```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

Import Data

```
df = pd.read_csv('https://github.com/YBI-Foundation/Dataset/raw/main/Bank%20Churn%20Modelling.csv')
```

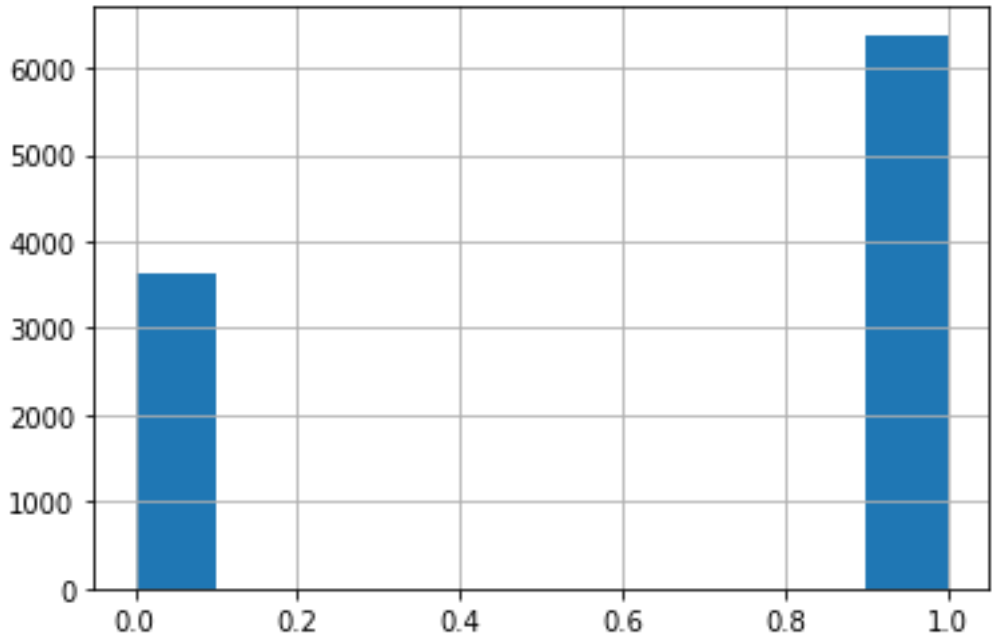
Analysing Data

```
df.head()
```

	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	Num Of Products	Has Credit Card	Is Active Member	Estimated Salary	Churn
0	15634602	Hargrave	619	France	Female	42	2	0.00	1	1	1	101348.88	1
1	15647311	Hill	608	Spain	Female	41	1	83807.86	1	0	1	112542.58	0
2	15619304	Onio	502	France	Female	42	8	159660.80	3	1	0	113931.57	1
3	15701354	Boni	699	France	Female	39	1	0.00	2	0	0	93826.63	0
4	15737888	Mitchell	850	Spain	Female	43	2	125510.82	1	1	1	79084.10	0

```
df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 13 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   CustomerId        10000 non-null  int64  
 1   Surname           10000 non-null  object 
 2   CreditScore       10000 non-null  int64  
 3   Geography         10000 non-null  object 
 4   Gender            10000 non-null  object 
 5   Age               10000 non-null  int64  
 6   Tenure            10000 non-null  int64  
 7   Balance           10000 non-null  float64
 8   Num Of Products   10000 non-null  int64  
 9   Has Credit Card   10000 non-null  int64  
 10  Is Active Member  10000 non-null  int64  
 11  Estimated Salary  10000 non-null  float64
 12  Churn             10000 non-null  int64  
dtypes: float64(2), int64(8), object(3)
memory usage: 1015.8+ KB
df.duplicated('CustomerId').sum()
0
df = df.set_index('CustomerId')
df.info()
<class 'pandas.core.frame.DataFrame'>
```

