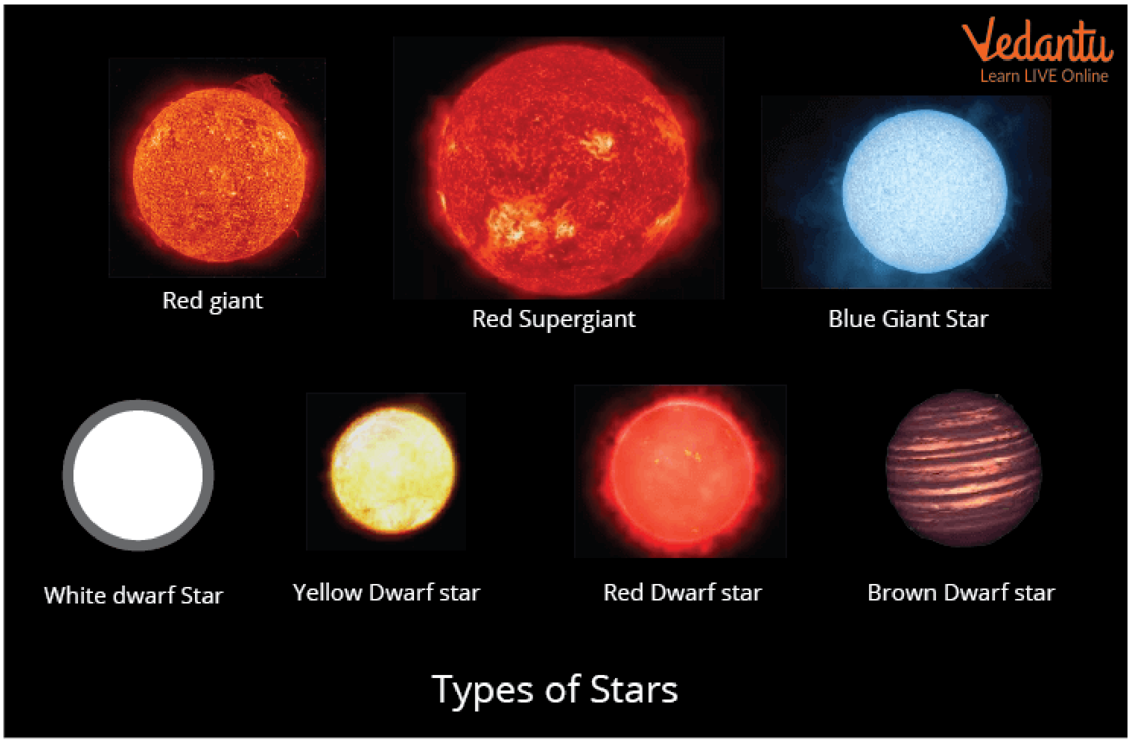
nasa-star-type-classification

November 20, 2023

1 NASA Star Type Classification

We have a set of 240 Stars with 5 Types. We will use Classification ML Models to predict the different Star Types from 0 to 5: * Red Dwarf - 0 * Brown Dwarf - 1 * White Dwarf - 2 * Main Sequence - 3 * Super Giants - 4 * Hyper Giants - 5



2 Import Libraries and Load Data

[ ]:
```
# import libraries
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings("ignore")
pd.set_option("display.max_columns",120)
```

```
import os
for dirname, _, filenames in os.walk(''):
    for filename in filenames:
        print(os.path.join(dirname, filename)) # file path
```

[ ]:
```
# load data
df=pd.read_csv("Stars.csv")
```

3 EDA - Exploratory Data Analysis

[ ]:
```
df.head() # first 5 entries
```

[ ]:
```
   Temperature         L       R    A_M Color Spectral_Class  Type
0         3068  0.002400  0.1700  16.12   Red              M     0
1         3042  0.000500  0.1542  16.60   Red              M     0
2         2600  0.000300  0.1020  18.70   Red              M     0
3         2800  0.000200  0.1600  16.65   Red              M     0
4         1939  0.000138  0.1030  20.06   Red              M     0
```

[ ]:
```
df.info() # infos about the samples, features and datatypes
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 240 entries, 0 to 239
Data columns (total 7 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Temperature     240 non-null    int64
 1   L               240 non-null    float64
 2   R               240 non-null    float64
 3   A_M             240 non-null    float64
 4   Color           240 non-null    object
 5   Spectral_Class  240 non-null    object
 6   Type            240 non-null    int64
dtypes: float64(3), int64(2), object(2)
memory usage: 13.3+ KB
```

[ ]:
```
df.isnull().sum() # checking for missing values
```

[ ]:
```
Temperature       0
L                 0
R                 0
A_M               0
Color             0
Spectral_Class    0
Type              0
dtype: int64
```

We have a total amount of 240 samples, 7 features and some missing values.

