step:1

Importing necessary imports.

In [1]:
```
# important imports
import sys
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.tree import DecisionTreeClassifier
import sklearn.tree as tree
```

In [ ]:
```

```

step:2

About Dataset.

In [2]:
```
# downloading the dataset and making a pandas dataframe from the dataset
df= pd.read_csv('https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud
df.head()
```

Out[2]:

	Age	Sex	BP	Cholesterol	Na_to_K	Drug
0	23	F	HIGH	HIGH	25.355	drugY
1	47	M	LOW	HIGH	13.093	drugC
2	47	M	LOW	HIGH	10.114	drugC
3	28	F	NORMAL	HIGH	7.798	drugX
4	61	F	LOW	HIGH	18.043	drugY

In [3]:
```
# inspect the size and important features of the dataset.
df.shape
```

Out[3]:
```
(200, 6)
```

In [4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 6 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   Age          200 non-null    int64  
 1   Sex          200 non-null    object 
 2   BP           200 non-null    object 
 3   Cholesterol  200 non-null    object 
 4   Na_to_K      200 non-null    float64
 5   Drug         200 non-null    object 
dtypes: float64(1), int64(1), object(4)
memory usage: 9.5+ KB
```

what we got?

The dataset contains 6 variables in total. **Age** and **Na_to_K** variables contain numerical values and are continuous variables. Rest of the variables are categorical variables and contain object type i.e. string type values. Our target variable is Drug. The rest are feature variables.

In [ ]:

step:3

Pre-processing.

In [5]:
```
# creating a matrix of feature variables from dataset.
X = df.loc[:,["Age","Sex","BP","Cholesterol","Na_to_K"]]
X.head()
```

Out[5]:

	Age	Sex	BP	Cholesterol	Na_to_K
0	23	F	HIGH	HIGH	25.355
1	47	M	LOW	HIGH	13.093
2	47	M	LOW	HIGH	10.114
3	28	F	NORMAL	HIGH	7.798
4	61	F	LOW	HIGH	18.043

In [6]:
```
X.shape
```

Out[6]:
```
(200, 5)
```

As there are categorical values in certain columns, so let us encode them into their numerical values.

In [7]:
```
from sklearn import preprocessing
```

In [8]:
```
encoder_for_sex = preprocessing.LabelEncoder()
encoder_for_sex.fit(['F','M'])
X["Sex"] = encoder_for_sex.transform(X['Sex'])
```

In [9]:
```
X.head()
```

Out[9]:

	Age	Sex	BP	Cholesterol	Na_to_K
0	23	0	HIGH	HIGH	25.355
1	47	1	LOW	HIGH	13.093
2	47	1	LOW	HIGH	10.114
3	28	0	NORMAL	HIGH	7.798
4	61	0	LOW	HIGH	18.043

So, now for female there is 0 and for male there is 1 in the dataset X

Doing the same for other variables which contain object type categorical values.

In [10]:
```
# doing the same for BP columns
X['BP'].unique()
```

Out[10]:
```
array(['HIGH', 'LOW', 'NORMAL'], dtype=object)
```

In [11]:
```
encoder_for_bp = preprocessing.LabelEncoder()
encoder_for_bp.fit(['HIGH', 'LOW', 'NORMAL'])
X["BP"] = encoder_for_bp.transform(X['BP'])
X.head()
```

Out[11]:

	Age	Sex	BP	Cholesterol	Na_to_K
0	23	0	0	HIGH	25.355
1	47	1	1	HIGH	13.093
2	47	1	1	HIGH	10.114
3	28	0	2	HIGH	7.798
4	61	0	1	HIGH	18.043

In [12]:
```
X['BP'].unique()
```

Out[12]:
```
array([0, 1, 2])
```

In [13]:
```
# doing the same for Cholesterol feature.
X['Cholesterol'].unique()
```

Out[13]:
```
array(['HIGH', 'NORMAL'], dtype=object)
```

In [14]:
```
encoder_for_cholesterol = preprocessing.LabelEncoder()
encoder_for_cholesterol.fit(['HIGH', 'NORMAL'])
X['Cholesterol'] = encoder_for_cholesterol.transform(X['Cholesterol'])
X.head()
```

Out[14]:

	Age	Sex	BP	Cholesterol	Na_to_K
0	23	0	0	0	25.355
1	47	1	1	0	13.093
2	47	1	1	0	10.114
3	28	0	2	0	7.798
4	61	0	1	0	18.043

In [15]:
```
X['Cholesterol'].unique()
```

Out[15]:
```
array([0, 1])
```

In [16]:
```
X_array = X.values
```

In [17]:
```
type(X_array)
```

Out[17]:
```
numpy.ndarray
```

In [18]:
```
# making arrray of response variable
y = df['Drug'].values
```

In [19]:
```
y[0:5]
```

Out[19]:
```
array(['drugY', 'drugC', 'drugC', 'drugX', 'drugY'], dtype=object)
```

Step:4

Setting up decision tree

In [20]:
```
#making and training and test sets.
```

In [21]:
```
from sklearn.model_selection import train_test_split
```

In [22]:
```
x_train,x_test,y_train,y_test = train_test_split(X,y,test_size = 0.25, shuffle=True
```

In [23]:
```
# printing the size of datasets
print(x_train.shape)
print(y_train.shape)
```

```
(150, 5)
(150,)
```

In [24]:
```
print(x_test.shape)
print(y_test.shape)
```

```
(50, 5)
(50,)
```

In [25]:
```
# Now building our decision tree model
```

In [26]:
```
decision_tree = DecisionTreeClassifier(criterion='entropy',max_depth=4)
```

In [27]:
```
decision_tree
```

Out[27]:
```
DecisionTreeClassifier(criterion='entropy', max_depth=4)
```

In [28]:
```
decision_tree.fit(x_train,y_train)
```

Out[28]:
```
DecisionTreeClassifier(criterion='entropy', max_depth=4)
```

In [ ]:

Step:5

Making prediction on the test dataset.

In [29]:
```
predictions = decision_tree.predict(x_test)
```

In [30]:
```
# Let us see whether the model works properly or not.
print(y_test[0:5])
print(predictions[0:5])
```

```
['drugX' 'drugY' 'drugX' 'drugC' 'drugY']
['drugX' 'drugY' 'drugX' 'drugC' 'drugY']
```

It seems that the model works properly.

In [ ]:

Step:6

Model evaluation.

In [31]:
```
from sklearn.metrics import accuracy_score
```

In [32]:
```
print(f'The accuracy score of the model is: {accuracy_score(y_test,predictions)}')
```

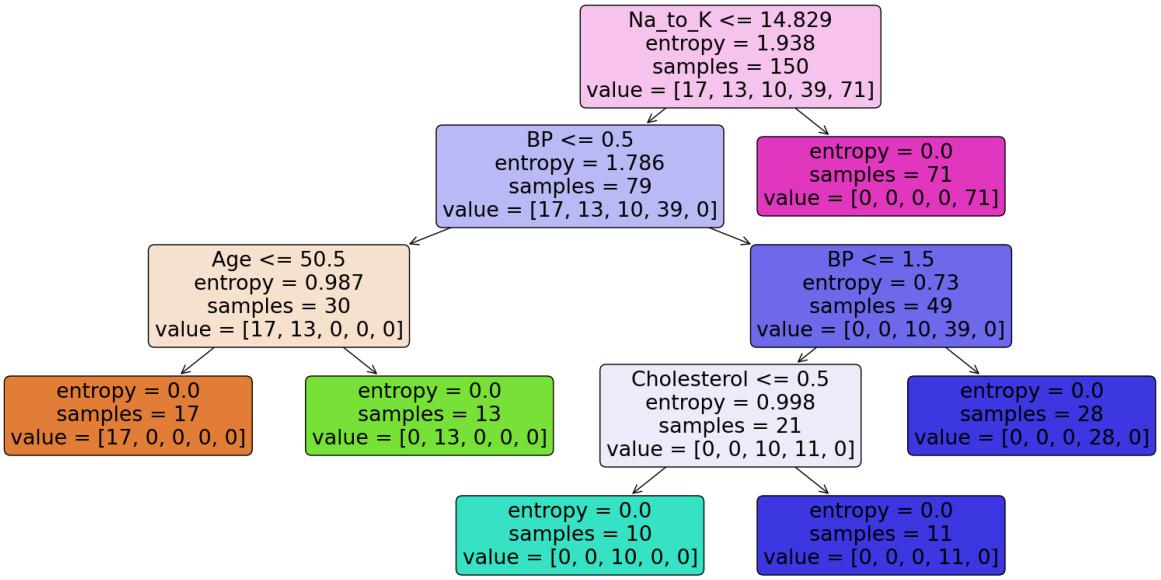
```
The accuracy score of the model is: 1.0
```

The accuracy score of 1.0 shows that our model works 100% accurately on the test data.

Step:7

Visualising the model tree.

In [33]:
```
# Plot the decision tree using matplotlib
plt.figure(figsize=(20,10))
tree.plot_tree(decision_tree, feature_names=["Age","Sex","BP","Cholesterol","Na_to_
plt.savefig("decision_tree.png")  # Save the plot as a PNG file
plt.show()  # Display the plot
```



In [ ]:

In [ ]:

Step:8

Comparing decesion tree model with KNN model

In [34]:
```
from sklearn.neighbors import KNeighborsClassifier
```

In [35]:
```
knn = KNeighborsClassifier(n_neighbors = 5)
knn.fit(x_train,y_train)
```

Out[35]:
```
KNeighborsClassifier
KNeighborsClassifier()
```

In [36]:
```
knn_pred = knn.predict(x_test)
```

In [37]:
```
from sklearn.metrics import confusion_matrix, classification_report
```

Confusion matrix, classification report and accuracy score of KNN model

In [38]:
```
print(confusion_matrix(knn_pred,y_test))
```

```
[[ 3  0  2  2  0]
 [ 0  1  2  3  0]
 [ 0  0  1  0  0]
 [ 3  2  1 10  0]
 [ 0  0  0  0 20]]
```

In [39]:
```
print(classification_report(knn_pred,y_test))
```

```
              precision    recall  f1-score   support

       drugA       0.50      0.43      0.46         7
       drugB       0.33      0.17      0.22         6
       drugC       0.17      1.00      0.29         1
       drugX       0.67      0.62      0.65        16
       drugY       1.00      1.00      1.00        20

    accuracy                           0.70        50
   macro avg       0.53      0.64      0.52        50
weighted avg       0.73      0.70      0.70        50
```

In [40]:
```
print(accuracy_score(knn_pred,y_test))
```

```
0.7
```

In [ ]:
```

```

confusion matrix , classification report, and accuracy score of Decision Tree model.

In [41]:
```
print(confusion_matrix(predictions,y_test))
```

```
[[ 6  0  0  0  0]
 [ 0  3  0  0  0]
 [ 0  0  6  0  0]
 [ 0  0  0 15  0]
 [ 0  0  0  0 20]]
```

In [42]:
```
print(classification_report(predictions,y_test))
```

```
                precision    recall  f1-score   support

         drugA       1.00      1.00      1.00         6
         drugB       1.00      1.00      1.00         3
         drugC       1.00      1.00      1.00         6
         drugX       1.00      1.00      1.00        15
         drugY       1.00      1.00      1.00        20

      accuracy                           1.00        50
     macro avg       1.00      1.00      1.00        50
  weighted avg       1.00      1.00      1.00        50
```

In [43]:
```
print(accuracy_score(predictions,y_test))
```

```
1.0
```

In [ ]:

Step:9

Conclusion:

From the above two models we can see that the decision tree model gives us the highest accuracy as compared to KNN model on this dataset. Hence we can assume that the decision tree model will perform very well on the unseen data.

In [ ]:

In [ ]: