Stroke Prediction

> According to the World Health Organization (WHO) stroke is the 2nd leading cause of death globally, responsible for approximately 11% of total deaths.

> This dataset is used to predict whether a patient is likely to get stroke based on the input parameters like gender, age, various diseases, and smoking status.

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from collections import Counter
from sklearn.metrics import accuracy_score,confusion_matrix,classification_report
import warnings
warnings.filterwarnings('ignore')
```

Exploratory Data Analysis

1. Correlation
2. Missing values
3. Outliers
4. Categorical Variables
5. Balancing Dataset

Read and count data

https://www.kaggle.com/fedesoriano/stroke-prediction-dataset

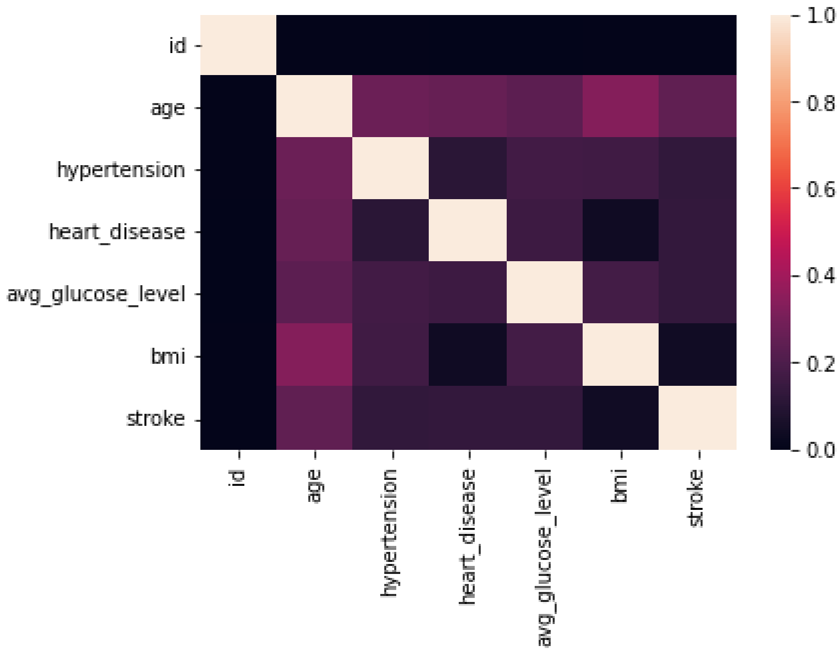
```
df=pd.read_csv("healthcare-dataset-stroke-data.csv")
df.shape
```

```
(5110, 12)
```

Correlation

```
sns.heatmap(df.corr())
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f55c3fd2c90>
```



Get column information

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5110 entries, 0 to 5109
Data columns (total 12 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   id                 5110 non-null   int64  
 1   gender             5110 non-null   object 
 2   age                5110 non-null   float64
 3   hypertension       5110 non-null   int64  
 4   heart_disease      5110 non-null   int64  
 5   ever_married       5110 non-null   object 
 6   work_type          5110 non-null   object 
 7   Residence_type     5110 non-null   object 
 8   avg_glucose_level  5110 non-null   float64
 9   bmi                4909 non-null   float64
 10  smoking_status     5110 non-null   object 
 11  stroke             5110 non-null   int64  
dtypes: float64(3), int64(4), object(5)
memory usage: 479.2+ KB
```

