Machine Learning Coursework

In [1]:
```
# libraries
import pandas as pd
from pandas import plotting
from sklearn import metrics#to calculate rootmean square
from sklearn import preprocessing
import numpy as np
from sklearn.preprocessing import MinMaxScaler

#DataVisualization Libraries
import matplotlib.pyplot as plt
import seaborn as sns

#Machine Learning Libraries
import os
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, classification_report
from sklearn.metrics import confusion_matrix, classification_report
import seaborn as sns
import matplotlib.pyplot as plt

!pip install pydotplus
!apt-get install graphviz
```

```
Requirement already satisfied: pydotplus in c:\users\ptrau\anaconda3\lib\site-packages (2.0.2)
Requirement already satisfied: pyparsing>=2.0.1 in c:\users\ptrau\anaconda3\lib\site-packages (f
rom pydotplus) (3.0.9)
"apt-get" no se reconoce como un comando interno o externo,
programa o archivo por lotes ejecutable.
```

1)Exploratory Data Analysis

A) Data Preview

In [2]:
```
dry =pd.read_excel('Dry_Bean_Dataset.xlsx')
dry.head()
```

Out[2]:

	Area	Perimeter	MajorAxisLength	MinorAxisLength	AspectRation	Eccentricity	ConvexArea	EquivDiameter
0	28395	610.291	208.178117	173.888747	1.197191	0.549812	28715	190.141097
1	28734	638.018	200.524796	182.734419	1.097356	0.411785	29172	191.272750
2	29380	624.110	212.826130	175.931143	1.209713	0.562727	29690	193.410904
3	30008	645.884	210.557999	182.516516	1.153638	0.498616	30724	195.467062
4	30140	620.134	201.847882	190.279279	1.060798	0.333680	30417	195.896503

In [3]:
```
le = preprocessing.LabelEncoder()
columns = ["Class"]
```

```
for col in columns:
    dry[col] = le.fit_transform(dry[col])
    print(le.classes_)

dry.head()
```

```
['BARBUNYA' 'BOMBAY' 'CALI' 'DERMASON' 'HOROZ' 'SEKER' 'SIRA']
```

Out[3]:

	Area	Perimeter	MajorAxisLength	MinorAxisLength	AspectRation	Eccentricity	ConvexArea	EquivDiameter
0	28395	610.291	208.178117	173.888747	1.197191	0.549812	28715	190.141097
1	28734	638.018	200.524796	182.734419	1.097356	0.411785	29172	191.272750
2	29380	624.110	212.826130	175.931143	1.209713	0.562727	29690	193.410904
3	30008	645.884	210.557999	182.516516	1.153638	0.498616	30724	195.467062
4	30140	620.134	201.847882	190.279279	1.060798	0.333680	30417	195.896503

In [4]:

```
# define the dictionary
diccionario = {0: 'BARBUNYA', 1: 'BOMBAY', 2: 'CALI', 3: 'DERMASON', 4: 'HOROZ', 5: 'SEKER', 6:

# Create a dataframe from the dictionary
df_clases = pd.DataFrame.from_dict(diccionario, orient='index', columns=['clases'])

# "Add a column of numbers to the dataframe
df_clases['Class'] = df_clases.index

print(df_clases)
```

```
     clases  Class
0  BARBUNYA      0
1    BOMBAY      1
2      CALI      2
3  DERMASON      3
4     HOROZ      4
5     SEKER      5
6      SIRA      6
```

In [5]:

```
df= pd.merge(dry, df_clases, on='Class')

print(df)
```

```
        Area  Perimeter  MajorAxisLength  MinorAxisLength  AspectRation  \
0      28395    610.291       208.178117       173.888747      1.197191
1      28734    638.018       200.524796       182.734419      1.097356
2      29380    624.110       212.826130       175.931143      1.209713
3      30008    645.884       210.557999       182.516516      1.153638
4      30140    620.134       201.847882       190.279279      1.060798
...      ...        ...              ...              ...           ...
13606  42097    759.696       288.721612       185.944705      1.552728
13607  42101    757.499       281.576392       190.713136      1.476439
13608  42139    759.321       281.539928       191.187979      1.472582
13609  42147    763.779       283.382636       190.275731      1.489326
13610  42159    772.237       295.142741       182.204716      1.619841

       Eccentricity  ConvexArea  EquivDiameter    Extent  Solidity  roundness  \
0          0.549812       28715     190.141097  0.763923  0.988856   0.958027
1          0.411785       29172     191.272750  0.783968  0.984986   0.887034
2          0.562727       29690     193.410904  0.778113  0.989559   0.947849
3          0.498616       30724     195.467062  0.782681  0.976696   0.903936
4          0.333680       30417     195.896503  0.773098  0.990893   0.984877
...             ...         ...            ...       ...       ...        ...
13606      0.765002       42508     231.515799  0.714574  0.990331   0.916603
13607      0.735702       42494     231.526798  0.799943  0.990752   0.922015
13608      0.734065       42569     231.631261  0.729932  0.989899   0.918424
13609      0.741055       42667     231.653248  0.705389  0.987813   0.907906
13610      0.786693       42600     231.686223  0.788962  0.989648   0.888380

       Compactness  ShapeFactor1  ShapeFactor2  ShapeFactor3  ShapeFactor4  \
0         0.913358      0.007332      0.003147      0.834222      0.998724
1         0.953861      0.006979      0.003564      0.909851      0.998430
2         0.908774      0.007244      0.003048      0.825871      0.999066
3         0.928329      0.007017      0.003215      0.861794      0.994199
4         0.970516      0.006697      0.003665      0.941900      0.999166
...            ...           ...           ...           ...           ...
13606     0.801865      0.006858      0.001749      0.642988      0.998385
13607     0.822252      0.006688      0.001886      0.676099      0.998219
13608     0.822730      0.006681      0.001888      0.676884      0.996767
13609     0.817457      0.006724      0.001852      0.668237      0.995222
13610     0.784997      0.007001      0.001640      0.616221      0.998180

       Class    clases
0          5     SEKER
1          5     SEKER
2          5     SEKER
3          5     SEKER
4          5     SEKER
...      ...       ...
13606      3  DERMASON
13607      3  DERMASON
13608      3  DERMASON
13609      3  DERMASON
13610      3  DERMASON

[13611 rows x 18 columns]
```

In [6]:
```
#Dataset information
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 13611 entries, 0 to 13610
Data columns (total 18 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   Area             13611 non-null  int64  
 1   Perimeter        13611 non-null  float64
 2   MajorAxisLength  13611 non-null  float64
 3   MinorAxisLength  13611 non-null  float64
 4   AspectRation     13611 non-null  float64
 5   Eccentricity     13611 non-null  float64
 6   ConvexArea       13611 non-null  int64  
 7   EquivDiameter    13611 non-null  float64
 8   Extent           13611 non-null  float64
 9   Solidity         13611 non-null  float64
 10  roundness        13611 non-null  float64
 11  Compactness      13611 non-null  float64
 12  ShapeFactor1     13611 non-null  float64
 13  ShapeFactor2     13611 non-null  float64
 14  ShapeFactor3     13611 non-null  float64
 15  ShapeFactor4     13611 non-null  float64
 16  Class            13611 non-null  int32  
 17  clases           13611 non-null  object 
dtypes: float64(14), int32(1), int64(2), object(1)
memory usage: 1.9+ MB
```

In [7]:
```
df.size
```

Out[7]:
```
244998
```

In [8]:
```
df.shape
```

Out[8]:
```
(13611, 18)
```

In [9]:
```
df.describe()
```

Out[9]:

	Area	Perimeter	MajorAxisLength	MinorAxisLength	AspectRation	Eccentricity	ConvexArea
count	13611.000000	13611.000000	13611.000000	13611.000000	13611.000000	13611.000000	13611.000000
mean	53048.284549	855.283459	320.141867	202.270714	1.583242	0.750895	53768.200206
std	29324.095717	214.289696	85.694186	44.970091	0.246678	0.092002	29774.915817
min	20420.000000	524.736000	183.601165	122.512653	1.024868	0.218951	20684.000000
25%	36328.000000	703.523500	253.303633	175.848170	1.432307	0.715928	36714.500000
50%	44652.000000	794.941000	296.883367	192.431733	1.551124	0.764441	45178.000000
75%	61332.000000	977.213000	376.495012	217.031741	1.707109	0.810466	62294.000000
max	254616.000000	1985.370000	738.860153	460.198497	2.430306	0.911423	263261.000000

In [10]:
```
df.isna().sum() #checking if there are missing values
```

Out[10]:
```
Area               0
Perimeter          0
MajorAxisLength    0
MinorAxisLength    0
AspectRation       0
Eccentricity       0
ConvexArea         0
EquivDiameter      0
Extent             0
Solidity           0
roundness          0
Compactness        0
ShapeFactor1       0
ShapeFactor2       0
ShapeFactor3       0
ShapeFactor4       0
Class              0
clases             0
dtype: int64
```

In [11]:
```
df_copy=df.copy()
```

In [12]:
```
#check duplicated
df_copy.duplicated()
```

Out[12]:
```
0        False
1        False
2        False
3        False
4        False
         ...
13606    False
13607    False
13608    False
13609    False
13610    False
Length: 13611, dtype: bool
```

In [13]:
```
# lets check summery for all the Classes

print("Average Area : {0:.2f}".format(df['Area'].mean()))
print("Average Perimeter : {0:.2f}".format(df['Perimeter'].mean()))
print("Average MajorAxisLength : {0:.2f}".format(df['MajorAxisLength'].mean()))
print("Average MinorAxisLength: {0:.2f}".format(df['MinorAxisLength'].mean()))
print("Average AspectRation : {0:.2f}".format(df['AspectRation'].mean()))
print("Average Eccentricity : {0:.2f}".format(df['Eccentricity'].mean()))
print("Average ConvexArea: {0:.2f}".format(df['ConvexArea'].mean()))
print("Average EquivDiameter: {0:.2f}".format(df['EquivDiameter'].mean()))
print("Average Extent : {0:.2f}".format(df['Extent'].mean()))
print("Average Solidity : {0:.2f}".format(df['Solidity'].mean()))
print("Average roundness: {0:.2f}".format(df['roundness'].mean()))
print("Average Compactness : {0:.2f}".format(df['Compactness'].mean()))
print("Average ShapeFactor1: {0:.2f}".format(df['ShapeFactor1'].mean()))
print("Average ShapeFactor2: {0:.2f}".format(df['ShapeFactor2'].mean()))
print("Average ShapeFactor3 : {0:.2f}".format(df['ShapeFactor3'].mean()))
print("Average ShapeFactor4 : {0:.2f}".format(df['ShapeFactor4'].mean()))
```

```
Average Area : 53048.28
Average Perimeter : 855.28
Average MajorAxisLength : 320.14
Average MinorAxisLength: 202.27
Average AspectRation : 1.58
Average Eccentricity : 0.75
Average ConvexArea: 53768.20
Average EquivDiameter: 253.06
Average Extent : 0.75
Average Solidity : 0.99
Average roundness: 0.87
Average Compactness : 0.80
Average ShapeFactor1: 0.01
Average ShapeFactor2: 0.00
Average ShapeFactor3 : 0.64
Average ShapeFactor4 : 1.00
```

