CONTENTS

SOURCE

```
Sources:

    (a) Creator: B. German

        -- Central Research Establishment

           Home Office Forensic Science Service

           Aldermaston, Reading, Berkshire RG7 4PN

    (b) Donor: Vina Spiehler, Ph.D., DABFT

               Diagnostic Products Corporation

               (213) 776-0180 (ext 3014)

    (c) Date: September, 1987
```

ATTRIBUTES INFORMATION

```
    Number of Instances: 214

    Number of Attributes: 10 (including an Id#) plus the class attribute all attributes are
continuously valued

    Attribute Information:

           1. Id number: 1 to 214

           2. RI: refractive index

           3. Na: Sodium (unit measurement: weight percent in corresponding oxide, as
                         are attributes 4-10)

           4. Mg: Magnesium

           5. Al: Aluminum

           6. Si: Silicon

           7. K: Potassium

           8. Ca: Calcium

           9. Ba: Barium

          10. Fe: Iron

          11. Type of glass: (class attribute)

              -- 1 building_windows_float_processed

              -- 2 building_windows_non_float_processed

              -- 3 vehicle_windows_float_processed

              -- 4 vehicle_windows_non_float_processed (none in this database)

              -- 5 containers

              -- 6 tableware

              -- 7 headlamps

    Missing Attribute Values: None

    ID, N    -- numeric identifier of the instance

    RI, N    -- refractive index

    NA2O, N  -- Sodium oxide

    MGO, N   -- magnesium oxide

    AL2O3, N -- aluminum oxide

    SIO2, N  -- silcon oxide

    K2O,  N  -- potassium oxide

    CAO, N   -- calcium oxide

    BAO, N   -- barium oxide

    FE2O3, N -- iron oxide

    TYPE, N  -- An unknown, but must correspond to the types in the paper

    CAMG, N  -- Unsure
```

ABOUT PROJECT

```
The dataset contains various features such as refractive index, percentage of different elements like
sodium,
magnesium, aluminum, silicon, potassium, calcium, barium, and iron, as well as the type of glass. The
objective of the
project is to build a machine learning model that can effectively identify the type of glass based on
these chemical
properties. This classification task is crucial in real-world applications, especially in forensic
investigations,
where identifying the type of glass found at crime scenes can provide valuable evidence. By employing
various
classification algorithms and techniques, the project seeks to achieve high accuracy and robustness in
predicting the
glass type, thereby contributing to the field of material identification and forensic sciences.
```

IMPORTING LIBRARIES

In [1]:
```
import warnings

import numpy as np

import pandas as pd

import sweetviz as sv

import seaborn as sns

import matplotlib.pyplot as plt

from xgboost import XGBClassifier

warnings.filterwarnings ( 'ignore' )

from sklearn.impute import SimpleImputer

from imblearn.over_sampling import SMOTE

pd.set_option ( 'display.max_columns' , None )

from sklearn.tree import DecisionTreeClassifier

from sklearn.linear_model import LogisticRegression , Ridge , Lasso

from sklearn.model_selection import train_test_split , GridSearchCV , KFold

from sklearn.preprocessing import LabelEncoder , MinMaxScaler , Normalizer , StandardScaler

from sklearn.ensemble import RandomForestClassifier , AdaBoostClassifier , GradientBoostingClassifier , Stackin

from sklearn.metrics import accuracy_score , precision_score , recall_score , f1_score , confusion_matrix , roc
```

IMPORTING DATA

In [2]:
```
DF = pd.read_csv ( "glass.data" , names = [ 'ID' , 'Refractive_Index' , 'Sodium_%' , 'Magnesium_%' , 'Aluminium
                                            'Silicon_%' , 'Potassium_%' , 'Calcium_%' , 'Barium_%' , 'Iron_%' ,
                                            'Type_Of_Glass' ]  )

DF
```

Out[2]:

	ID	Refractive_Index	Sodium_%	Magnesium_%	Aluminium_%	Silicon_%	Potassium_%	Calcium_%	Barium_%	Iron_%	Type_Of_Glass
0	1	1.52101	13.64	4.49	1.10	71.78	0.06	8.75	0.00	0.0	1
1	2	1.51761	13.89	3.60	1.36	72.73	0.48	7.83	0.00	0.0	1
2	3	1.51618	13.53	3.55	1.54	72.99	0.39	7.78	0.00	0.0	1
3	4	1.51766	13.21	3.69	1.29	72.61	0.57	8.22	0.00	0.0	1
4	5	1.51742	13.27	3.62	1.24	73.08	0.55	8.07	0.00	0.0	1
...	...	...	...	...	...	...	...	...	...	...	...
209	210	1.51623	14.14	0.00	2.88	72.61	0.08	9.18	1.06	0.0	7
210	211	1.51685	14.92	0.00	1.99	73.06	0.00	8.40	1.59	0.0	7
211	212	1.52065	14.36	0.00	2.02	73.42	0.00	8.44	1.64	0.0	7
212	213	1.51651	14.38	0.00	1.94	73.61	0.00	8.48	1.57	0.0	7
213	214	1.51711	14.23	0.00	2.08	73.36	0.00	8.62	1.67	0.0	7

214 rows × 11 columns

DATA DESCRIPTION

STATISTICAL SUMMARY

In [3]:
```
Description = pd.DataFrame ( DF.describe ( ) ).transpose ( )

Description
```

Out[3]:

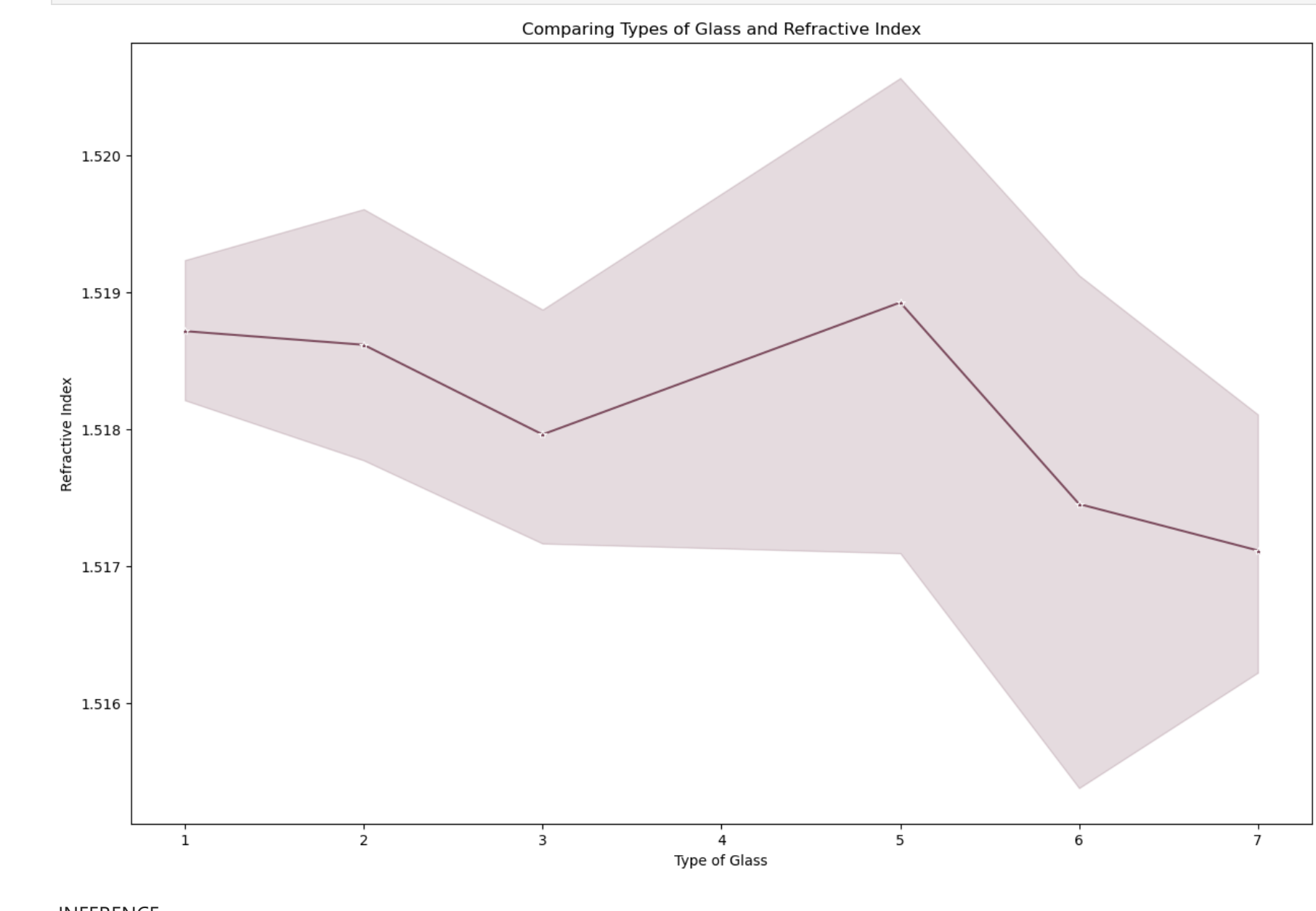
	count	mean	std	min	25%	50%	75%	max
ID	214.0	107.500000	61.920648	1.00000	54.250000	107.50000	160.750000	214.00000
Refractive_Index	214.0	1.518365	0.003037	1.51115	1.516522	1.51768	1.519157	1.53393
Sodium_%	214.0	13.407850	0.816604	10.73000	12.907500	13.30000	13.825000	17.38000
Magnesium_%	214.0	2.684533	1.442408	0.00000	2.115000	3.48000	3.600000	4.49000
Aluminium_%	214.0	1.444907	0.499270	0.29000	1.190000	1.36000	1.630000	3.50000
Silicon_%	214.0	72.650935	0.774546	69.81000	72.280000	72.79000	73.087500	75.41000
Potassium_%	214.0	0.497056	0.652192	0.00000	0.122500	0.55500	0.610000	6.21000
Calcium_%	214.0	8.956963	1.423153	5.43000	8.240000	8.60000	9.172500	16.19000
Barium_%	214.0	0.175047	0.497219	0.00000	0.000000	0.00000	0.000000	3.15000
Iron_%	214.0	0.057009	0.097439	0.00000	0.000000	0.00000	0.100000	0.51000
Type_Of_Glass	214.0	2.780374	2.103739	1.00000	1.000000	2.00000	3.000000	7.00000

EXPLORATORY DATA ANALYSIS

DATA VISUALIZATION

REFRACTIVE INDEX VS TYPES OF GLASS

In [4]:
```
plt.figure ( figsize = ( 15 , 10 ) );

sns.lineplot ( y = 'Refractive_Index' , x = 'Type_Of_Glass', data = DF , color = '#7E4E60' , marker = '*');

plt.xlabel ( "Type of Glass" );

plt.ylabel ( "Refractive Index" );

plt.title ( "Comparing Types of Glass and Refractive Index" );
```



INFERENCE

```
1. Containers have the highest refractive index 1.53

   - The glass used in containers has the highest refractive index, measuring at 1.53.

   - The refractive index of a material is a measure of how much light bends when it passes through
that material.

   - The higher the refractive index, the more the light bends.

   - The higher the refractive index, the more the light bends, indicating a denser glass composition.

2. Headlamps have the lowest refractive index of 1.511

   -  The glass used in headlamps has the lowest refractive index, measuring at 1.511.

   - This indicates that headlamp glass is less dense compared to the glass used in containers.
```

CHEMICAL COMPOSITION

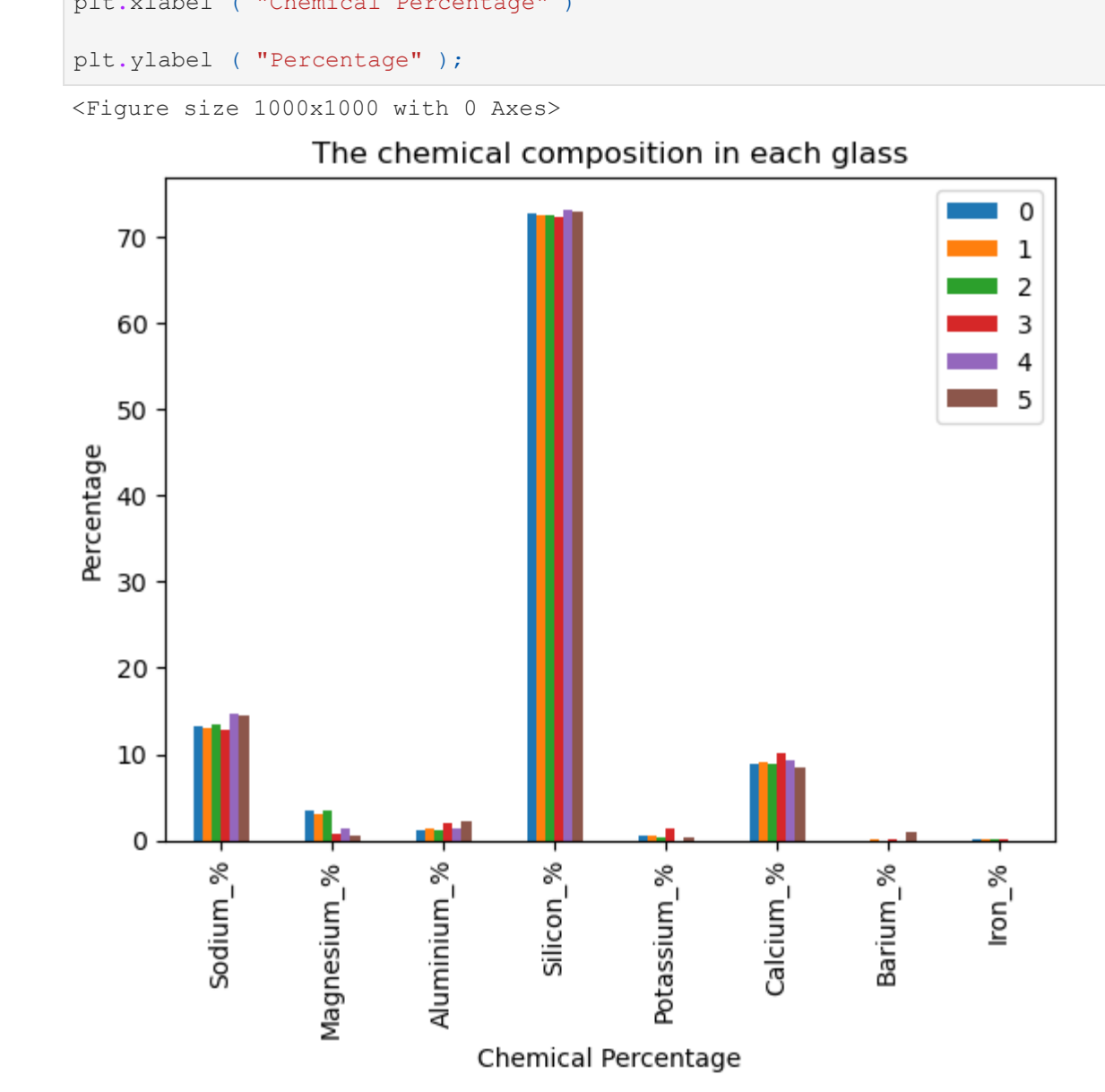
In [5]:
```
Chemicals = DF.groupby ( by = DF.Type_Of_Glass ).mean ( ).reset_index( ).transpose ( )

Chemicals
```