Describe Data

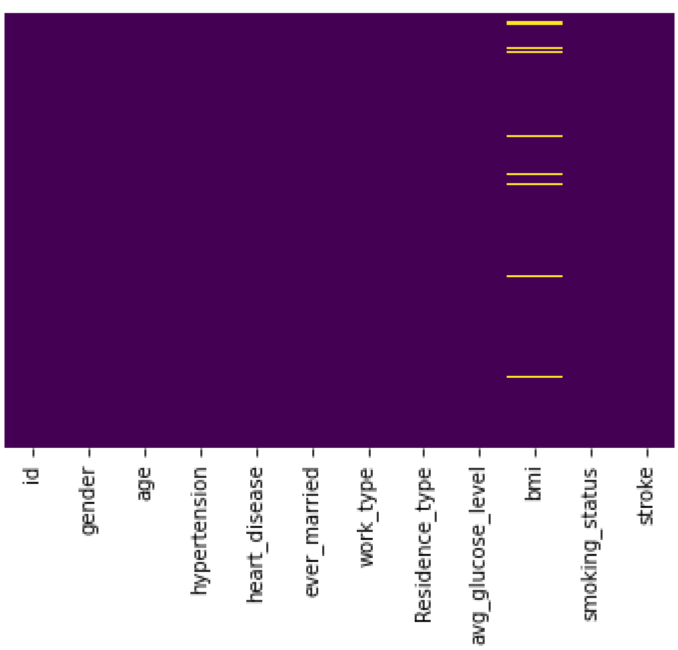
```
df.describe()
```

	id	age	hypertension	heart_disease	avg_glucose_level	
count	5110.000000	5110.000000	5110.000000	5110.000000	5110.000000	490
mean	36517.829354	43.226614	0.097456	0.054012	106.147677	28
std	21161.721625	22.612647	0.296607	0.226063	45.283560	
min	67.000000	0.080000	0.000000	0.000000	55.120000	10
25%	17741.250000	25.000000	0.000000	0.000000	77.245000	23
50%	36932.000000	45.000000	0.000000	0.000000	91.885000	28
75%	54682.000000	61.000000	0.000000	0.000000	114.090000	33
max	72940.000000	82.000000	1.000000	1.000000	271.740000	97

HeatMap to check the Missing values/Null values of all columns

```
sns.heatmap(df.isnull(),yticklabels=False,cbar=False,cmap='viridis')
```

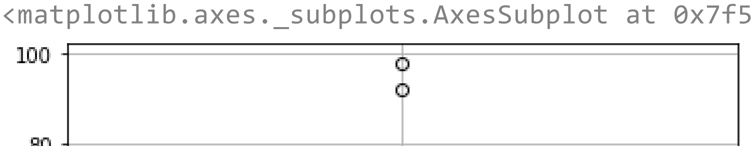
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f55c11b9ad0>
```

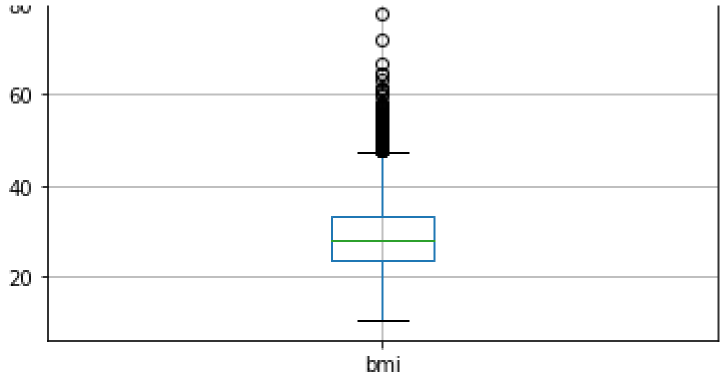


Identifying and Handling Outliers

```
df.boxplot(column='bmi')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f55c10ed290>
```






```
min_threshold, max_threshold = df.bmi.quantile([0.001, 0.999])
min_threshold, max_threshold
```

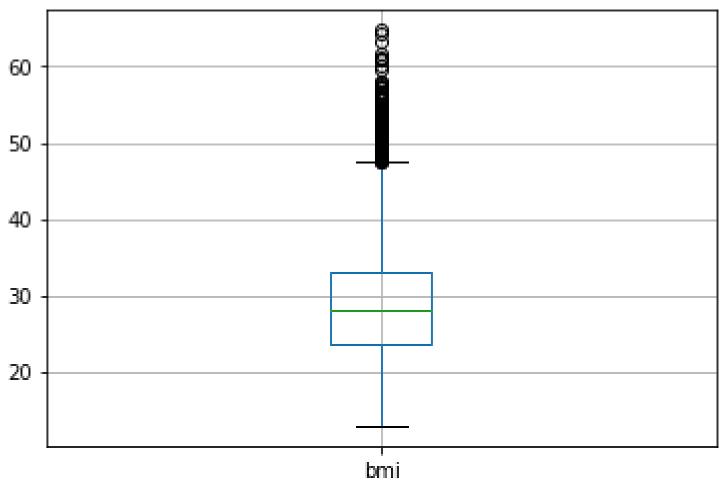
```
(12.754000000000001, 64.9840000000011)
```