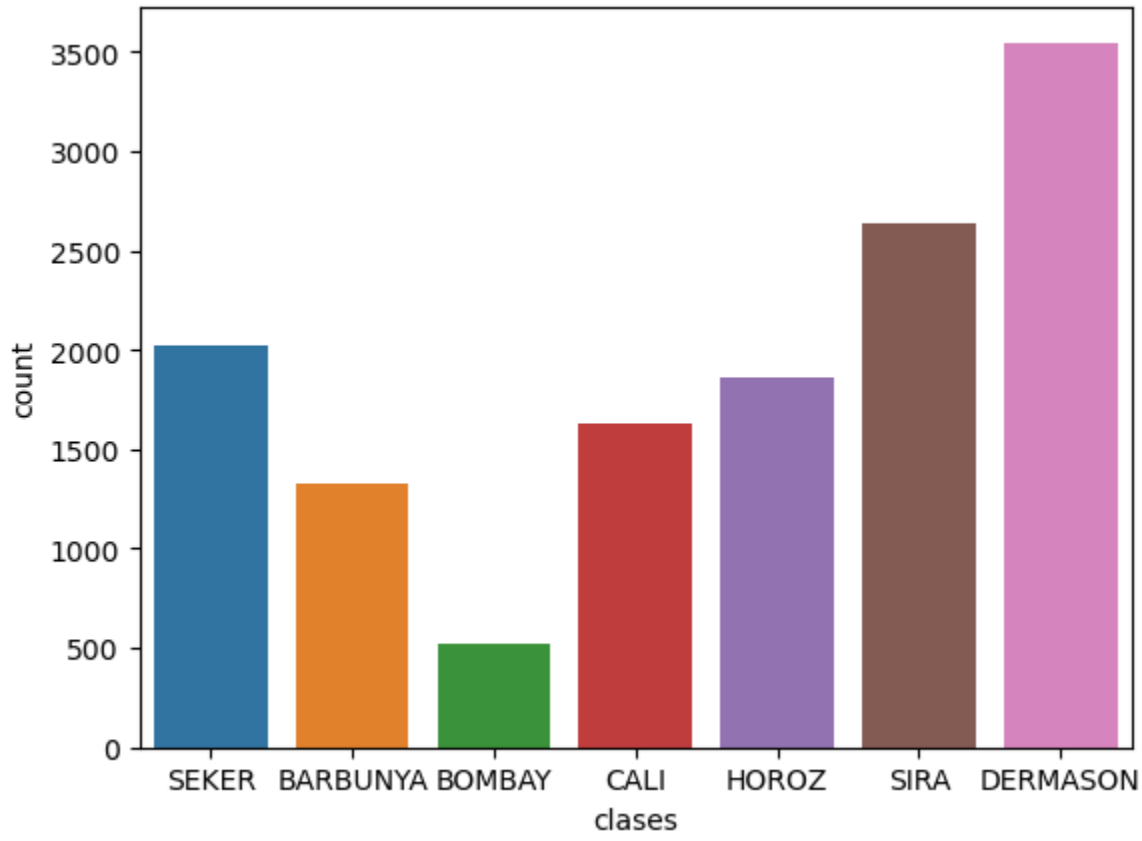
B)Cleaning the data

In [14]:
```
df.drop_duplicates(inplace=True)
```

c) Data Visualization

In [15]:
```
print(dry['Class'].value_counts())
_=sns.countplot(x='clases', data=df)
```

