svm

March 22, 2023

1 SVM CLASSIFIER(LINEAR, POLY, SIGMOID)

Pulsars are a rare type of Neutron star that produce radio emission detectable here on Earth. They are of considerable scientific interest as probes of space-time, the inter-stellar medium, and states of matter. Machine learning tools are now being used to automatically label pulsar candidates to facilitate rapid analysis. Classification systems in particular are being widely adopted,which treat the candidate data sets as binary classification problems.

Attribute Information: Each candidate is described by 8 continuous variables, and a single class variable. The first four are simple statistics obtained from the integrated pulse profile (folded profile). This is an array of continuous variables that describe a longitude-resolved version of the signal that has been averaged in both time and frequency . The remaining four variables are similarly obtained from the DM-SNR curve . These are summarised below:

1. Mean of the integrated profile.
2. Standard deviation of the integrated profile.
3. Excess kurtosis of the integrated profile.
4. Skewness of the integrated profile.
5. Mean of the DM-SNR curve.
6. Standard deviation of the DM-SNR curve.
7. Excess kurtosis of the DM-SNR curve.
8. Skewness of the DM-SNR curve.
9. class

Classification Label: Class

2 1. DATA LOADING AND EXPLORATION

[1]:
```
#importing libraries
import numpy as np
import pandas as pd

import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from sklearn import tree
```

```python
from sklearn import metrics
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score,precision_score,recall_score,␣
↪classification_report,confusion_matrix, f1_score,make_scorer

import missingno as msno
from sklearn.svm import SVC
from sklearn.model_selection import GridSearchCV
```

3 SVM-LINEAR CLASSIFICATION ALGORITHM IMPLEMENTED FROM SCRATCH

[2]:
```python
#Own linear-SVM algorithm from scratch
class My_SVM_classifier():





    # initiating the hyperparameters
    def __init__(self, learning_rate=0.001, lambda_parameter=0.01,␣
↪no_of_iterations=1000):

        self.learning_rate = learning_rate
        self.no_of_iterations = no_of_iterations
        self.lambda_parameter = lambda_parameter


    def getW(self):
        return self.w
    def getB(self):
        return self.b

    # fitting the dataset to SVM Classifier
    def fit(self, X, Y):

        # m  --> number of Data points --> number of rows
        # n  --> number of input features --> number of columns
        self.m, self.n = X.shape

        # initiating the weight value and bias value

        self.w = np.zeros(self.n)

        self.b = 0
```

```
        self.X = X

        self.Y = Y

        # implementing Gradient Descent algorithm for Optimization

        for i in range(self.no_of_iterations):
            self.update_weights()

        print(self.w, " ", self.b, "\n")



    # function for updating the weight and bias value
    def update_weights(self):

        # label encoding
        y_label = np.where(self.Y <= 0, -1, 1)



        # gradients ( dw, db)
        for index, x_i in enumerate(self.X):
            condition = y_label[index] * (np.dot(x_i, self.w) - self.b) >= 1

            if (condition == True):

                dw = 2 * self.lambda_parameter * self.w
                db = 0

            else:

                dw = 2 * self.lambda_parameter * self.w - np.dot(x_i, y_label[index])
                db = y_label[index]


            self.w = self.w - self.learning_rate * dw

            self.b = self.b - self.learning_rate * db



    # predict the label for a given input value
    def predict(self, X):

        output = np.dot(X, self.w) - self.b
```

```python
        predicted_labels = np.sign(output)

        y_hat = np.where(predicted_labels <= -1, 0, 1)

        return y_hat
```

[3]:
```python
#for visualizing the hyperplane
class VisualizeSVM():
    def __init__(self, X, Y, w, b):
        self.X = X
        self.Y = Y
        self.w = w
        self.b = b

    def visualizeHyperplane(self):

        def get_hyperplane_value(x, w, b, offset):
            return (-w[0] * x + b + offset) / w[1]

        fig = plt.figure()
        ax = fig.add_subplot(1, 1, 1)
        plt.scatter(self.X[:, 0], self.X[:, 1], marker="o", c=self.Y)

        x0_1 = np.amin(self.X[:, 0])
        x0_2 = np.amax(self.X[:, 0])

        x1_1 = get_hyperplane_value(x0_1, self.w, self.b, 0)
        x1_2 = get_hyperplane_value(x0_2, self.w, self.b, 0)

        x1_1_m = get_hyperplane_value(x0_1, self.w, self.b, -1)
        x1_2_m = get_hyperplane_value(x0_2, self.w, self.b, -1)

        x1_1_p = get_hyperplane_value(x0_1, self.w, self.b, 1)
        x1_2_p = get_hyperplane_value(x0_2, self.w, self.b, 1)

        ax.plot([x0_1, x0_2], [x1_1, x1_2], "y--")
        ax.plot([x0_1, x0_2], [x1_1_m, x1_2_m], "k")
        ax.plot([x0_1, x0_2], [x1_1_p, x1_2_p], "k")

        x1_min = np.amin(self.X[:, 1])
        x1_max = np.amax(self.X[:, 1])
        ax.set_ylim([x1_min - 3, x1_max + 3])

        plt.show()
```