```
new_df = df[(df.bmi<max_threshold) & (df.bmi>min_threshold)]
new_df.shape
```

```
(4899, 12)
```

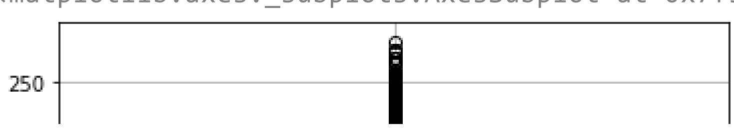
```
new_df.boxplot(column='bmi')
```

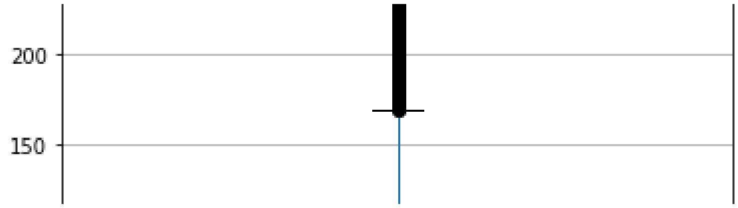
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f55c1028550>
```




```
df.boxplot(column='avg_glucose_level')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f55c1005390>
```






```
min_threshold_glucose, max_threshold_glucose = new_df.avg_glucose_level.quantile([0.001,
min_threshold_glucose, max_threshold_glucose
```

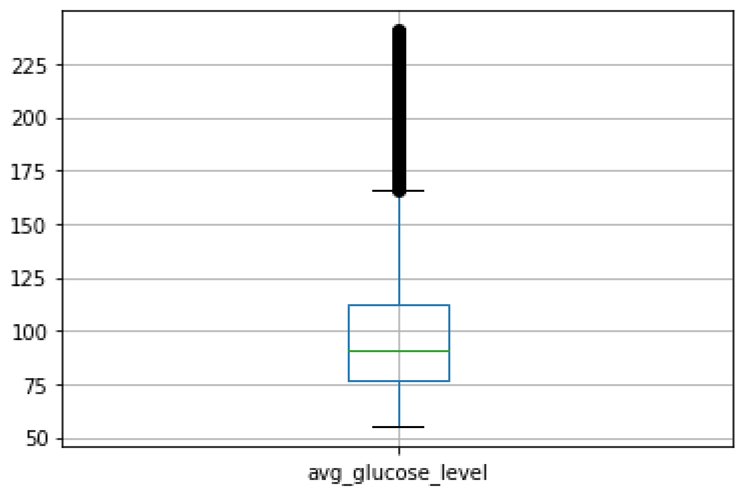
```
(55.26898, 240.59239999999994)
```

```
new_df = new_df[(new_df.avg_glucose_level<max_threshold_glucose) & (new_df.avg_glucose_le
new_df.shape
```

```
(4845, 12)
```

```
new_df.boxplot(column='avg_glucose_level')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f55c0e66c50>
```



Describe data after handling outliers

```
new_df.describe()
```

	id	age	hypertension	heart_disease	avg_glucose_level	
count	4845.000000	4845.000000	4845.000000	4845.000000	4845.000000	484

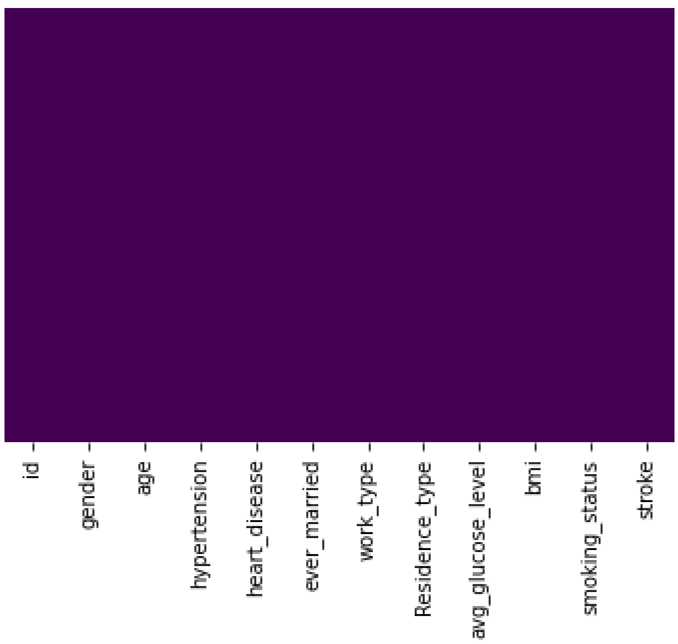
mean	37004.718885	42.672008	0.089783	0.048504	103.904778	2
std	20992.945627	22.516498	0.285901	0.214850	42.134289	
min	77.000000	0.080000	0.000000	0.000000	55.270000	1