```
Int64Index: 10000 entries, 15634602 to 15628319
Data columns (total 12 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   Surname           10000 non-null  object 
 1   CreditScore       10000 non-null  int64  
 2   Geography         10000 non-null  object 
 3   Gender            10000 non-null  object 
 4   Age               10000 non-null  int64  
 5   Tenure            10000 non-null  int64  
 6   Balance           10000 non-null  float64
 7   Num Of Products   10000 non-null  int64  
 8   Has Credit Card   10000 non-null  int64  
 9   Is Active Member  10000 non-null  int64  
 10  Estimated Salary  10000 non-null  float64
 11  Churn             10000 non-null  int64  
dtypes: float64(2), int64(7), object(3)
memory usage: 1015.6+ KB
df['Geography'].value_counts()
France     5014
Germany    2509
Spain      2477
Name: Geography, dtype: int64
df.replace({'Geography': {'France': 2,'Germany' : 1, 'Spain':
0}},inplace=True )
df['Gender'].value_counts()
Male      5457
Female    4543
Name: Gender, dtype: int64
df.replace({'Gender': {'Male': 0, 'Female':1}},inplace=True)
df['Num Of Products'].value_counts()
1    5084
2    4590
3     266
4      60
Name: Num Of Products, dtype: int64
df.replace({'Num Of Products': {1: 0,2:1,3:1,4:1}},inplace=True)
df['Has Credit Card'].value_counts()
1    7055
0    2945
Name: Has Credit Card, dtype: int64
df['Is Active Member'].value_counts()
1    5151
0    4849
Name: Is Active Member, dtype: int64
df.loc[(df['Balance']==0), 'Churn'].value_counts()
0    3117
1     500
Name: Churn, dtype: int64
df['Zero Balance'] =np.where(df['Balance']>0,1,0)
df['Zero Balance'].hist()
<matplotlib.axes._subplots.AxesSubplot at 0x7f068100a490>
```



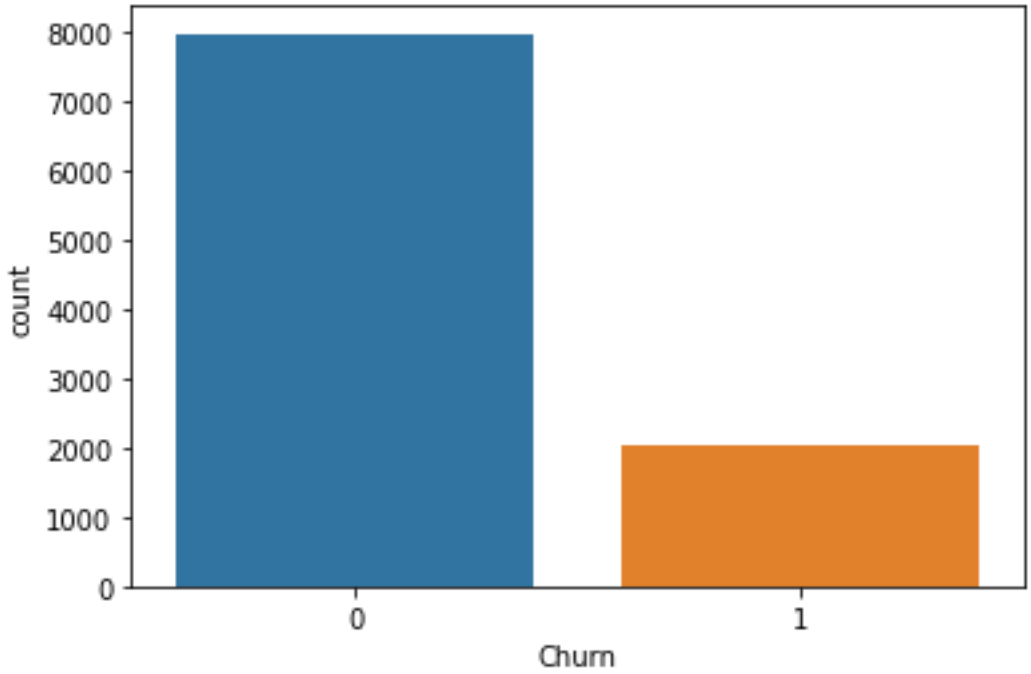

```
df.groupby(['Churn', 'Geography']).count()
```

		Surname	CreditScore	Gender	Age	Tenure	Balance	Num Of Products	Has Credit Card	Is Active Member	Estimated Salary	Zero Balance
Churn	**Geography**											
0	**0**	2064	2064	2064	2064	2064	2064	2064	2064	2064	2064	2064
	1	1695	1695	1695	1695	1695	1695	1695	1695	1695	1695	1695
	2	4204	4204	4204	4204	4204	4204	4204	4204	4204	4204	4204
1	**0**	413	413	413	413	413	413	413	413	413	413	413
	1	814	814	814	814	814	814	814	814	814	814	814
	2	810	810	810	810	810	810	810	810	810	810	810

Define Label and Features

