Data preprocessing

```
df.isnull().sum()
```

```
ID        0
Age       0
Gender    0
Height    0
Weight    0
BMI       0
Label     0
dtype: int64
```

```
df.shape
```

```
(108, 7)
```

```
# converting cat. variable('Gender') to num. variable
df['Gender'] = df['Gender'].astype('category')
df['Gender'] = df['Gender'].cat.codes
df.head()
```

	ID	Age	Gender	Height	Weight	BMI	Label
0	1	25	1	175	80	25.3	Normal Weight
1	2	30	0	160	60	22.5	Normal Weight
2	3	35	1	180	90	27.3	Overweight
3	4	40	0	150	50	20.0	Underweight
4	5	45	1	190	100	31.2	Obese

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 108 entries, 0 to 107
Data columns (total 7 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   ID      108 non-null    int64  
 1   Age     108 non-null    int64  
 2   Gender  108 non-null    int8   
 3   Height  108 non-null    int64  
 4   Weight  108 non-null    int64  
 5   BMI     108 non-null    float64
 6   Label   108 non-null    object 
dtypes: float64(1), int64(4), int8(1), object(1)
memory usage: 5.3+ KB
```

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

```
Label
Underweight      47
Normal Weight    29
Overweight       20
Obese            12
Name: count, dtype: int64
```

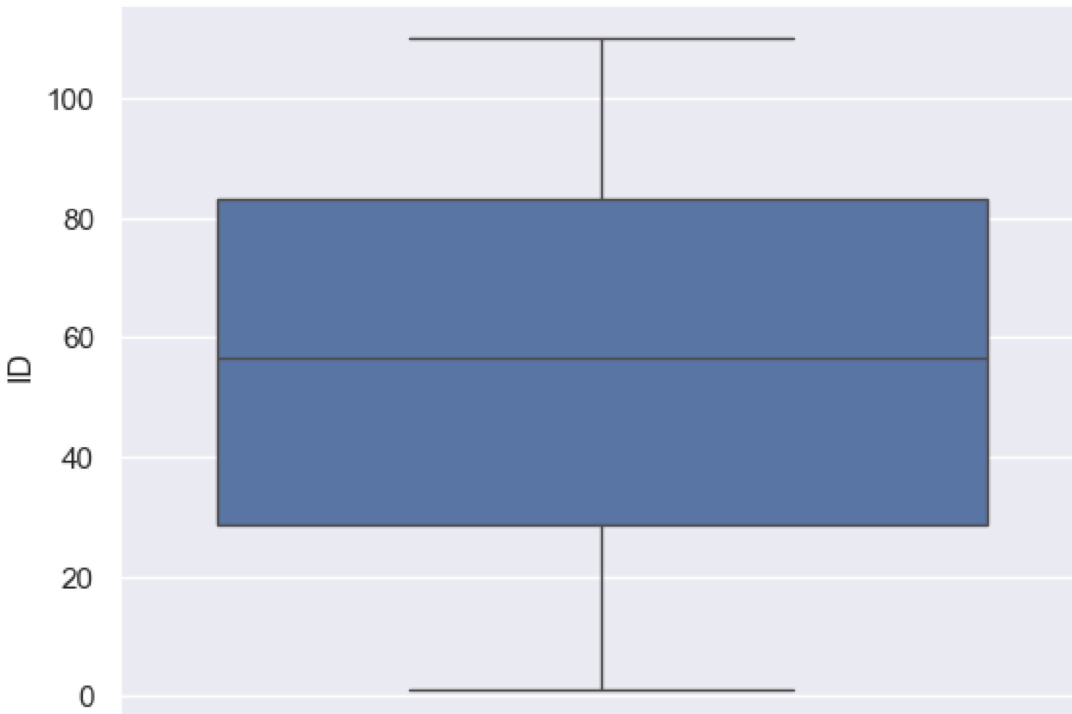
```python
# using Label encoder to encode the dependent variable('Label')

from sklearn.preprocessing import LabelEncoder
encoder = LabelEncoder()
df['Label'] = encoder.fit_transform(df['Label'])

df.head()
```

```
   ID  Age  Gender  Height  Weight   BMI  Label
0   1   25       1     175      80  25.3      0
1   2   30       0     160      60  22.5      0
2   3   35       1     180      90  27.3      2
3   4   40       0     150      50  20.0      3
4   5   45       1     190     100  31.2      1
```