Out[5]:

	0	1	2	3	4	5
Type_Of_Glass	1.000000	2.000000	3.000000	5.000000	6.000000	7.000000
ID	35.500000	108.500000	155.000000	170.000000	181.000000	200.000000
Refractive_Index	1.518718	1.518619	1.517964	1.518928	1.517456	1.517116
Sodium_%	13.242286	13.111711	13.437059	12.827692	14.646667	14.442069
Magnesium_%	3.552429	3.002105	3.543529	0.773846	1.305556	0.538276
Aluminium_%	1.163857	1.408158	1.201176	2.033846	1.366667	2.122759
Silicon_%	72.619143	72.598026	72.404706	72.366154	73.206667	72.965862
Potassium_%	0.447429	0.521053	0.406471	1.470000	0.000000	0.325172
Calcium_%	8.797286	9.073684	8.782941	10.123846	9.356667	8.491379
Barium_%	0.012714	0.050263	0.008824	0.187692	0.000000	1.040000
Iron_%	0.057000	0.079737	0.057059	0.060769	0.000000	0.013448

In [6]:
```
plt.figure ( figsize = ( 10 , 10 ) )

Chemicals.iloc [ 3 : , : ].plot ( kind = 'bar' , label = [ 'building_windows_float_processed' ,

                                                    'building_windows_non_float_processed' ,

                                                    'vehicle_windows_float_processed' , 'containers' , 'tableware

                                                    'headlamps' ] );

plt.title ( "The chemical composition in each glass" )

plt.xlabel ( "Chemical Percentage" )

plt.ylabel ( "Percentage" );
```

<Figure size 1000x1000 with 0 Axes>



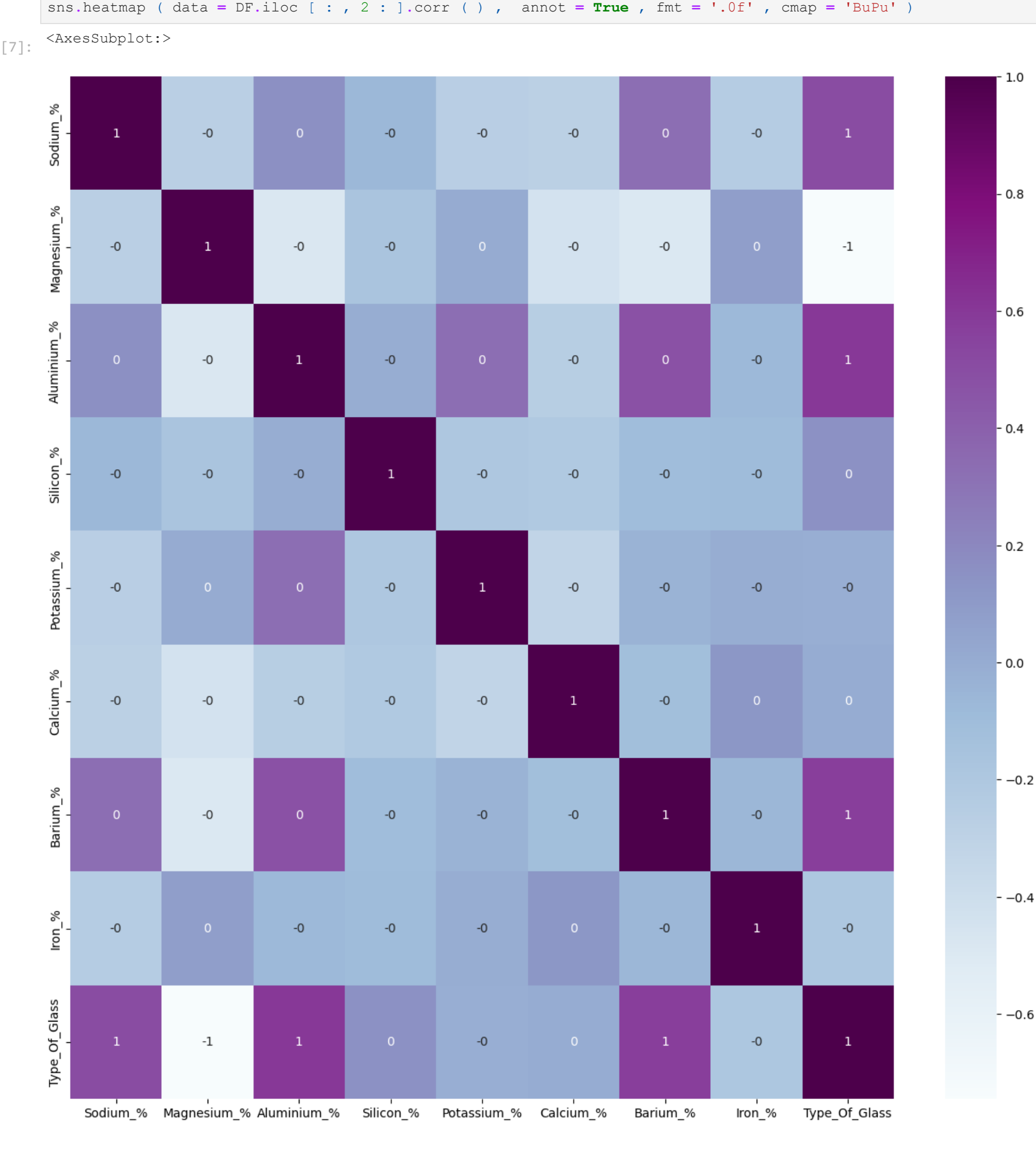
INFERENCE

```
1. We can see that every type of glass has at least 70 % of silicon in it

    - Silicon plays a significant role in the structural properties of glass. Silicon dioxide (SiO2) is
the main
      component of most types of glass, and it provides stability and strength to the glass structure.
```

HEATMAP

In [7]:
```
plt.figure ( figsize = ( 15 , 15) )
sns.heatmap ( data = DF.iloc [ : , 2 : ].corr ( ) ,  annot = True , fmt = '.0f' , cmap = 'BuPu' )
```

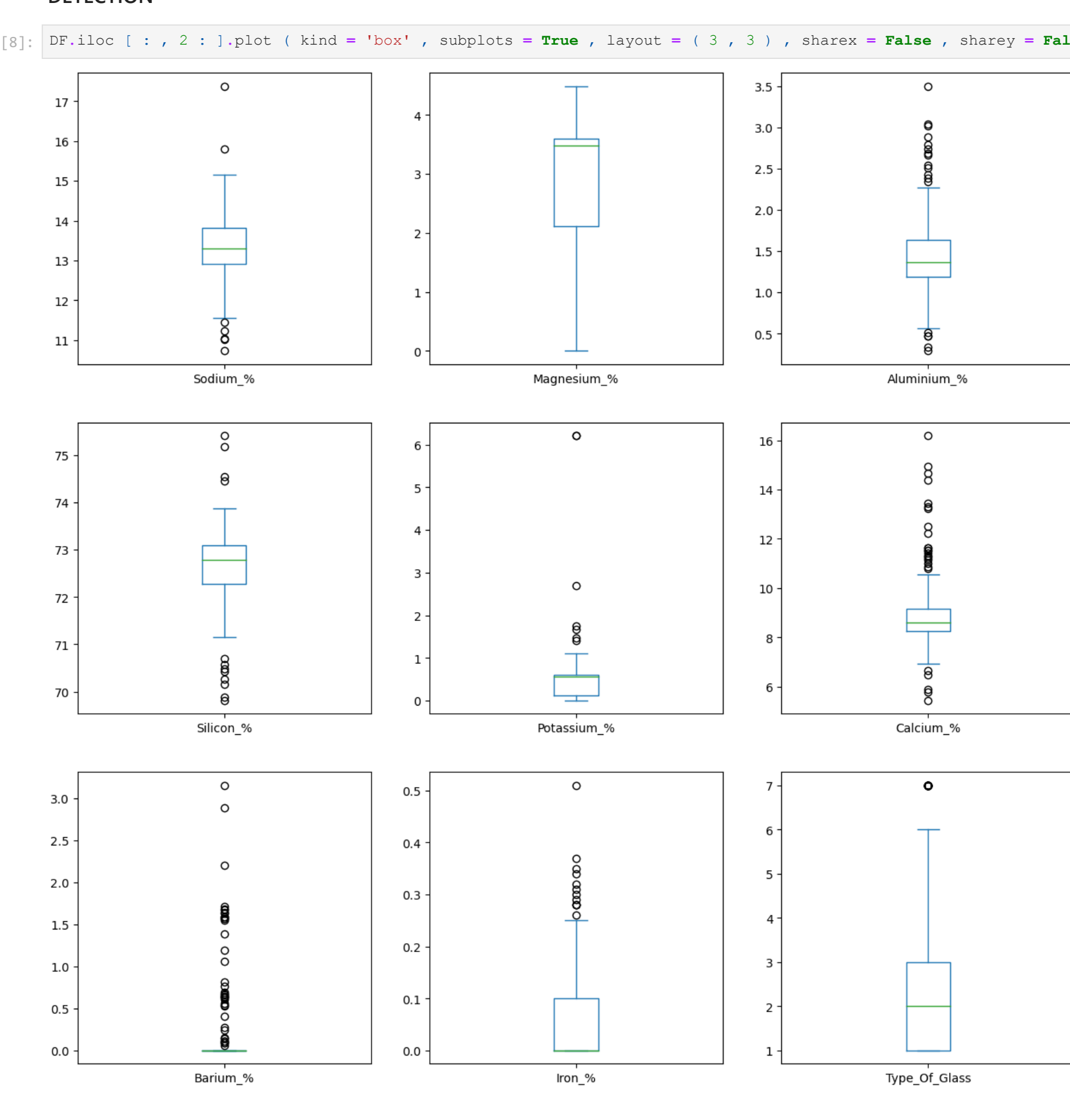
Out[7]: <AxesSubplot:>



OUTLIERS

DETECTION

In [8]:
```
DF.iloc [ : , 2 : ].plot ( kind = 'box' , subplots = True , layout = ( 3 , 3 ) , sharex = False , sharey = Fals
```



TREATMENT

In [9]:
```
Outliers = DF.iloc [ : , 2 : -1 ]

Outliers
```

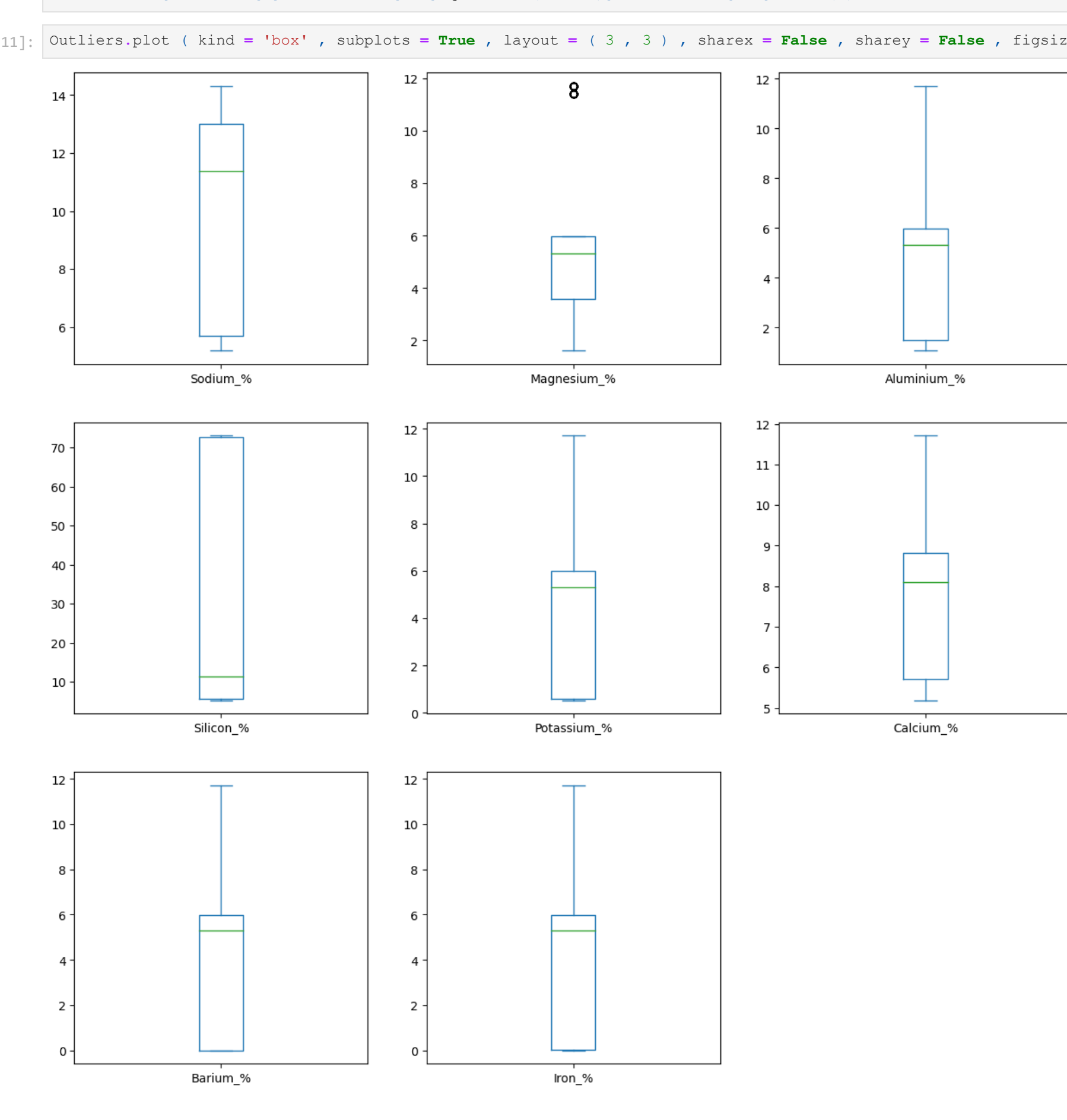
Out[9]:

	Sodium_%	Magnesium_%	Aluminium_%	Silicon_%	Potassium_%	Calcium_%	Barium_%	Iron_%
0	13.64	4.49	1.10	71.78	0.06	8.75	0.00	0.0
1	13.89	3.60	1.36	72.73	0.48	7.83	0.00	0.0
2	13.53	3.55	1.54	72.99	0.39	7.78	0.00	0.0
3	13.21	3.69	1.29	72.61	0.57	8.22	0.00	0.0
4	13.27	3.62	1.24	73.08	0.55	8.07	0.00	0.0
...	...	...	...	...	...	...	...	...
209	14.14	0.00	2.88	72.61	0.08	9.18	1.06	0.0
210	14.92	0.00	1.99	73.06	0.00	8.40	1.59	0.0
211	14.36	0.00	2.02	73.42	0.00	8.44	1.64	0.0
212	14.38	0.00	1.94	73.61	0.00	8.48	1.57	0.0
213	14.23	0.00	2.08	73.36	0.00	8.62	1.67	0.0

214 rows × 8 columns

In [10]:
```
for i in Outliers :

    Outliers[Outliers [i] < Outliers [ i ].quantile ( 0.10 )] = Outliers [ i ].mean ( )

    Outliers[Outliers [i] > Outliers [ i ].quantile ( 0.90 )] = Outliers [ i ].mean ( )
```

In [11]:
```
Outliers.plot ( kind = 'box' , subplots = True , layout = ( 3 , 3 ) , sharex = False , sharey = False , figsize
```



RANDOM SAMPLING

In [12]:
```
DF.drop ( columns = [ 'ID' ] , inplace = True )

Train , Test = train_test_split ( DF , test_size = 0.15 , random_state = 42 )

Train_X = Train.iloc [ : , : - 1 ]

Train_Y = Train.iloc [ : ,  -1 ]

Test_X = Test.iloc [ : , : - 1 ]

Test_Y = Test.iloc [ : ,  -1 ]

print ( "The shapes of the data sets are : " )

print ( "\nTrain >> {} , Test >> {}\n\nTrain_X >> {} , Train_Y >> {}\n\nTest_X >> {} , Test_Y >> {}".format ( T
```

```
The shapes of the data sets are :

Train >> (181, 10) , Test >> (33, 10)

Train_X >> (181, 9) , Train_Y >> (181,)

Test_X >> (33, 9) , Test_Y >> (33,)
```

PREDICTIVE ANALYSIS

LOGISTIC REGRESSION

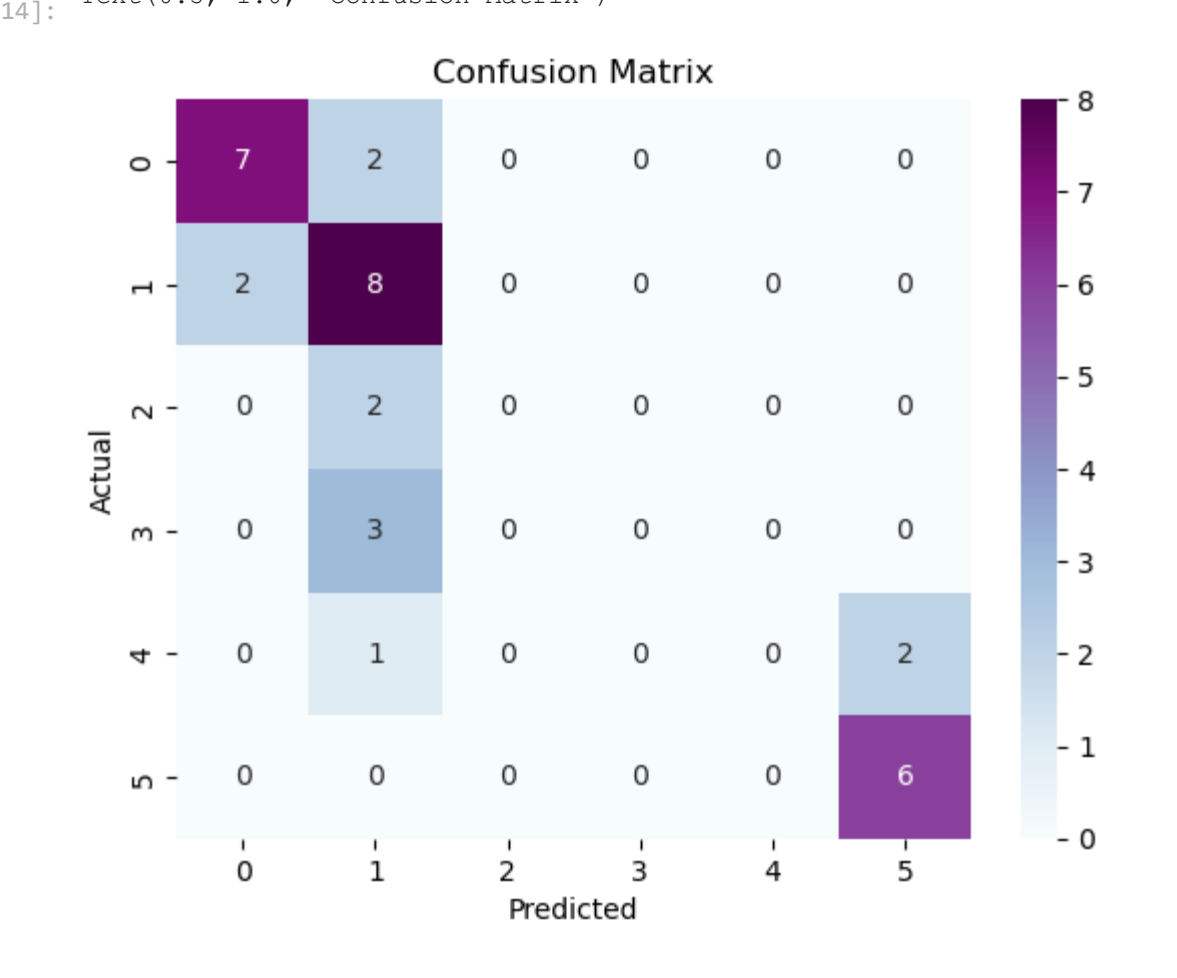
TRAINING AND TESTING

In [13]:
```
LR = LogisticRegression ( )

LR.fit ( Train_X ,Train_Y )

Y_LR = LR.predict ( Test_X )

Accuracy_LR = np.round ( accuracy_score ( Test_Y , Y_LR ) * 100 , 2 )

print ( "The accuracy of the Test Data is : " , Accuracy_LR )
```

The accuracy of the Test Data is : 63.64

In [14]:
```
Confusion_Matrix_LR = confusion_matrix ( Test_Y , Y_LR )

sns.heatmap ( Confusion_Matrix_LR , annot = True , fmt = '.0f' , cmap = 'BuPu' )

plt.xlabel ( "Predicted" )

plt.ylabel ( "Actual" )

plt.title ( "Confusion Matrix" )
```

Out[14]: Text(0.5, 1.0, 'Confusion Matrix')



CHECKING FOR OVER FITTING

In [15]:
```
train_predictions = LR.predict(Train_X)

test_predictions = LR.predict(Test_X)

train_accuracy = np.round ( accuracy_score ( Train_Y, train_predictions ) * 100 , 2 )

test_accuracy = np.round ( accuracy_score ( Test_Y, test_predictions ) * 100 , 2 )

print ( "Train Accuracy >> {}\n\nTest Accuracy >> {}".format ( train_accuracy , test_accuracy ) )
```

```
Train Accuracy >> 63.54

Test Accuracy >> 63.64
```

RANDOM FOREST

TUNING

In [16]:
```
RF = RandomForestClassifier ( )

Parameters = { 'n_estimators' : [ 50 , 100 , 150 , 200 ],

               'criterion' : [ 'gini' , 'entropy' ],

               'max_depth' : [ 5 , 10 , 15 ] ,

               'min_samples_split' : [ 5 , 10 , 15 ] }

GS = GridSearchCV ( estimator = RF , param_grid = Parameters , cv = 5 )

GS.fit ( Train_X , Train_Y )

Parameters = GS.best_params_

print ( "The best parameters are : \n\n" , Parameters )
```

```
The best parameters are :

 {'criterion': 'entropy', 'max_depth': 15, 'min_samples_split': 5, 'n_estimators': 150}
```