[ ]:
```python
df.describe() # statistical infos about features
```

[ ]:

	Temperature	L	R	A_M	Type
count	240.000000	240.000000	240.000000	240.000000	240.000000
mean	10497.462500	107188.361635	237.157781	4.382396	2.500000
std	9552.425037	179432.244940	517.155763	10.532512	1.711394
min	1939.000000	0.000080	0.008400	-11.920000	0.000000
25%	3344.250000	0.000865	0.102750	-6.232500	1.000000
50%	5776.000000	0.070500	0.762500	8.313000	2.500000
75%	15055.500000	198050.000000	42.750000	13.697500	4.000000
max	40000.000000	849420.000000	1948.500000	20.060000	5.000000

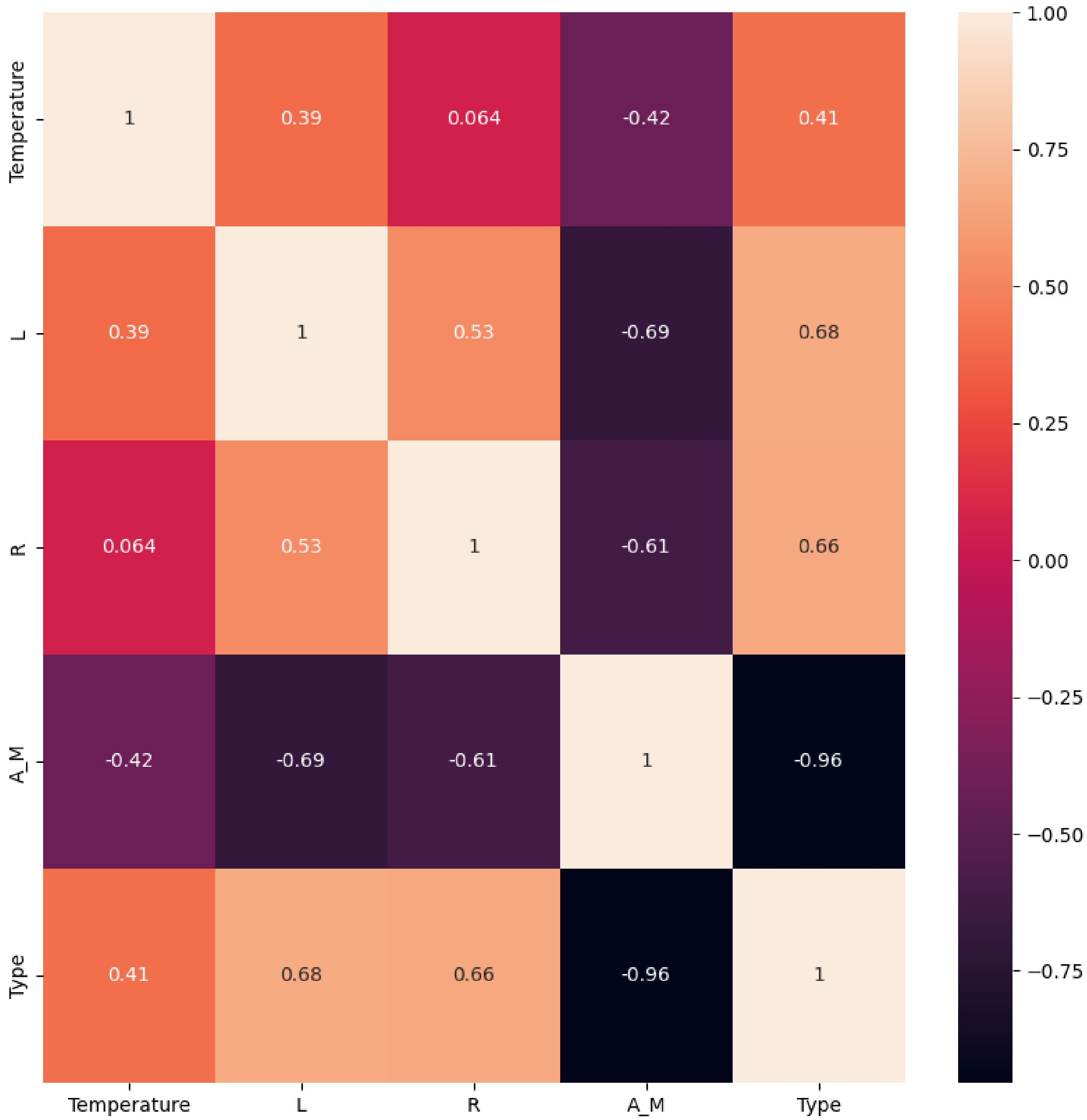
[ ]:
```python
string_columns=df.select_dtypes(include=['object', 'string']).columns
df1=df.drop(columns=string_columns)
```

