Hamdard University Islamabad

Assignment#4 Report

Title: Comparative Analysis of Nu-Support Vector Machines (Nu-SVM) and C-Support Vector Machines (C-SVM)

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1. Introduction:

Support Vector Machines (SVM) are powerful machine learning algorithms used for classification and regression tasks. Nu-SVM and C-SVM are two variants of SVM that differ in their formulation and parameterization. This report provides a comparative analysis of Nu-SVM and C-SVM, highlighting their key differences, advantages, and applications.

2. Overview of Nu-SVM and C-SVM:

2.1 Nu-Support Vector Machines (Nu-SVM): Nu-SVM is an extension of the traditional C-SVM that uses a different parameterization. Instead of the regularization parameter C, Nu-SVM uses a new parameter, denoted as ν (nu), which represents an upper bound on the fraction of margin errors and a lower bound on the fraction of support vectors. The nu parameter offers a more intuitive way to control the trade-off between training error and model complexity.

2.2 C-Support Vector Machines (C-SVM): C-SVM is the classical formulation of SVM, where the regularization parameter C is used to control the trade-off between achieving a low training error and maintaining a simple decision boundary. C-SVM aims to find a hyperplane that maximizes the margin between classes while penalizing misclassifications.

3. Comparative Analysis:

3.1 Model Complexity: Nu-SVM allows for a more direct control over the complexity of the model through the nu parameter. The nu parameter serves as an upper bound on the fraction of support vectors, providing a clear interpretation of the model complexity. In contrast, C-SVM uses the regularization parameter C, which indirectly influences model complexity.

3.2 Interpretability: Nu-SVM offers better interpretability due to the direct control over the fraction of support vectors. Users can set a desired upper bound on the fraction of margin errors, allowing for a more intuitive specification of model constraints. C-SVM, on the other hand, may require tuning the regularization parameter C to achieve similar control, which might be less straightforward.

3.3 Robustness to Outliers: Nu-SVM tends to be more robust to outliers than C-SVM. The nu parameter explicitly limits the influence of outliers on the model by constraining the fraction of margin errors. C-SVM, with its reliance on the regularization parameter C, might be more sensitive to outliers.

4. Applications:

4.1 Nu-SVM Applications: Nu-SVM is particularly suitable for scenarios where interpretability and explicit control over the fraction of support vectors are crucial. It is often preferred in applications where outliers are present, and robustness to noise is essential, such as in bioinformatics, finance, and outlier detection.

4.2 C-SVM Applications: C-SVM is widely used in various applications, including image classification, text categorization, and speech recognition. It is suitable for scenarios where a balance between achieving a high level of accuracy and controlling model complexity is desired.

5. Conclusion:

In conclusion, both Nu-SVM and C-SVM are powerful tools with distinct advantages. The choice between them depends on the specific requirements of the problem at hand, with Nu-SVM offering more interpretability and robustness to outliers, and C-SVM being a versatile choice for a wide range of applications. Understanding the characteristics of each algorithm is crucial for making informed decisions in machine learning tasks.

Code:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVC, NuSVC
from sklearn.metrics import accuracy_score, classification_report
```

```
df = pd.read_csv('diabetes_binary_5050split_health_indicators_BRFSS2021.csv')
df
```

```
       Diabetes_binary  HighBP  HighChol  CholCheck   BMI  Smoker  Stroke  
0                  0.0       1       0.0          1  33.0     0.0     0.0  \
1                  0.0       0       1.0          1  27.0     1.0     0.0   
2                  0.0       0       1.0          1  26.0     1.0     0.0   
3                  0.0       0       0.0          1  19.0     1.0     0.0   
4                  0.0       1       0.0          1  37.0     0.0     0.0   
...                ...     ...       ...        ...   ...     ...     ...   
67131              1.0       1       0.0          1  27.0     0.0     0.0   
67132              1.0       1       1.0          1  26.0     0.0     0.0   
67133              1.0       1       1.0          1  32.0     0.0     0.0   
67134              1.0       1       1.0          1  33.0     0.0     0.0   
67135              1.0       1       1.0          1  21.0     0.0     0.0   

       HeartDiseaseorAttack  PhysActivity  Fruits  ...  AnyHealthcare  
0                       0.0             1       1  ...              1  \
1                       0.0             1       0  ...              1   
2                       0.0             0       0  ...              1   
3                       0.0             1       1  ...              1   
4                       0.0             1       1  ...              1   
...                     ...           ...     ...  ...            ...   
67131                   0.0             1       1  ...              1   
```

```
67132                  0.0            0       1  ...             1
67133                  1.0            1       0  ...             1
67134                  0.0            0       0  ...             1
67135                  0.0            1       1  ...             1

       NoDocbcCost  GenHlth  MentHlth  PhysHlth  DiffWalk  Sex  Age  \
0              0.0      2.0      15.0       0.0       1.0    1    7   
1              0.0      2.0       1.0       2.0       0.0    1    7   
2              0.0      3.0       0.0      30.0       0.0    1   13   
3              0.0      3.0       0.0       0.0       0.0    0   11   
4              0.0      2.0       0.0       0.0       0.0    0    5   
...            ...      ...       ...       ...       ...  ...  ...   
67131          0.0      3.0       0.0       0.0       0.0    1   11   
67132          0.0      4.0       0.0       0.0       0.0    0   11   
67133          1.0      2.0      10.0       0.0       0.0    1    8   
67134          0.0      2.0       0.0       0.0       1.0    1   10   
67135          0.0      4.0       0.0       0.0       0.0    1   10   

       Education  Income  
0            6.0     9.0  
1            6.0     6.0  
2            4.0     3.0  
3            5.0     7.0  
4            5.0     3.0  
...          ...     ...  
67131        5.0     6.0  
67132        4.0     2.0  
67133        6.0     6.0  
67134        4.0     5.0  
67135        2.0     3.0  