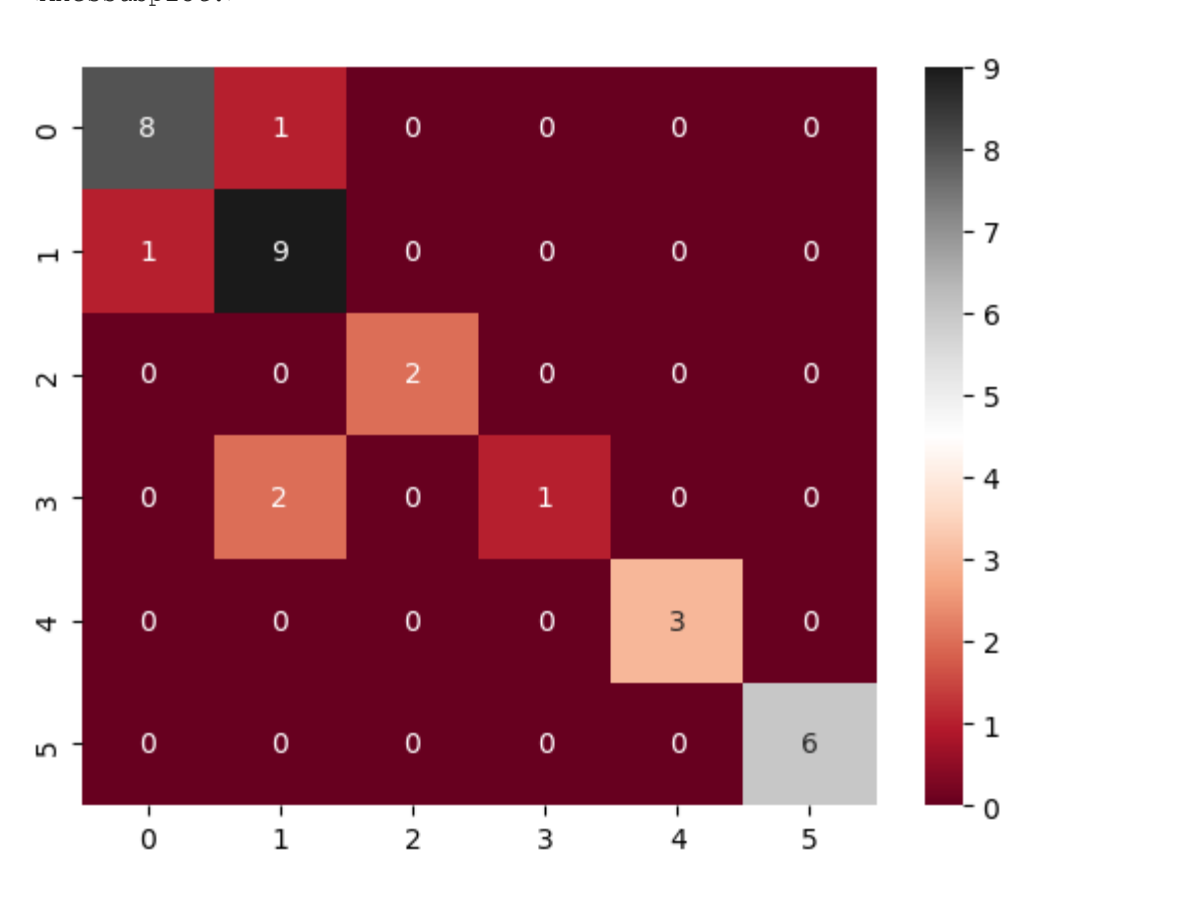
TRAINING AND TESTING

In [17]:
```
RF = RandomForestClassifier ( **Parameters )

RF.fit ( Train_X , Train_Y )

Y_RF = RF.predict ( Test_X )

Accuracy_RF = np.round ( accuracy_score ( Test_Y , Y_RF ) * 100 , 2 )

print ( "The accuracy of the Test Data is : " , Accuracy_RF )
```

The accuracy of the Test Data is : 87.88

In [18]:
```
Confusion_Matrix_RF = confusion_matrix ( Test_Y , Y_RF )

Confusion_Matrix_RF = sns.heatmap ( Confusion_Matrix_RF , fmt = '0.0f' , annot = True , cmap = 'RdGy' )

Confusion_Matrix_RF
```

Out[18]: <AxesSubplot:>



CHECKING FOR OVERFITTING

In [19]:
```
train_predictions = RF.predict ( Train_X )

test_predictions = RF.predict ( Test_X )

train_accuracy = np.round ( accuracy_score ( Train_Y, train_predictions ) * 100 , 2 )

test_accuracy = np.round ( accuracy_score ( Test_Y, test_predictions ) * 100 , 2 )

print ( "Train Accuracy >> {}\n\nTest Accuracy >> {}".format ( train_accuracy , test_accuracy ) )
```

```
Train Accuracy >> 98.9

Test Accuracy >> 87.88
```

```
* The training accuracy is very high (98.34%), indicating that the model has learned the training data
extremely well
  and  can accurately predict the training samples.

* However, the test accuracy is significantly lower (93.94%), suggesting that the model's performance
drops when
  applied to new, unseen data.
```

DECISION TREE

HYPER PARAMETER TUNING

In [20]:
```python
DT = DecisionTreeClassifier (  )

Parameters = { 'criterion' : [ 'gini' , 'entropy' ],

               'splitter' : [ 'best' , 'random' ],

               'max_depth' : [ None ,  5 , 10 , 15 ] ,

               'max_features' : [ "auto", "sqrt", "log2" ] }

GS = GridSearchCV ( estimator = DT , param_grid = Parameters , cv = 5 )

GS.fit ( Train_X , Train_Y )

Parameters = GS.best_params_

print ( "The best parameters of decision tree are : \n\n" , Parameters )
```

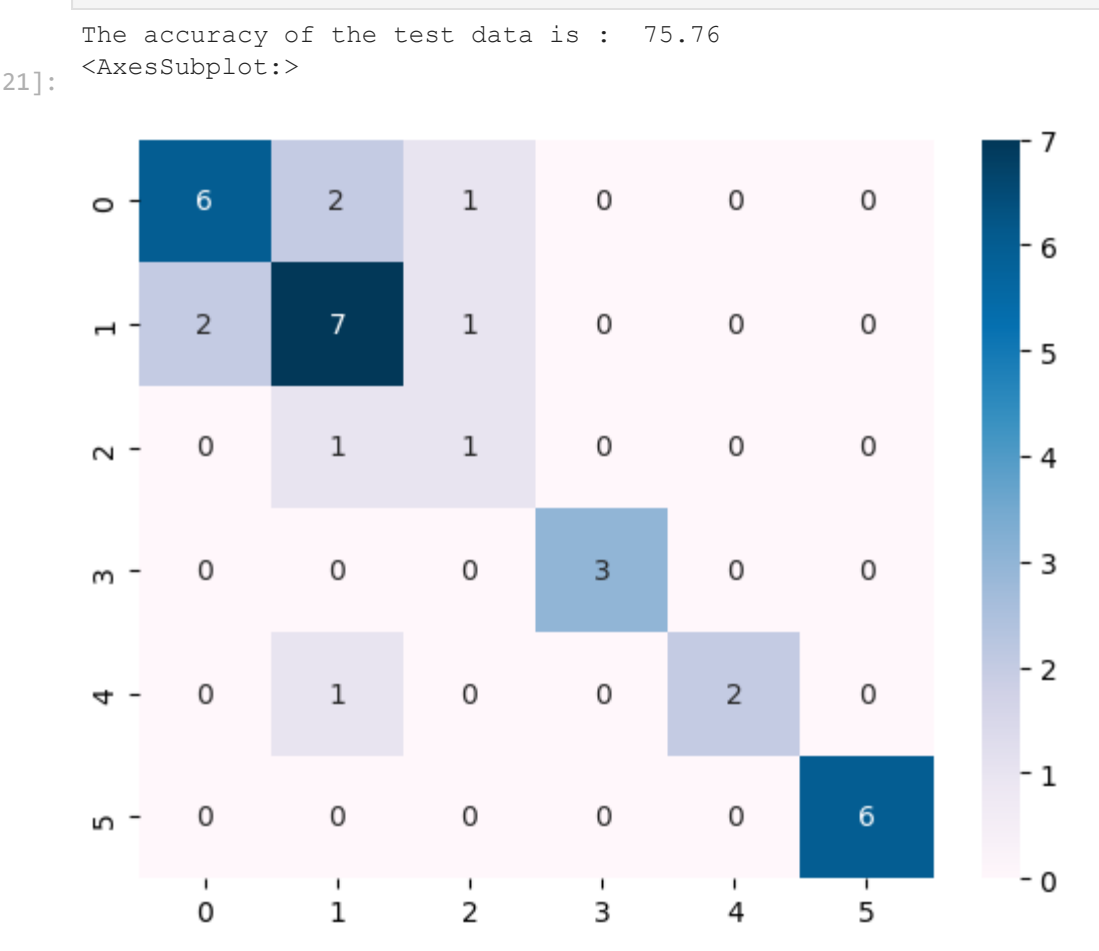
```
The best parameters of decision tree are :

 {'criterion': 'entropy', 'max_depth': None, 'max_features': 'log2', 'splitter': 'best'}
```