```
df.columns
Index(['Surname', 'CreditScore', 'Geography', 'Gender', 'Age', 'Tenure',
       'Balance', 'Num Of Products', 'Has Credit Card', 'Is Active Member',
       'Estimated Salary', 'Churn', 'Zero Balance'],
      dtype='object')
X = df.drop(['Surname', 'Churn'],axis =1)
y = df['Churn']
X.shape,y.shape
```

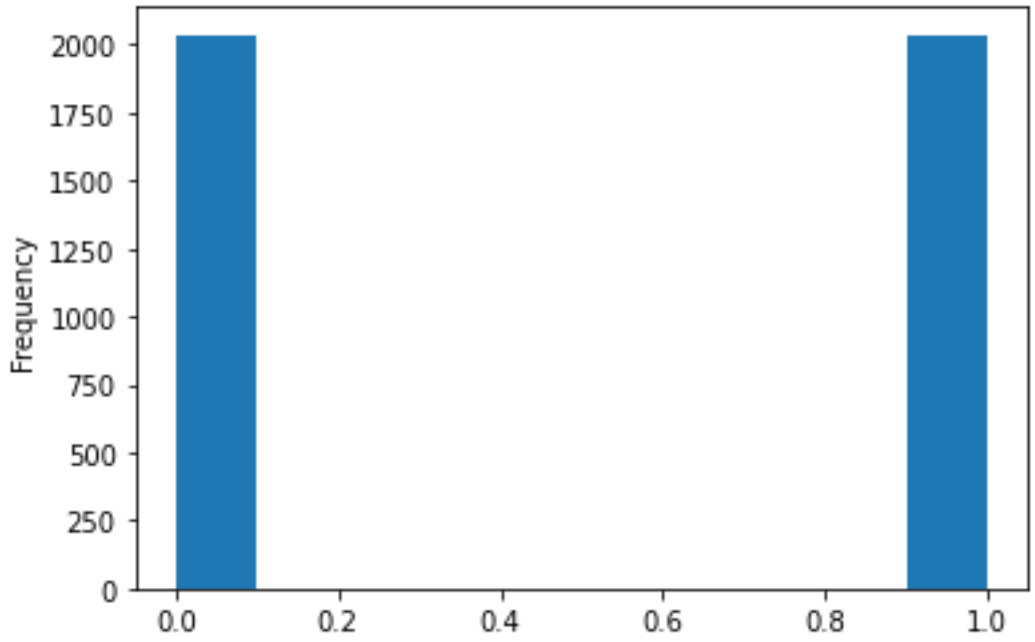
```
((10000, 11), (10000,))
df['Churn'].value_counts()
0    7963
1    2037
Name: Churn, dtype: int64
sns.countplot(x = 'Churn', data =df);
```




```
X.shape,y.shape
((10000, 11), (10000,))
```

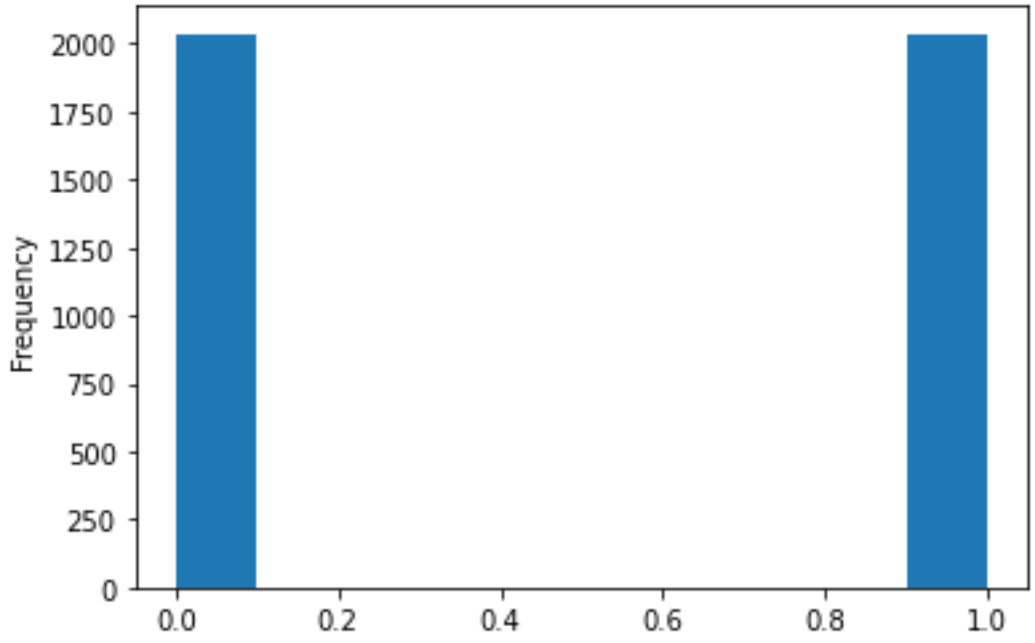
Random Under Sampling