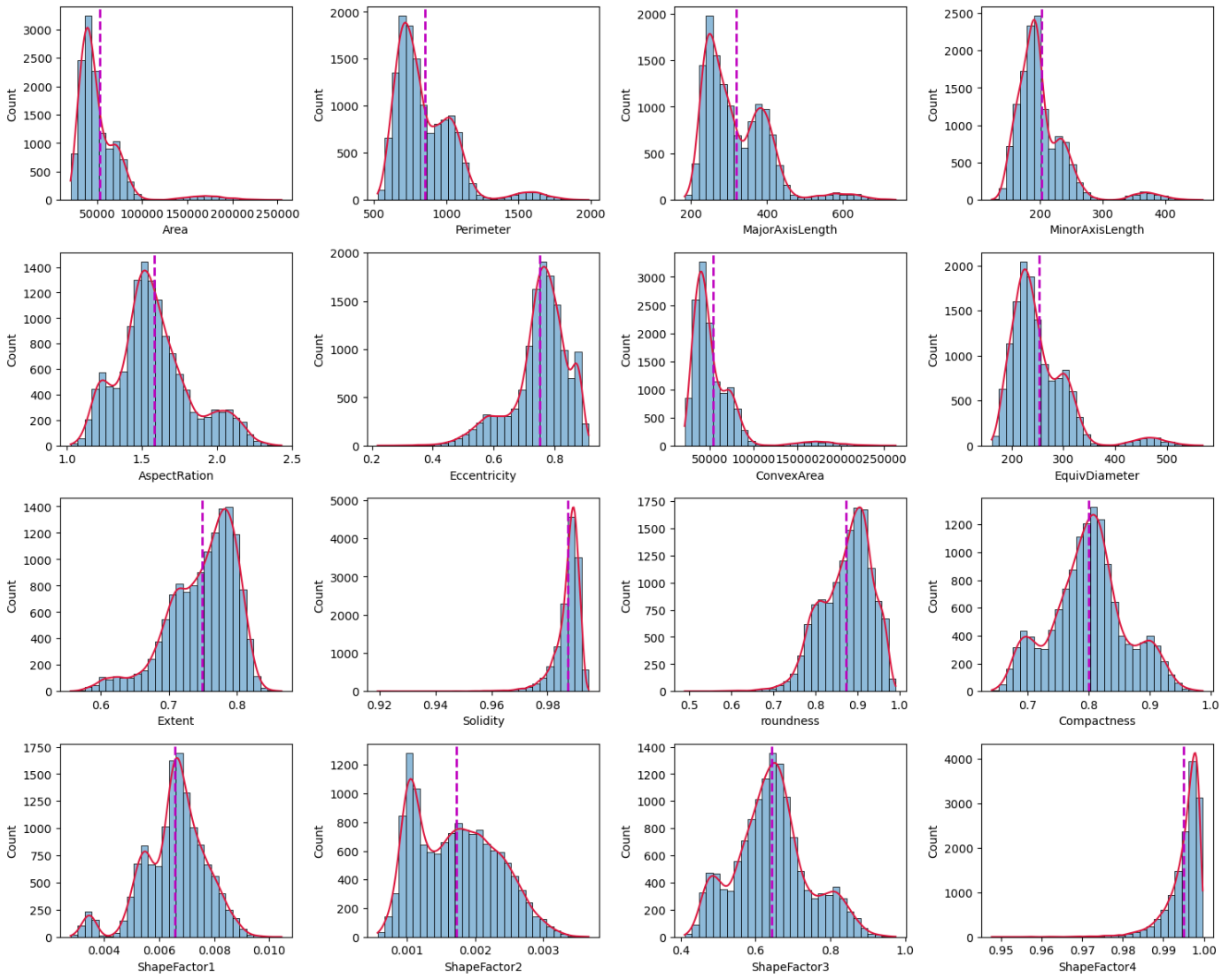
```
3    3546
6    2636
5    2027
4    1928
2    1630
0    1322
1     522
Name: Class, dtype: int64
```



In [16]:
```
#Columns name definition
df_col = df.columns
df_col
```

Out[16]:
```
Index(['Area', 'Perimeter', 'MajorAxisLength', 'MinorAxisLength',
       'AspectRation', 'Eccentricity', 'ConvexArea', 'EquivDiameter', 'Extent',
       'Solidity', 'roundness', 'Compactness', 'ShapeFactor1', 'ShapeFactor2',
       'ShapeFactor3', 'ShapeFactor4', 'Class', 'clases'],
      dtype='object')
```

In [17]:
```
#This code is creating a 4x4 grid of subplots using the subplots() function from the matplotlib.
#figure size of 15x12. Then, for each of the columns in the DataFrame dry that are numeric (excl

Numeric_cols = dry.drop(columns=['Class']).columns

fig, ax = plt.subplots(4, 4, figsize=(15, 12))
for variable, subplot in zip(Numeric_cols, ax.flatten()):
    g=sns.histplot(dry[variable],bins=30, kde=True, ax=subplot)
    g.lines[0].set_color('crimson')
    g.axvline(x=dry[variable].mean(), color='m', label='Mean', linestyle='--', linewidth=2)
plt.tight_layout()
```

