# **EXPERIMENT 8**

# Aim

To implement and evaluate a dataset using SVM based classification algorithm

### **Software Used**

Google Colab

# **Program Code and Output**

```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import matplotlib.pyplot as plt # for data visualization
import seaborn as sns # for statistical data visualization
%matplotlib inline
```

```
[ ] data = '/content/pulsar_data_train.csv'
    #data = 'kaggle datasets download -d colearninglounge/predicting-pulsar-starintermediate'

df = pd.read_csv(data)
```

```
[ ] # view dimensions of dataset

df.shape
```

(12528, 9)

```
[ ] # let's preview the dataset

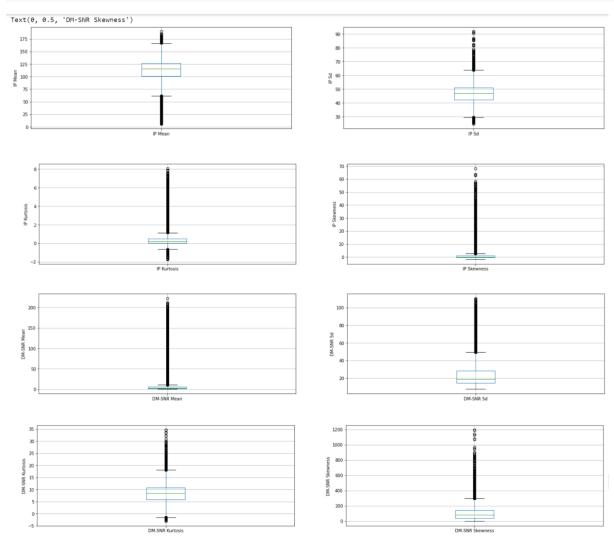
df.head()
```

	Mean of the integrated profile	Standard deviation of the integrated profile	Excess kurtosis of the integrated profile	Skewness of the integrated profile	Mean of the DM-SNR curve	Standard deviation of the DM-SNR curve	Excess kurtosis of the DM-SNR curve	Skewness of the DM-SNR curve	target_class
0	121.156250	48.372971	0.375485	-0.013165	3.168896	18.399367	7.449874	65.159298	0.0
1	76.968750	36.175557	0.712898	3.388719	2.399666	17.570997	9.414652	102.722975	0.0
2	130.585938	53.229534	0.133408	-0.297242	2.743311	22.362553	8.508364	74.031324	0.0
3	156.398438	48.865942	-0.215989	-0.171294	17.471572	NaN	2.958066	7.197842	0.0
4	84.804688	36.117659	0.825013	3.274125	2.790134	20.618009	8.405008	76.291128	0.0

```
# check for missing values in variables
    df.isnull().sum()
☐→ IP Mean
                      0
    IP Sd
    IP Kurtosis 1735
    IP Skewness
    DM-SNR Mean
                       0
                   1178
9
    DM-SNR Sd
    DM-SNR Kurtosis
                      0
    DM-SNR Skewness 625
    target_class
                       0
    dtype: int64
# draw boxplots to visualize outliers
   plt.figure(figsize=(24,20))
   plt.subplot(4, 2, 1)
   fig = df.boxplot(column='IP Mean')
   fig.set_title('')
   fig.set_ylabel('IP Mean')
   plt.subplot(4, 2, 2)
   fig = df.boxplot(column='IP Sd')
   fig.set_title('')
   fig.set_ylabel('IP Sd')
   plt.subplot(4, 2, 3)
   fig = df.boxplot(column='IP Kurtosis')
   fig.set_title('')
   fig.set_ylabel('IP Kurtosis')
    plt.subplot(4, 2, 4)
    fig = df.boxplot(column='IP Skewness')
    fig.set_title('')
    fig.set_ylabel('IP Skewness')
    plt.subplot(4, 2, 5)
    fig = df.boxplot(column='DM-SNR Mean')
    fig.set_title('')
    fig.set_ylabel('DM-SNR Mean')
    plt.subplot(4, 2, 6)
    fig = df.boxplot(column='DM-SNR Sd')
    fig.set_title('')
    fig.set_ylabel('DM-SNR Sd')
```

```
plt.subplot(4, 2, 7)
fig = df.boxplot(column='DM-SNR Kurtosis')
fig.set_title('')
fig.set_ylabel('DM-SNR Kurtosis')

plt.subplot(4, 2, 8)
fig = df.boxplot(column='DM-SNR Skewness')
fig.set_title('')
fig.set_ylabel('DM-SNR Skewness')
```



```
[ ] X = df.drop(['target_class'], axis=1)

y = df['target_class']
```

```
[ ] # split X and y into training and testing sets
     from sklearn.model_selection import train_test_split
     X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 0)
[ ] # check the shape of X_train and X_test
     X_train.shape, X_test.shape
     ((10022, 8), (2506, 8))
 [ ] cols = X_train.columns
  from sklearn.preprocessing import StandardScaler
       scaler = StandardScaler()
       X_train = scaler.fit_transform(X_train)
       X_test = scaler.transform(X_test)
 [ ] X_train = pd.DataFrame(X_train, columns=[cols])
 [ ] X_test = pd.DataFrame(X_test, columns=[cols])
 [ ] X_train.describe()
                                                                                    DM-SNR Kurtosis DM-SNR Skewness
            IP Mean
                                    IP Kurtosis IP Skewness DM-SNR Mean DM-SNR Sd
      count 1.002200e+04 1.002200e+04 8.616000e+03 1.002200e+04 1.002200e+04 9.090000e+03
                                                                                       1.002200e+04
                                                                                                      9.500000e+03
      mean -2.580698e-16 -7.770453e-16 -5.154239e-17 -1.595212e-17 -3.030902e-17 -9.028348e-17
                                                                                       -1.318708e-16
                                                                                                      6.731457e-18
      std 1.000050e+00 1.000050e+00 1.000058e+00 1.000050e+00 1.000050e+00 1.000055e+00 1.000050e+00
                                                                                                    1.000053e+00
      min -4.059253e+00 -3.121855e+00 -2.060343e+00 -5.703669e-01 -4.225211e-01 -9.665725e-01
                                                                                      -2.526379e+00
                                                                                                      -9.997646e-01
      25% -3.943394e-01 -6.101706e-01 -4.266826e-01 -3.175801e-01 -3.653436e-01 -6.094788e-01
                                                                                       -5.589324e-01
                                                                                                      -6.565951e-01
      50% 1.619199e-01 5.986146e-02 -2.415742e-01 -2.549120e-01 -3.355278e-01 -4.066791e-01
                                                                                       2.442155e-02
                                                                                                      -2.086985e-01
      75% 6.265131e-01 6.579129e-01 -1.143402e-02 -1.397269e-01 -2.459675e-01 1.018419e-01 5.276848e-01 3.194451e-01
      max 3.045294e+00 6.647182e+00 7.026077e+00 1.045442e+01 7.074053e+00 4.281896e+00
                                                                                                      1.009101e+01
                                                                                       5.769814e+00
```

[29] X\_train = X\_train.replace((np.inf, -np.inf, np.nan), 0).reset\_index(drop=True)
#y\_train = y\_train.replace((np.inf, -np.inf, np.nan), 0).reset\_index(drop=True)
X\_test = X\_test.replace((np.inf, -np.inf, np.nan), 0).reset\_index(drop=True)

```
from sklearn.svm import SVC
    # import metrics to compute accuracy
    from sklearn.metrics import accuracy_score
    # instantiate classifier with default hyperparameters
    svc=SVC()
    # fit classifier to training set
    svc.fit(X_train,y_train)
    # make predictions on test set
   y_pred=svc.predict(X_test)
    # compute and print accuracy score
   print('Model accuracy score with default hyperparameters: {0:0.4f}'. format(accuracy_score(y_test, y_pred)))

    Model accuracy score with default hyperparameters: 0.9796

[ ] # instantiate classifier with rbf kernel and C=100
    svc=SVC(C=100.0)
    # fit classifier to training set
    svc.fit(X_train,y_train)
    # make predictions on test set
    y_pred=svc.predict(X_test)
    # compute and print accuracy score
  print('Model accuracy score with rbf kernel and C=100.0 : {0:0.4f}'. format(accuracy_score(y_test, y_pred)))
    Model accuracy score with rbf kernel and C=100.0 : 0.9804
[ ] # instantiate classifier with rbf kernel and C=1000
     svc=SVC(C=1000.0)
     # fit classifier to training set
     svc.fit(X_train,y_train)
     # make predictions on test set
     y_pred=svc.predict(X_test)
     # compute and print accuracy score
     print('Model accuracy score with rbf kernel and C=1000.0 : {0:0.4f}'. format(accuracy_score(y_test, y_pred)))
     Model accuracy score with rbf kernel and C=1000.0 : 0.9808
     print('Training set score: {:.4f}'.format(svc.score(X_train, y_train)))
      print('Test set score: {:.4f}'.format(svc.score(X_test, y_test)))
```

Training set score: 0.9871 Test set score: 0.9808

#### **Discussion and Conclusion**

Support Vector Machine classifier is implemented on a pulsar dataset. Dataset is scaled using z score normalisation. Dataset is visualised with Boxplots and checked for outliers, since the dataset contains outliers, so the value of C should be high while training the model. Soft-margin variant of SVM is used and in this case, we can have a few points incorrectly classified or classified with a margin less than 1. But for every such point, we have to pay a penalty in the form of C parameter, which controls the outliers. Low C implies we are allowing more outliers and high C implies less outliers. Since accuracy of train and test data is comparable so the problem of overfitting will not arise.

CRITERIA	TOTAL MARKS	MARKS OBTAINED	COMMENTS
Concept (A)	2		
Implementation (B)	2		
Performance (C)	2		
Total	6		