```
from imblearn.under_sampling import RandomUnderSampler
rus =RandomUnderSampler(random_state=192529)
X_rus, y_rus = rus.fit_resample(X,y)
X_rus.shape,y_rus.shape,X.shape,y.shape
((4074, 11), (4074,), (10000, 11), (10000,))
y.value_counts()
0    7963
1    2037
Name: Churn, dtype: int64
y_rus.value_counts()
0    2037
1    2037
Name: Churn, dtype: int64
y_rus.plot(kind ='hist')
<matplotlib.axes._subplots.AxesSubplot at 0x7f0680ed9a10>
```



Random Over Sampling

```
from imblearn.over_sampling import RandomOverSampler
ros = RandomUnderSampler(random_state=192529)
X_ros, y_ros = ros.fit_resample(X,y)
X_ros.shape, y_ros.shape, X.shape,y.shape
((4074, 11), (4074,), (10000, 11), (10000,))
y.value_counts()
0    7963
1    2037
Name: Churn, dtype: int64
y_ros.plot(kind ='hist')
<matplotlib.axes._subplots.AxesSubplot at 0x7f0680deacd0>
```



Train Test Split

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

Split Original Data

```
X_train,X_test,y_train, y_test
=train_test_split(X,y,test_size=0.3,random_state =192529)
```

Split Random Under Sample Data

```
X_train_rus,X_test_rus,y_train_rus,y_test_rus =
train_test_split(X_rus,y_rus,test_size=0.7)
```

Split Random Over Sample Data

```
X_train_ros,X_test_ros,y_train_ros,y_test_ros =
train_test_split(X_ros,y_ros, test_size=0.7)
```

Standardize Features

```
from sklearn.preprocessing import StandardScaler
sc= StandardScaler()
```

satandarize Original Data

```
X_train[['CreditScore','Age', 'Tenure','Balance','Estimated Salary']] =
sc.fit_transform(X_train[['CreditScore','Age','Tenure','Balance','Estimated
Salary']])
X_test[['CreditScore','Age', 'Tenure','Balance','Estimated Salary']] =
sc.fit_transform(X_test[['CreditScore','Age','Tenure','Balance','Estimated
Salary']])
```

Standardize Random Under Sample Data

```
X_train_rus[['CreditScore','Age', 'Tenure','Balance','Estimated Salary']] =
sc.fit_transform(X_train_rus[['CreditScore','Age','Tenure','Balance','Estim
ated Salary']])
X_test_rus[['CreditScore','Age', 'Tenure','Balance','Estimated Salary']] =
sc.fit_transform(X_test_rus[['CreditScore','Age','Tenure','Balance','Estima
ted Salary']])
```

Standardize Random Over Sample Data

```
X_train_ros[['CreditScore','Age', 'Tenure','Balance','Estimated Salary']] =
sc.fit_transform(X_train_ros[['CreditScore','Age','Tenure','Balance','Estim
ated Salary']])
X_test_ros[['CreditScore','Age', 'Tenure','Balance','Estimated Salary']] =
sc.fit_transform(X_test_ros[['CreditScore','Age','Tenure','Balance','Estima
ted Salary']])
```

Support Vector Machine Classifier

```
from sklearn.svm import SVC
svc =SVC()
svc.fit(X_train,y_train)
SVC()
y_pred = svc.predict(X_test)
```

Model Accuracy

```
from sklearn.metrics import confusion_matrix, classification_report
confusion_matrix(y_test, y_pred)
array([[2379,   44],
       [ 424,  153]])
print(classification_report(y_test,y_pred))
              precision    recall  f1-score   support