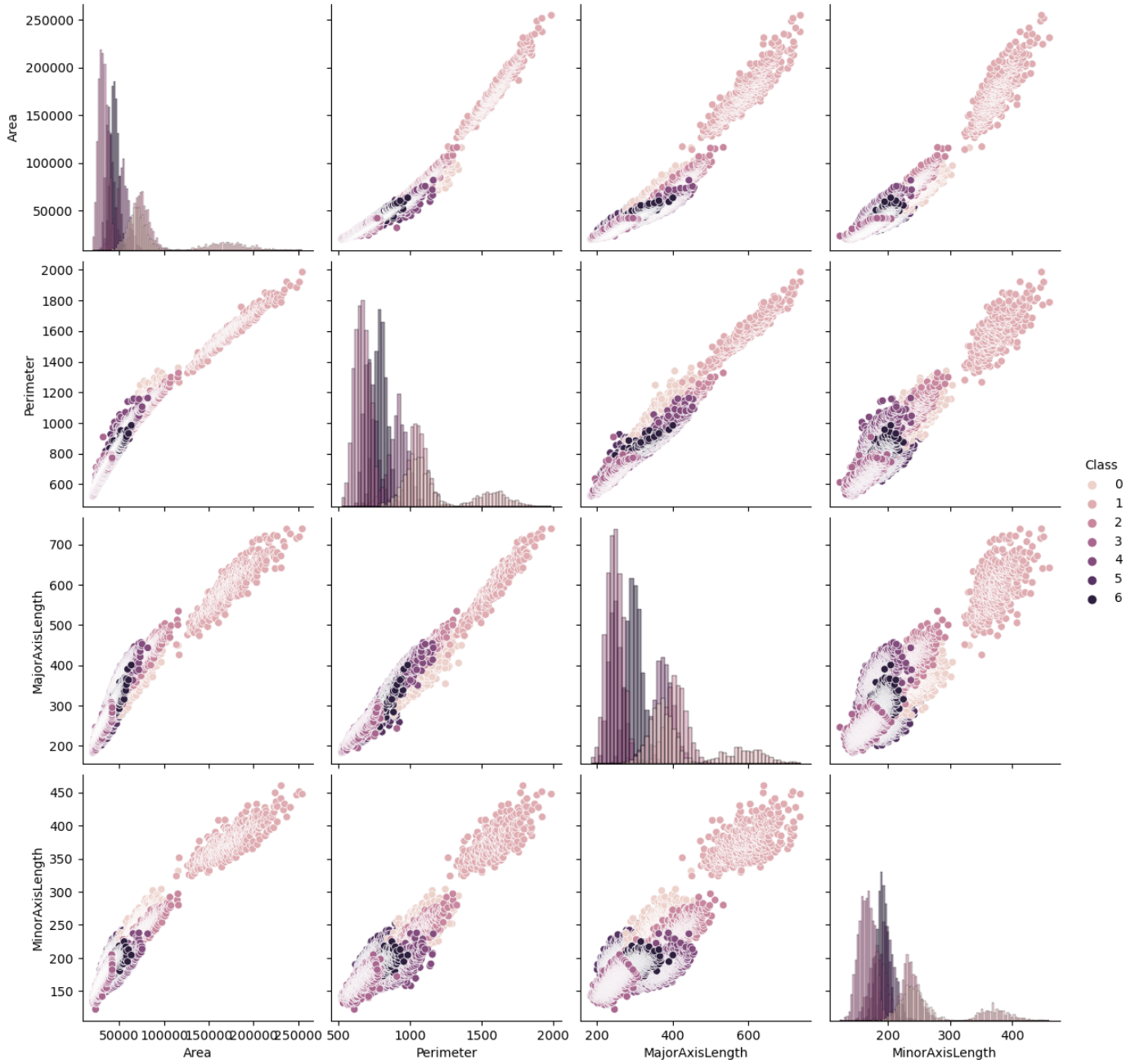


In [18]:
```
sns.pairplot(dry.drop(['AspectRation','Eccentricity','ConvexArea',
    'EquivDiameter',
    'Extent',
    'Solidity',
    'roundness',
```

```
    'Compactness',
    'ShapeFactor1',
    'ShapeFactor2',
    'ShapeFactor3',
    'ShapeFactor4'], axis=1), hue='Class', height=3, diag_kind='hist')
```

Out[18]:

```
<seaborn.axisgrid.PairGrid at 0x240ca04da30>
```

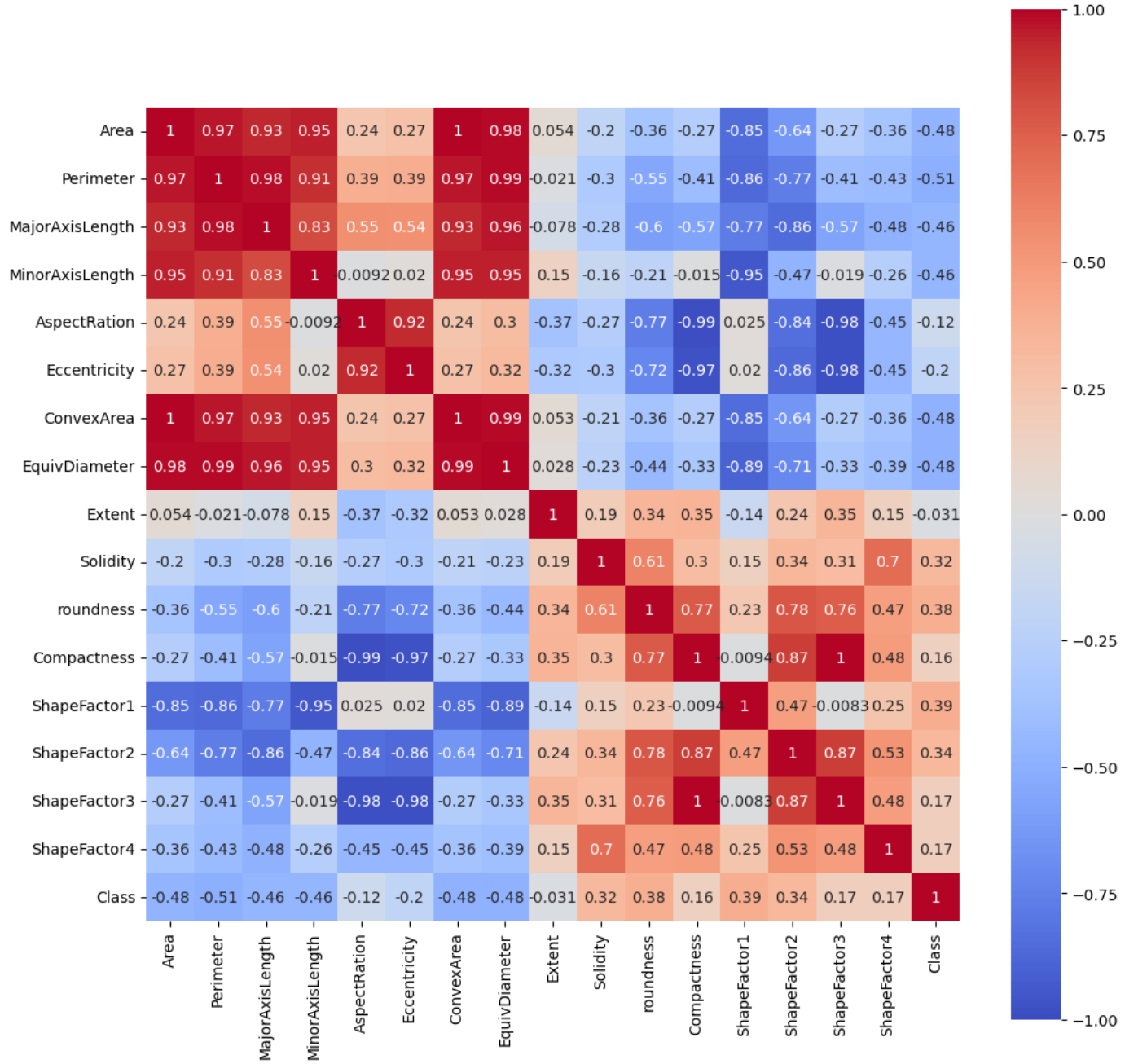


In [19]:

```
plt.figure(figsize=(12,12))
sns.heatmap(dry.corr("pearson"),vmin=-1, vmax=1,cmap='coolwarm',annot=True, square=True)
```

Out[19]:

```
<AxesSubplot:>
```



Defining X and y

In [20]:

```
X = dry[[
    'Area',
    'Perimeter',
    'MajorAxisLength',
    'MinorAxisLength',
    'AspectRation',
    'Eccentricity',
    'ConvexArea',
    'EquivDiameter',
    'Extent',
    'Solidity',
    'roundness',
    'Compactness',
    'ShapeFactor1',
    'ShapeFactor2',
    'ShapeFactor3',
```

```
    'ShapeFactor4']].values
y = dry[['Class']]
```

In [21]:
```
# If the distribution is symmetric, then the skewness is 0. If the tail of the distribution exte
#then the distribution is considered positively skewed and the skewness is positive.
#If the tail of the distribution extends to the left,
#then the distribution is considered negatively skewed and the skewness is negative
df.skew().sort_values(ascending=True)
```

```
C:\Users\ptrau\AppData\Local\Temp\ipykernel_23124\3356257674.py:5: FutureWarning: Dropping of nu
isance columns in DataFrame reductions (with 'numeric_only=None') is deprecated; in a future ver
sion this will raise TypeError.  Select only valid columns before calling the reduction.
  df.skew().sort_values(ascending=True)
```

Out[21]:
```
ShapeFactor4      -2.760125
Solidity          -2.546877
Eccentricity      -1.064932
Extent            -0.895655
roundness         -0.648725
ShapeFactor1      -0.530427
Class             -0.319689
Compactness        0.036309
ShapeFactor3       0.242767
ShapeFactor2       0.294332
AspectRation       0.589045
MajorAxisLength    1.365813
Perimeter          1.628018
EquivDiameter      1.947303
MinorAxisLength    2.232013
ConvexArea         2.936102
Area               2.947136
dtype: float64
```

Choosing the best model

for this presentation, we are choosing Desicion tree and SVM

Normalizing the data

In [22]:
```
# Separate features and labels
X = dry.drop('Class', axis=1)  # características
y = df['Class']              # etiquetas

# Scale features using Min-Max Scaling
scaler = MinMaxScaler()
X_scaled = scaler.fit_transform(X)

# Create a new dataframe with the scaled features and labels
df_scaled = pd.DataFrame(X_scaled, columns=X.columns)
df_scaled['Class'] = y
```

In [23]:
```
df_scaled
```

Out[23]:

	Area	Perimeter	MajorAxisLength	MinorAxisLength	AspectRation	Eccentricity	ConvexArea	EquivDiar
0	0.034053	0.058574	0.044262	0.152142	0.122612	0.477797	0.033107	0.0
1	0.035500	0.077557	0.030479	0.178337	0.051577	0.278472	0.034991	0.0
2	0.038259	0.068035	0.052633	0.158190	0.131521	0.496448	0.037126	0.0
3	0.040940	0.082942	0.048548	0.177691	0.091623	0.403864	0.041389	0.0
4	0.041504	0.065313	0.032862	0.200679	0.025565	0.165680	0.040123	0.0
...	...	...	...	...	...	...	...	
13606	0.092559	0.160862	0.189318	0.187843	0.375584	0.788553	0.089967	0.1
13607	0.092576	0.159358	0.176450	0.201964	0.321303	0.746241	0.089910	0.1
13608	0.092739	0.160605	0.176384	0.203370	0.318558	0.743877	0.090219	0.1
13609	0.092773	0.163657	0.179703	0.200669	0.330472	0.753971	0.090623	0.1
13610	0.092824	0.169448	0.200882	0.176768	0.423337	0.819877	0.090347	0.1

13611 rows × 17 columns

In [24]:
```
df_sin_nulos = df_scaled.dropna()
```

Desicion Tree

Tuning the desicion tree:

In [26]:
```
# Splitting data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(df_sin_nulos.drop('Class', axis=1), df_sin_n

# Creating the decision tree classifier object
clf= DecisionTreeClassifier(max_depth =9, min_samples_leaf=5, min_samples_split=2 )

# Training the classifier on the training data
clf.fit(X_train, y_train)

# Predicting on the test data
y_pred = clf.predict(X_test)

# Evaluating the performance of the classifier using confusion matrix and classification report
print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))
```

```
[[232   0  17   0   2   1   7]
 [  0 114   0   0   0   0   0]
 [ 16   0 284   0   2   1   2]
 [  0   0   0 651   3  17  36]
 [  3   0   7   4 351   0  11]
 [  5   0   0  26   0 374   9]
 [  2   0   1  51  11   8 461]]
              precision    recall  f1-score   support

         0.0       0.90      0.90      0.90       259
         1.0       1.00      1.00      1.00       114
         2.0       0.92      0.93      0.93       305
         3.0       0.89      0.92      0.90       707
         4.0       0.95      0.93      0.94       376
         5.0       0.93      0.90      0.92       414
         6.0       0.88      0.86      0.87       534

    accuracy                           0.91      2709
   macro avg       0.92      0.92      0.92      2709
weighted avg       0.91      0.91      0.91      2709
```

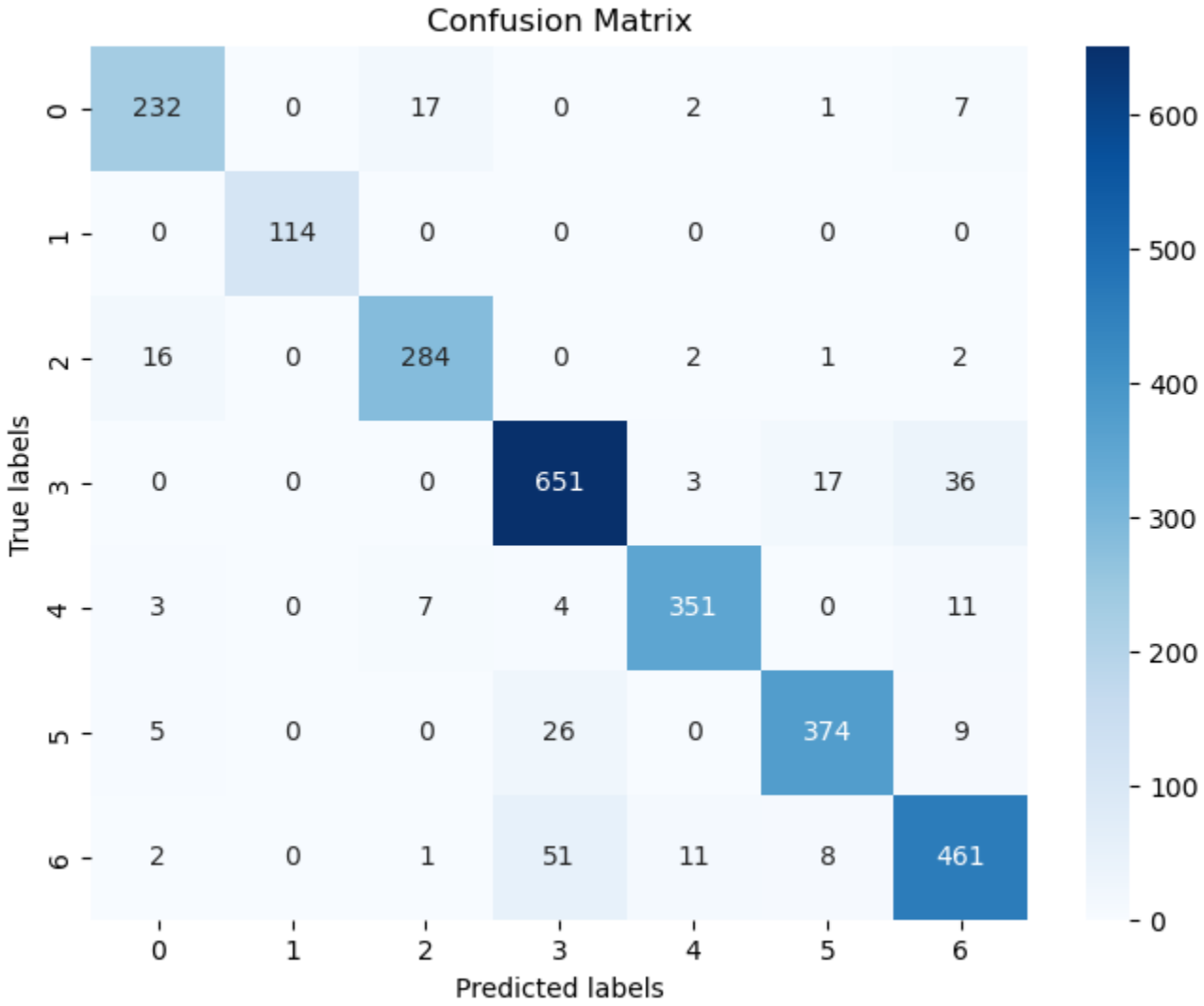
In [27]:

```python
# Create the classifier object for the decision tree
clf = DecisionTreeClassifier(random_state=42)

# Defining the parameters to search
params = {
    'max_depth': [3, 5, 7, 9, 11],
    'min_samples_split': [2, 4, 6, 8, 10],
    'min_samples_leaf': [1, 2, 3, 4, 5]
}

# Create the GridSearchCV object and fit it to the data
grid_search = GridSearchCV(clf, params, cv=5, scoring='accuracy')
grid_search.fit(X_train, y_train)

# Print the best parameters and the accuracy
print("Best Parameters: ", grid_search.best_params_)
print("Best Accuracy: {:.2f}%".format(grid_search.best_score_ * 100))
```

```
Best Parameters:  {'max_depth': 7, 'min_samples_leaf': 5, 'min_samples_split': 2}
Best Accuracy: 90.86%
```

In [28]:

```python
# how to obtain the confusion matrix
cm = confusion_matrix(y_test, y_pred)

# Set up the figure
fig, ax = plt.subplots(figsize=(8, 6))

# Create the heatmap
sns.heatmap(cm, annot=True, cmap='Blues', fmt='g')

# Add labels to the axes
ax.set_xlabel('Predicted labels')
ax.set_ylabel('True labels')
ax.set_title('Confusion Matrix')

# Show the figure
plt.show()
```

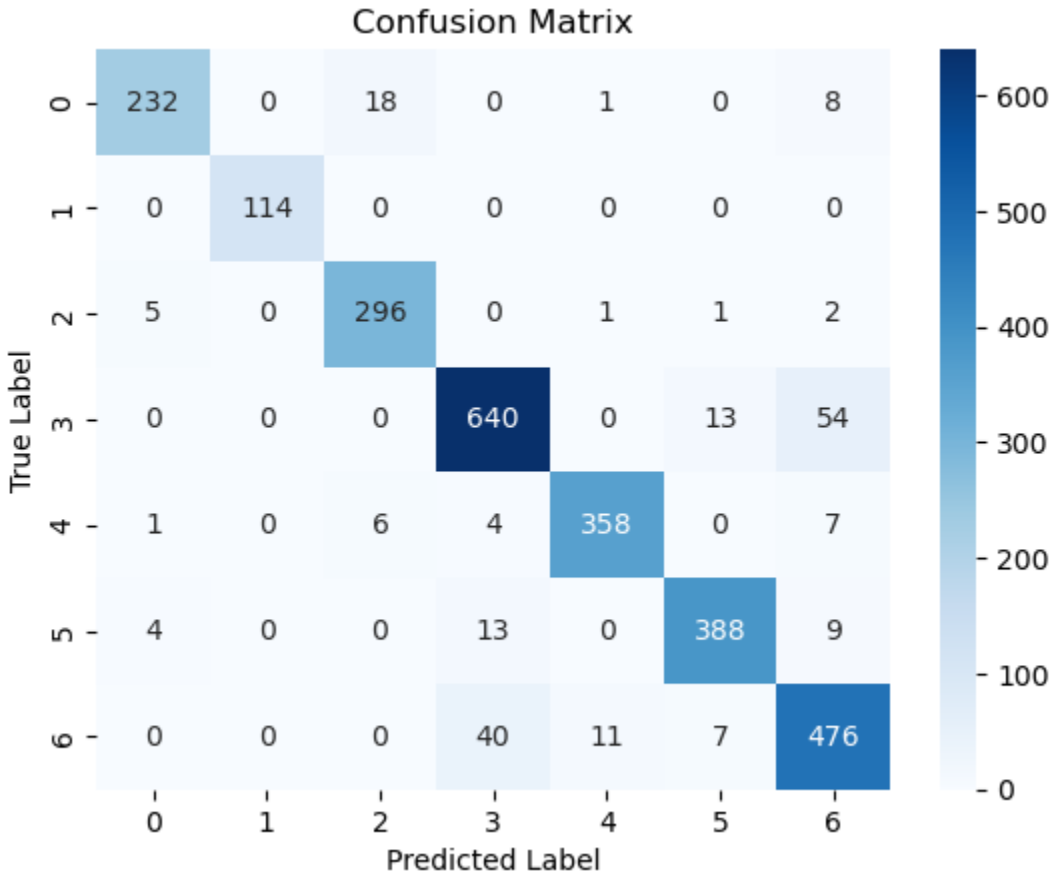


Support Vector Machine

In [29]:

```
# Creating the SVM classifier object
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score


svm = SVC()

# Training the classifier on the training data
svm.fit(X_train, y_train)

# Predicting on the test data
y_pred = svm.predict(X_test)

# Calculating the accuracy of the classifier
accuracy = accuracy_score(y_test, y_pred)

# Creating the confusion matrix
cm = confusion_matrix(y_test, y_pred)

# Plotting the confusion matrix
sns.heatmap(cm, annot=True, cmap="Blues", fmt="d")
plt.title("Confusion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```

```
# Generating the classification report
report = classification_report(y_test, y_pred)
print("Classification Report:\n", report)
```




```
Classification Report:
               precision    recall  f1-score   support

         0.0       0.96      0.90      0.93       259
         1.0       1.00      1.00      1.00       114
         2.0       0.93      0.97      0.95       305
         3.0       0.92      0.91      0.91       707
         4.0       0.96      0.95      0.96       376
         5.0       0.95      0.94      0.94       414
         6.0       0.86      0.89      0.87       534

    accuracy                           0.92      2709
   macro avg       0.94      0.94      0.94      2709
weighted avg       0.93      0.92      0.92      2709
```

Submission File GenerationSubmission File Generation

In [41]:

```
import pandas as pd
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report

import pandas as pd
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score
```

```
# Creating the SVM classifier object
svm = SVC()

# Training the classifier on the training data
svm.fit(X_train, y_train)

# Predicting on the test data
y_pred = svm.predict(X_test)

# Creating a DataFrame with IDs and predicted labels
results_df = pd.DataFrame({'Predicted Label': y_pred})

# Saving the results to a CSV file
results_df.to_csv('predicciones.csv', index=False)
```

In [34]:

In [ ]: