209309086_V V Prasanth G

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
from sklearn import tree
from sklearn.tree import plot_tree
```

Data Cleaning

```
 data= pd.read_csv("water_potability.csv")
```

```
data.head(5)
```

```
         ph    Hardness        Solids  Chloramines     Sulfate  
Conductivity  \
0       NaN  204.890455  20791.318981     7.300212  368.516441  
564.308654   
1  3.716080  129.422921  18630.057858     6.635246         NaN  
592.885359   
2  8.099124  224.236259  19909.541732     9.275884         NaN  
418.606213   
3  8.316766  214.373394  22018.417441     8.059332  356.886136  
363.266516   
4  9.092223  181.101509  17978.986339     6.546600  310.135738  
398.410813   

   Organic_carbon  Trihalomethanes  Turbidity  Potability  
0       10.379783        86.990970   2.963135           0  
1       15.180013        56.329076   4.500656           0  
2       16.868637        66.420093   3.055934           0  
3       18.436524       100.341674   4.628771           0  
4       11.558279        31.997993   4.075075           0  
```

```
data.shape
```

```
(3276, 10)
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3276 entries, 0 to 3275
Data columns (total 10 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   ph               2785 non-null   float64
 1   Hardness         3276 non-null   float64
 2   Solids           3276 non-null   float64
 3   Chloramines      3276 non-null   float64
```

```
 4   Sulfate          2495 non-null   float64
 5   Conductivity     3276 non-null   float64
 6   Organic_carbon   3276 non-null   float64
 7   Trihalomethanes  3114 non-null   float64
 8   Turbidity        3276 non-null   float64
 9   Potability       3276 non-null   int64
dtypes: float64(9), int64(1)
memory usage: 256.1 KB
```

```
data.isnull().sum()
```

```
ph                 491
Hardness             0
Solids               0
Chloramines          0
Sulfate            781
Conductivity         0
Organic_carbon       0
Trihalomethanes    162
Turbidity            0
Potability           0
dtype: int64
```

```
data.describe()
```

```
                ph     Hardness        Solids  Chloramines
Sulfate  \
count  2785.000000  3276.000000   3276.000000  3276.000000
2495.000000
mean      7.080795   196.369496  22014.092526     7.122277
333.775777
std       1.594320    32.879761   8768.570828     1.583085
41.416840
min       0.000000    47.432000    320.942611     0.352000
129.000000
25%       6.093092   176.850538  15666.690297     6.127421
307.699498
50%       7.036752   196.967627  20927.833607     7.130299
333.073546
75%       8.062066   216.667456  27332.762127     8.114887
359.950170
max      14.000000   323.124000  61227.196008    13.127000
481.030642

       Conductivity  Organic_carbon  Trihalomethanes    Turbidity
Potability
count   3276.000000     3276.000000      3114.000000  3276.000000
3276.000000
mean     426.205111       14.284970        66.396293     3.966786
0.390110
std       80.824064        3.308162        16.175008     0.780382
```

```
0.487849
min      181.483754        2.200000          0.738000     1.450000
0.000000
25%      365.734414       12.065801         55.844536     3.439711
0.000000
50%      421.884968       14.218338         66.622485     3.955028
0.000000
75%      481.792304       16.557652         77.337473     4.500320
1.000000
max      753.342620       28.300000        124.000000     6.739000
1.000000
```

```
data.fillna(data.mean(),inplace=True)
```

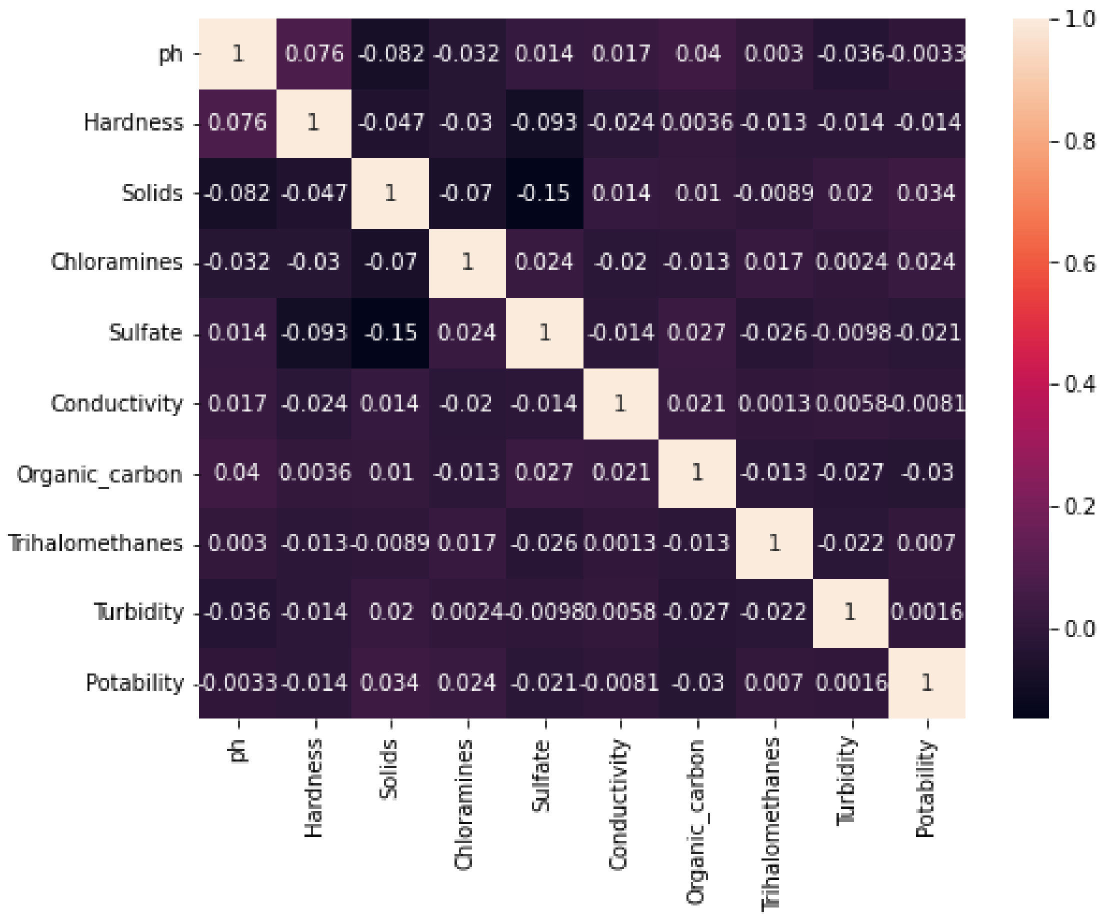
```
data.isnull().sum()
```

```
ph                 0
Hardness           0
Solids             0
Chloramines        0
Sulfate            0
Conductivity       0
Organic_carbon     0
Trihalomethanes    0
Turbidity          0
Potability         0
dtype: int64
```

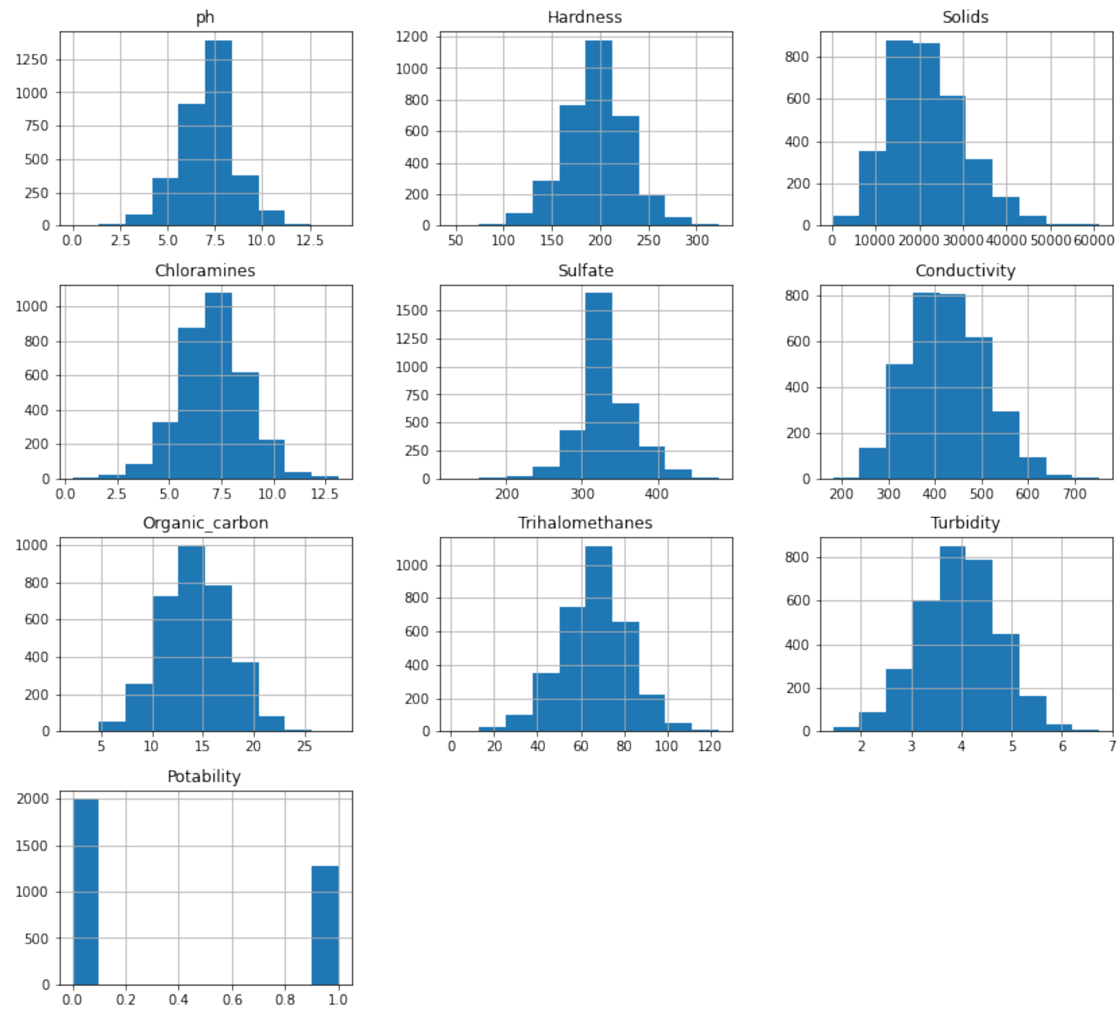
```
data.Potability.value_counts()
```

```
0    1998
1    1278
Name: Potability, dtype: int64
```

```
sns.heatmap(data.corr(),annot=True)
fig=plt.gcf()
fig.set_size_inches(8,6)
plt.show()
```




```
data.hist(figsize=(14,13))
plt.show()
```



Partioning

```
X = data.drop('Potability',axis=1)

Y= data['Potability']

from sklearn.model_selection import train_test_split
X_train, X_test, Y_train, Y_test = train_test_split(X,Y, test_size=
0.3, random_state=0)

Y_train.value_counts()

0    1388
1     905
Name: Potability, dtype: int64

Y_test.value_counts()

0    610
1    373
Name: Potability, dtype: int64
```

```
from sklearn.preprocessing import StandardScaler
sc_X = StandardScaler()
X_train = sc_X.fit_transform(X_train)
X_test = sc_X.transform(X_test)
```

Decision Tree

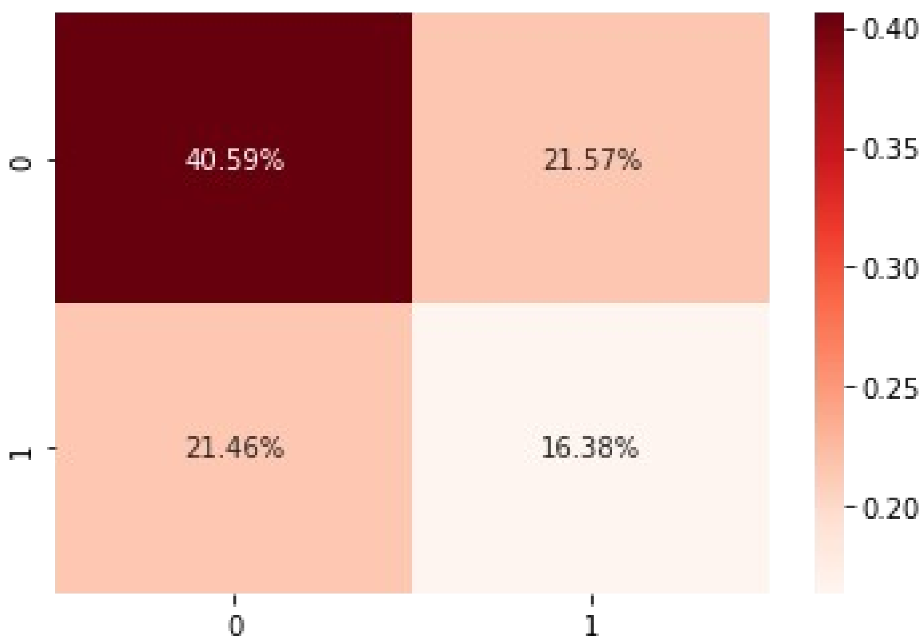
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score,confusion_matrix
dt=DecisionTreeClassifier()
dt.fit(X_train,Y_train)
```

```
DecisionTreeClassifier()
```

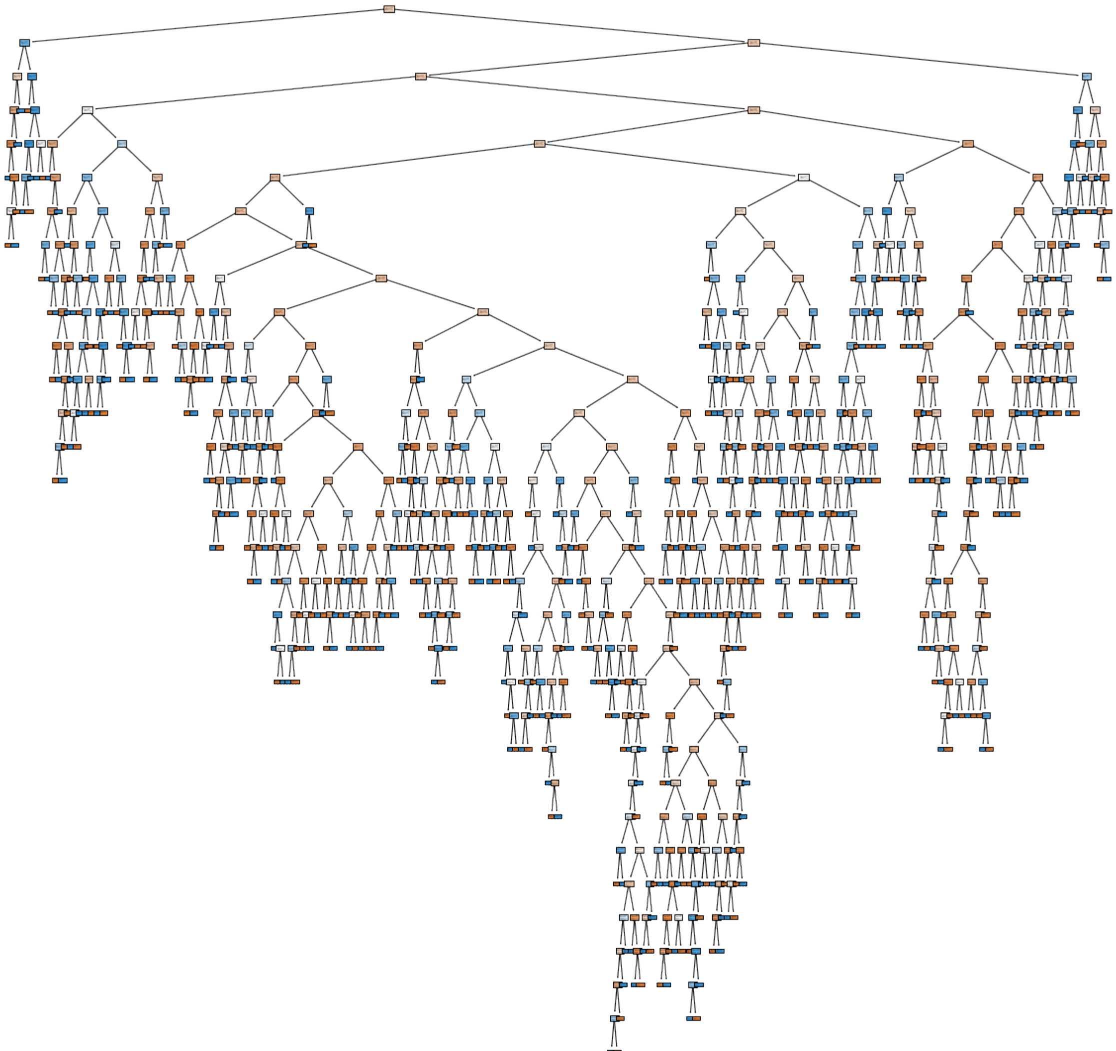
```
pred_dt=dt.predict(X_test)
accuracy_dt=accuracy_score(pred_dt,Y_test,)
print(accuracy_dt*100)
```

```
56.96846388606307
```

```
cm1=confusion_matrix(pred_dt,Y_test)
sns.heatmap(cm1/np.sum(cm1), annot = True, fmt=  '0.2%', cmap =
'Reds')
plt.show()
```

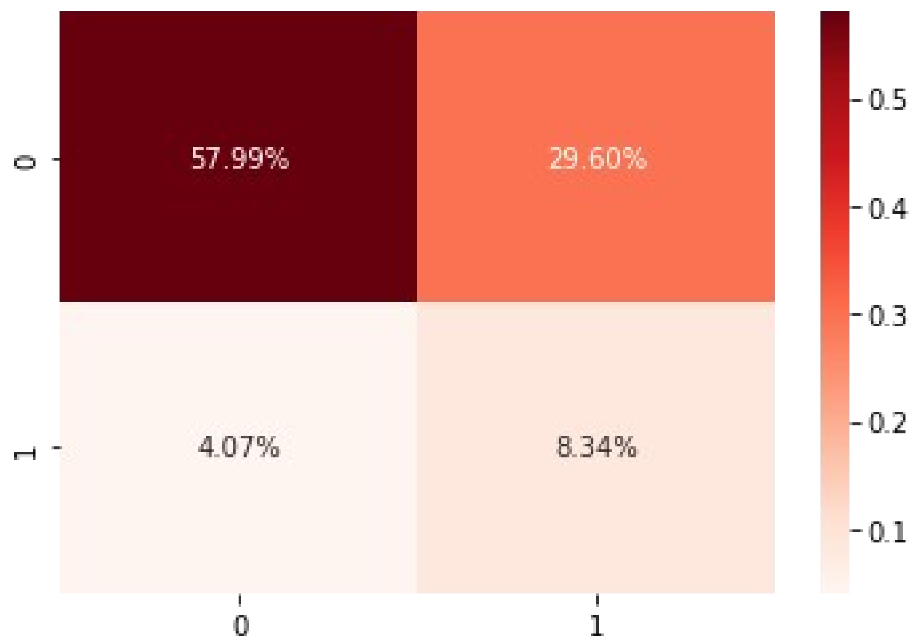



```
plt.figure(figsize = (20,20))
tree.plot_tree(dt,filled = True)
plt.show()
```



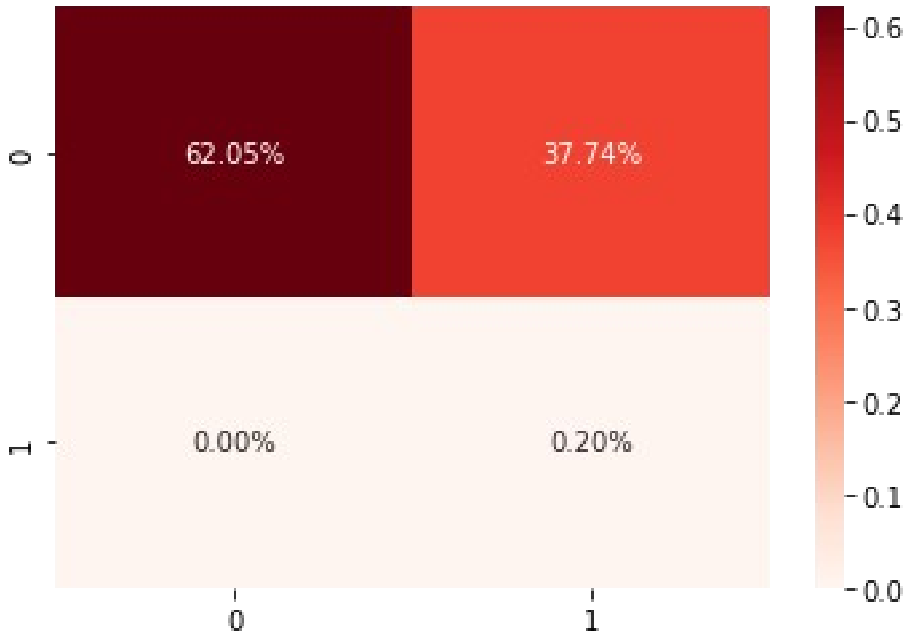
KNN

```
from sklearn.neighbors import KNeighborsClassifier

knn=KNeighborsClassifier(metric='manhattan', n_neighbors=22)
knn.fit(X_train,Y_train)

KNeighborsClassifier(metric='manhattan', n_neighbors=22)

pred_knn=knn.predict(X_test)
accuracy_knn=accuracy_score(pred_knn,Y_test)
print(accuracy_knn*100)

66.32756866734486

cm2=confusion_matrix(pred_knn,Y_test)
sns.heatmap(cm2/np.sum(cm2), annot = True, fmt=  '0.2%', cmap =
'Reds')
plt.show()
```



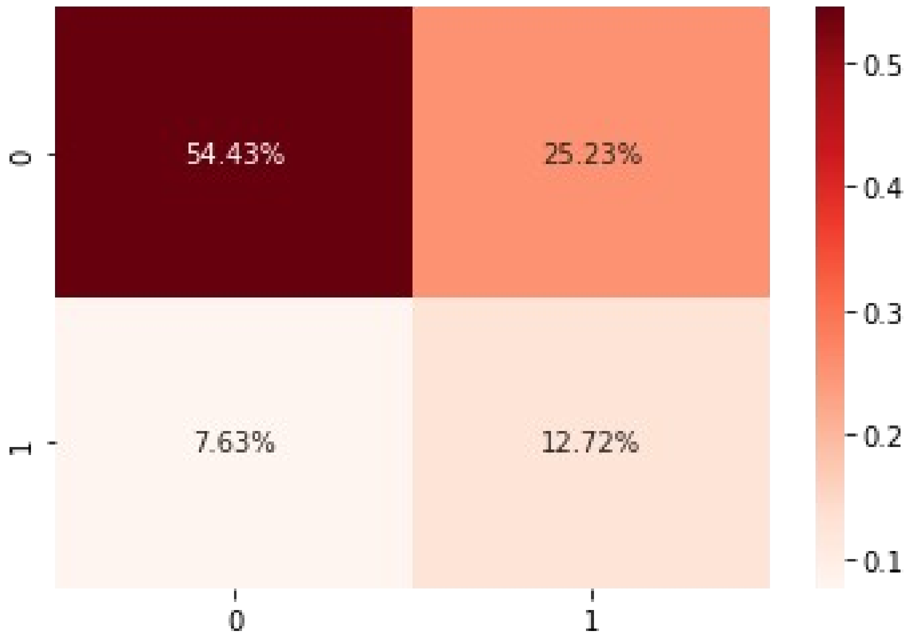
Logistic Regression

```
from sklearn.linear_model import LogisticRegression

lor= LogisticRegression()

lor.fit(X_train,Y_train)

LogisticRegression()

pred_lor = lor.predict(X_test)
accuracy_lor= accuracy_score(pred_lor,Y_test)
print(accuracy_lor*100)

62.25839267548321

cm3 = confusion_matrix(pred_lor,Y_test)
sns.heatmap(cm3/np.sum(cm3), annot = True, fmt=  '0.2%', cmap =
'Reds')
plt.show()
```

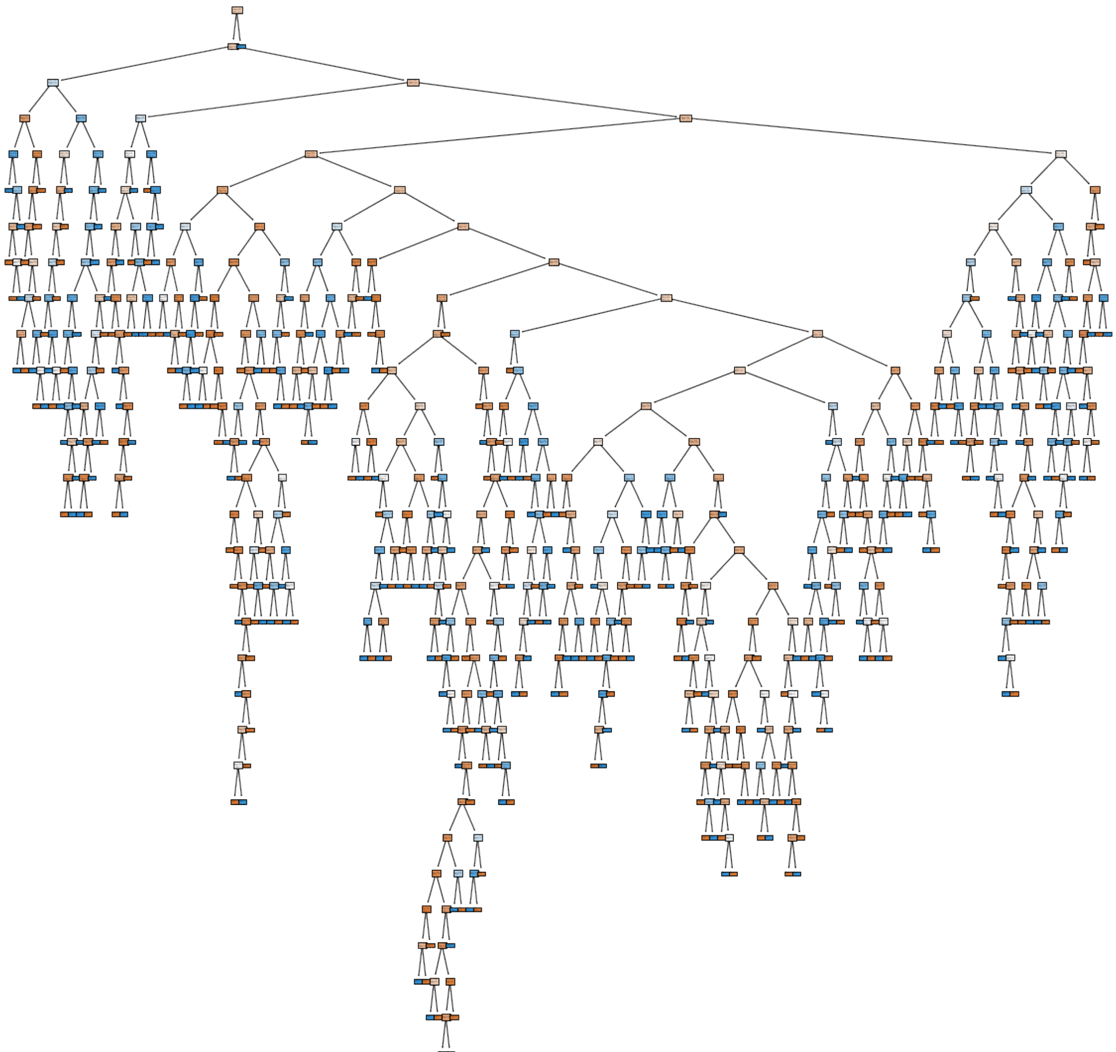


Random Forest

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report

rf =
RandomForestClassifier(n_estimators=54,criterion='entropy',random_stat
e=0)

rf.fit(X_train,Y_train)

RandomForestClassifier(criterion='entropy', n_estimators=54,
random_state=0)

pred_rf = rf.predict(X_test)

accuracy_rf = accuracy_score(pred_rf,Y_test)
print(accuracy_rf*100)

67.1414038657172

cm4 = confusion_matrix(pred_rf,Y_test)
sns.heatmap(cm4/np.sum(cm4), annot = True, fmt=  '0.2%', cmap =
'Reds')
plt.show()
```




```
plt.figure(figsize = (20,20))
tree.plot_tree(rf.estimators_[1],filled = True)
plt.show()
```



Naive Bayes

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

```
nb = GaussianNB()
```

```
nb.fit(X_train,Y_train)
```

```
GaussianNB()
```

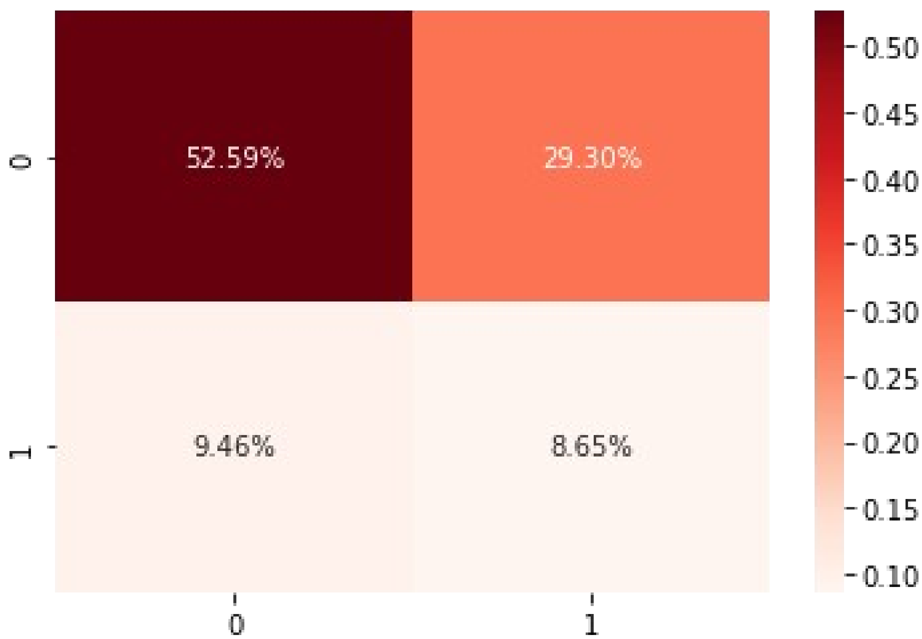
```
pred_nb = nb.predict(X_test)
```

```
accuracy_nb = accuracy_score(pred_nb,Y_test)
print(accuracy_nb*100)
```

```
61.241098677517805
```

```
cm5 = confusion_matrix(pred_nb,Y_test)
sns.heatmap(cm5/np.sum(cm5), annot = True, fmt=  '0.2%', cmap =
```

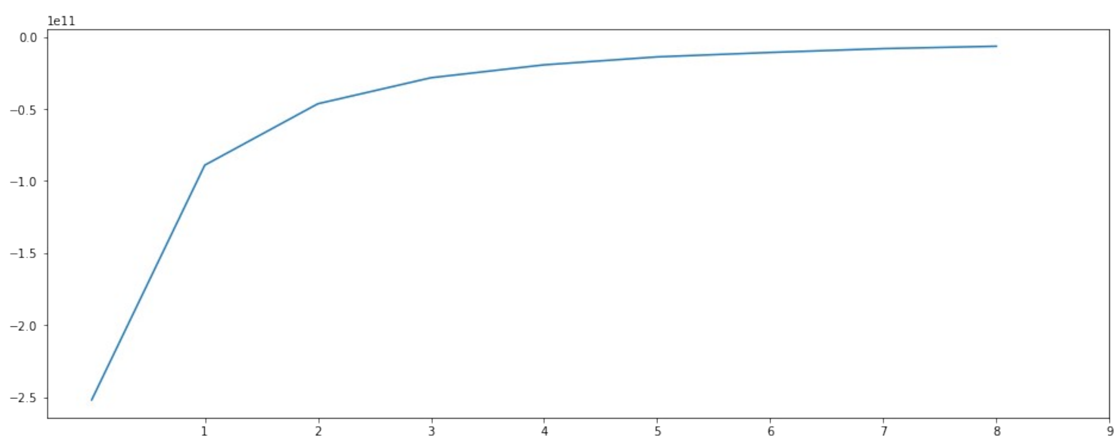
```
'Reds')
plt.show()
```



KMeans

```
from sklearn.cluster import KMeans
```

```
n_cluster = range(1,10)
kmeans = [KMeans(n_clusters=i).fit(data) for i in n_cluster]
scores = [kmeans[i].score(data)for i in range(len(kmeans))]
f = plt.figure(1,figsize=(16,6))
plt.plot(scores)
_=plt.xticks(n_cluster)
```




```
km = KMeans(n_clusters=1)
km.fit(X_train,Y_train)
```

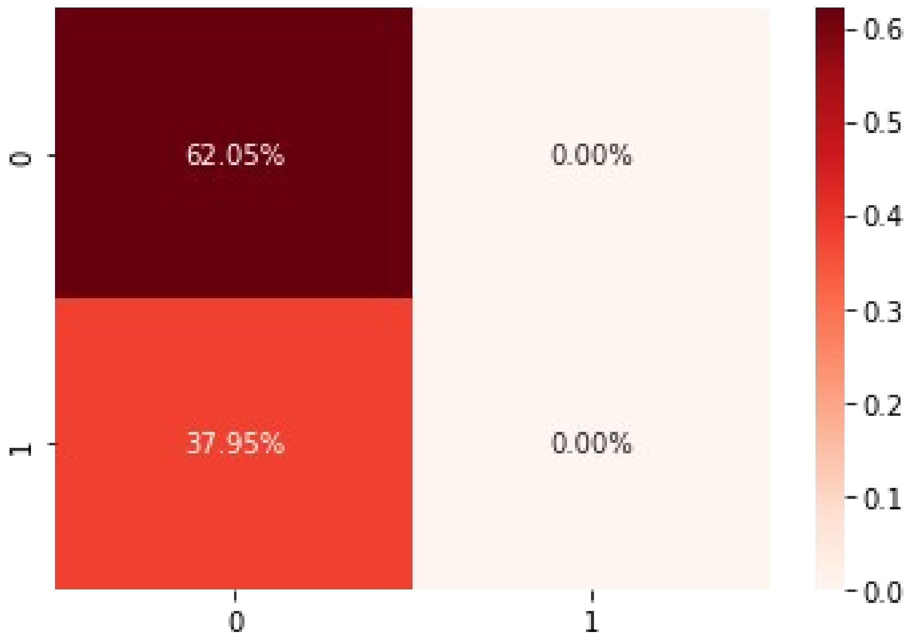
```
KMeans(n_clusters=1)
```

```
pred_km =km.predict(X_test)
```

```
accuracy_km = accuracy_score(pred_km,Y_test)
print(accuracy_km*100)
```

```
62.05493387589013
```

```
cm6 = confusion_matrix(Y_test,pred_km)
sns.heatmap(cm6/np.sum(cm6), annot = True, fmt=  '0.2%', cmap = 
'Reds')
plt.show()
```



SVM

```
from sklearn.svm import SVC, LinearSVC
```

```
svm = SVC(kernel='rbf', random_state = 42)
svm.fit(X_train, Y_train)
```

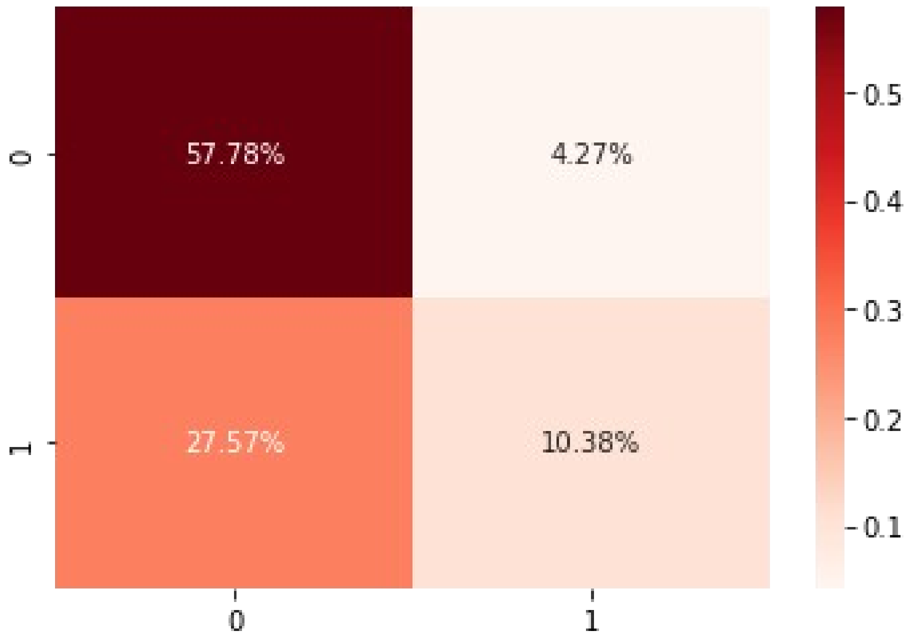
```
SVC(random_state=42)
```

```
pred_svm = svm.predict(X_test)
```

```
accuracy_svm = accuracy_score(Y_test,pred_svm)
print(accuracy_svm*100)
```

```
68.1586978636826
```

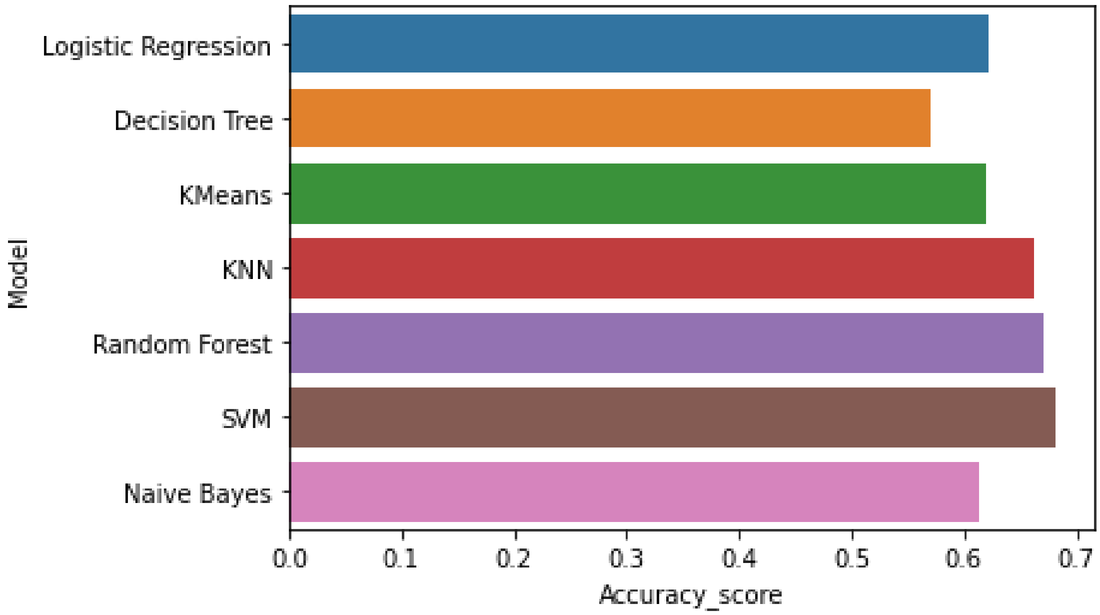
```
cm7 = confusion_matrix(Y_test,pred_svm)
sns.heatmap(cm7/np.sum(cm7), annot = True, fmt=  '0.2%', cmap = 
'Reds')
plt.show()
```



Summary

```
models = pd.DataFrame({
    'Model':['Logistic Regression', 'Decision Tree', 'KMeans', 'KNN',
'Random Forest', 'SVM', 'Naive Bayes'],
    'Accuracy_score' :[accuracy_lor, accuracy_dt, accuracy_km,
accuracy_knn, accuracy_rf, accuracy_svm, accuracy_nb]
})
models
sns.barplot(x='Accuracy_score', y='Model', data=models)

models.sort_values(by='Accuracy_score', ascending=False)
```

	Model	Accuracy_score
5	SVM	0.681587
4	Random Forest	0.671414
3	KNN	0.663276
0	Logistic Regression	0.622584
2	KMeans	0.620549
6	Naive Bayes	0.612411
1	Decision Tree	0.569685


Logistic Regression
Decision Tree
KMeans
KNN
Random Forest
SVM
Naive Bayes
Model
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
Accuracy_score