           0       0.85      0.98      0.91      2423
           1       0.78      0.27      0.40       577

    accuracy                           0.84      3000
   macro avg       0.81      0.62      0.65      3000
weighted avg       0.83      0.84      0.81      3000
```

Hyper Parmeter Tunning

```
from sklearn.model_selection import GridSearchCV
param_grid = {'C': [0.1,1,10],
              'gamma': [1,0.1,0.01],'kernel': ['rbf'],
              'class_weight': ['balanced']}
grid = GridSearchCV(SVC(),param_grid, refit =True,verbose=2,cv= 2)
grid.fit(X_train,y_train)
Fitting 2 folds for each of 9 candidates, totalling 18 fits
[CV] END ..C=0.1, class_weight=balanced, gamma=1, kernel=rbf; total time=
3.7s
[CV] END ..C=0.1, class_weight=balanced, gamma=1, kernel=rbf; total time=
4.1s
[CV] END C=0.1, class_weight=balanced, gamma=0.1, kernel=rbf; total time=
3.6s
[CV] END C=0.1, class_weight=balanced, gamma=0.1, kernel=rbf; total time=
3.1s
[CV] END C=0.1, class_weight=balanced, gamma=0.01, kernel=rbf; total time=
3.4s
[CV] END C=0.1, class_weight=balanced, gamma=0.01, kernel=rbf; total time=
3.2s
[CV] END ....C=1, class_weight=balanced, gamma=1, kernel=rbf; total time=
3.2s
[CV] END ....C=1, class_weight=balanced, gamma=1, kernel=rbf; total time=
1.5s
[CV] END ..C=1, class_weight=balanced, gamma=0.1, kernel=rbf; total time=
1.1s
[CV] END ..C=1, class_weight=balanced, gamma=0.1, kernel=rbf; total time=
1.1s
[CV] END .C=1, class_weight=balanced, gamma=0.01, kernel=rbf; total time=
1.2s
[CV] END .C=1, class_weight=balanced, gamma=0.01, kernel=rbf; total time=
1.2s
[CV] END ...C=10, class_weight=balanced, gamma=1, kernel=rbf; total time=
1.4s
[CV] END ...C=10, class_weight=balanced, gamma=1, kernel=rbf; total time=
1.4s
[CV] END .C=10, class_weight=balanced, gamma=0.1, kernel=rbf; total time=
1.1s
[CV] END .C=10, class_weight=balanced, gamma=0.1, kernel=rbf; total time=
1.2s
[CV] END C=10, class_weight=balanced, gamma=0.01, kernel=rbf; total time=
1.1s
```

```
[CV] END C=10, class_weight=balanced, gamma=0.01, kernel=rbf; total time=
1.2s
GridSearchCV(cv=2, estimator=SVC(),
             param_grid={'C': [0.1, 1, 10], 'class_weight': ['balanced'],
                         'gamma': [1, 0.1, 0.01], 'kernel': ['rbf']},
             verbose=2)
print(grid.best_estimator_)
SVC(C=10, class_weight='balanced', gamma=1)
grid_predictions = grid.predict(X_test)
confusion_matrix(y_test,grid_predictions)
array([[2187,  236],
       [ 369,  208]])
print(classification_report(y_test,grid_predictions))
              precision    recall  f1-score   support

           0       0.86      0.90      0.88      2423
           1       0.47      0.36      0.41       577

    accuracy                           0.80      3000
   macro avg       0.66      0.63      0.64      3000
weighted avg       0.78      0.80      0.79      3000
```

Model with Random Under Sampling

```
svc_rus =SVC()
svc_rus.fit(X_train_rus,y_train_rus)
SVC()
svc.predict(X_test_rus)
array([0, 0, 0, ..., 0, 0, 1])
```

Model Accuracy

```
confusion_matrix(y_test,grid_predictions)
array([[2187,  236],
       [ 369,  208]])
print(classification_report(y_test,grid_predictions))
              precision    recall  f1-score   support

           0       0.86      0.90      0.88      2423
           1       0.47      0.36      0.41       577

    accuracy                           0.80      3000
   macro avg       0.66      0.63      0.64      3000
weighted avg       0.78      0.80      0.79      3000
```

Hyperparameter Tunning

```
param_grid = {'C': [0.1,1,10],
              'gamma': [1,0.1,0.01],'kernel': ['rbf'],
              'class_weight': ['balanced']}
grid_rus = GridSearchCV(SVC(),param_grid, refit =True,verbose=2,cv= 2)
grid_rus.fit(X_train,y_train)
Fitting 2 folds for each of 9 candidates, totalling 18 fits
[CV] END ..C=0.1, class_weight=balanced, gamma=1, kernel=rbf; total time=
1.7s
[CV] END ..C=0.1, class_weight=balanced, gamma=1, kernel=rbf; total time=
1.7s
```

```
[CV] END C=0.1, class_weight=balanced, gamma=0.1, kernel=rbf; total time=
1.2s
[CV] END C=0.1, class_weight=balanced, gamma=0.1, kernel=rbf; total time=
1.3s
[CV] END C=0.1, class_weight=balanced, gamma=0.01, kernel=rbf; total time=
1.3s
[CV] END C=0.1, class_weight=balanced, gamma=0.01, kernel=rbf; total time=
1.4s
[CV] END ....C=1, class_weight=balanced, gamma=1, kernel=rbf; total time=
1.5s
[CV] END ....C=1, class_weight=balanced, gamma=1, kernel=rbf; total time=
1.5s
[CV] END ..C=1, class_weight=balanced, gamma=0.1, kernel=rbf; total time=
1.1s
[CV] END ..C=1, class_weight=balanced, gamma=0.1, kernel=rbf; total time=
1.1s
[CV] END .C=1, class_weight=balanced, gamma=0.01, kernel=rbf; total time=
1.2s
[CV] END .C=1, class_weight=balanced, gamma=0.01, kernel=rbf; total time=
1.2s
[CV] END ...C=10, class_weight=balanced, gamma=1, kernel=rbf; total time=
1.4s
[CV] END ...C=10, class_weight=balanced, gamma=1, kernel=rbf; total time=
1.4s
[CV] END .C=10, class_weight=balanced, gamma=0.1, kernel=rbf; total time=
1.1s
[CV] END .C=10, class_weight=balanced, gamma=0.1, kernel=rbf; total time=
1.2s
[CV] END C=10, class_weight=balanced, gamma=0.01, kernel=rbf; total time=
1.1s
[CV] END C=10, class_weight=balanced, gamma=0.01, kernel=rbf; total time=
1.2s
GridSearchCV(cv=2, estimator=SVC(),
             param_grid={'C': [0.1, 1, 10], 'class_weight': ['balanced'],
                         'gamma': [1, 0.1, 0.01], 'kernel': ['rbf']},
             verbose=2)
print(grid_rus.best_estimator_)
SVC(C=10, class_weight='balanced', gamma=1)
grid_predictions_rus = grid_rus.predict(X_test_rus)
confusion_matrix(y_test_rus,grid_rus.predict(X_test_rus))
array([[1378,   45],
       [ 283, 1146]])
print(classification_report(y_test_rus,grid_predictions_rus))
              precision    recall  f1-score   support

           0       0.83      0.97      0.89      1423
           1       0.96      0.80      0.87      1429

    accuracy                           0.88      2852
   macro avg       0.90      0.89      0.88      2852
weighted avg       0.90      0.88      0.88      2852
```

Model with Random over Sampling

```
svc_ros = SVC()
svc_ros.fit(X_train_ros,y_train_ros)
SVC()
y_pred_ros = svc_ros.predict(X_test_ros)
```

Model Accuracy

```
confusion_matrix(y_test_ros,y_pred_ros)
array([[1071,  372],
       [ 416,  993]])
print(classification_report(y_test_ros,y_pred_ros))
              precision    recall  f1-score   support

           0       0.72      0.74      0.73      1443
           1       0.73      0.70      0.72      1409

    accuracy                           0.72      2852
   macro avg       0.72      0.72      0.72      2852
weighted avg       0.72      0.72      0.72      2852
```

Hyperparameter Tunning

```
param_grid = {'C': [0.1,1,10],
              'gamma': [1,0.1,0.01],'kernel': ['rbf'],
              'class_weight': ['balanced']}
grid_ros = GridSearchCV(SVC(),param_grid, refit =True,verbose=2,cv= 2)
grid_ros.fit(X_train,y_train)
Fitting 2 folds for each of 9 candidates, totalling 18 fits
[CV] END ..C=0.1, class_weight=balanced, gamma=1, kernel=rbf; total time=
1.7s
[CV] END ..C=0.1, class_weight=balanced, gamma=1, kernel=rbf; total time=
1.7s
[CV] END C=0.1, class_weight=balanced, gamma=0.1, kernel=rbf; total time=
1.2s
[CV] END C=0.1, class_weight=balanced, gamma=0.1, kernel=rbf; total time=
1.3s
[CV] END C=0.1, class_weight=balanced, gamma=0.01, kernel=rbf; total time=
1.3s
[CV] END C=0.1, class_weight=balanced, gamma=0.01, kernel=rbf; total time=
1.4s
[CV] END ....C=1, class_weight=balanced, gamma=1, kernel=rbf; total time=
1.5s
[CV] END ....C=1, class_weight=balanced, gamma=1, kernel=rbf; total time=
1.5s
[CV] END ..C=1, class_weight=balanced, gamma=0.1, kernel=rbf; total time=
1.1s
[CV] END ..C=1, class_weight=balanced, gamma=0.1, kernel=rbf; total time=
1.1s
[CV] END .C=1, class_weight=balanced, gamma=0.01, kernel=rbf; total time=
1.2s
[CV] END .C=1, class_weight=balanced, gamma=0.01, kernel=rbf; total time=
1.2s
[CV] END ...C=10, class_weight=balanced, gamma=1, kernel=rbf; total time=
1.5s
[CV] END ...C=10, class_weight=balanced, gamma=1, kernel=rbf; total time=
1.4s
[CV] END .C=10, class_weight=balanced, gamma=0.1, kernel=rbf; total time=
1.1s
[CV] END .C=10, class_weight=balanced, gamma=0.1, kernel=rbf; total time=
1.2s
[CV] END C=10, class_weight=balanced, gamma=0.01, kernel=rbf; total time=
1.1s
[CV] END C=10, class_weight=balanced, gamma=0.01, kernel=rbf; total time=
1.2s
```

```
GridSearchCV(cv=2, estimator=SVC(),
             param_grid={'C': [0.1, 1, 10], 'class_weight': ['balanced'],
                         'gamma': [1, 0.1, 0.01], 'kernel': ['rbf']},
             verbose=2)
print(grid_ros.best_estimator_)
SVC(C=10, class_weight='balanced', gamma=1)
grid_predictions_ros = grid_ros.predict(X_test_ros)
confusion_matrix(y_test_ros,grid_predictions_ros)
array([[1404,   39],
       [ 281, 1128]])
print(classification_report(y_test_ros,grid_predictions_ros))
              precision    recall  f1-score   support

           0       0.83      0.97      0.90      1443
           1       0.97      0.80      0.88      1409

    accuracy                           0.89      2852
   macro avg       0.90      0.89      0.89      2852
weighted avg       0.90      0.89      0.89      2852
```

Lets compare

```
print(classification_report(y_test,y_pred))
              precision    recall  f1-score   support

           0       0.85      0.98      0.91      2423
           1       0.78      0.27      0.40       577

    accuracy                           0.84      3000
   macro avg       0.81      0.62      0.65      3000
weighted avg       0.83      0.84      0.81      3000

print(classification_report(y_test,grid_predictions))
              precision    recall  f1-score   support

           0       0.86      0.90      0.88      2423
           1       0.47      0.36      0.41       577

    accuracy                           0.80      3000
   macro avg       0.66      0.63      0.64      3000
weighted avg       0.78      0.80      0.79      3000

print(classification_report(y_test_rus,grid_predictions_rus))
              precision    recall  f1-score   support

           0       0.83      0.97      0.89      1423
           1       0.96      0.80      0.87      1429

    accuracy                           0.88      2852
   macro avg       0.90      0.89      0.88      2852
weighted avg       0.90      0.88      0.88      2852

print(classification_report(y_test_ros,y_pred_ros))
              precision    recall  f1-score   support

           0       0.72      0.74      0.73      1443
           1       0.73      0.70      0.72      1409

    accuracy                           0.72      2852
```

```
   macro avg       0.72      0.72      0.72      2852
weighted avg       0.72      0.72      0.72      2852

print(classification_report(y_test_ros,grid_predictions_ros))
              precision    recall  f1-score   support

           0       0.83      0.97      0.90      1443
           1       0.97      0.80      0.88      1409

    accuracy                           0.89      2852
   macro avg       0.90      0.89      0.89      2852
weighted avg       0.90      0.89      0.89      2852
```