TRAINING AND TESTING

In [21]:
```python
DT = DecisionTreeClassifier ( **Parameters )

DT.fit ( Train_X , Train_Y )

Y_DT = DT.predict ( Test_X )

Accuracy_DT = np.round ( accuracy_score ( Test_Y , Y_DT ) * 100 , 2 )

print ( "The accuracy of the test data is : " , Accuracy_DT )

Confusion_Matrix_DT = sns.heatmap ( confusion_matrix ( Test_Y , Y_DT ) , fmt = '0.0f' , annot = True , cmap = '

Confusion_Matrix_DT
```

```
The accuracy of the test data is :  75.76
&lt;AxesSubplot:&gt;
```

Out[21]:



CHECKING FOR OVER FITTING

In [22]:
```python
Y_DT_Train = DT.predict ( Train_X )

Train_Accuracy = np.round ( accuracy_score ( Train_Y , Y_DT_Train ) * 100 , 2 )


if int ( Train_Accuracy - Accuracy_DT ) > 5.0  :

    print ( "There is overfitting"  )

else :

    print ( "There is no overfitting\n"  )

print ( "\nThe Training accuracy is : {} \n\nThe Testing accuracy is : {}".format( Train_Accuracy , Accuracy_DT
```

```
There is overfitting

The Training accuracy is : 100.0

The Testing accuracy is : 75.76
```

ENSEMBLE TECHNIQUES : BOOSTING

GRADIENT BOOSTING

HYPER PARAMETER TUNING

In [23]:
```python
GB = GradientBoostingClassifier ( )

Parameters = {  'loss' : [ 'log_loss' ,'deviance', 'exponential' ] ,

                'learning_rate' : [ 0.1 , 0.01 , 0.001 ] ,

                'n_estimators' : [ 50 , 100 , 150  ] }

GS = GridSearchCV ( estimator = GB , param_grid = Parameters )

GS.fit ( Train_X , Train_Y )

Parameters = GS.best_params_

print ( "The the most optimum parameters are : \n\n" , Parameters )
```

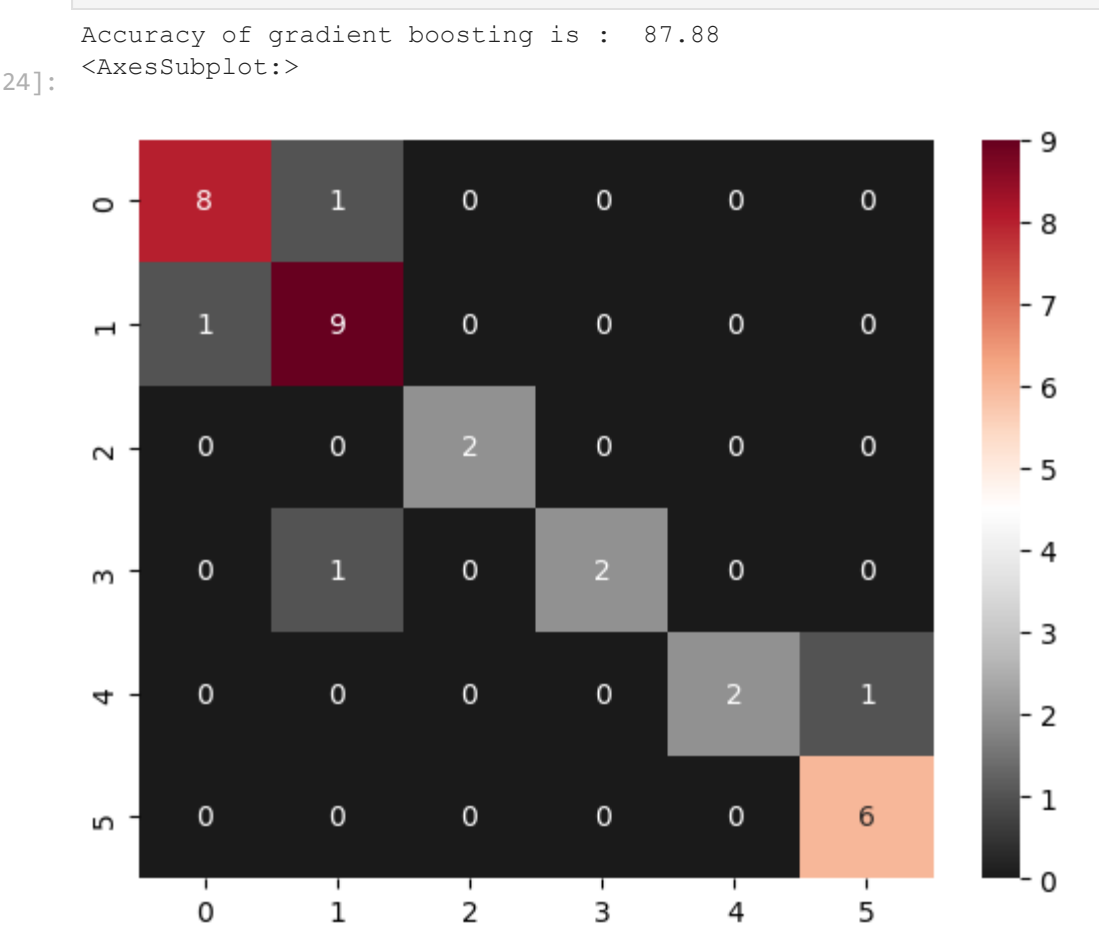
```
The the most optimum parameters are :

 {'learning_rate': 0.1, 'loss': 'log_loss', 'n_estimators': 150}
```

TRAINING AND TESTING

In [24]:
```python
GB = GradientBoostingClassifier ( **Parameters )

GB.fit ( Train_X , Train_Y )

Y_GB = GB.predict ( Test_X )

Accuracy_GB = np.round ( accuracy_score ( Test_Y , Y_GB ) * 100 , 2 )

print ( "Accuracy of gradient boosting is : " ,  Accuracy_GB )

Confusion_Matrix_GB = sns.heatmap ( confusion_matrix ( Test_Y , Y_GB ) , annot = True , fmt = '0.0f' , cmap = '

Confusion_Matrix_GB
```

```
Accuracy of gradient boosting is :  87.88
&lt;AxesSubplot:&gt;
```

Out[24]:



CHECKING FOR OVER FITTING

In [25]:
```python
Y_GB_Train = GB.predict ( Train_X )

Train_Accuracy = np.round ( accuracy_score ( Train_Y , Y_GB_Train ) * 100 , 2 )


if int ( Train_Accuracy - Accuracy_GB ) > 5.0  :

    print ( "There is overfitting"  )

else :

    print ( "There is no overfitting\n"  )

print ( "\nThe Training accuracy is : {} \n\nThe Testing accuracy is : {}".format( Train_Accuracy , Accuracy_GB
```

```
There is overfitting

The Training accuracy is : 100.0

The Testing accuracy is : 87.88
```

EXTREME GRADIENT BOOSTING

HYPER PARAMETER TUNING

In [26]:
```python
XGB = XGBClassifier ( )

Parameters = {

    'n_estimators': [100, 200, 300],

    'learning_rate': [ 0.5 , 0.1, 0.01, 0.001],

    'max_depth': [3, 5, 7]

}

LE = LabelEncoder ( )

Train_Y = LE.fit_transform ( Train_Y )

Test_Y = LE.fit_transform ( Test_Y )

GS = GridSearchCV ( estimator = XGBClassifier ( ) , param_grid = Parameters )

GS.fit ( Train_X , Train_Y )

Parameters = GS.best_params_

print ( "The the most optimum parameters are : \n\n" , Parameters )
```

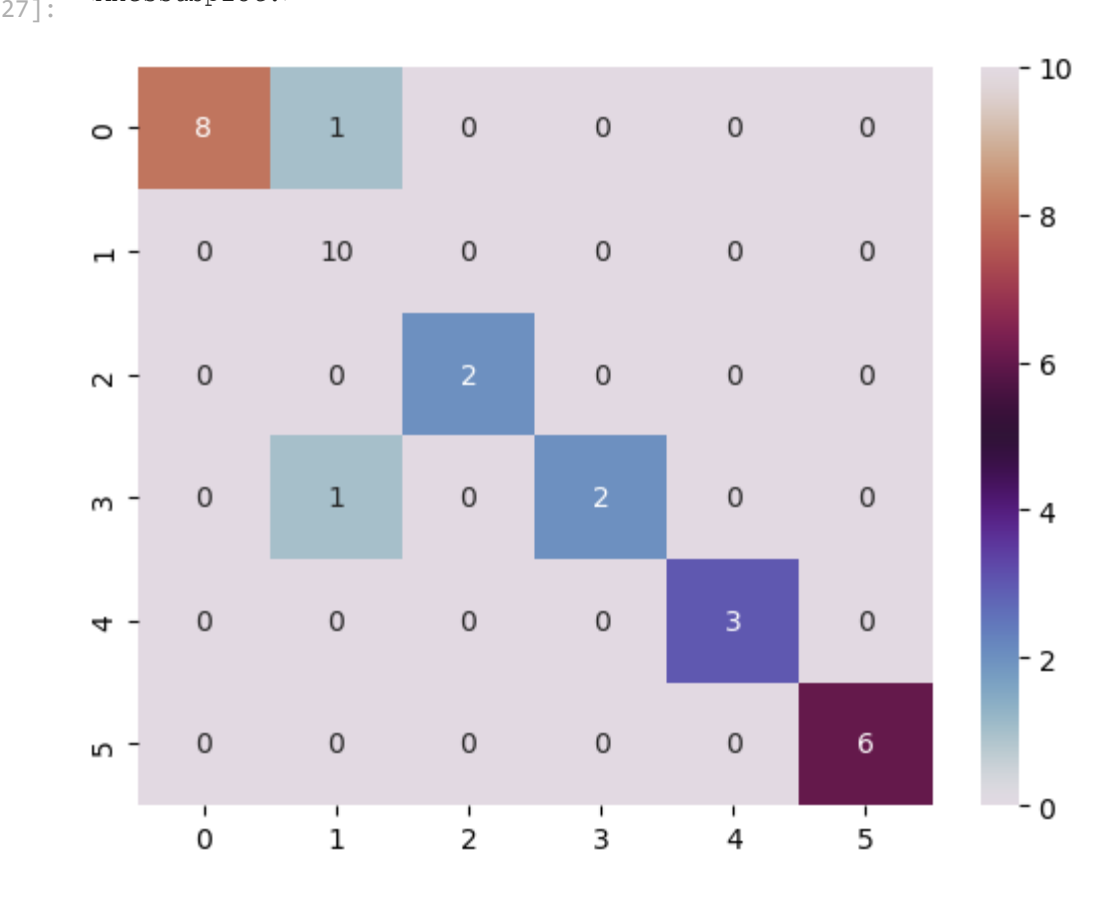
```
The the most optimum parameters are :

 {'learning_rate': 0.1, 'max_depth': 7, 'n_estimators': 200}
```

TRAINING AND TESTING

In [27]:
```python
XGB = XGBClassifier ( **Parameters )

XGB.fit ( Train_X , Train_Y )

Y_XGB = XGB.predict ( Test_X )

Accuracy_XGB = np.round ( accuracy_score ( Test_Y , Y_XGB ) * 100 , 2 )

print ( "Accuracy of extreme gradient boosting is : " ,  Accuracy_XGB )

Confusion_Matrix_XGB = sns.heatmap ( confusion_matrix ( Test_Y , Y_XGB ) , annot = True , fmt = '0.0f' , cmap =

Confusion_Matrix_XGB
```

```
Accuracy of extreme gradient boosting is :  93.94
&lt;AxesSubplot:&gt;
```

Out[27]:



CHECKING FOR OVER FITTING

In [28]:
```python
Y_XGB_Train = XGB.predict ( Train_X )

Train_Accuracy = np.round ( accuracy_score ( Train_Y , Y_XGB_Train ) * 100 , 2 )


if int ( Train_Accuracy - Accuracy_XGB ) > 5.0  :

    print ( "There is overfitting"  )

else :

    print ( "There is no overfitting\n"  )

print ( "\nThe Training accuracy is : {} \n\nThe Testing accuracy is : {}".format( Train_Accuracy , Accuracy_XG
```

```
There is overfitting

The Training accuracy is : 100.0

The Testing accuracy is : 93.94
```

COMPARISON

In [29]:
```python
Accuracies = [ Accuracy_DT , Accuracy_LR , Accuracy_GB , Accuracy_RF , Accuracy_XGB ]

Accuracies_Names = [ 'Accuracy_DT' , 'Accuracy_LR' , 'Accuracy_GB' , 'Accuracy_RF' , 'Accuracy_XGB' ]

Performance_Metrics = { 'Accuracies' : Accuracies , 'Values' : Accuracies_Names }

Performance_Metrics = pd.DataFrame(Performance_Metrics)

Performance_Metrics
```

Out[29]:

	Accuracies	Values
0	75.76	Accuracy_DT
1	63.64	Accuracy_LR
2	87.88	Accuracy_GB
3	87.88	Accuracy_RF
4	93.94	Accuracy_XGB

CONCLUSION

```
The results clearly demonstrate that the XGBoost algorithm outperforms the other methods, achieving the
highest
accuracy among all evaluated classifiers.

Random Forest also performed admirably, showing competitive performance with an accuracy close to
XGBoost.

However, Decision Tree and Logistic Regression exhibited relatively lower accuracies, indicating that
they might not be
the best choices for this specific dataset.
```