[67136 rows x 22 columns]
```

Exploring Data

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 67136 entries, 0 to 67135
Data columns (total 22 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   Diabetes_binary       67136 non-null  float64
 1   HighBP                67136 non-null  int64  
 2   HighChol              67136 non-null  float64
 3   CholCheck             67136 non-null  int64  
 4   BMI                   67136 non-null  float64
 5   Smoker                67136 non-null  float64
 6   Stroke                67136 non-null  float64
 7   HeartDiseaseorAttack  67136 non-null  float64
 8   PhysActivity          67136 non-null  int64  
 9   Fruits                67136 non-null  int64  
 10  Veggies               67136 non-null  int64  
 11  HvyAlcoholConsump     67136 non-null  int64  
```

```
 12  AnyHealthcare         67136 non-null  int64
 13  NoDocbcCost           67136 non-null  float64
 14  GenHlth               67136 non-null  float64
 15  MentHlth              67136 non-null  float64
 16  PhysHlth              67136 non-null  float64
 17  DiffWalk              67136 non-null  float64
 18  Sex                   67136 non-null  int64
 19  Age                   67136 non-null  int64
 20  Education             67136 non-null  float64
 21  Income                67136 non-null  float64
dtypes: float64(13), int64(9)
memory usage: 11.3 MB
```

```
df.describe()
```

```
       Diabetes_binary        HighBP      HighChol     CholCheck  
count     67136.000000  67136.000000  67136.000000  67136.000000   \
mean          0.500000      0.548320      0.500238      0.976227
std           0.500004      0.497663      0.500004      0.152341
min           0.000000      0.000000      0.000000      0.000000
25%           0.000000      0.000000      0.000000      1.000000
50%           0.500000      1.000000      1.000000      1.000000
75%           1.000000      1.000000      1.000000      1.000000
max           1.000000      1.000000      1.000000      1.000000

                BMI        Smoker        Stroke  HeartDiseaseorAttack  
count  67136.000000  67136.000000  67136.000000          67136.000000   \
mean      30.288340      0.440151      0.058866              0.136633
std        7.095737      0.496409      0.235375              0.343462
min       12.000000      0.000000      0.000000              0.000000
25%       26.000000      0.000000      0.000000              0.000000
50%       29.000000      0.000000      0.000000              0.000000
75%       34.000000      1.000000      0.000000              0.000000
max       99.000000      1.000000      1.000000              1.000000

       PhysActivity        Fruits  ...  AnyHealthcare   NoDocbcCost  
count  67136.000000  67136.000000  ...   67136.000000  67136.000000   \
mean       0.717260      0.605919  ...       0.967260      0.066522
std        0.450334      0.488656  ...       0.177955      0.249194
min        0.000000      0.000000  ...       0.000000      0.000000
25%        0.000000      0.000000  ...       1.000000      0.000000
50%        1.000000      1.000000  ...       1.000000      0.000000
75%        1.000000      1.000000  ...       1.000000      0.000000
max        1.000000      1.000000  ...       1.000000      1.000000

            GenHlth      MentHlth      PhysHlth      DiffWalk           Sex  
count  67136.000000  67136.000000  67136.000000  67136.000000  67136.000000   \
mean       2.774756      4.230845      5.136752      0.231202      0.493431
std        1.073759      8.323138      9.593837      0.421605      0.499961
min        1.000000      0.000000      0.000000      0.000000      0.000000
25%        2.000000      0.000000      0.000000      0.000000      0.000000
50%        3.000000      0.000000      0.000000      0.000000      0.000000
75%        3.000000      4.000000      5.000000      0.000000      1.000000
max        5.000000     30.000000     30.000000      1.000000      1.000000
```

```
                Age     Education        Income
count  67136.000000  67136.000000  67136.000000
mean       8.501743      5.035912      6.563885
std        3.019624      0.981610      2.422641
min        1.000000      1.000000      1.000000
25%        7.000000      4.000000      5.000000
50%        9.000000      5.000000      7.000000
75%       11.000000      6.000000      8.000000
max       13.000000      6.000000     11.000000

[8 rows x 22 columns]
```

```
df.duplicated().sum()
```

```
737
```

Data Cleaning

```
# Dropping unnecessary features

df.drop(['Income', 'Education'], axis = 1, inplace = True)
df
```

```
       Diabetes_binary  HighBP  HighChol  CholCheck   BMI  Smoker  Stroke  
0                  0.0       1       0.0          1  33.0     0.0     0.0  \
1                  0.0       0       1.0          1  27.0     1.0     0.0   
2                  0.0       0       1.0          1  26.0     1.0     0.0   
3                  0.0       0       0.0          1  19.0     1.0     0.0   
4                  0.0       1       0.0          1  37.0     0.0     0.0   
...                ...     ...       ...        ...   ...     ...     ...   
67131              1.0       1       0.0          1  27.0     0.0     0.0   
67132              1.0       1       1.0          1  26.0     0.0     0.0   
67133              1.0       1       1.0          1  32.0     0.0     0.0   
67134              1.0       1       1.0          1  33.0     0.0     0.0   
67135              1.0       1       1.0          1  21.0     0.0     0.0   

       HeartDiseaseorAttack  PhysActivity  Fruits  Veggies  HvyAlcoholConsump  
0                       0.0             1       1        1                  0  \
1                       0.0             1       0        0                  0   
2                       0.0             0       0        0                  0   
3                       0.0             1       1        1                  0   
4                       0.0             1       1        1                  0   
...                     ...           ...     ...      ...                ...   
67131                   0.0             1       1        1                  0   
67132                   0.0             0       1        1                  0   
67133                   1.0             1       0        0                  0   
67134                   0.0             0       0        1                  0   
67135                   0.0             1       1        1                  0   

       AnyHealthcare  NoDocbcCost  GenHlth  MentHlth  PhysHlth  DiffWalk  Sex  
0                  1          0.0      2.0      15.0       0.0       1.0    1  \
1                  1          0.0      2.0       1.0       2.0       0.0    1   
2                  1          0.0      3.0       0.0      30.0       0.0    1   
```

```
3                  1          0.0      3.0       0.0       0.0       0.0    0
4                  1          0.0      2.0       0.0       0.0       0.0    0
...              ...          ...      ...       ...       ...       ...  ...
67131              1          0.0      3.0       0.0       0.0       0.0    1
67132              1          0.0      4.0       0.0       0.0       0.0    0
67133              1          1.0      2.0      10.0       0.0       0.0    1
67134              1          0.0      2.0       0.0       0.0       1.0    1
67135              1          0.0      4.0       0.0       0.0       0.0    1

       Age
0        7
1        7
2       13
3       11
4        5
...    ...
67131   11
67132   11
67133    8
67134   10
67135   10

[67136 rows x 20 columns]
```

```
# Dropping Duplicates

df = df.drop_duplicates()
print(df.duplicated().sum())
```

```
0
```

```
# Converting datatypes of some features

df['Diabetes_binary']=df['Diabetes_binary'].astype(int)
df['Age']=df['Age'].astype(int)
df['Sex']=df['Sex'].astype(int)
df['Smoker']=df['Smoker'].astype(int)
df['Stroke']=df['Stroke'].astype(int)
```

```
C:\Users\hassa\AppData\Local\Temp\ipykernel_10000\3309364861.py:3:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df['Diabetes_binary']=df['Diabetes_binary'].astype(int)
C:\Users\hassa\AppData\Local\Temp\ipykernel_10000\3309364861.py:4:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
```

```
  df['Age']=df['Age'].astype(int)
C:\Users\hassa\AppData\Local\Temp\ipykernel_10000\3309364861.py:5: 
SettingWithCopyWarning: 
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df['Sex']=df['Sex'].astype(int)
C:\Users\hassa\AppData\Local\Temp\ipykernel_10000\3309364861.py:6: 
SettingWithCopyWarning: 
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df['Smoker']=df['Smoker'].astype(int)
C:\Users\hassa\AppData\Local\Temp\ipykernel_10000\3309364861.py:7: 
SettingWithCopyWarning: 
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df['Stroke']=df['Stroke'].astype(int)
```

```
df.shape
```

```
(61709, 20)
```

```
df['Diabetes_binary'].value_counts()
```

```
Diabetes_binary
1    31768
0    29941
Name: count, dtype: int64
```

Data Preprocessing

```
X = df[df.columns[1:]]
```

```
Y = df['Diabetes_binary']
```

```
from sklearn.model_selection import train_test_split
xtrain, xtest, ytrain, ytest = train_test_split(X,Y, test_size = 0.2, 
random_state = 50)
```

```
columnss = X.columns
```

```
# Use MinMaxScaler to scale the features in the DataFrame 'X'
from sklearn.preprocessing import MinMaxScaler

# Create MinMaxScaler object
min_max_scaler = MinMaxScaler()
```

```
# Scale the features and create a new DataFrame 'X'
x_scaled_minmax = min_max_scaler.fit_transform(X)
X = pd.DataFrame(x_scaled_minmax, columns = columnss)

# Display the head of the scaled features DataFrame
X.head()
```

```
   HighBP  HighChol  CholCheck       BMI  Smoker  Stroke  \
0     1.0       0.0        1.0  0.241379     0.0     0.0
1     0.0       1.0        1.0  0.172414     1.0     0.0
2     0.0       1.0        1.0  0.160920     1.0     0.0
3     0.0       0.0        1.0  0.080460     1.0     0.0
4     1.0       0.0        1.0  0.287356     0.0     0.0

   HeartDiseaseorAttack  PhysActivity  Fruits  Veggies  HvyAlcoholConsump  \
0                   0.0           1.0     1.0      1.0                0.0
1                   0.0           1.0     0.0      0.0                0.0
2                   0.0           0.0     0.0      0.0                0.0
3                   0.0           1.0     1.0      1.0                0.0
4                   0.0           1.0     1.0      1.0                0.0

   AnyHealthcare  NoDocbcCost  GenHlth  MentHlth  PhysHlth  DiffWalk  Sex  \
0            1.0          0.0     0.25  0.500000  0.000000       1.0  1.0
1            1.0          0.0     0.25  0.033333  0.066667       0.0  1.0
2            1.0          0.0     0.50  0.000000  1.000000       0.0  1.0
3            1.0          0.0     0.50  0.000000  0.000000       0.0  0.0
4            1.0          0.0     0.25  0.000000  0.000000       0.0  0.0

        Age
0  0.500000
1  0.500000
2  1.000000
3  0.833333
4  0.333333
```

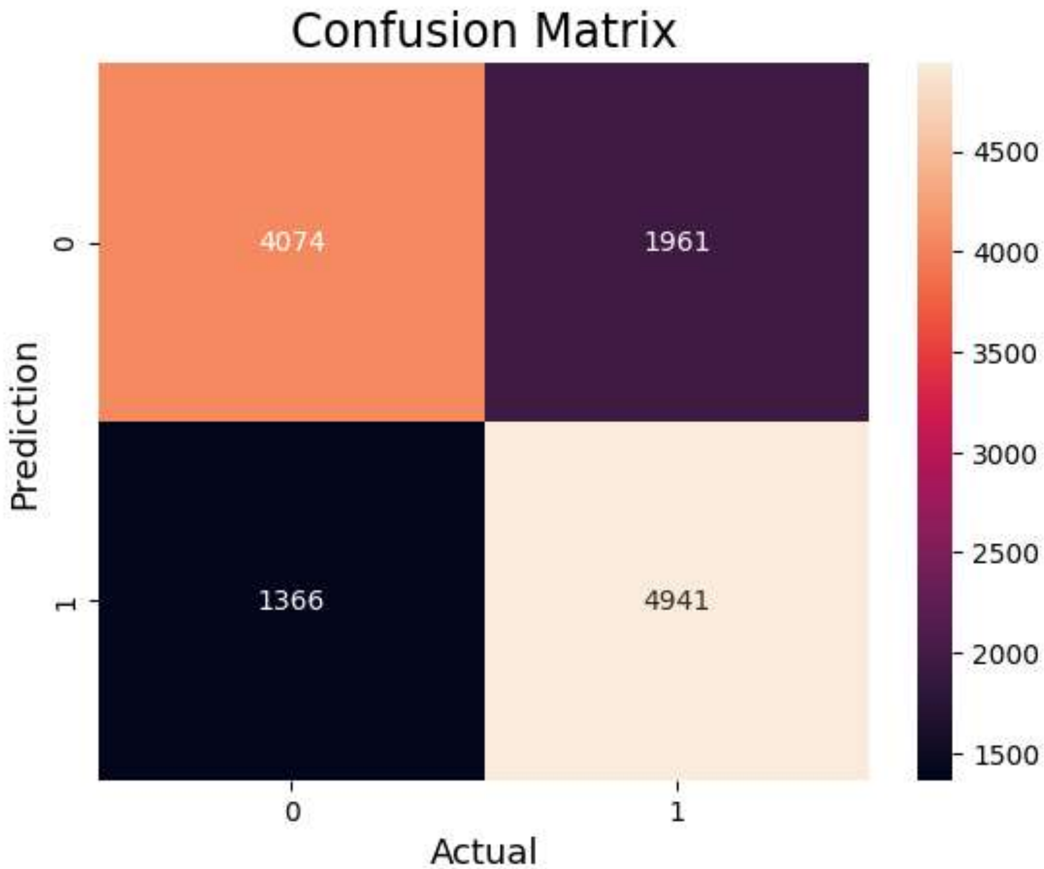
C-SVC

Linear

```
svm = SVC(C=1, kernel='linear', random_state=42 , decision_function_shape='ovr')

svm.fit(xtrain, ytrain)

SVC(C=1, kernel='linear', random_state=42)

pred = svm.predict(xtest)

c_lr_acc = accuracy_score(ytest, pred)
print(f'Accuracy: {c_lr_acc}')
print(classification_report(ytest,pred))

Accuracy: 0.7304326689353428
              precision    recall  f1-score   support

           0       0.75      0.68      0.71      6035
```

```
           1       0.72      0.78      0.75      6307

    accuracy                           0.73     12342
   macro avg       0.73      0.73      0.73     12342
weighted avg       0.73      0.73      0.73     12342
```

```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(ytest,pred)
sns.heatmap(cm, annot=True,fmt='g')
plt.ylabel('Prediction',fontsize=13)
plt.xlabel('Actual',fontsize=13)
plt.title('Confusion Matrix',fontsize=17)
plt.show()
```

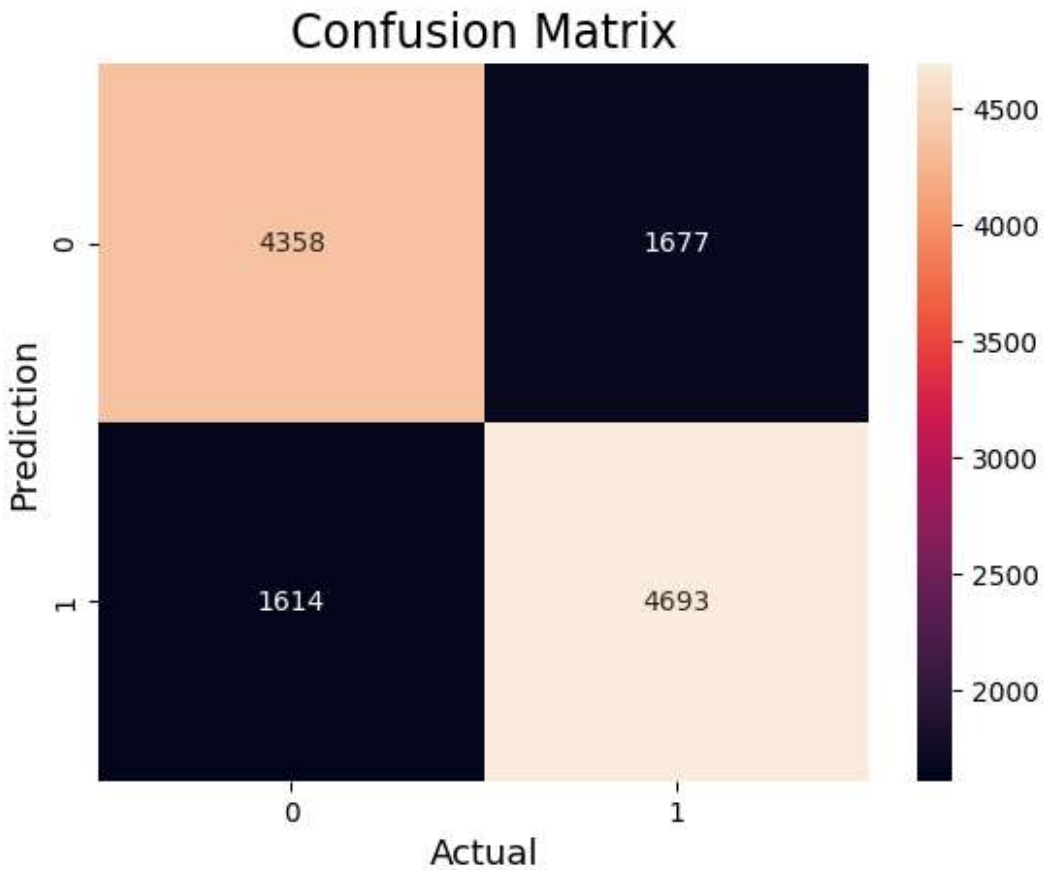


Polynomial

```
svm = SVC(C=1, kernel='poly', random_state=42 , decision_function_shape='ovr')

svm.fit(xtrain, ytrain)

SVC(C=1, kernel='poly', random_state=42)

pred = svm.predict(xtest)

c_poly_acc = accuracy_score(ytest, pred)
print(f'Accuracy: {c_poly_acc}')
print(classification_report(ytest,pred))
```

```
Accuracy: 0.7333495381623724
              precision    recall  f1-score   support

           0       0.73      0.72      0.73      6035
           1       0.74      0.74      0.74      6307

    accuracy                           0.73     12342
   macro avg       0.73      0.73      0.73     12342
weighted avg       0.73      0.73      0.73     12342
```

```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(ytest,pred)
sns.heatmap(cm, annot=True,fmt='g')
plt.ylabel('Prediction',fontsize=13)
plt.xlabel('Actual',fontsize=13)
plt.title('Confusion Matrix',fontsize=17)
plt.show()
```