Heat map after handling outliers

50%	37483.000000	44.000000	0.000000	0.000000	91.350000	2

```
sns.heatmap(new_df.isnull(),yticklabels=False,cbar=False,cmap='viridis')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f55c0dde890>
```



Handling Categorical Variable using One Hot Encoding

We have below Categorical variables in our dataset:

gender, ever_married, work_type, Residence_type, smoking_status

```
ndf_gender=pd.get_dummies(new_df['gender'])
ndf_gender=ndf_gender.drop(['Other'],axis=1)
ndf_ever_Married=pd.get_dummies(new_df['ever_married'])
ndf_work_type=pd.get_dummies(new_df['work_type'])
ndf_Residence_type=pd.get_dummies(new_df['Residence_type'])
ndf_smoking_status=pd.get_dummies(new_df['smoking_status'])
new_df=pd.concat([new_df,ndf_gender,ndf_ever_Married,ndf_work_type,ndf_Residence_type,ndf
new_df=new_df.drop(['gender','ever_married','work_type','Residence_type','smoking_status'
new_df.rename(columns={"Yes":"Married","No":"UnMarried"},inplace=True)
new_df.head(5)
```

	id	age	hypertension	heart_disease	avg_glucose_level	bmi	stroke	Female
0	9046	67.0	0	1	228.69	36.6	1	0

2	31112	80.0	0	1	105.92	32.5	1	0
3	60182	49.0	0	0	171.23	34.4	1	1
4	1665	79.0	1	0	174.12	24.0	1	1
5	56669	81.0	0	0	186.21	29.0	1	0

Segregating Predictors and Target

```
Preds=new_df.drop(["id", "stroke"],axis=1)
Target=new_df["stroke"]
```

Check for Data Distribution and handle the imbalances(if any)

```
def get_labels(a,b):
  if a==0:
    label1="Stroke"
  else:
    label1="Not a Stroke"
  if b==0:
    label2="Stroke"
  else:
    label2="Not a Stroke"
  return label1,label2
```

```
labels=list(Counter(Target).keys())
Data = [Counter(Target)[0],Counter(Target)[1]]
label1,label2=get_labels(labels[0],labels[1])
my_labels = label1,label2
plt.pie(Data,labels=my_labels,autopct='%1.1f%%')
plt.title('DataSet Distribution of Raw Data w.r.t Target')
plt.axis('equal')
plt.show()
```

The above chart indicates that data is Imbalanced

Handle Imbalance using RamdomOversampling Technique

RamdomOversampling Technique is effective for the machine learning algorithms that seek good splits of the data, such as support vector machines and decision trees.

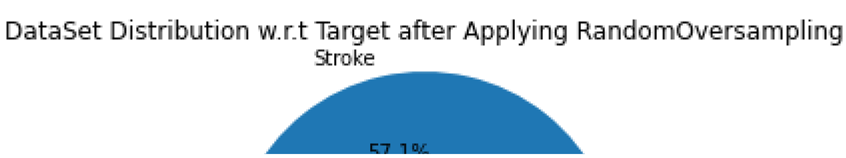
```
from sklearn.model_selection import train_test_split
X_Train,X_Test,y_Train,y_Test=train_test_split(Preds,Target,train_size=0.7)
```

```
from imblearn.over_sampling import RandomOverSampler

os=RandomOverSampler(.75)
X_Train_os,y_Train_os=os.fit_resample(X_Train,y_Train)
Counter(y_Train_os)
```

```
Counter({0: 3252, 1: 2439})
```

```
labels=list(Counter(y_Train_os).keys())
Data = [Counter(y_Train_os)[0],Counter(y_Train_os)[1]]
label1,label2=get_labels(labels[0],labels[1])
my_labels = label1,label2
plt.pie(Data,labels=my_labels,autopct='%1.1f%%')
plt.title('DataSet Distribution w.r.t Target after Applying RandomOversampling')
plt.axis('equal')
plt.show()
```



After applying RandomOverSampling on training dataset,now the data distrbution looks balanced

Model Training and Evaluation

1. Decision Tree Classification.
2. Support Vector Classification.
3. KNN with RandomSearchCV
4. XGBoost

Decision Tree Classification

> *Inputs: X_Train_os, y_Train_os*
>
> *Output: y_pred*
>
> *Tools: DecisionTreeClassifier from sklearn.tree*

```
from sklearn.tree import DecisionTreeClassifier
model_dt=DecisionTreeClassifier()
model_dt.fit(X_Train_os,y_Train_os)
```

```
DecisionTreeClassifier()
```

```
y_pred_dt=model_dt.predict(X_Test)
print("Metricies of Deccision Tress Classifier Model")
print("Confustion Matrix is as follows  \n{}".format(confusion_matrix(y_Test,y_pred_dt)))
print("Accuracy : {} ".format(accuracy_score(y_Test,y_pred_dt)))
print("Classification Reports are as follows  \n{}".format(classification_report(y_Test,y
```

```
Metricies of Deccision Tress Classifier Model
Confustion Matrix is as follows
[[1336   57]
 [  57    4]]
Accuracy : 0.921595598349381
Classification Reports are as follows
              precision    recall  f1-score   support

           0       0.96      0.96      0.96      1393
           1       0.07      0.07      0.07        61

    accuracy                           0.92      1454
   macro avg       0.51      0.51      0.51      1454
weighted avg       0.92      0.92      0.92      1454
```

Support Vector Classification Model

> *Inputs: X_Train_os, y_Train_os*
>
> *Output: y_pred*
>
> *Tools: SVC from sklearn.svm*

```
from sklearn.svm import SVC
model_svc=SVC()
model_svc.fit(X_Train_os,y_Train_os)
```

```
SVC()
```

```
y_pred_svm=model_svc.predict(X_Test)
print("Metricies of Support Vector Classification Model")
print("Confustion Matrix is as follows  \n{}".format(confusion_matrix(y_Test,y_pred_svm))
print("Accuracy : {} ".format(accuracy_score(y_Test,y_pred_svm)))
print("Classification Reports are as follows  \n{}".format(classification_report(y_Test,y
```

```
Metricies of Support Vector Classification Model
Confustion Matrix is as follows
[[1044  349]
 [  13   48]]
Accuracy : 0.7510316368638239
Classification Reports are as follows
              precision    recall  f1-score   support

           0       0.99      0.75      0.85      1393
           1       0.12      0.79      0.21        61

    accuracy                           0.75      1454
   macro avg       0.55      0.77      0.53      1454
weighted avg       0.95      0.75      0.83      1454
```

KNN with RandomSearchCV

> *Inputs: X_Train_os, y_Train_os, cv, random_state*
>
> *Output: y_pred*
>
> *Tools: KNeighborsClassifier from sklearn.neighbours; KFold, RandomizedSearchCV from sklearn.model_selection*

```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import KFold, RandomizedSearchCV

model_knn=KNeighborsClassifier()
```

```
grid={'n_neighbors':[5]}
cv=KFold(n_splits=30,random_state=None,shuffle=False)


model_rscv = RandomizedSearchCV(model_knn, grid,cv=cv,random_state=0)
model_rscv.fit(X_Train_os,y_Train_os)
```

```
RandomizedSearchCV(cv=KFold(n_splits=30, random_state=None, shuffle=False),
                   estimator=KNeighborsClassifier(),
                   param_distributions={'n_neighbors': [5]}, random_state=0)
```

```
model_rscv.best_params_
```

```
{'n_neighbors': 5}
```

```
y_pred_rscv=model_rscv.predict(X_Test)
print("Metricies of RandomizedSearchCV Model")
print("Confustion Matrix is as follows  \n{}".format(confusion_matrix(y_Test,y_pred_rscv)
print("Accuracy : {} ".format(accuracy_score(y_Test,y_pred_rscv)))
print("Classification Reports are as follows  \n{}".format(classification_report(y_Test,y
```

```
Metricies of RandomizedSearchCV Model
Confustion Matrix is as follows
[[1242  151]
 [  46   15]]
Accuracy : 0.8645116918844566
Classification Reports are as follows
              precision    recall  f1-score   support

           0       0.96      0.89      0.93      1393
           1       0.09      0.25      0.13        61

    accuracy                           0.86      1454
   macro avg       0.53      0.57      0.53      1454
weighted avg       0.93      0.86      0.89      1454
```

XGBoost

> *Inputs: X_Train_os, y_Train_os*
>
> *Output: y_pred*
>
> *Tools: XGBClassifier from xgboost*

```
from xgboost import XGBClassifier

model_xg=XGBClassifier()
model_xg.fit(X_Train_os,y_Train_os)
```

```
XGBClassifier()
```

```
y_pred_xg=model_xg.predict(X_Test)
print("Metricies of XGBOOST Model")
print("Confustion Matrix is as follows  \n{}".format(confusion_matrix(y_Test,y_pred_xg)))
print("Accuracy : {} ".format(accuracy_score(y_Test,y_pred_xg)))
print("Classification Reports are as follows  \n{}".format(classification_report(y_Test,y
```

```
Metricies of XGBOOST Model
Confustion Matrix is as follows
[[1163  230]
 [  29   32]]
Accuracy : 0.8218707015130674
Classification Reports are as follows
              precision    recall  f1-score   support

           0       0.98      0.83      0.90      1393
           1       0.12      0.52      0.20        61

    accuracy                           0.82      1454
   macro avg       0.55      0.68      0.55      1454
weighted avg       0.94      0.82      0.87      1454
```

Plotting ROC curve

```
from sklearn.metrics import plot_roc_curve
disp=plot_roc_curve(model_dt,X_Test,y_Test)
plot_roc_curve(model_svc,X_Test,y_Test,ax=disp.ax_)
plot_roc_curve(model_rscv,X_Test,y_Test,ax=disp.ax_)
plot_roc_curve(model_xg,X_Test,y_Test,ax=disp.ax_)
```

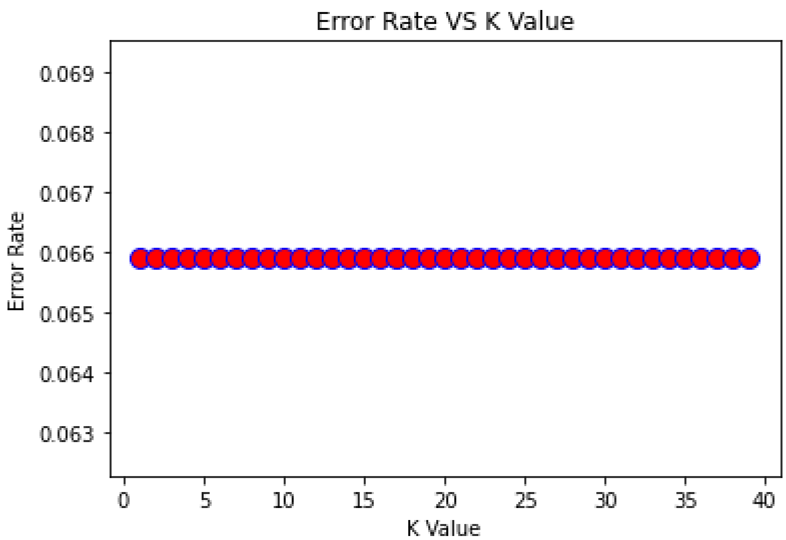
```
<sklearn.metrics._plot.roc_curve.RocCurveDisplay at 0x7f55b6c47190>
```

```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import cross_val_score
```

```
from sklearn.model_selection import cross_val_score
error=[]
for i in range(1,40):
  knn=KNeighborsClassifier(n_neighbors=i)
  score=cross_val_score(model_knn,X_Train_os,y_Train_os,cv=10)
  error.append(1-score.mean())
```


```
plt.plot(range(1,40),error,color='blue',linestyle='dashed',marker='o',markerfacecolor='re
plt.title('Error Rate VS K Value')
plt.xlabel('K Value')
plt.ylabel('Error Rate')
```

```
Text(0, 0.5, 'Error Rate')
```



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