[4]:
```
df=pd.read_csv('./pulsar_stars.csv')
```

[5]:
```
df.head()
```

[5]:
```
    Mean of the integrated profile  \
0                       140.562500
1                       102.507812
2                       103.015625
3                       136.750000
4                        88.726562

    Standard deviation of the integrated profile  \
0                                      55.683782
1                                      58.882430
2                                      39.341649
3                                      57.178449
4                                      40.672225

    Excess kurtosis of the integrated profile  \
0                                  -0.234571
1                                   0.465318
2                                   0.323328
3                                  -0.068415
4                                   0.600866

    Skewness of the integrated profile   Mean of the DM-SNR curve  \
0                            -0.699648                  3.199833
1                            -0.515088                  1.677258
2                             1.051164                  3.121237
3                            -0.636238                  3.642977
4                             1.123492                  1.178930

    Standard deviation of the DM-SNR curve  \
0                               19.110426
1                               14.860146
2                               21.744669
3                               20.959280
4                               11.468720

    Excess kurtosis of the DM-SNR curve   Skewness of the DM-SNR curve  \
0                              7.975532                      74.242225
1                             10.576487                     127.393580
2                              7.735822                      63.171909
3                              6.896499                      53.593661
4                             14.269573                     252.567306

   target_class
```

```
0            0
1            0
2            0
3            0
4            0
```

[6]:
```python
df.describe()
```

[6]:
```
        Mean of the integrated profile  \
count                     17898.000000
mean                        111.079968
std                          25.652935
min                           5.812500
25%                         100.929688
50%                         115.078125
75%                         127.085938
max                         192.617188

        Standard deviation of the integrated profile  \
count                                   17898.000000
mean                                       46.549532
std                                         6.843189
min                                        24.772042
25%                                        42.376018
50%                                        46.947479
75%                                        51.023202
max                                        98.778911

        Excess kurtosis of the integrated profile  \
count                                17898.000000
mean                                     0.477857
std                                      1.064040
min                                     -1.876011
25%                                      0.027098
50%                                      0.223240
75%                                      0.473325
max                                      8.069522

        Skewness of the integrated profile   Mean of the DM-SNR curve  \
count                         17898.000000              17898.000000
mean                              1.770279                 12.614400
std                               6.167913                 29.472897
min                              -1.791886                  0.213211
25%                              -0.188572                  1.923077
50%                               0.198710                  2.801839
75%                               0.927783                  5.464256
max                              68.101622                223.392141
```

```
       Standard deviation of the DM-SNR curve  \
count                             17898.000000
mean                                 26.326515
std                                  19.470572
min                                   7.370432
25%                                  14.437332
50%                                  18.461316
75%                                  28.428104
max                                 110.642211

       Excess kurtosis of the DM-SNR curve   Skewness of the DM-SNR curve  \
count                          17898.000000                   17898.000000
mean                               8.303556                     104.857709
std                                4.506092                     106.514540
min                               -3.139270                      -1.976976
25%                                5.781506                      34.960504
50%                                8.433515                      83.064556
75%                               10.702959                     139.309330
max                               34.539844                    1191.000837

       target_class
count  17898.000000
mean       0.091574
std        0.288432
min        0.000000
25%        0.000000
50%        0.000000
75%        0.000000
max        1.000000
```

4 2. DATA CLEANING

[7]:
```
col_names = df.columns
col_names
```

[7]:
```
Index([' 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'],
      dtype='object')
```

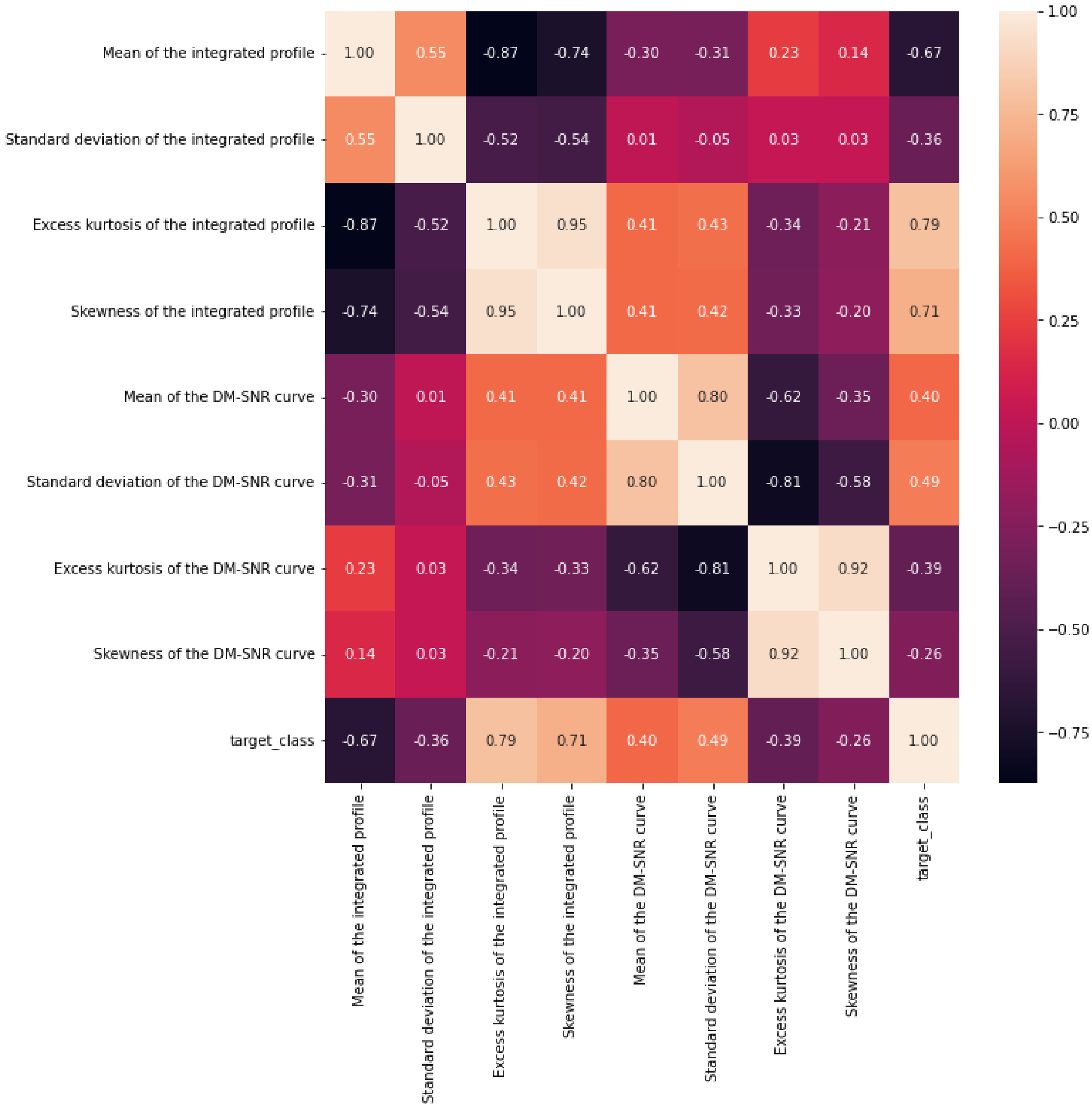
[8]:
```
#We can see that there are leading spaces (spaces at the start of the string␣
↪name) in the dataframe. So, I will remove these leading spaces.

df.columns = df.columns.str.strip()
```

[9]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 17898 entries, 0 to 17897
Data columns (total 9 columns):
 #   Column                                        Non-Null Count  Dtype
---  ------                                        --------------  -----
 0   Mean of the integrated profile                17898 non-null  float64
 1   Standard deviation of the integrated profile  17898 non-null  float64
 2   Excess kurtosis of the integrated profile     17898 non-null  float64
 3   Skewness of the integrated profile            17898 non-null  float64
 4   Mean of the DM-SNR curve                      17898 non-null  float64
 5   Standard deviation of the DM-SNR curve        17898 non-null  float64
 6   Excess kurtosis of the DM-SNR curve           17898 non-null  float64
 7   Skewness of the DM-SNR curve                  17898 non-null  float64
 8   target_class                                  17898 non-null  int64
dtypes: float64(8), int64(1)
memory usage: 1.2 MB
```

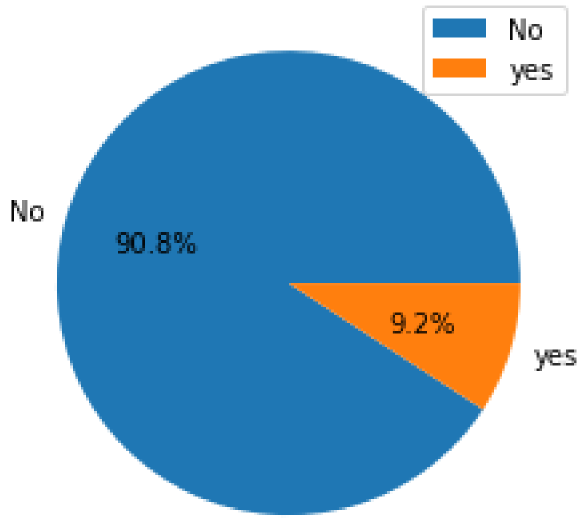
[10]:
```
fig=plt.figure(figsize=(10,10))
sns.heatmap(df.corr(),annot=True,fmt='.2f')
```

[10]: <AxesSubplot:>

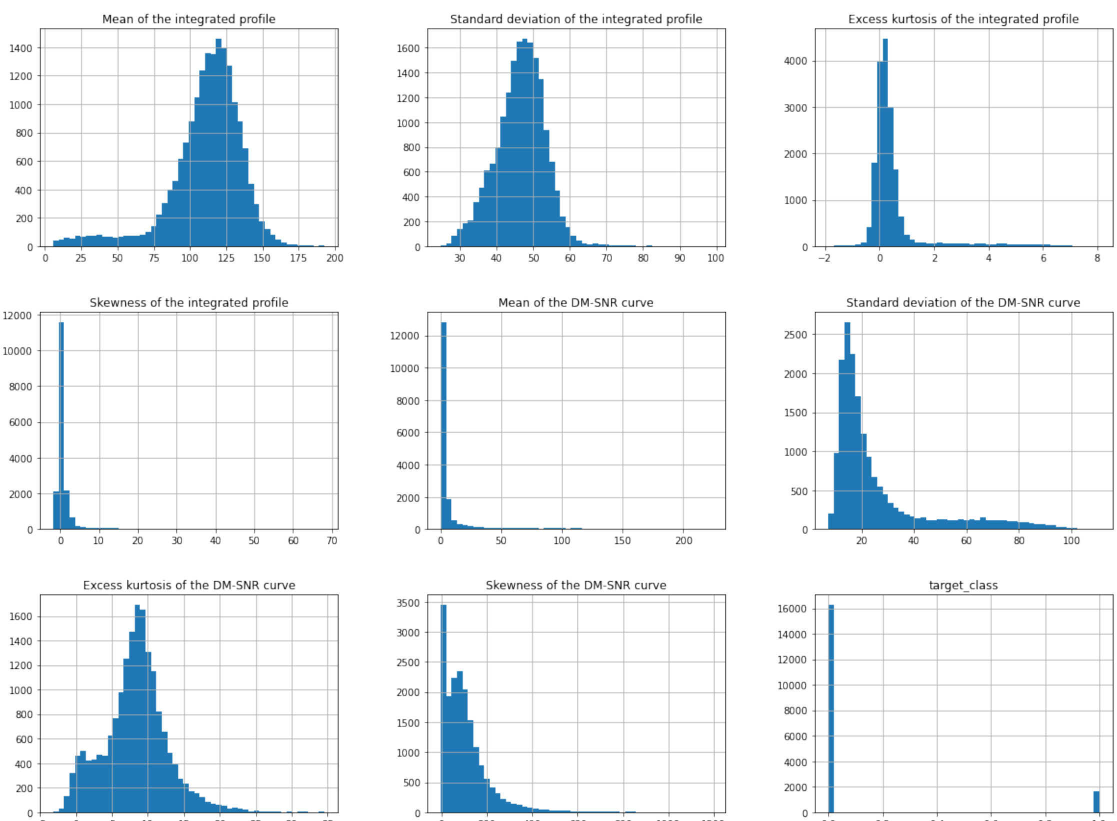


[11]:

```
#Checking the % of the the targe_class

plt.pie(df['target_class'].value_counts(),autopct="%1.1f%%",labels=['No','yes'])
plt.legend();
```

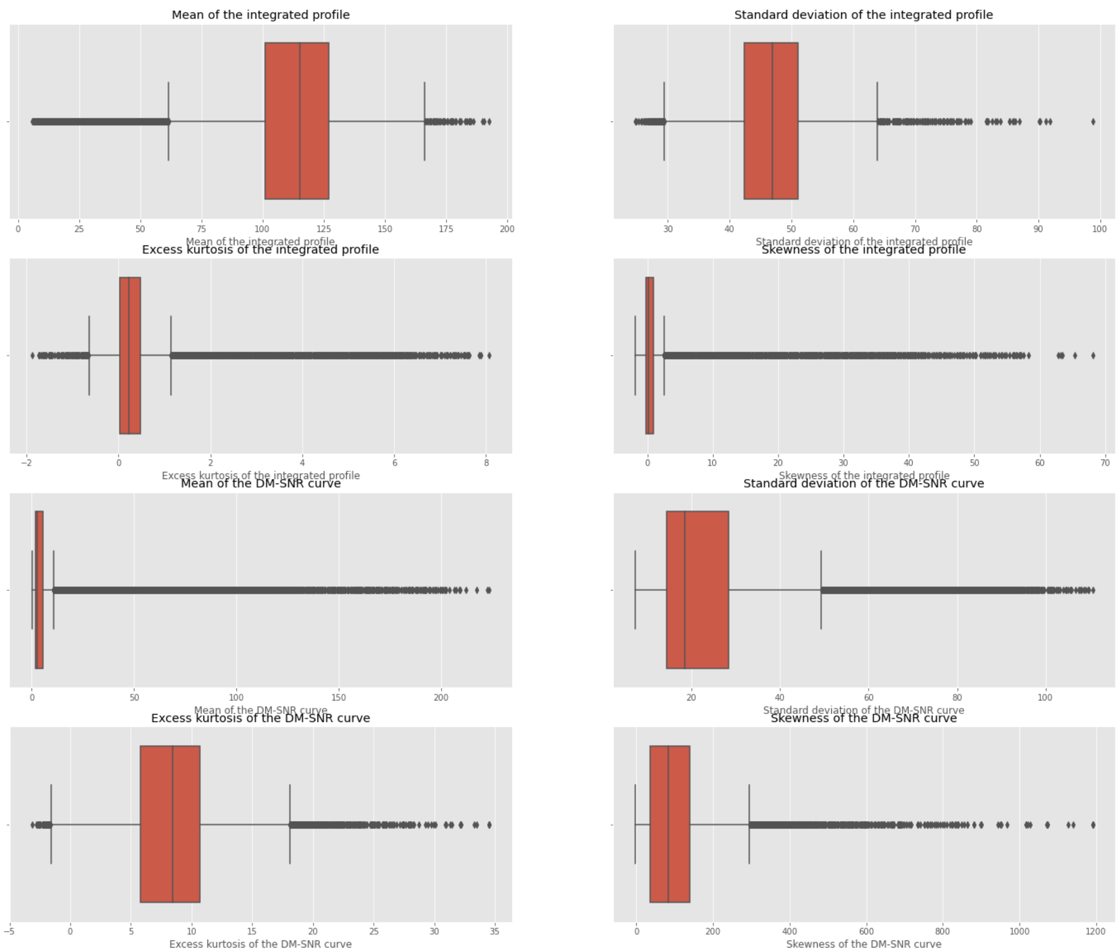


[12]:
```
df.hist(bins=50, figsize=(20,15))
plt.show()
```



4.0.1 OUTLIERS analysis:

[13]:
```
plt.style.use('ggplot')
plt.figure(figsize=(24,20))

col_names = df.columns[:-1]
for i,col in enumerate(col_names):
    plt.subplot(4,2,i+1)
    sns.boxplot(x=df[col])
    plt.title(col)
```



*>There are a lot pof outliers in our data #### Handle outliers with SVMs There are 2 variants of SVMs. They are hard-margin variant of SVM and soft-margin variant of SVM.

The hard-margin variant of SVM does not deal with outliers. In this case, we want to find the hyperplane with maximum margin such that every training point is correctly classified with margin at least 1. This technique does not handle outliers well.

Another version of SVM is called soft-margin variant of SVM. 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.

The message is that since the dataset contains outliers, so the value of C should be high while training the model.

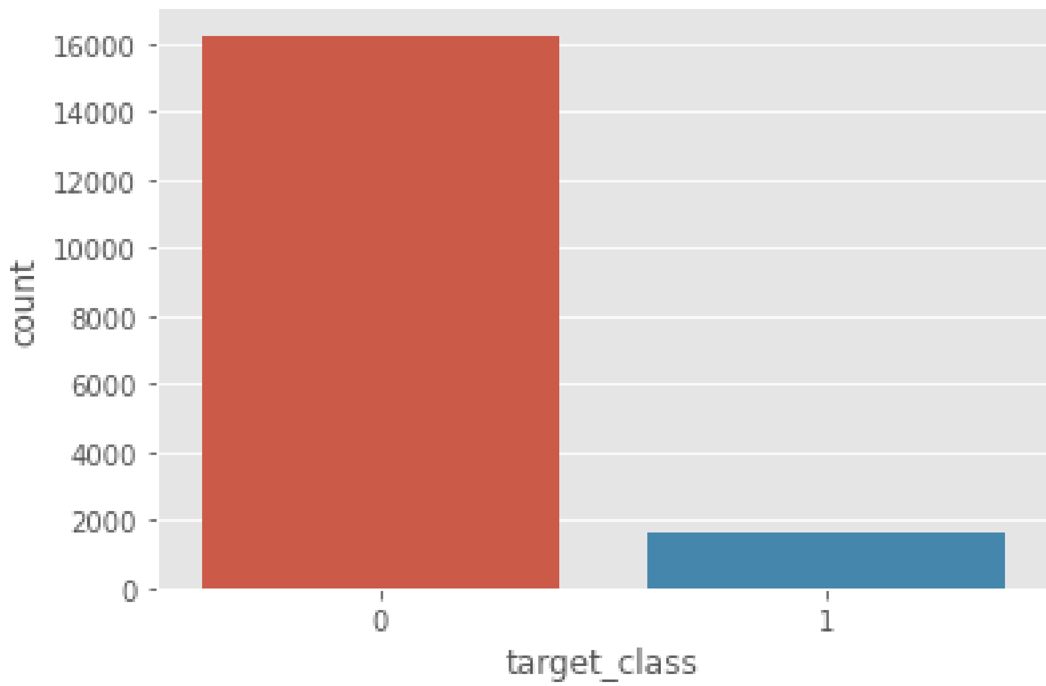
[14]:
```
df.isnull().sum()
```

[14]:
```
Mean of the integrated profile                  0
Standard deviation of the integrated profile    0
Excess kurtosis of the integrated profile       0
Skewness of the integrated profile              0
Mean of the DM-SNR curve                        0
Standard deviation of the DM-SNR curve          0
Excess kurtosis of the DM-SNR curve             0
Skewness of the DM-SNR curve                    0
target_class                                    0
dtype: int64
```

[15]:
```
df['target_class'].value_counts()
```

[15]:
```
0    16259
1     1639
Name: target_class, dtype: int64
```

[16]:
```
sns.countplot(x=df['target_class'])
plt.show()
```



[17]:
```
x= df.drop(columns='target_class', axis=1)

y = df['target_class']
```

[18]:
```
x.shape, y.shape
```

[18]: ((17898, 8), (17898,))

[19]:
```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.3,␣
↪random_state=101)
```

4.0.2 Feature scaling

[20]:
```
scaler = StandardScaler()
scaler.fit(x_train)
x_train = scaler.transform(x_train)
x_test = scaler.transform(x_test)
```

4.1 A) (i) LINEAR SVM MODEL USING ALGORITHM IMPLEMENTED FROM SCRATCH

[21]:

```
print("\nLINEAR SVM - ALGORITHM FROM SCRATCH!!!")
print("---------------------------------------")


C_values = [0.1, 10.0, 100.0, 1000.0]

for c in C_values:
    my_classifier = My_SVM_classifier(learning_rate=0.001, lambda_parameter=0.
 ↪01, no_of_iterations=100)
    my_classifier.fit(x_train, y_train)
    y_pred=my_classifier.predict(x_test)

    print("\nC=", c)
    print("Accuracy = ", round(accuracy_score(y_test, y_pred)*100, 2), "%")
    print("Precision = ",precision_score(y_test, y_pred))
    print("Recall = ",recall_score(y_test, y_pred),"\n")

    print(classification_report(y_pred,y_test))

    cm=metrics.confusion_matrix(y_test,y_pred)
    print("\nconfusion matrix: \n",cm)
    print("---------------------------------------")
```

```
LINEAR SVM - ALGORITHM FROM SCRATCH!!!
---------------------------------------
[-0.12769276  0.10828137  0.76165964  0.36030059 -0.13420155  0.18155098
 -0.10353578 -0.0605165 ]   1.313999999999966


C= 0.1
Accuracy =  97.82 %
Precision =  0.9609375
Recall =  0.7834394904458599

              precision    recall  f1-score   support

           0       1.00      0.98      0.99      4986
           1       0.78      0.96      0.86       384

    accuracy                           0.98      5370
   macro avg       0.89      0.97      0.93      5370
weighted avg       0.98      0.98      0.98      5370
```

```
confusion matrix:
 [[4884   15]
 [ 102  369]]
---------------------------------------
[-0.12769276  0.10828137  0.76165964  0.36030059 -0.13420155  0.18155098
 -0.10353578 -0.0605165 ]   1.313999999999966


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              precision    recall  f1-score   support

           0       1.00      0.98      0.99      4986
           1       0.78      0.96      0.86       384

    accuracy                           0.98      5370
   macro avg       0.89      0.97      0.93      5370
weighted avg       0.98      0.98      0.98      5370


confusion matrix:
 [[4884   15]
 [ 102  369]]
---------------------------------------
[-0.12769276  0.10828137  0.76165964  0.36030059 -0.13420155  0.18155098
 -0.10353578 -0.0605165 ]   1.313999999999966


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              precision    recall  f1-score   support

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           1       0.78      0.96      0.86       384

    accuracy                           0.98      5370
   macro avg       0.89      0.97      0.93      5370
weighted avg       0.98      0.98      0.98      5370


confusion matrix:
 [[4884   15]
```

```
 [ 102  369]]
---------------------------------------
[-0.12769276  0.10828137  0.76165964  0.36030059 -0.13420155  0.18155098
 -0.10353578 -0.0605165 ]   1.3139999999999966


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              precision    recall  f1-score   support

           0       1.00      0.98      0.99      4986
           1       0.78      0.96      0.86       384

    accuracy                           0.98      5370
   macro avg       0.89      0.97      0.93      5370
weighted avg       0.98      0.98      0.98      5370


confusion matrix:
 [[4884   15]
 [ 102  369]]
---------------------------------------
```

5 (ii) LINEAR-SVM using sklearn module

[27]:

```python
print("\nSVM kernel = LINEAR")
print("---------------------------------------")


C_values = [0.1, 10.0, 100.0, 1000.0]

for c in C_values:
    svm_linear = SVC(kernel='linear', C = c)
    svm_linear.fit(x_train, y_train)
    y_pred=svm_linear.predict(x_test)

    print("\nC=", c)
    print("Accuracy = ", round(accuracy_score(y_test, y_pred)*100, 2), "%")
    print("Precision = ",precision_score(y_test, y_pred))
    print("Recall = ",recall_score(y_test, y_pred),"\n")

    print(classification_report(y_pred,y_test))

    cm=metrics.confusion_matrix(y_test,y_pred)
```

```
    print("\nconfusion matrix: \n",cm)
    print("---------------------------------------")
```

```
SVM kernel = LINEAR
---------------------------------------

C= 0.1
Accuracy =  98.1 %
Precision =  0.9424460431654677
Recall =  0.8343949044585988

              precision    recall  f1-score   support

           0       1.00      0.98      0.99      4953
           1       0.83      0.94      0.89       417

    accuracy                           0.98      5370
   macro avg       0.91      0.96      0.94      5370
weighted avg       0.98      0.98      0.98      5370


confusion matrix:
 [[4875   24]
 [  78  393]]
---------------------------------------

C= 10.0
Accuracy =  98.16 %
Precision =  0.9325581395348838
Recall =  0.851380042462845

              precision    recall  f1-score   support

           0       0.99      0.99      0.99      4940
           1       0.85      0.93      0.89       430

    accuracy                           0.98      5370
   macro avg       0.92      0.96      0.94      5370
weighted avg       0.98      0.98      0.98      5370


confusion matrix:
 [[4870   29]
 [  70  401]]
---------------------------------------
```

```
C= 100.0
Accuracy =  98.16 %
Precision =  0.9325581395348838
Recall =  0.851380042462845

              precision    recall  f1-score   support

           0       0.99      0.99      0.99      4940
           1       0.85      0.93      0.89       430

    accuracy                           0.98      5370
   macro avg       0.92      0.96      0.94      5370
weighted avg       0.98      0.98      0.98      5370


confusion matrix:
 [[4870   29]
 [  70  401]]
---------------------------------------

C= 1000.0
Accuracy =  98.16 %
Precision =  0.9325581395348838
Recall =  0.851380042462845

              precision    recall  f1-score   support

           0       0.99      0.99      0.99      4940
           1       0.85      0.93      0.89       430

    accuracy                           0.98      5370
   macro avg       0.92      0.96      0.94      5370
weighted avg       0.98      0.98      0.98      5370


confusion matrix:
 [[4870   29]
 [  70  401]]
---------------------------------------
```

6 B) SVM KERNEL-POLYNOMIAL using sklearn module

[28]:
```
print("SVM kernel = POLYNOMIAL")
print("---------------------------------------")


C_values = [0.1, 10.0, 100.0, 1000.0]
```

```python
for c in C_values:
    svm_poly = SVC(kernel='poly', C = c)
    svm_poly.fit(x_train, y_train)
    y_pred=svm_poly.predict(x_test)

    print("\nC=", c)
    print("Accuracy = ", round(accuracy_score(y_test, y_pred)*100, 2), "%")
    print("Precision = ",precision_score(y_test, y_pred))
    print("Recall = ",recall_score(y_test, y_pred),"\n")

    print(classification_report(y_pred,y_test))

    cm=metrics.confusion_matrix(y_test,y_pred)
    print("\nconfusion matrix: \n",cm)
    print("---------------------------------------")
```

```
SVM kernel = POLYNOMIAL
---------------------------------------

C= 0.1
Accuracy =  97.77 %
Precision =  0.95822454308094
Recall =  0.7791932059447984

              precision    recall  f1-score   support

           0       1.00      0.98      0.99      4987
           1       0.78      0.96      0.86       383

    accuracy                           0.98      5370
   macro avg       0.89      0.97      0.92      5370
weighted avg       0.98      0.98      0.98      5370


confusion matrix:
 [[4883   16]
 [ 104  367]]
---------------------------------------

C= 10.0
Accuracy =  98.04 %
Precision =  0.937799043062201
Recall =  0.832271762208068

              precision    recall  f1-score   support
```

```
           0       0.99      0.98      0.99      4952
           1       0.83      0.94      0.88       418

    accuracy                           0.98      5370
   macro avg       0.91      0.96      0.94      5370
weighted avg       0.98      0.98      0.98      5370


confusion matrix:
 [[4873   26]
 [  79  392]]
---------------------------------------

C= 100.0
Accuracy =  98.08 %
Precision =  0.931924882629108
Recall =  0.8428874734607219

              precision    recall  f1-score   support

           0       0.99      0.99      0.99      4944
           1       0.84      0.93      0.89       426

    accuracy                           0.98      5370
   macro avg       0.92      0.96      0.94      5370
weighted avg       0.98      0.98      0.98      5370


confusion matrix:
 [[4870   29]
 [  74  397]]
---------------------------------------

C= 1000.0
Accuracy =  98.16 %
Precision =  0.9366197183098591
Recall =  0.8471337579617835

              precision    recall  f1-score   support

           0       0.99      0.99      0.99      4944
           1       0.85      0.94      0.89       426

    accuracy                           0.98      5370
   macro avg       0.92      0.96      0.94      5370
weighted avg       0.98      0.98      0.98      5370
```

```
confusion matrix:
 [[4872   27]
 [  72  399]]
---------------------------------------
```

6.1 SIGMOID kernel-SIGMOID using sklearn module

[ ]:
```
#Training the classifier model
#Predicting the test sample
#Checking with different values of C (hyperparameter)

print("SVM kernel = SIGMOID")
print("---------------------------------------")

C_values = [0.1, 10.0, 100.0, 1000.0]

for c in C_values:
    svm_sigmoid = SVC(kernel='sigmoid', C = c)
    svm_sigmoid.fit(x_train, y_train)
    y_pred=svm_sigmoid.predict(x_test)


    print("\nC=", c)
    print("Accuracy = ", round(accuracy_score(y_test, y_pred)*100, 2), "%")
    print("Precision = ",precision_score(y_test, y_pred))
    print("Recall = ",recall_score(y_test, y_pred),"\n")

    print(classification_report(y_pred,y_test))

    cm=metrics.confusion_matrix(y_test,y_pred)
    print("\nconfusion matrix: \n",cm)
    print("---------------------------------------")
```

[ ]:
```

```

6.2 4. EVALUATE THE PERFORMANCE OF THE ALGORITHMS:

6.3 COMPARISON OF PERFORMANCE OF BOTH IMPLEMENTATION:

6.3.1 (i) SVM-linear from scratch:

from scratch *c = 100.0* 1. Accuracy = 97.82 % 2. Precision = 0.9609375 3. Recall = 0.7834394904458599

using sklearn module: *C = 100.0* 1. Accuracy = 98.16 % 2. Precision = 0.9325581395348838 3. Recall = 0.851380042462845

6.3.2 (i) SVM-poly from scratch:

C = 1000.0 1. Accuracy = 98.16 % 2. Precision = 0.9366197183098591 3. Recall = 0.8471337579617835

6.3.3 (i) SVM-sigmoid from scratch:

C = 0.1 1. Accuracy = 87.52 % 2. Precision = 0.28874734607218683 3. Recall = 0.28874734607218683