```python
df.describe()
```

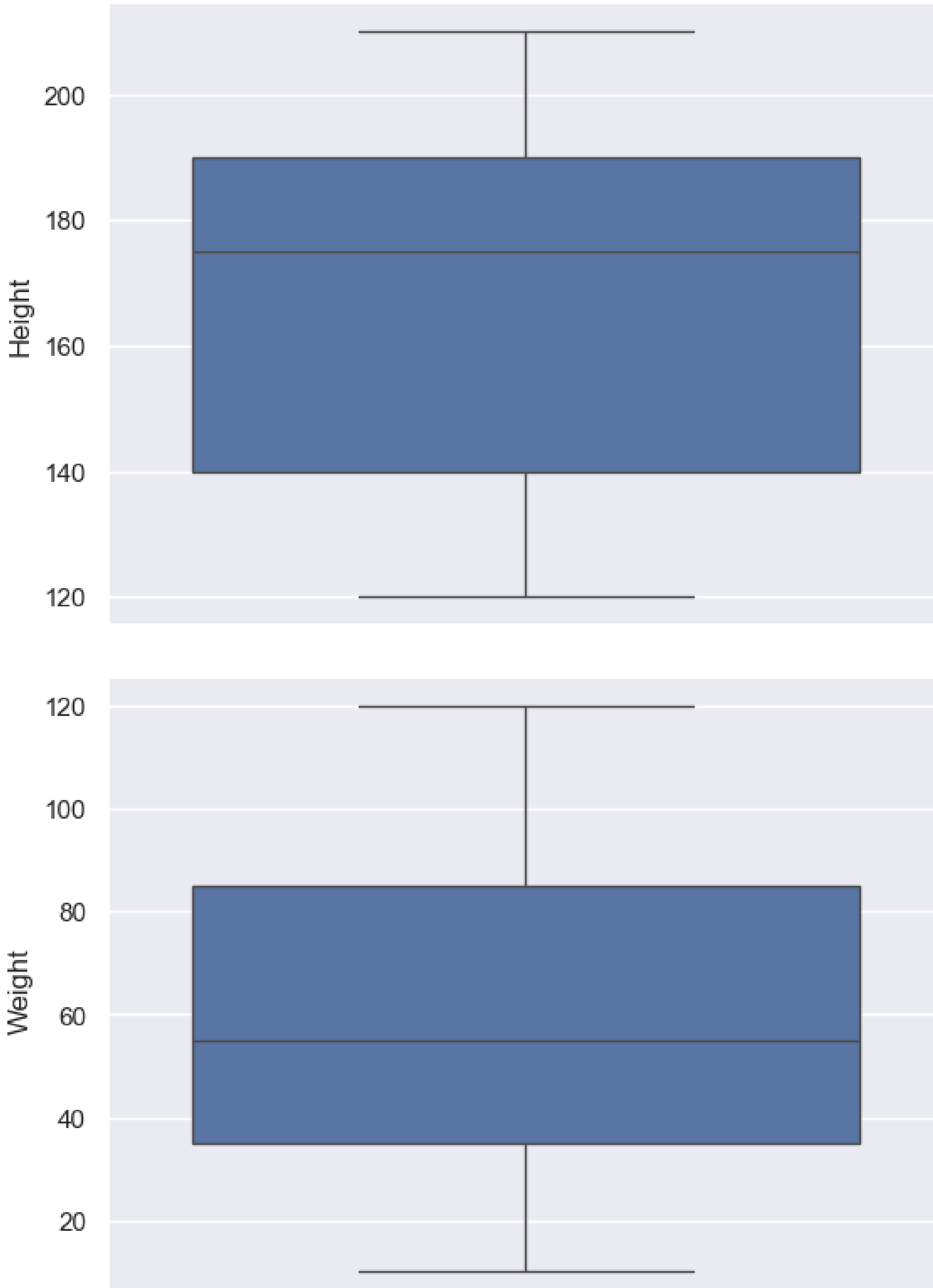
```
               ID         Age      Gender      Height      Weight
BMI  \
count  108.000000  108.000000  108.000000  108.000000  108.000000
108.000000
mean    56.046296   46.555556    0.518519  166.574074   59.490741
20.549074
std     31.917939   24.720620    0.501986   27.873615   28.856233
7.583818
min      1.000000   11.000000    0.000000  120.000000   10.000000
3.900000
25%     28.750000   27.000000    0.000000  140.000000   35.000000
16.700000
50%     56.500000   42.500000    1.000000  175.000000   55.000000
21.200000
75%     83.250000   59.250000    1.000000  190.000000   85.000000
26.100000
max    110.000000  112.000000    1.000000  210.000000  120.000000
37.200000

            Label
count  108.000000
mean     1.787037
std      1.260848
min      0.000000
25%      0.000000
50%      2.000000
```

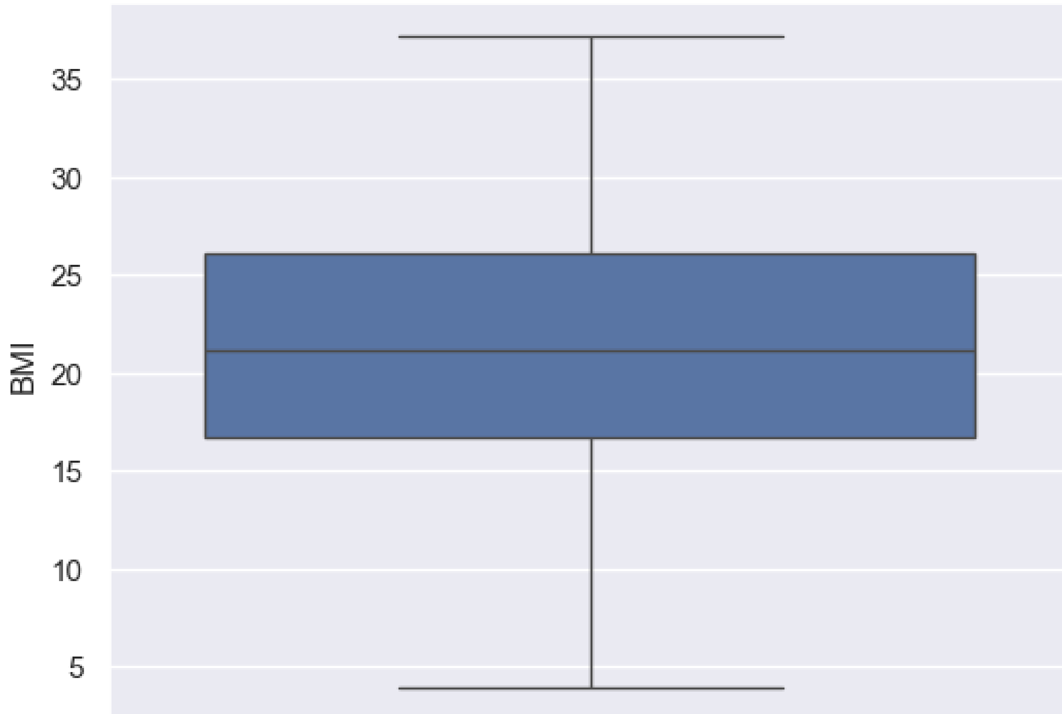
```
75%        3.000000
max        3.000000

# Checking outliers
def boxplots(col):
    sns.boxplot(df[col])
    plt.show()

for i in list(df.select_dtypes(exclude =['object']).columns)[0:]:
    boxplots(i)
```

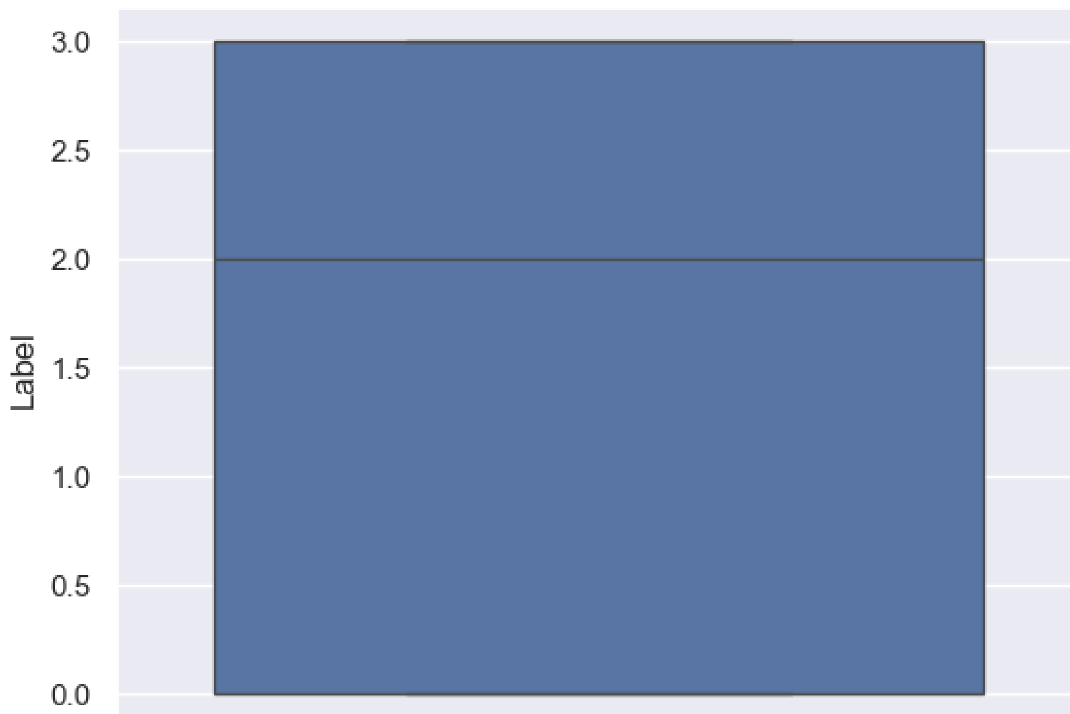



100
80
60
40
20
Age


1.0
0.8
0.6
0.4
0.2
0.0
Gender


200
180
160
140
120
Height
120
100
80
60
40
20
Weight





Outlier treatment

```
# Finding the IQR
Q1 = df['Age'].quantile(0.25)
```

```
Q3 = df['Age'].quantile(0.75)
IQR = Q3 - Q1

print("Percentile25 :", Q1)
print("Percentile75 :", Q3)
print("InterQuartileRange :", IQR)
```

```
Percentile25 : 27.0
Percentile75 : 59.25
InterQuartileRange : 32.25
```

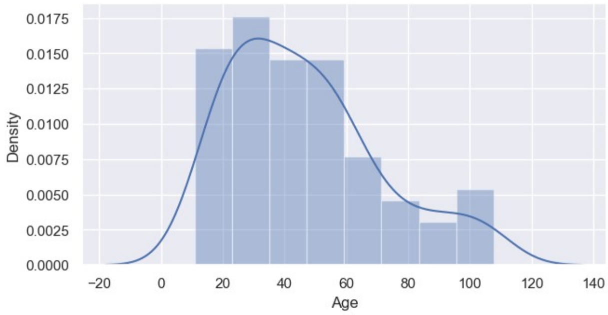
```
upper_limit = Q3 + 1.5 * IQR
lower_limit = Q1 - 1.5 * IQR

print("Upper Limit :", upper_limit)
print("Lower Limit :", lower_limit)
```

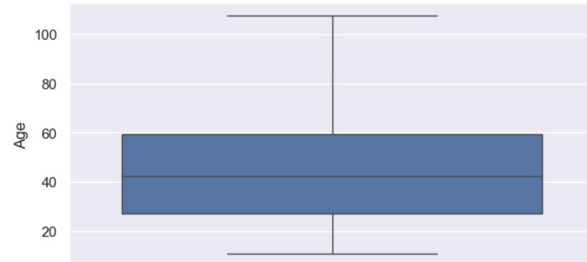
```
Upper Limit : 107.625
Lower Limit : -21.375
```

```
df['Age'] = np.where(df['Age'] > upper_limit,
                                             upper_limit,
                                              np.where(df['Age'] <
lower_limit,
                                                       lower_limit,
                                                      df['Age']))

df['Age'].describe()
```

```
count    108.000000
mean      46.511574
std       24.607008
min       11.000000
25%       27.000000
50%       42.500000
75%       59.250000
max      107.625000
Name: Age, dtype: float64
```

```
plt.figure(figsize=(16,8))
plt.subplot(2,2,1)
sns.distplot(df['Age'])
plt.subplot(2,2,2)
sns.boxplot(df['Age'])

plt.show()
```

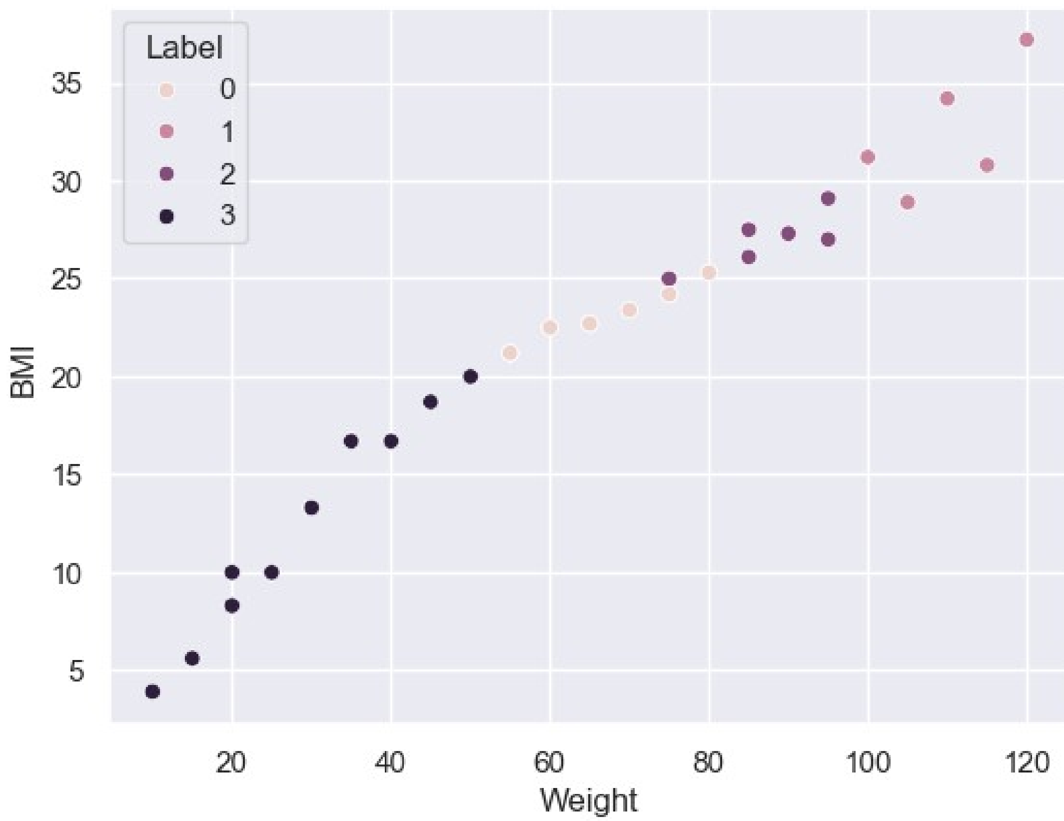




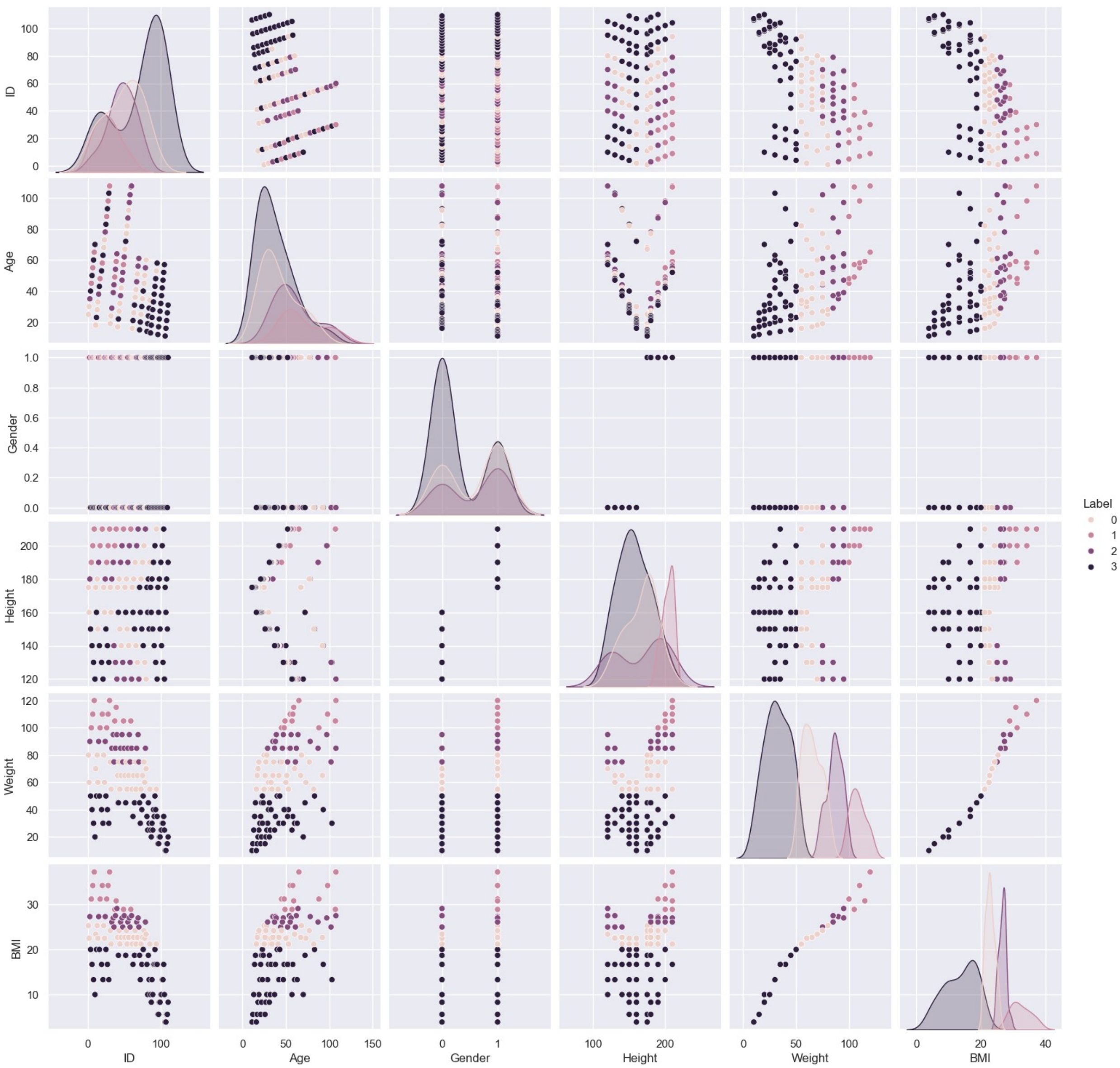

```python
import dtale
dtale.show(df)
```

```
<IPython.lib.display.IFrame at 0x1f794c1bbc0>
```

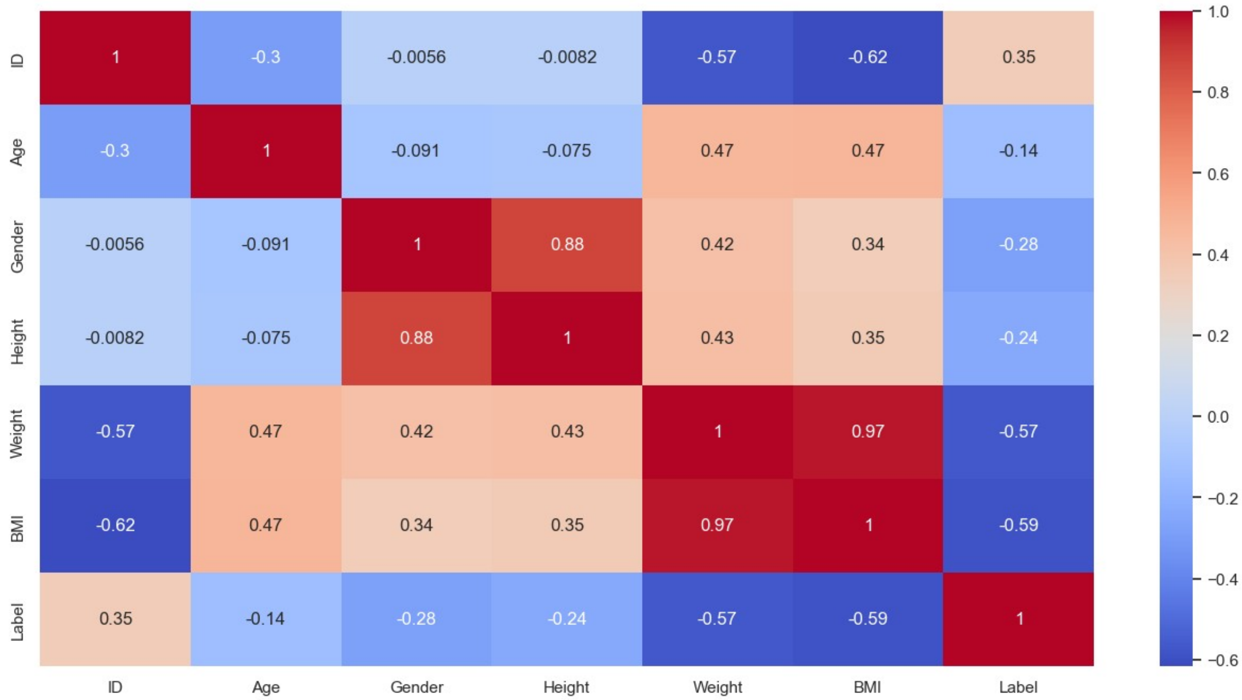
```python
sns.scatterplot(x ='Weight', y='BMI', data=df, hue='Label')
plt.show()
```




```python
sns.pairplot(data=df, hue='Label')
plt.show()
```

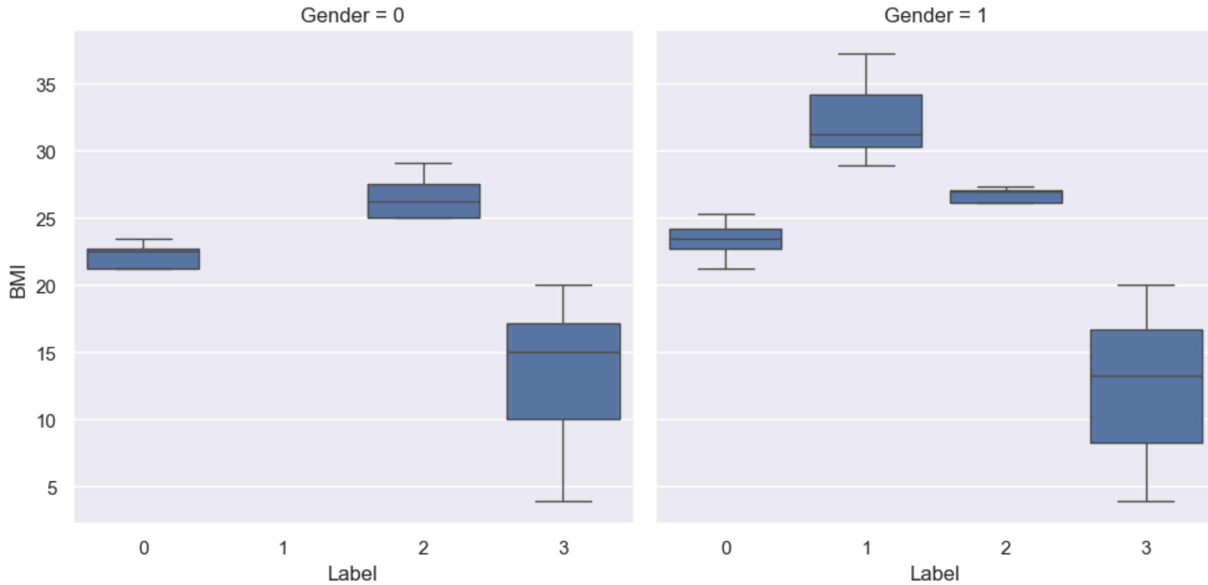



```
plt.figure(figsize=(16,8))
sns.heatmap(df.corr(), annot=True, cmap='coolwarm')
plt.show()
```




```python
sns.catplot(data=df, x='Label', y='BMI', kind='box', col='Gender')
plt.show()
```

```
2025-04-22 09:38:49,624 - INFO     - Using categorical units to plot a list of strings that are all parsable as floats or dates. If these strings should be plotted as numbers, cast to the appropriate data type before plotting.
2025-04-22 09:38:49,748 - INFO     - Using categorical units to plot a list of strings that are all parsable as floats or dates. If these strings should be plotted as numbers, cast to the appropriate data type before plotting.
```




```
# split the data into independent and dependent variable
x = df.iloc[:,0:-1]
y = df.iloc[:,-1]

x.head()
```

	ID	Age	Gender	Height	Weight	BMI
0	1	25.0	1	175	80	25.3
1	2	30.0	0	160	60	22.5
2	3	35.0	1	180	90	27.3
3	4	40.0	0	150	50	20.0
4	5	45.0	1	190	100	31.2

```
y.head()
```

```
0    0
1    0
2    2
3    3
4    1
Name: Label, dtype: int32
```

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

```
Label
3    47
0    29
2    20
1    12
Name: count, dtype: int64
```

Imbalance treatement

```
# Imbalance treatement
import imblearn

from imblearn.over_sampling import RandomOverSampler
ros = RandomOverSampler()
x_over, y_over = ros.fit_resample(x,y)
print("Imbalanced datapoint :", y.value_counts())
print()
print("Balanced datapoint :", y_over.value_counts())
```

```
Imbalanced datapoint : Label
3    47
0    29
2    20
1    12
Name: count, dtype: int64

Balanced datapoint : Label
0    47
2    47
3    47
1    47
Name: count, dtype: int64
```

```
# split the data into training and test

from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x_over, y_over,
train_size=0.75,random_state=42,
                                                    stratify=y_over)
```

Building Decision Tree Model

```
from sklearn.tree import DecisionTreeClassifier
# approach 1 = Gini
dtree1 = DecisionTreeClassifier(criterion='gini')
dtree1.fit(x_train, y_train)

# approach 2 = entropy
dtree2 = DecisionTreeClassifier(criterion='entropy')
dtree2.fit(x_train, y_train)
```

```
DecisionTreeClassifier(criterion='entropy')
```

Predict the test data

```
y_pred_dt1_train = dtree1.predict(x_train)
y_pred_dt1_test = dtree1.predict(x_test)
```

```
y_pred_dt2_train = dtree2.predict(x_train)
y_pred_dt2_test = dtree2.predict(x_test)

y_pred_dt2_test
```

```
array([2, 3, 1, 1, 3, 0, 3, 0, 0, 3, 0, 0, 1, 3, 3, 2, 3, 2, 0, 1, 3,
1,
       0, 3, 1, 0, 2, 1, 0, 0, 1, 2, 1, 2, 2, 3, 2, 3, 3, 0, 2, 2, 2,
1,
       2, 0, 1])
```

Evaluate the model

```
from sklearn.metrics import classification_report, confusion_matrix,
accuracy_score

print(classification_report(y_train, y_pred_dt1_train))
print()
print(classification_report(y_test, y_pred_dt1_test))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        35
           1       1.00      1.00      1.00        36
           2       1.00      1.00      1.00        35
           3       1.00      1.00      1.00        35

    accuracy                           1.00       141
   macro avg       1.00      1.00      1.00       141
weighted avg       1.00      1.00      1.00       141


              precision    recall  f1-score   support

           0       1.00      1.00      1.00        12
           1       1.00      1.00      1.00        11
           2       1.00      1.00      1.00        12
           3       1.00      1.00      1.00        12

    accuracy                           1.00        47
   macro avg       1.00      1.00      1.00        47
weighted avg       1.00      1.00      1.00        47
```

```
print(classification_report(y_train, y_pred_dt2_train))
print()
print(classification_report(y_test, y_pred_dt2_test))
```

```
              precision    recall  f1-score   support
```

```
           0       1.00      1.00      1.00        35
           1       1.00      1.00      1.00        36
           2       1.00      1.00      1.00        35
           3       1.00      1.00      1.00        35

    accuracy                           1.00       141
   macro avg       1.00      1.00      1.00       141
weighted avg       1.00      1.00      1.00       141


              precision    recall  f1-score   support

           0       1.00      1.00      1.00        12
           1       1.00      1.00      1.00        11
           2       1.00      1.00      1.00        12
           3       1.00      1.00      1.00        12

    accuracy                           1.00        47
   macro avg       1.00      1.00      1.00        47
weighted avg       1.00      1.00      1.00        47
```

```python
print(confusion_matrix(y_train, y_pred_dt1_train))
print()
print(confusion_matrix(y_test, y_pred_dt1_test))
```

```
[[35  0  0  0]
 [ 0 36  0  0]
 [ 0  0 35  0]
 [ 0  0  0 35]]

[[12  0  0  0]
 [ 0 11  0  0]
 [ 0  0 12  0]
 [ 0  0  0 12]]
```

```python
print(confusion_matrix(y_train, y_pred_dt2_train))
print()
print(confusion_matrix(y_test, y_pred_dt2_test))
```

```
[[35  0  0  0]
 [ 0 36  0  0]
 [ 0  0 35  0]
 [ 0  0  0 35]]

[[12  0  0  0]
 [ 0 11  0  0]
 [ 0  0 12  0]
 [ 0  0  0 12]]
```

```python
print("Train Accuracy - Gini :",accuracy_score(y_train,
y_pred_dt1_train))
print()
print("Test Accuracy - Gini :",accuracy_score(y_test,
y_pred_dt1_test))
```

```
Train Accuracy - Gini : 1.0

Test Accuracy - Gini : 1.0
```

```python
print("Train Accuracy - entropy :",accuracy_score(y_train,
y_pred_dt2_train))
print()
print("Test Accuracy - entropy :",accuracy_score(y_test,
y_pred_dt2_test))
```

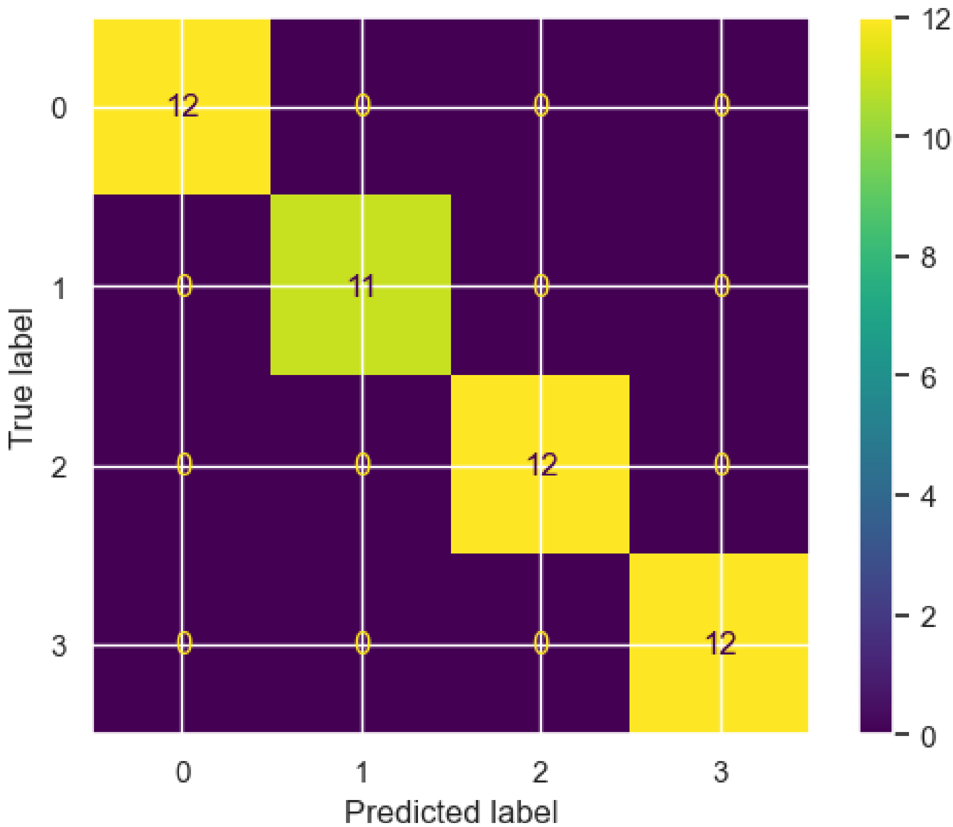
```
Train Accuracy - entropy : 1.0

Test Accuracy - entropy : 1.0
```

Cross Validation - K_Fold_Method

```python
from sklearn.model_selection import cross_val_score
accuracy = cross_val_score(dtree1, x_train, y_train, cv=10)
print(accuracy)
print()
print(accuracy.mean())
print()
print(accuracy.max())
```

```
[1.         1.         0.92857143 1.         0.92857143 1.
 1.         1.         1.         1.        ]

0.9857142857142858

1.0
```

```python
from sklearn.metrics import ConfusionMatrixDisplay

ConfusionMatrixDisplay.from_estimator(dtree1, x_test, y_test)
plt.show()
```



Post-prunning

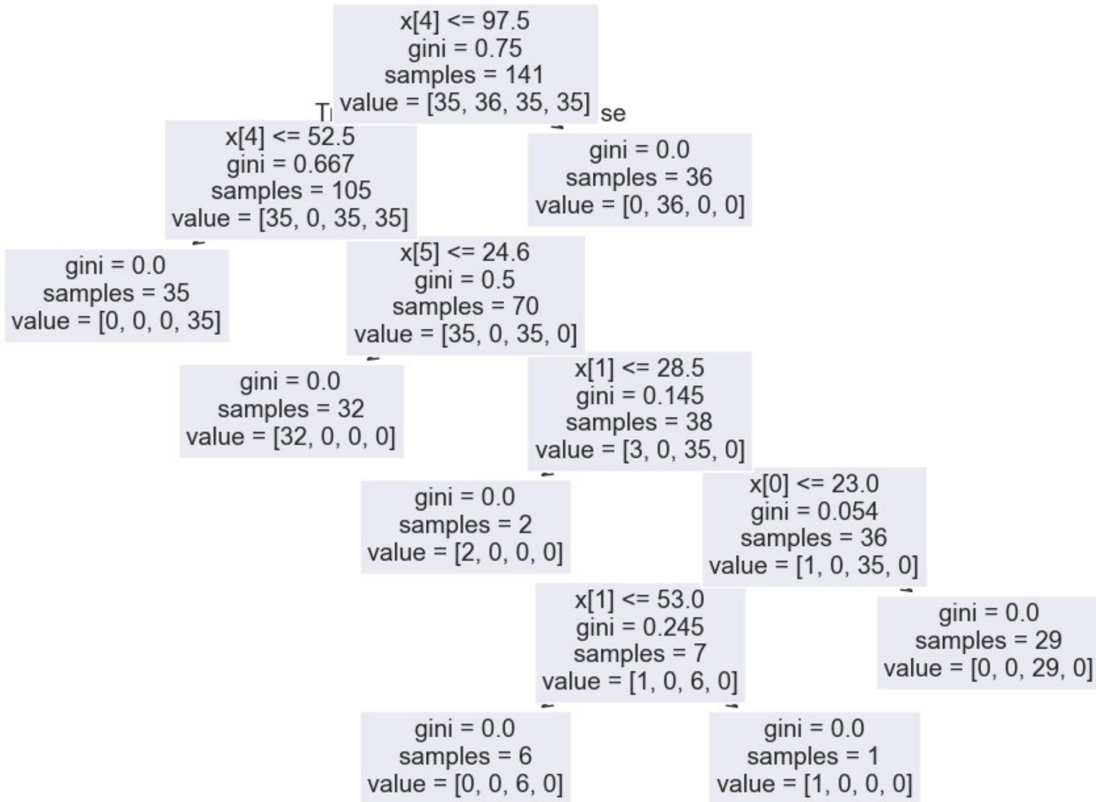
```
dtree1.feature_importances_
```

```
array([0.00217655, 0.05008438, 0.        , 0.        , 0.66901408,
       0.27872498])
```

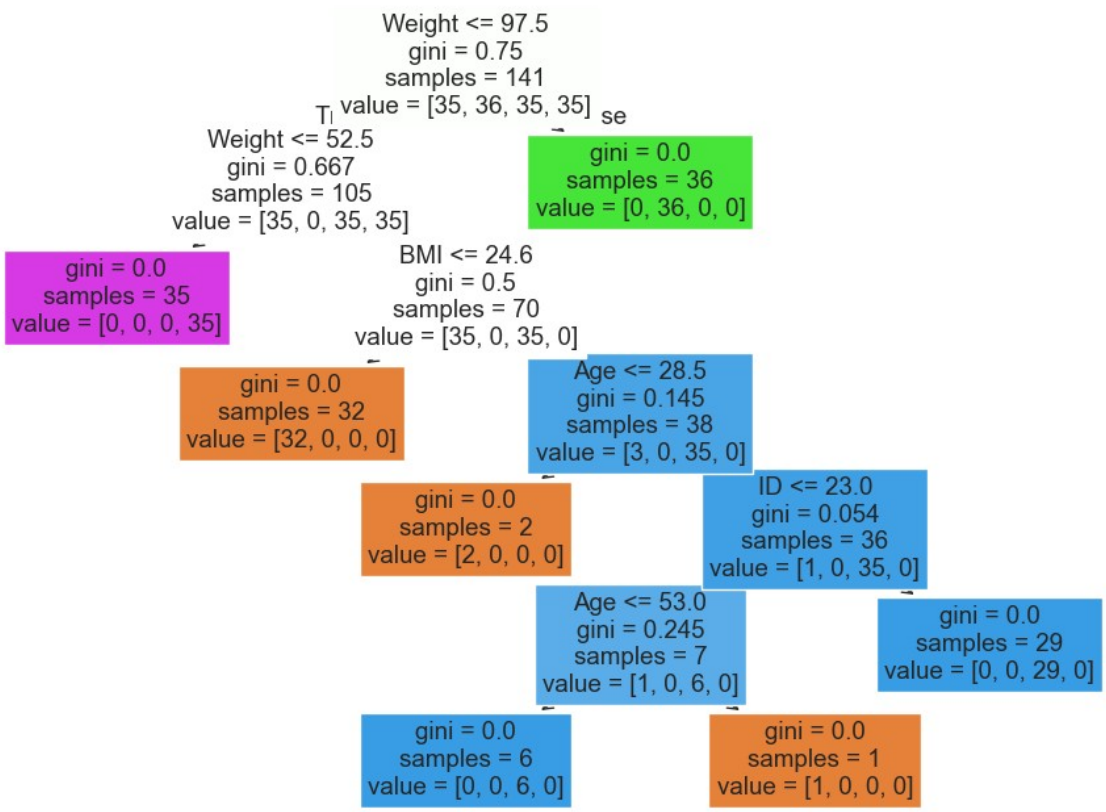
```
pd.DataFrame(index = x.columns, data=dtree1.feature_importances_,
            columns=["Feature Importance"])
```

	Feature Importance
ID	0.002177
Age	0.050084
Gender	0.000000
Height	0.000000
Weight	0.669014
BMI	0.278725

```
from sklearn.tree import plot_tree
plt.figure(figsize=(12,8))
plot_tree(dtree1)
plt.show()
```




```
y_train.value_counts()

Label
1    36
0    35
2    35
3    35
Name: count, dtype: int64

from sklearn.tree import plot_tree
plt.figure(figsize=(12,8))
plot_tree(dtree1, filled=True, feature_names = x.columns)
plt.show()
```



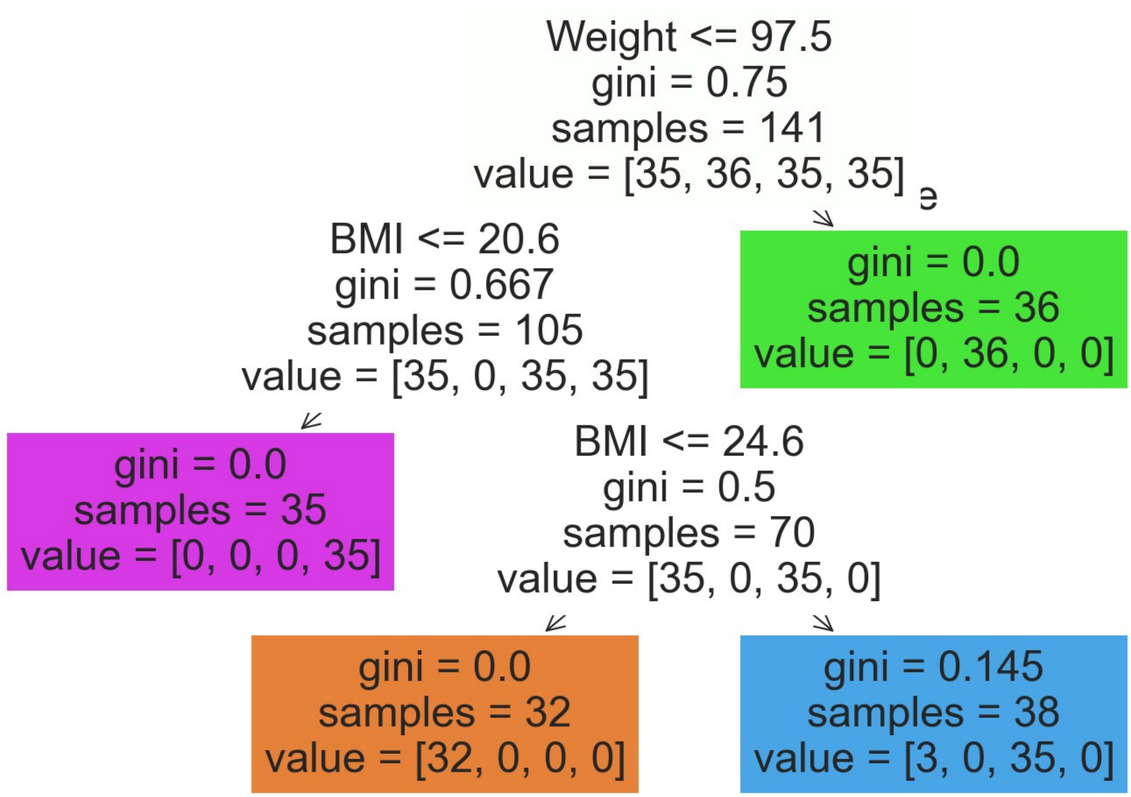

```
# Using hyperparameter in Decision tree to apply post-prunning method
prunned_tree = DecisionTreeClassifier(criterion='gini', max_depth=3)
prunned_tree.fit(x_train, y_train)
```

```
DecisionTreeClassifier(max_depth=3)
```

```
# User define function
def report_model(model):
    model_preds = model.predict(x_test)
    print(classification_report(y_test, model_preds))
    print('\n')
    print(accuracy_score(y_test, model_preds))
    print('\n')
    plt.figure(figsize=(12,8), dpi=150)
    plot_tree(model, filled=True, feature_names = x.columns)

report_model(prunned_tree)
plt.show()
```

```
              precision    recall  f1-score   support

           0       1.00      0.92      0.96        12
           1       1.00      1.00      1.00        11
           2       0.92      1.00      0.96        12
           3       1.00      1.00      1.00        12
```

```
    accuracy                           0.98        47
   macro avg       0.98      0.98      0.98        47
weighted avg       0.98      0.98      0.98        47


0.9787234042553191
```



LogisticRegression

```
from sklearn.linear_model import LogisticRegression
logit = LogisticRegression()
logit.fit(x_train, y_train)

LogisticRegression()

y_pred_train_logit = logit.predict(x_train)
y_pred_test_logit = logit.predict(x_test)

print("Train Accuracy - Logit :",accuracy_score(y_train,
y_pred_train_logit))
print()
```

```
print("Test Accuracy - Logit :",accuracy_score(y_test,
y_pred_test_logit))
```

```
Train Accuracy - Logit : 0.7943262411347518

Test Accuracy - Logit : 0.9148936170212766
```