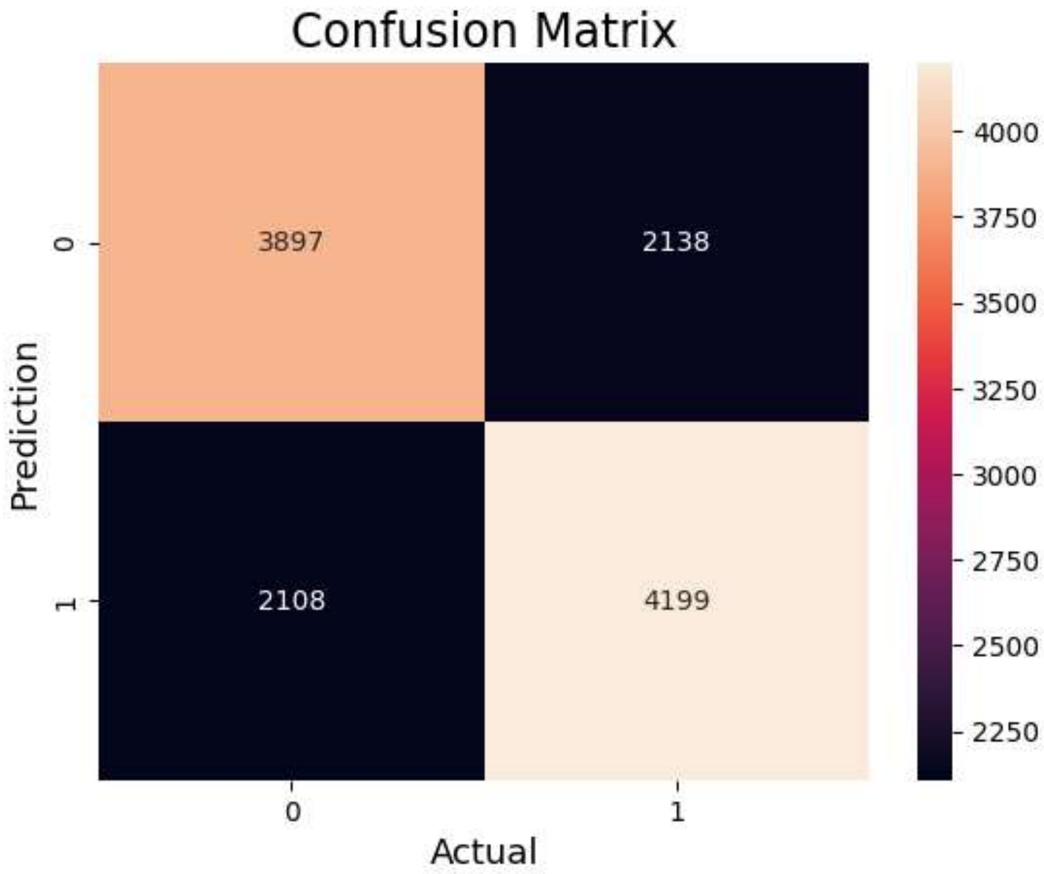
Sigmoid

```
svm = SVC(C=1, kernel='sigmoid', random_state=42 ,
decision_function_shape='ovr')

svm.fit(xtrain, ytrain)

SVC(C=1, kernel='sigmoid', random_state=42)
```

```
pred = svm.predict(xtest)

c_sigmoid_acc = accuracy_score(ytest, pred)
print(f'Accuracy: {c_sigmoid_acc}')
print(classification_report(ytest,pred))
```

```
Accuracy: 0.6559714795008913
              precision    recall  f1-score   support

           0       0.65      0.65      0.65      6035
           1       0.66      0.67      0.66      6307

    accuracy                           0.66     12342
   macro avg       0.66      0.66      0.66     12342
weighted avg       0.66      0.66      0.66     12342
```

```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(ytest,pred)
sns.heatmap(cm, annot=True,fmt='g')
plt.ylabel('Prediction',fontsize=13)
plt.xlabel('Actual',fontsize=13)
plt.title('Confusion Matrix',fontsize=17)
plt.show()
```



RBF

```
svm = SVC(C=1, kernel='rbf', random_state=42 , decision_function_shape='ovr')
```

```
svm.fit(xtrain, ytrain)
```

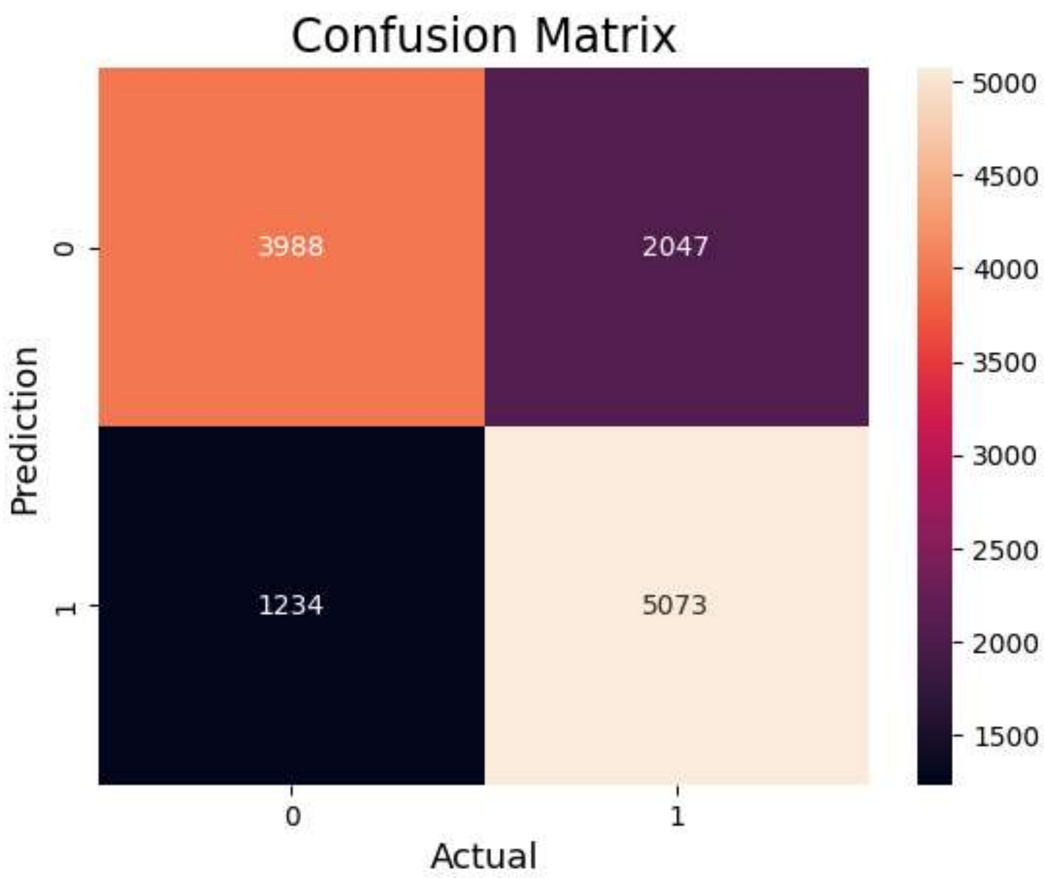
```
SVC(C=1, random_state=42)
```

```
pred = svm.predict(xtest)
```

```
c_rbf_acc = accuracy_score(ytest, pred)
print(f'Accuracy: {c_rbf_acc}')
print(classification_report(ytest,pred))
```

```
Accuracy: 0.7341597796143251
              precision    recall  f1-score   support

           0       0.76      0.66      0.71      6035
           1       0.71      0.80      0.76      6307

    accuracy                           0.73     12342
   macro avg       0.74      0.73      0.73     12342
weighted avg       0.74      0.73      0.73     12342
```

```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(ytest,pred)
sns.heatmap(cm, annot=True,fmt='g')
plt.ylabel('Prediction',fontsize=13)
plt.xlabel('Actual',fontsize=13)
plt.title('Confusion Matrix',fontsize=17)
plt.show()
```



Nu-SVM

Linear

```
nu_svr = NuSVC(kernel='linear', nu=0.1, random_state=42, verbose=True, 
decision_function_shape='ovr')  # You can adjust the 'nu' parameter
nu_svr.fit(xtrain, ytrain)
```

```
[LibSVM]
```

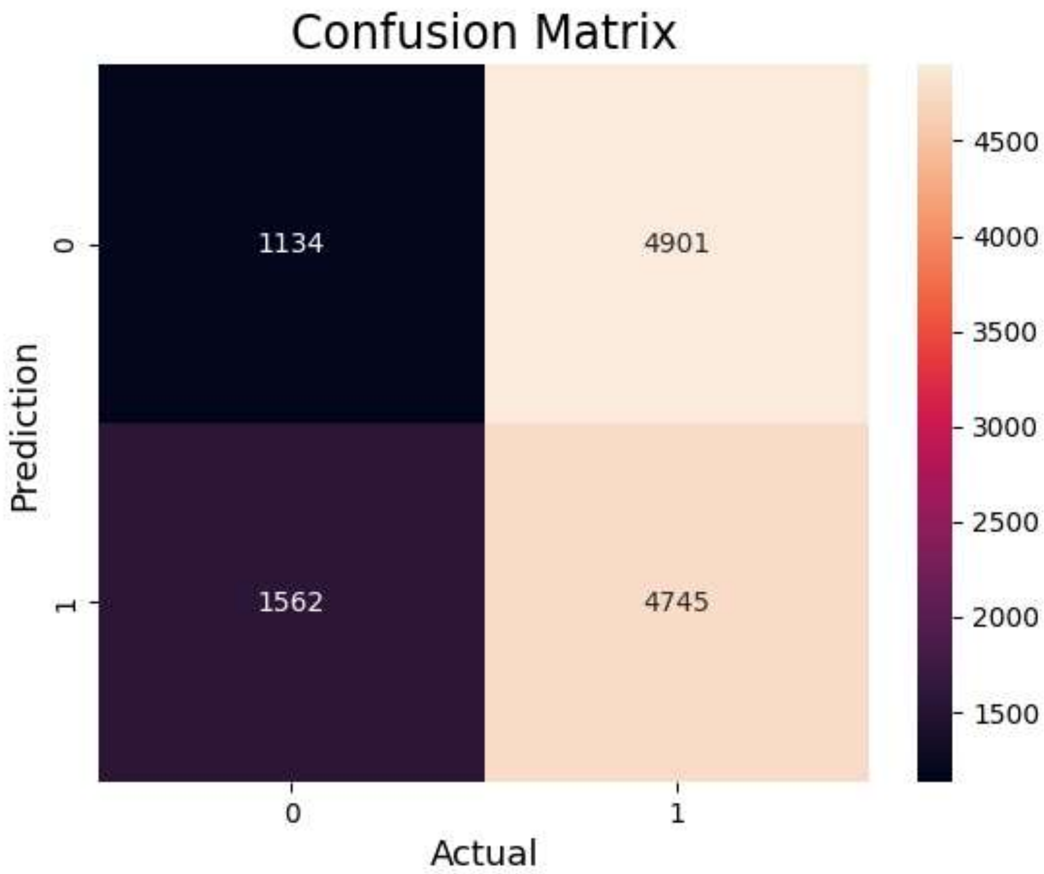
```
NuSVC(kernel='linear', nu=0.1, random_state=42, verbose=True)
```

```
pred = nu_svr.predict(xtest)
```

```
nu_lr_acc = accuracy_score(ytest, pred)
print(f'Accuracy: {nu_lr_acc}')
print(classification_report(ytest,pred))
```

```
Accuracy: 0.4763409496029817
              precision    recall  f1-score   support

           0       0.42      0.19      0.26      6035
           1       0.49      0.75      0.59      6307

    accuracy                           0.48     12342
   macro avg       0.46      0.47      0.43     12342
weighted avg       0.46      0.48      0.43     12342
```

```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(ytest,pred)
sns.heatmap(cm, annot=True,fmt='g')
plt.ylabel('Prediction',fontsize=13)
plt.xlabel('Actual',fontsize=13)
plt.title('Confusion Matrix',fontsize=17)
plt.show()
```



Polynomial

```
nu_svr = NuSVC(kernel='poly', nu=0.1, random_state=42, verbose=True,
decision_function_shape='ovr')  # You can adjust the 'nu' parameter
nu_svr.fit(xtrain, ytrain)
```

```
[LibSVM]
```

```
NuSVC(kernel='poly', nu=0.1, random_state=42, verbose=True)
```

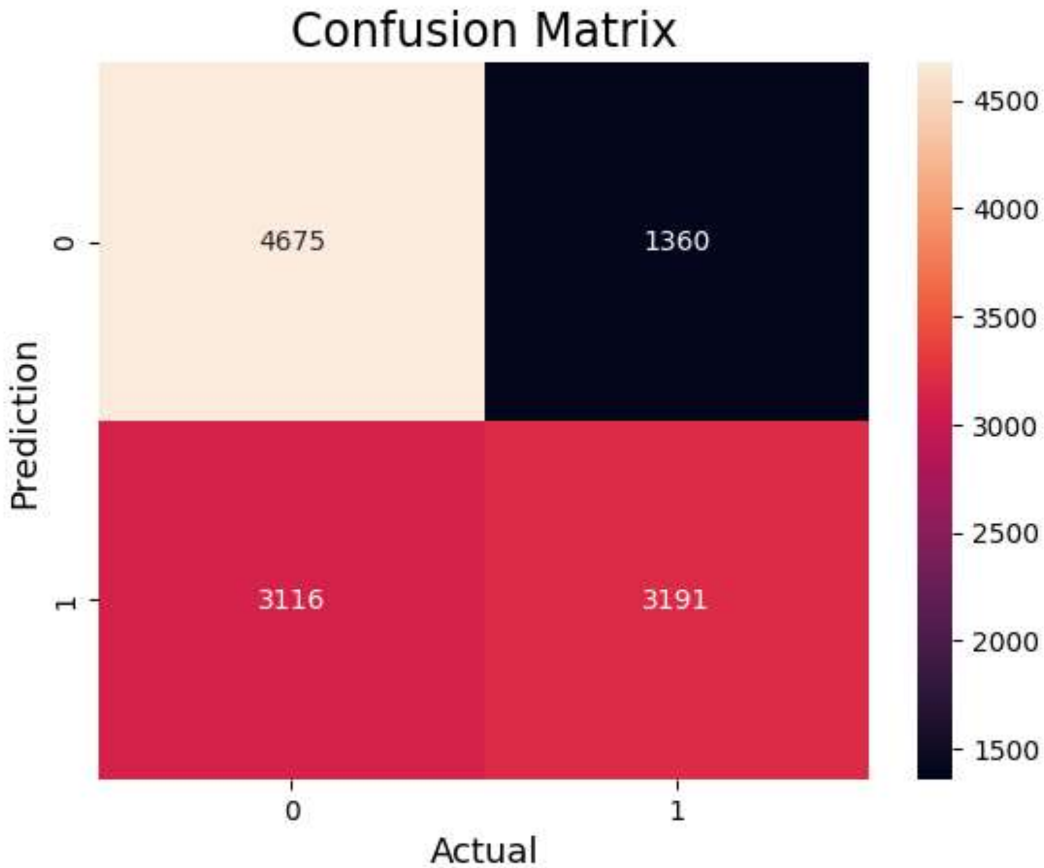
```
pred = nu_svr.predict(xtest)
```

```
nu_poly_acc = accuracy_score(ytest, pred)
print(f'Accuracy: {nu_poly_acc}')
print(classification_report(ytest,pred))
```

```
Accuracy: 0.6373359261059796
              precision    recall  f1-score   support

           0       0.60      0.77      0.68      6035
           1       0.70      0.51      0.59      6307

    accuracy                           0.64     12342
   macro avg       0.65      0.64      0.63     12342
weighted avg       0.65      0.64      0.63     12342
```

```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(ytest,pred)
```

```
sns.heatmap(cm, annot=True,fmt='g')
plt.ylabel('Prediction',fontsize=13)
plt.xlabel('Actual',fontsize=13)
plt.title('Confusion Matrix',fontsize=17)
plt.show()
```



Sigmoid

```
nu_svr = NuSVC(kernel='sigmoid', nu=0.1, random_state=42, verbose=True,
decision_function_shape='ovr')  # You can adjust the 'nu' parameter
nu_svr.fit(xtrain, ytrain)
```

```
[LibSVM]
```

```
NuSVC(kernel='sigmoid', nu=0.1, random_state=42, verbose=True)
```

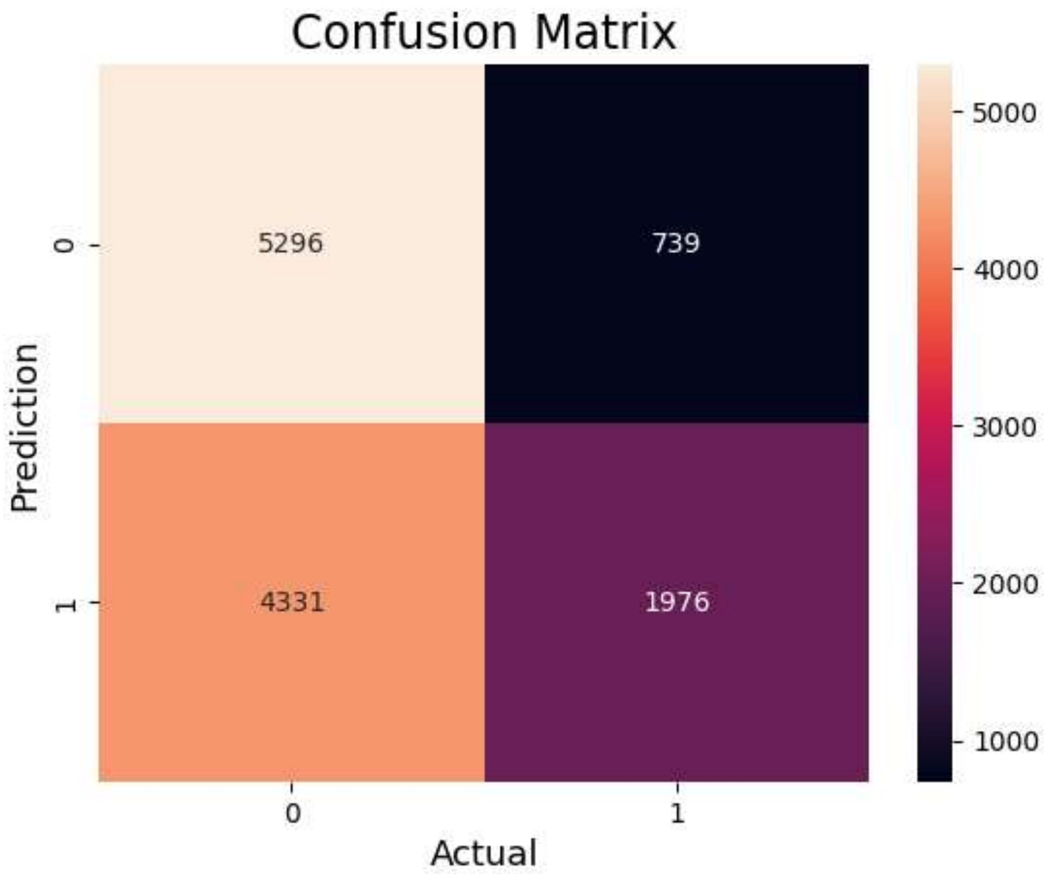
```
pred = nu_svr.predict(xtest)
```

```
nu_sigmoid_acc = accuracy_score(ytest, pred)
print(f'Accuracy: {nu_sigmoid_acc}')
print(classification_report(ytest,pred))
```

```
Accuracy: 0.5892075838599903
              precision    recall  f1-score   support

           0       0.55      0.88      0.68      6035
           1       0.73      0.31      0.44      6307

    accuracy                           0.59     12342
```

```
   macro avg       0.64      0.60      0.56     12342
weighted avg       0.64      0.59      0.55     12342
```

```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(ytest,pred)
sns.heatmap(cm, annot=True,fmt='g')
plt.ylabel('Prediction',fontsize=13)
plt.xlabel('Actual',fontsize=13)
plt.title('Confusion Matrix',fontsize=17)
plt.show()
```



RBF

```
nu_svr = NuSVC(kernel='rbf', nu=0.1, random_state=42, verbose=True,
decision_function_shape='ovr')  # You can adjust the 'nu' parameter
nu_svr.fit(xtrain, ytrain)
```

```
[LibSVM]
```

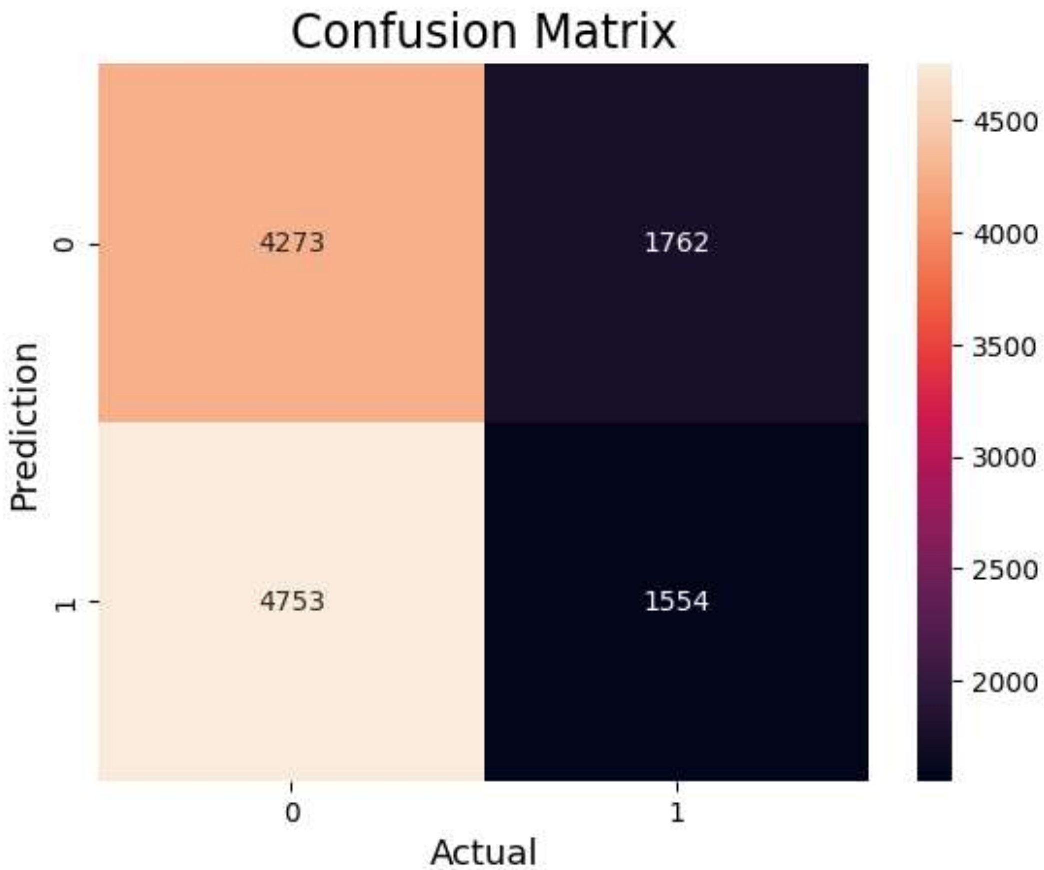
```
NuSVC(nu=0.1, random_state=42, verbose=True)
```

```
pred = nu_svr.predict(xtest)
```

```
nu_rbf_acc = accuracy_score(ytest, pred)
print(f'Accuracy: {nu_rbf_acc}')
print(classification_report(ytest,pred))
```

```
Accuracy: 0.47212769405282773
              precision    recall  f1-score   support

           0       0.47      0.71      0.57      6035
           1       0.47      0.25      0.32      6307

    accuracy                           0.47     12342
   macro avg       0.47      0.48      0.45     12342
weighted avg       0.47      0.47      0.44     12342
```

```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(ytest,pred)
sns.heatmap(cm, annot=True,fmt='g')
plt.ylabel('Prediction',fontsize=13)
plt.xlabel('Actual',fontsize=13)
plt.title('Confusion Matrix',fontsize=17)
plt.show()
```



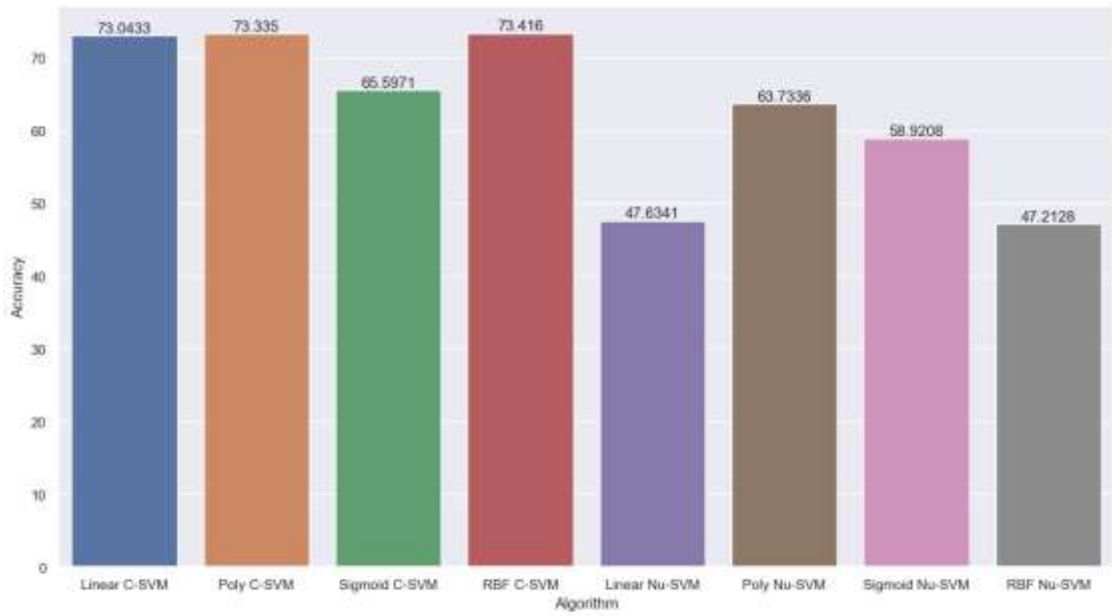
Comparison

```
comparison_dict={"Algorithm":["Linear C-SVM","Poly C-SVM","Sigmoid C-SVM","RBF C-SVM","Linear Nu-SVM","Poly Nu-SVM","Sigmoid Nu-SVM","RBF Nu-SVM"],

"Accuracy":[c_lr_acc*100,c_poly_acc*100,c_sigmoid_acc*100,c_rbf_acc*100,nu_lr_acc*100,nu_poly_acc*100,nu_sigmoid_acc*100,nu_rbf_acc*100],
```

```
                }

comparison = pd.DataFrame(comparison_dict)
comparison.sort_values(['Accuracy'], ascending=False)
```

	Algorithm	Accuracy
3	RBF C-SVM	73.415978
1	Poly C-SVM	73.334954
0	Linear C-SVM	73.043267
2	Sigmoid C-SVM	65.597148
5	Poly Nu-SVM	63.733593
6	Sigmoid Nu-SVM	58.920758
4	Linear Nu-SVM	47.634095
7	RBF Nu-SVM	47.212769

```
ax = sns.barplot(x='Algorithm', y='Accuracy', data=comparison )
sns.set(rc={'figure.figsize':(15,9)})
for bars in ax.containers:
  ax.bar_label(bars)
```



From the above table its shows that the C-SVM perform well rather than Nu-SVM on large and unbalance dataset.