[ ]:
```python
df1.corr() # the correlation between the features
```

[ ]:

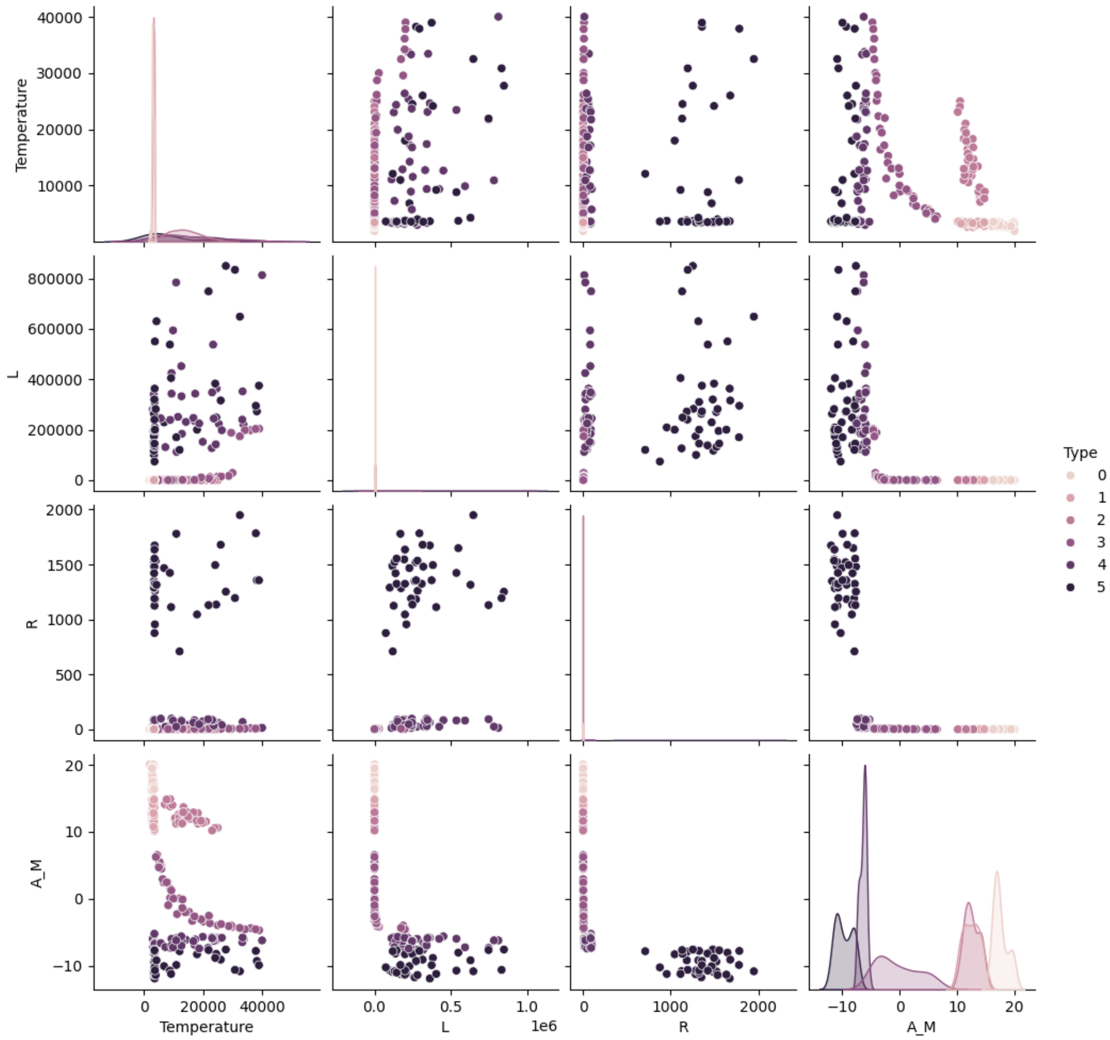
	Temperature	L	R	A_M	Type
Temperature	1.000000	0.393404	0.064216	-0.420261	0.411129
L	0.393404	1.000000	0.526516	-0.692619	0.676845
R	0.064216	0.526516	1.000000	-0.608728	0.660975
A_M	-0.420261	-0.692619	-0.608728	1.000000	-0.955276
Type	0.411129	0.676845	0.660975	-0.955276	1.000000

[ ]:
```python
# Correlation of the columns shown in a heatmap
plt.figure(figsize=(10,10))
sns.heatmap(df1.corr(),annot=True);
```

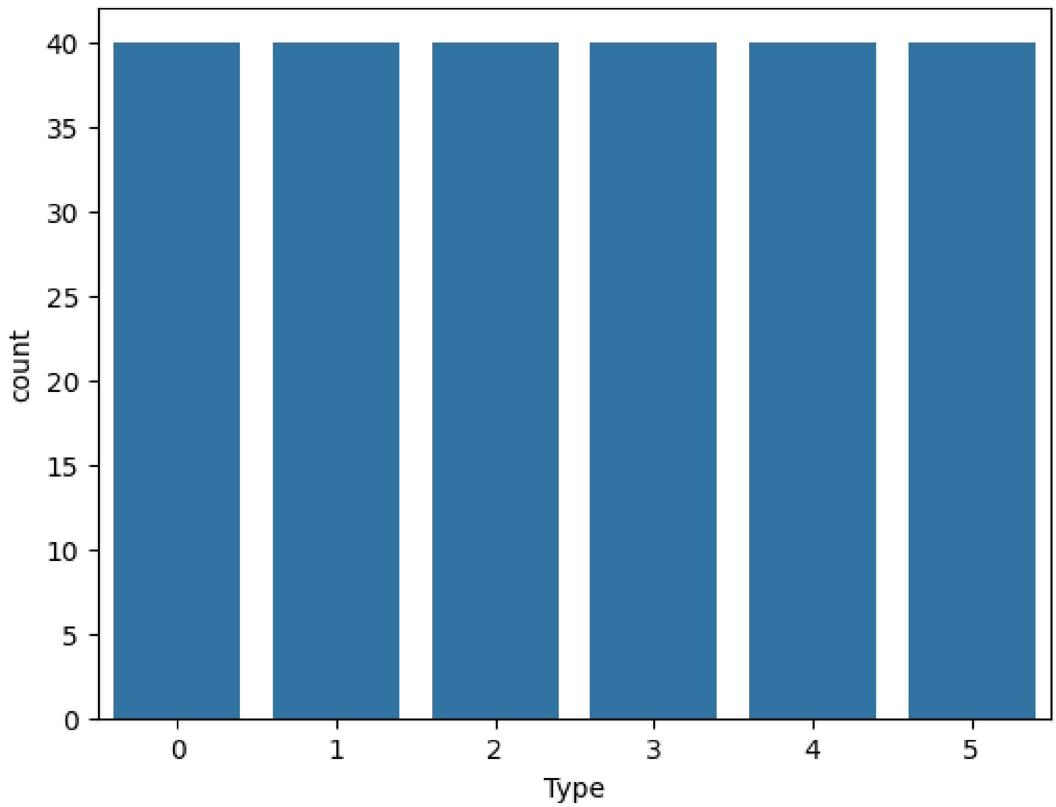


3.1 Data Visualization & Data Preprocessing

[ ]:
```
sns.pairplot(data=df, hue='Type'); # pairplot all columns
```

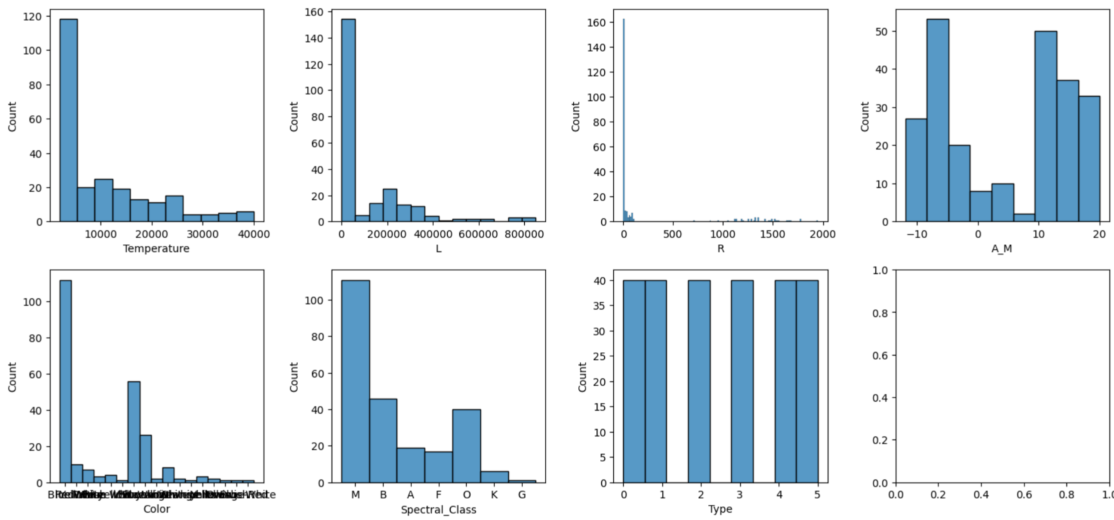



```
[ ]: sns.countplot(x=df.Type); # plot Type column
```



We have an even distribution of Star Types.

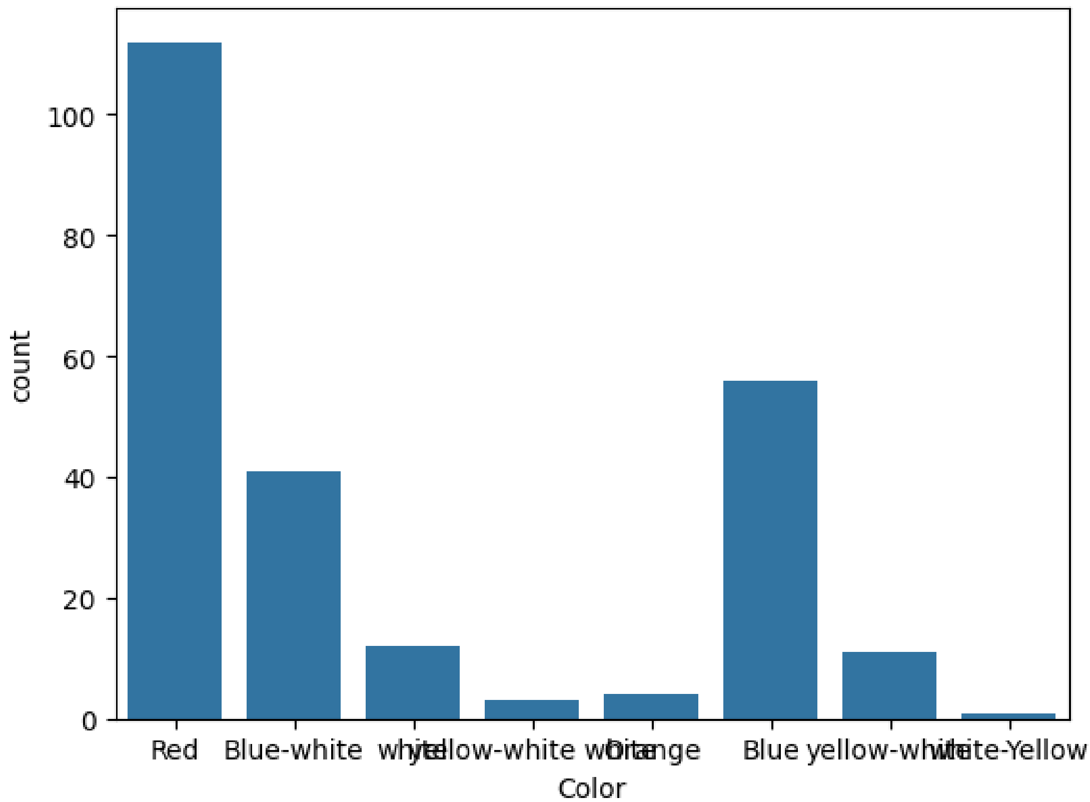
[ ]:
```
# create histplots for each column
fig, axes = plt.subplots(nrows=2, ncols=4, figsize=(15,7))
axes = axes.flatten()

# Create a histplot for each column in the DataFrame
for ax, col in zip(axes, df.columns):
    sns.histplot(data=df, x=col, ax=ax)
plt.tight_layout()
plt.show()
```



3.1.1 Feature Engineering

```
[ ]: # combine the colors which are same but written differtently
replacements = {
    r'Blue[\s-]?White|Blue white': 'Blue-white',
    r'yellowish|Yellowish|Yellowish White|yellow-white white|white-Yellow': 'yellow-white',
    r'White|Whitish': 'white',
    r'Orange-Red|Pale yellow orange': 'Orange'
}
df.replace(replacements, regex=True, inplace=True) # let this code run 2 times
```

```
[ ]: sns.countplot(x=df.Color);
```



4 Modelling

```
[ ]: # Function to call all Classification Algorithms
def classification_funct(dataset,column_to_be_studied):
    #importing Classification libraries
    from sklearn.ensemble import RandomForestClassifier
    from sklearn.linear_model import LogisticRegression
    from xgboost import XGBClassifier

    from sklearn.model_selection import train_test_split
    from imblearn.over_sampling import SMOTE
    from sklearn.preprocessing import StandardScaler
    scaler = StandardScaler()

    from sklearn.metrics import␣
 ↪accuracy_score,precision_score,recall_score,f1_score
    from sklearn.metrics import confusion_matrix,classification_report

    # assign x and y
    dataset=dataset[dataset[column_to_be_studied].notnull()]
```

```
    x,y=dataset.
↪drop(column_to_be_studied,axis=1),dataset[[column_to_be_studied]]
    x=pd.get_dummies(x,drop_first=True) # one-hot encoding
    scaler.fit(x) # Scale the features
    x = scaler.transform(x)
    # split data in train and test
    x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.
↪2,random_state=42)

    # create an instance of each classification algorithm
    R=RandomForestClassifier()
    Log=LogisticRegression()
    XGB=XGBClassifier()

    algos=[R,Log,XGB]
    algo_names=['RandomForestClassifier','LogisticRegression','XGBClassifier']

    accuracy_scored=[]
    precision_scored=[]
    recall_scored=[]
    f1_scored=[]

    for item in algos:
        item.fit(x_train,y_train)
        item.predict(x_test)
        accuracy_scored.append(accuracy_score(y_test,item.predict(x_test)))
        precision_scored.append(precision_score(y_test, item.predict(x_test),␣
↪average='macro'))
        recall_scored.append(recall_score(y_test, item.predict(x_test),␣
↪average='macro'))
        f1_scored.append(f1_score(y_test, item.predict(x_test),␣
↪average='macro'))

    # create dataframe with results
    result=pd.
↪DataFrame(columns=['f1_score','recall_score','precision_score','accuracy_score'],index=algo
    result['f1_score']=f1_scored
    result['recall_score']=recall_scored
    result['precision_score']=precision_scored
    result['accuracy_score']=accuracy_scored
    return result.sort_values('accuracy_score',ascending=False)
```

[ ]:
```
classification_funct(df,"Type")  # call classification function and see results␣
↪in a Dataframe
```

[ ]:

```
                        f1_score  recall_score  precision_score  \
RandomForestClassifier  1.000000      1.000000         1.000000
LogisticRegression      0.976068      0.979167         0.976190
XGBClassifier           0.977778      0.979167         0.979167

                        accuracy_score
RandomForestClassifier        1.000000
LogisticRegression            0.979167
XGBClassifier                 0.979167
```

Since our dataset is very small, the results are not that logic, but **LogisticRegression** shows an **Accuracy of 97,92%**.

5 Evaluation - Confusion Matrix

[ ]:

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from xgboost import XGBClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, ConfusionMatrixDisplay,␣
↪confusion_matrix
```

[ ]:

```
x,y=df.drop('Type',axis=1),df[['Type']]  # assign x and y
x=pd.get_dummies(x,drop_first=True) # one-hot encoding
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.
↪2,random_state=42)
```

[ ]:

```
model = LogisticRegression() # fit and predict model
y_preds = model.fit(x_train, y_train).predict(x_test)
```

[ ]:

```
print(classification_report(y_test,y_preds))
```

```
              precision    recall  f1-score   support

           0       0.62      1.00      0.76         8
           1       0.00      0.00      0.00         7
           2       0.55      1.00      0.71         6
           3       1.00      0.50      0.67         8
           4       0.89      1.00      0.94         8
           5       1.00      1.00      1.00        11

    accuracy                           0.77        48
   macro avg       0.67      0.75      0.68        48
weighted avg       0.71      0.77      0.71        48
```

[ ]:
```
x_pred = model.predict(x_test)
x_true = y_test

cm1 = confusion_matrix(x_true, x_pred)

disp = ConfusionMatrixDisplay(confusion_matrix=cm1, display_labels=np.
    ↪unique(x_true))
disp.plot(cmap=plt.cm.Blues)

plt.show()
```