LOAN STATUS PREDICTION

```
DATA INFO...
Problem Statement
About Company
Dream Housing Finance company deals in all home loans. They have presence across all urban, semi urban and rural areas.
Customer first apply for home loan after that company validates the customer eligibility for loan.

Problem
Company wants to automate the loan eligibility process (real time) based on customer detail provided while filling online
application form. These details are Gender, Marital Status, Education, Number of Dependents, Income, Loan Amount, Credit
History and others. To automate this process, they have given a problem to identify the customers segments, those are eligible
for loan amount so that they can specifically target these customers. Here they have provided a partial data set.
```

In [1]:

```
import pandas as pd
import numpy as np
import seaborn as sb
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings("ignore")
```

Impoet data file

In [2]:

```
loan=pd.read_csv("C:/Users/sohel/Downloads/loan data.csv")
loan
```

Out[2]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_H
0	LP001002	Male	No	0	Graduate	No	5849	0.0	NaN	360.0	
1	LP001003	Male	Yes	1	Graduate	No	4583	1508.0	128.0	360.0	
2	LP001005	Male	Yes	0	Graduate	Yes	3000	0.0	66.0	360.0	
3	LP001006	Male	Yes	0	Not Graduate	No	2583	2358.0	120.0	360.0	
4	LP001008	Male	No	0	Graduate	No	6000	0.0	141.0	360.0	
...	...	...	...	...	...	...	...	...	...	...	
609	LP002978	Female	No	0	Graduate	No	2900	0.0	71.0	360.0	
610	LP002979	Male	Yes	3+	Graduate	No	4106	0.0	40.0	180.0	
611	LP002983	Male	Yes	1	Graduate	No	8072	240.0	253.0	360.0	
612	LP002984	Male	Yes	2	Graduate	No	7583	0.0	187.0	360.0	
613	LP002990	Female	No	0	Graduate	Yes	4583	0.0	133.0	360.0	

614 rows × 13 columns

In [3]:

```
loan.shape # Dimention of the data set
```

Out[3]:

```
(614, 13)
```

In [4]:

```
loan.size # Total number of observations of the data set
```

Out[4]:

```
7982
```

In [5]:

```
loan.head() # First five rows of the dataset
```

Out[5]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_His
0	LP001002	Male	No	0	Graduate	No	5849	0.0	NaN	360.0	
1	LP001003	Male	Yes	1	Graduate	No	4583	1508.0	128.0	360.0	
2	LP001005	Male	Yes	0	Graduate	Yes	3000	0.0	66.0	360.0	
3	LP001006	Male	Yes	0	Not Graduate	No	2583	2358.0	120.0	360.0	
4	LP001008	Male	No	0	Graduate	No	6000	0.0	141.0	360.0	

In [6]:

```
loan.tail() # Last five rows of the dataset
```

Out[6]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_H
609	LP002978	Female	No	0	Graduate	No	2900	0.0	71.0	360.0	
610	LP002979	Male	Yes	3+	Graduate	No	4106	0.0	40.0	180.0	
611	LP002983	Male	Yes	1	Graduate	No	8072	240.0	253.0	360.0	
612	LP002984	Male	Yes	2	Graduate	No	7583	0.0	187.0	360.0	
613	LP002990	Female	No	0	Graduate	Yes	4583	0.0	133.0	360.0	

In [7]:

```
loan.describe() # it gives discriptive ststistics of all columns
```

Out[7]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
count	614.000000	614.000000	592.000000	600.00000	564.000000
mean	5403.459283	1621.245798	146.412162	342.00000	0.842199
std	6109.041673	2926.248369	85.587325	65.12041	0.364878
min	150.000000	0.000000	9.000000	12.00000	0.000000
25%	2877.500000	0.000000	100.000000	360.00000	1.000000
50%	3812.500000	1188.500000	128.000000	360.00000	1.000000
75%	5795.000000	2297.250000	168.000000	360.00000	1.000000
max	81000.000000	41667.000000	700.000000	480.00000	1.000000

In [8]:

```
# checking missing value in dataset
loan.isnull().sum()
```

Out[8]:

```
Loan_ID               0
Gender               13
Married               3
Dependents           15
Education             0
Self_Employed        32
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount           22
Loan_Amount_Term     14
Credit_History       50
Property_Area         0
Loan_Status           0
dtype: int64
```

Data cleaning

In [9]:

```
loan["Gender"]=loan["Gender"].fillna(loan["Gender"].mode().iloc[0])
```

In [10]:

```
loan["Married"]=loan["Married"].fillna(loan["Married"].mode().iloc[0])
```

In [11]:

```
loan["Dependents"]=loan["Dependents"].fillna(loan["Dependents"].mode().iloc[0])
```

In [12]:

```
loan["Self_Employed"]=loan["Self_Employed"].fillna(loan["Self_Employed"].mode().iloc[0])
```

In [13]:

```
loan["LoanAmount"]=loan["LoanAmount"].fillna(loan["LoanAmount"].mean())
```

In [14]:

```
loan["Loan_Amount_Term"]=loan["Loan_Amount_Term"].fillna(loan["Loan_Amount_Term"].mean())
```

In [15]:

```
loan["Credit_History"]=loan["Credit_History"].fillna(loan["Credit_History"].mean())
```

In [16]:

```
loan
```

Out[16]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_H
0	LP001002	Male	No	0	Graduate	No	5849	0.0	146.412162	360.0	
1	LP001003	Male	Yes	1	Graduate	No	4583	1508.0	128.000000	360.0	
2	LP001005	Male	Yes	0	Graduate	Yes	3000	0.0	66.000000	360.0	
3	LP001006	Male	Yes	0	Not Graduate	No	2583	2358.0	120.000000	360.0	
4	LP001008	Male	No	0	Graduate	No	6000	0.0	141.000000	360.0	
...	...	...	...	...	...	...	...	...	...	...	
609	LP002978	Female	No	0	Graduate	No	2900	0.0	71.000000	360.0	
610	LP002979	Male	Yes	3+	Graduate	No	4106	0.0	40.000000	180.0	
611	LP002983	Male	Yes	1	Graduate	No	8072	240.0	253.000000	360.0	
612	LP002984	Male	Yes	2	Graduate	No	7583	0.0	187.000000	360.0	
613	LP002990	Female	No	0	Graduate	Yes	4583	0.0	133.000000	360.0	

614 rows × 13 columns

In [17]:

```
loan.isnull().sum()
```

Out[17]:

```
Loan_ID              0
Gender               0
Married              0
Dependents           0
Education            0
Self_Employed        0
ApplicantIncome      0
CoapplicantIncome    0
LoanAmount           0
Loan_Amount_Term     0
Credit_History       0
Property_Area        0
Loan_Status          0
dtype: int64
```

In [18]:

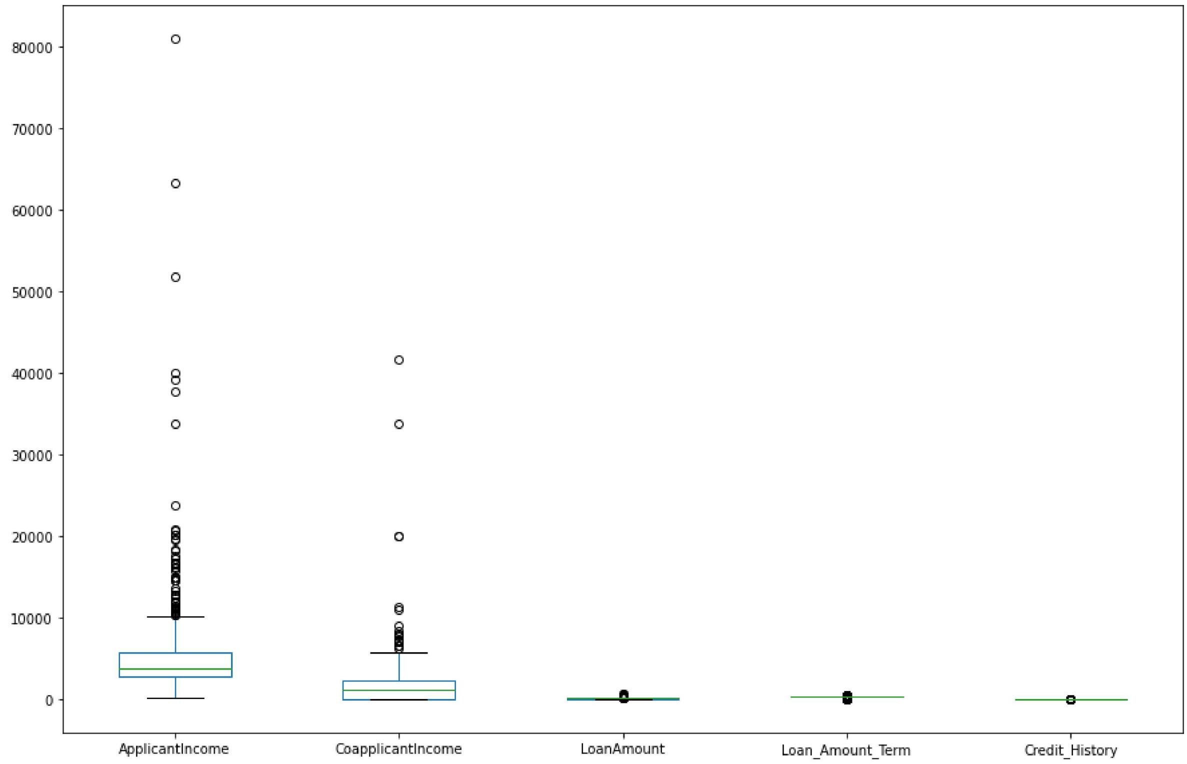
```
# Now there is no missing observation in our dataset
```

In [19]:

```
#Drowing Box plot
loan.plot(kind="box",figsize=(15,10))
```

Out[19]:

```
<AxesSubplot:>
```



In [20]:

```
loan=loan[loan.ApplicantIncome<7500]
```

In [21]:

```
loan.shape
```

Out[21]:

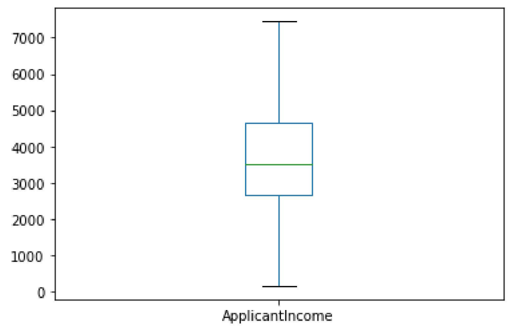
```
(521, 13)
```

In [22]:

```
loan.ApplicantIncome.plot(kind="box")
```

Out[22]:

```
<AxesSubplot:>
```

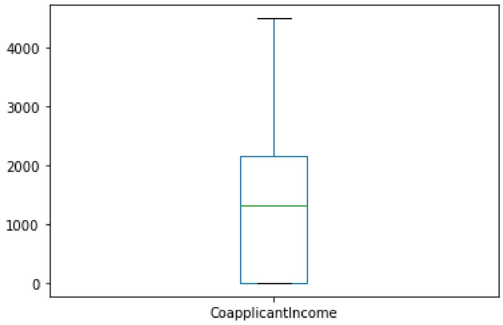


In [114]:

```
loan=loan[loan.CoapplicantIncome<4500]
loan.CoapplicantIncome.plot(kind="box")
```

Out[114]:

```
<AxesSubplot:>
```

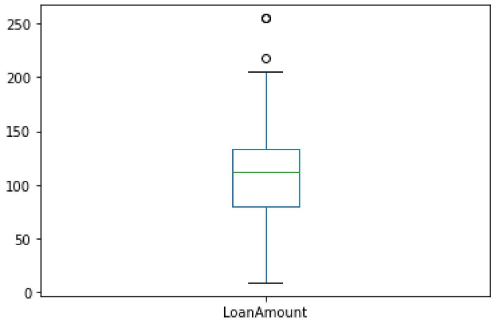


In [116]:

```
loan=loan[loan.CoapplicantIncome<200]
loan.LoanAmount.plot(kind="box")
```

Out[116]:

```
<AxesSubplot:>
```



In [23]:

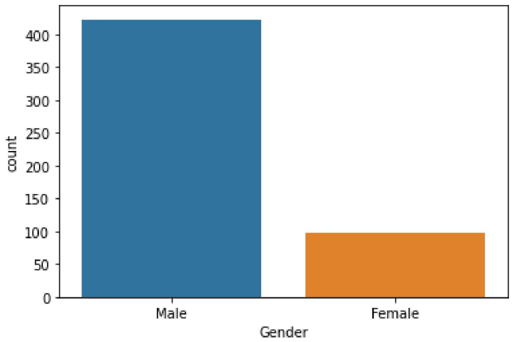
```
loan["Gender"].value_counts()
```

Out[23]:

```
Male      423
Female     98
Name: Gender, dtype: int64
```

In [24]:

```
sb.countplot(loan["Gender"])
plt.show()
```



In [25]:

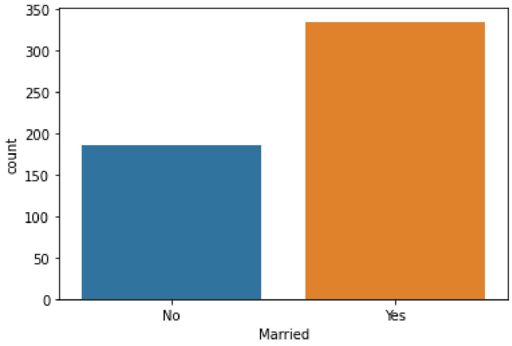
```
loan["Married"].value_counts()
```

Out[25]:

```
Yes    335
No     186
Name: Married, dtype: int64
```

In [26]:

```
sb.countplot(loan["Married"])
plt.show()
```



In [27]:

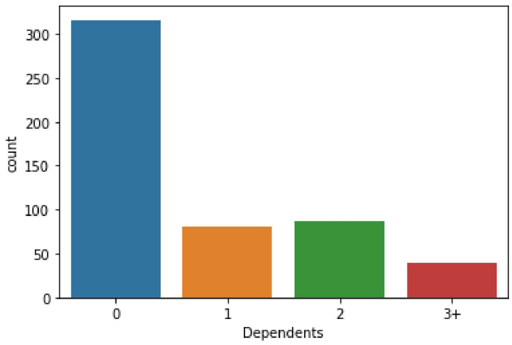
```
loan["Dependents"].value_counts()
```

Out[27]:

```
0     316
2      86
1      80
3+     39
Name: Dependents, dtype: int64
```

In [28]:

```
sb.countplot(loan["Dependents"])
plt.show()
```



In [29]:

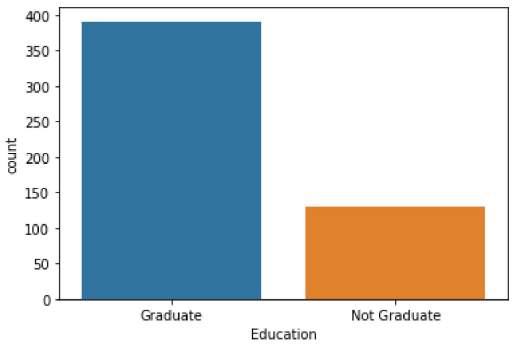
```
loan["Education"].value_counts()
```

Out[29]:

```
Graduate        391
Not Graduate    130
Name: Education, dtype: int64
```

In [30]:

```
sb.countplot(loan["Education"])
plt.show()
```



In [31]:

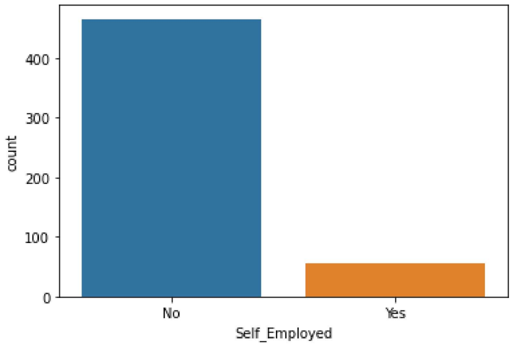
```
loan["Self_Employed"].value_counts()
```

Out[31]:

```
No     465
Yes     56
Name: Self_Employed, dtype: int64
```

In [32]:

```
sb.countplot(loan["Self_Employed"])
plt.show()
```



In [33]:

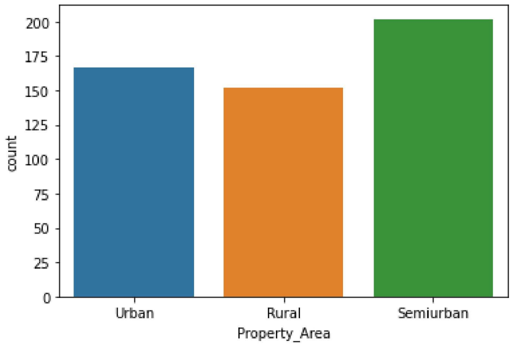
```
loan["Property_Area"].value_counts()
```

Out[33]:

```
Semiurban    202
Urban        167
Rural        152
Name: Property_Area, dtype: int64
```

In [34]:

```
sb.countplot(loan["Property_Area"])
plt.show()
```



In [35]:

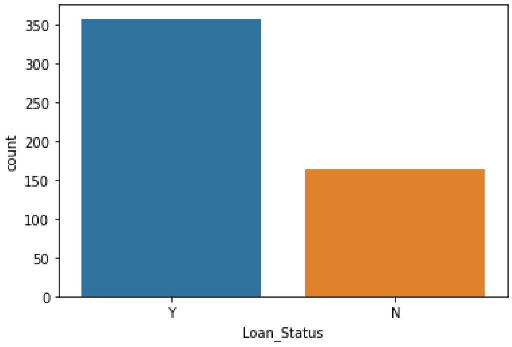
```
loan["Loan_Status"].value_counts()
```

Out[35]:

```
Y    357
N    164
Name: Loan_Status, dtype: int64
```

In [36]:

```
sb.countplot(loan["Loan_Status"])
plt.show()
```

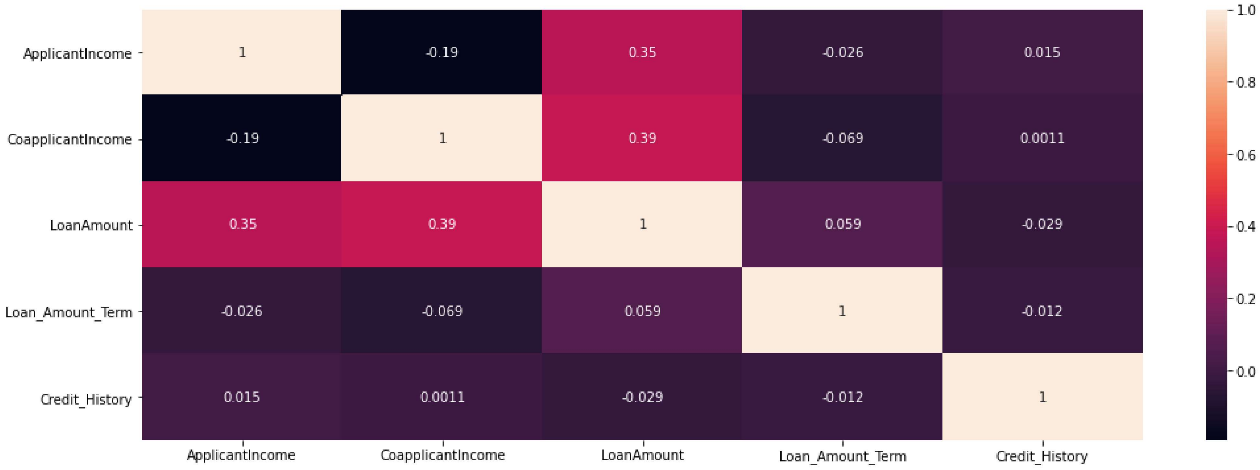


In [37]:

```
plt.figure(figsize=(17,6))
sb.heatmap(loan.corr(),annot=True)
```

Out[37]:

```
<AxesSubplot:>
```



In [38]:

```
loan.shape
```

Out[38]:

```
(521, 13)
```

In [39]:

```
loan.columns
```

Out[39]:

```
Index(['Loan_ID', 'Gender', 'Married', 'Dependents', 'Education',
       'Self_Employed', 'ApplicantIncome', 'CoapplicantIncome', 'LoanAmount',
       'Loan_Amount_Term', 'Credit_History', 'Property_Area', 'Loan_Status'],
      dtype='object')
```

In [40]:

```
from sklearn.preprocessing import LabelEncoder
L=LabelEncoder
```

In [41]:

```
loan["Gender"].replace(["Male","Female"],[1,0], inplace=True)
```

In [42]:

```
loan["Married"].replace(["Yes","No"],[1,0],inplace=True)
```

In [43]:

```
loan["Dependents"].replace(["0","1","2","3+"],[0,1,2,3], inplace=True)
```

In [44]:

```
loan["Education"].replace(["Not Graduate","Graduate"],[0,1], inplace=True)
```

In [45]:

```
loan["Self_Employed"].replace(["No","Yes"],[0,1], inplace=True)
```

In [46]:

```
loan["Property_Area"].replace(["Semiurban","Urban","Rural"],[0,1,2], inplace=True)
```

In [47]:

```
loan["Loan_Status"].replace(["Y","N"],[1,0], inplace=True)
```

In [48]:

```
loan.head()
```

Out[48]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_His
0	LP001002	1	0	0	1	0	5849	0.0	146.412162	360.0	
1	LP001003	1	1	1	1	0	4583	1508.0	128.000000	360.0	
2	LP001005	1	1	0	1	1	3000	0.0	66.000000	360.0	
3	LP001006	1	1	0	0	0	2583	2358.0	120.000000	360.0	
4	LP001008	1	0	0	1	0	6000	0.0	141.000000	360.0	

spliting the data for train and test

In [50]:

```
x=loan.drop(["Loan_ID","Loan_Status"],axis=True)
```

In [51]:

```
y=loan["Loan_Status"]
```

In [52]:

```
from sklearn.model_selection import train_test_split
```

In [53]:

```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2,random_state=12)
```

In [54]:

```
x_train.shape,x_test.shape
```

Out[54]:

```
((416, 11), (105, 11))
```

In [55]:

```
y_train.shape,y_test.shape
```

Out[55]:

```
((416,), (105,))
```

Logistic Regression

In [56]:

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

In [57]:

```
model=LogisticRegression()
```

In [58]:

```
model.fit(x_train,y_train)
```

Out[58]:

```
LogisticRegression()
```

In [59]:

```
pred=model.predict(x_test)
```

In [60]:

```
pred
```

Out[60]:

```
array([1, 1, 1, 1, 1, 1, 0, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 0, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 0, 1], dtype=int64)
```

In [61]:

```
len(pred)
```

Out[61]:

```
105
```

In [62]:

```
accuracy_score(y_test,pred)
```

Out[62]:

```
0.8
```

In [63]:

```
confusion_matrix(y_test,pred)
```

Out[63]:

```
array([[15, 19],
       [ 2, 69]], dtype=int64)
```

In [64]:

```
(15+69)/(15+19+2+69)
```

Out[64]:

```
0.8
```

Decision Tree classifier

In [65]:

```
from sklearn.tree import DecisionTreeClassifier
```

In [66]:

```
model=DecisionTreeClassifier()
```

In [67]:

```
model.fit(x_train,y_train)
```

Out[67]:

```
DecisionTreeClassifier()
```

In [68]:

```
pred=model.predict(x_test)
```

In [69]:

```
pred
```

Out[69]:

```
array([0, 1, 1, 1, 1, 1, 0, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 0,
       1, 0, 1, 0, 1, 1, 0, 1, 1, 1, 1, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 1,
       0, 0, 1, 1, 0, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 0, 1, 1,
       1, 1, 1, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 1, 1, 0, 1], dtype=int64)
```

In [70]:

```
accuracy_score(y_test,pred)
```

Out[70]:

```
0.7333333333333333
```

In [87]:

```
confusion_matrix(y_test,pred)
```

Out[87]:

```
array([[19, 15],
       [13, 58]], dtype=int64)
```

In [88]:

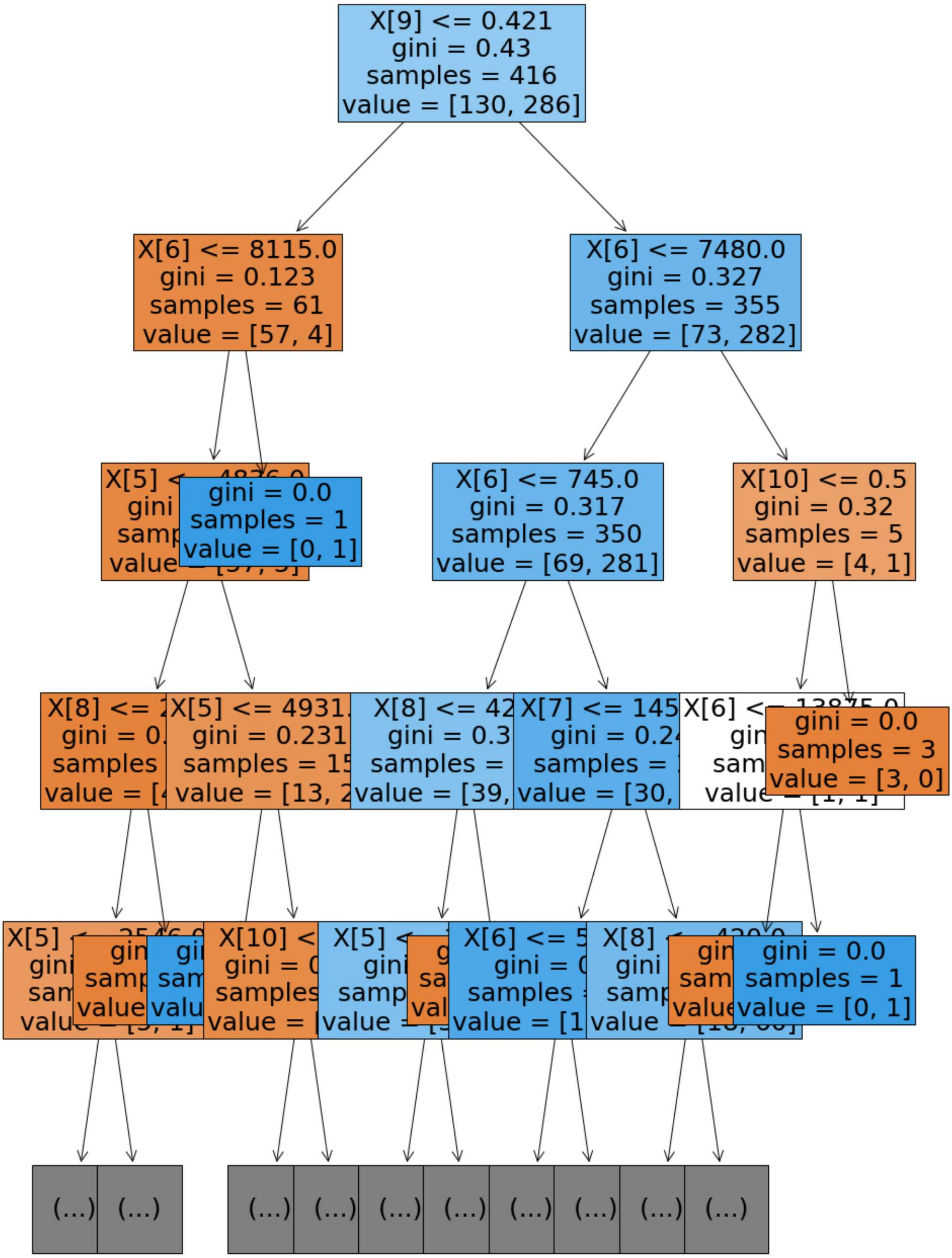
```
(19+58)/(19+15+13+58)
```

Out[88]:

```
0.7333333333333333
```

In [83]:

```
import matplotlib.pyplot as plt
%matplotlib inline
plt.figure(figsize=(15,25))
from sklearn import tree
tr=tree.plot_tree(model,filled=True,fontsize=25,max_depth=4)
```



KNN Classifier

In [92]:

```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score,confusion_matrix
```

In [93]:

```
model=KNeighborsClassifier(n_neighbors=5)
```

In [95]:

```
model.fit(x_train,y_train)
```

Out[95]:

```
KNeighborsClassifier()
```

In [96]:

```
pred=model.predict(x_test)
```

In [97]:

```
pred
```

Out[97]:

```
array([1, 0, 1, 1, 1, 1, 1, 0, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1,
       1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1,
       0, 0, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1], dtype=int64)
```

In [98]:

```
accuracy_score(y_test,pred)
```

Out[98]:

```
0.6285714285714286
```

In [99]:

```
confusion_matrix(y_test,pred)
```

Out[99]:

```
array([[ 6, 28],
       [11, 60]], dtype=int64)
```

In [100]:

```
(6+60)/(6+28+11+60)
```

Out[100]:

```
0.6285714285714286
```

Naive Bayes Algorithm

In [102]:

```
from sklearn.naive_bayes import GaussianNB
```

In [103]:

```
nb=GaussianNB()
```

In [105]:

```
nb.fit(x_train,y_train)
```

Out[105]:

```
GaussianNB()
```

In [108]:

```
pred=nb.predict(x_test)
```

In [109]:

```
pred
```

Out[109]:

```
array([1, 1, 1, 1, 1, 1, 0, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 0, 1,
       1, 0, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 0, 1], dtype=int64)
```

In [110]:

```
accuracy_score(y_test,pred)
```

Out[110]:

```
0.780952380952381
```

In [111]:

```
confusion_matrix(y_test,pred)
```

Out[111]:

```
array([[15, 19],
       [ 4, 67]], dtype=int64)
```

In [112]:

```
(15+67)/(15+19+4+67)
```

Out[112]:

```
0.780952380952381
```

In [ ]:

```

```