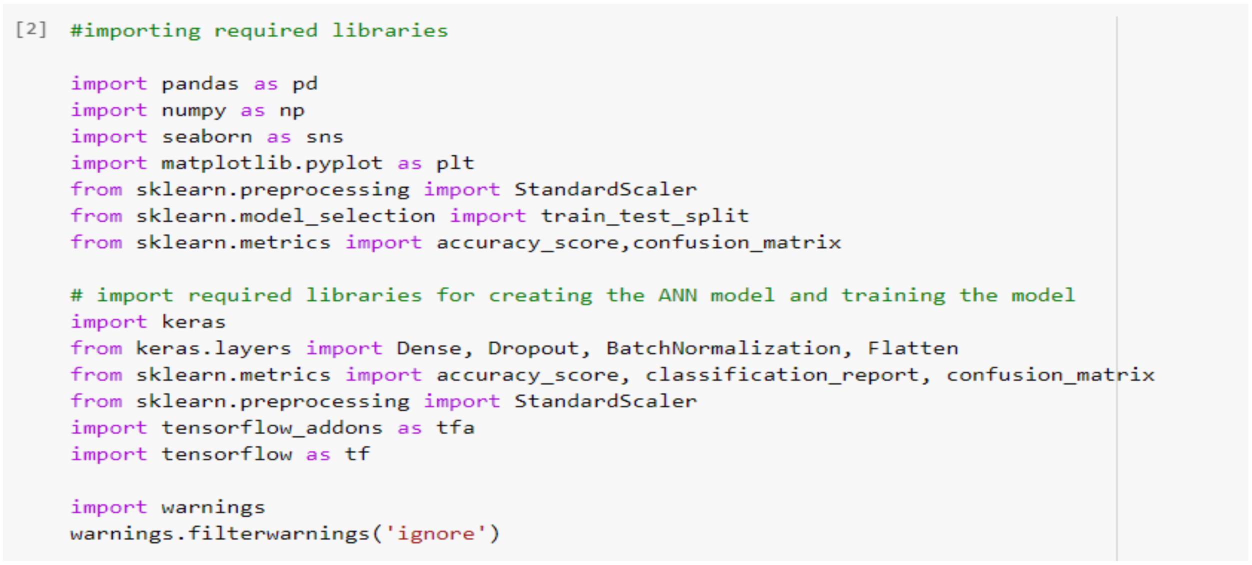
Football Match Outcome Prediction using Artificial Neural Network

Load required libraries

First of all, to begin with, the dataset preprocessing and training, the necessary libraries need to be import into the notebook environment. To handle the dataset, here, I mainly used the Pandas library. For plotting various figures, I have used Seaborn and Matplot libraries. Fig. 1 shows the coding example to import all the required libraries for this project.



```
[2] #importing required libraries

    import pandas as pd
    import numpy as np
    import seaborn as sns
    import matplotlib.pyplot as plt
    from sklearn.preprocessing import StandardScaler
    from sklearn.model_selection import train_test_split
    from sklearn.metrics import accuracy_score,confusion_matrix

    # import required libraries for creating the ANN model and training the model
    import keras
    from keras.layers import Dense, Dropout, BatchNormalization, Flatten
    from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
    from sklearn.preprocessing import StandardScaler
    import tensorflow_addons as tfa
    import tensorflow as tf

    import warnings
    warnings.filterwarnings('ignore')
```

Fig. 1. Code example for importing libraries.

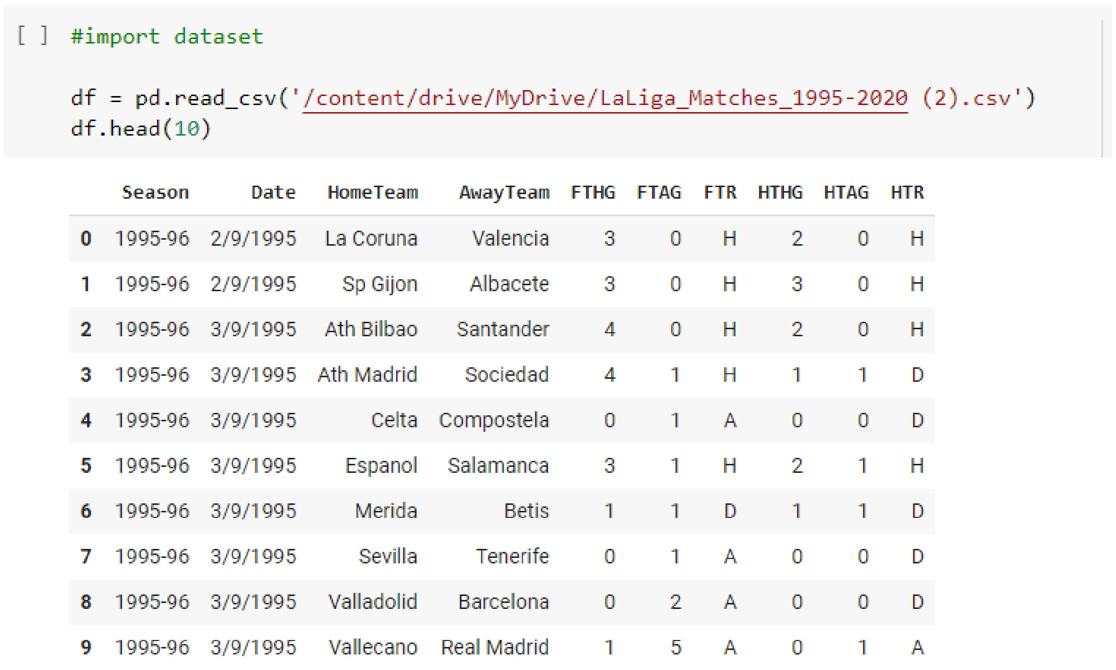
Dataset Introduction

The football dataset contains various features to predict the outcome of a specific match. Initially, the dataset has a total of 10 columns or features and 9662 rows. The name of the columns of the dataset are-

- Season
- Date
- Home Team
- Away Team
- HTR - Half Time Result
- FTR - Full Time Result
- HTHG - Half Time Home Goals
- HTAG - Half Time Away Goals
- FTHG - Full Time Home Goals
- FTAG - Full Time Away Goals

Load Dataset

To load the dataset, I have used Pandas library which will read the dataset as a CSV format. Fig. 2 shows the code example of loading the dataset using pandas.



```
[ ] #import dataset

    df = pd.read_csv('/content/drive/MyDrive/LaLiga_Matches_1995-2020 (2).csv')
    df.head(10)
```

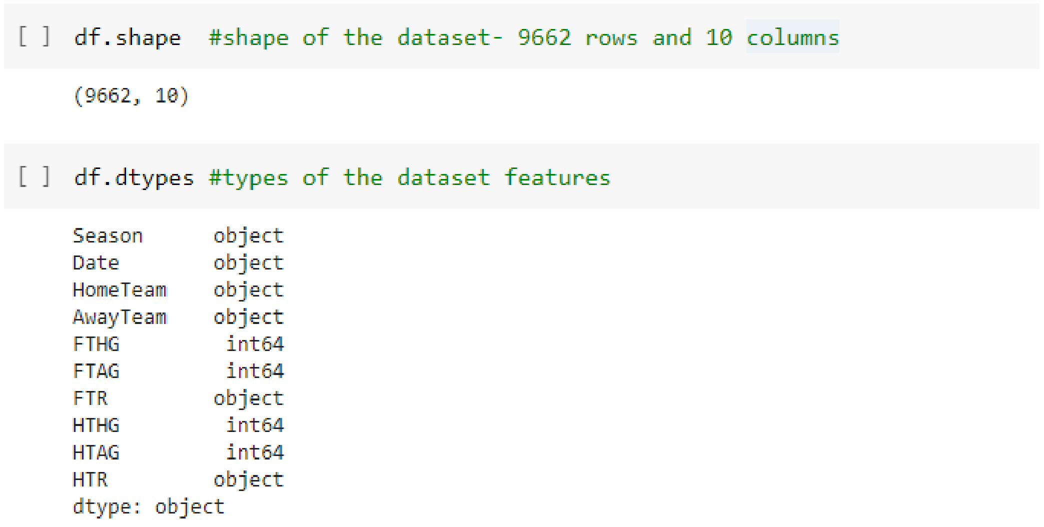
	Season	Date	HomeTeam	AwayTeam	FTHG	FTAG	FTR	HTHG	HTAG	HTR
0	1995-96	2/9/1995	La Coruna	Valencia	3	0	H	2	0	H
1	1995-96	2/9/1995	Sp Gijon	Albacete	3	0	H	3	0	H
2	1995-96	3/9/1995	Ath Bilbao	Santander	4	0	H	2	0	H
3	1995-96	3/9/1995	Ath Madrid	Sociedad	4	1	H	1	1	D
4	1995-96	3/9/1995	Celta	Compostela	0	1	A	0	0	D
5	1995-96	3/9/1995	Espanol	Salamanca	3	1	H	2	1	H
6	1995-96	3/9/1995	Merida	Betis	1	1	D	1	1	D
7	1995-96	3/9/1995	Sevilla	Tenerife	0	1	A	0	0	D
8	1995-96	3/9/1995	Valladolid	Barcelona	0	2	A	0	0	D
9	1995-96	3/9/1995	Vallecano	Real Madrid	1	5	A	0	1	A

Fig. 2. Loading the dataset using Pandas.

Fig. 2 shows also the first 10 rows of the main dataset where the each columns are representing their corresponding values.

Cleaning and representation of the dataset

First, the dataset needs to be clean and finalizing with required and supported data types to begin the work with the dataset. Also, the dataset should not include any empty or null values, which can make our model perform poorly. To analyze the data types of values containing each column, the following code need to be run on the coding environment.

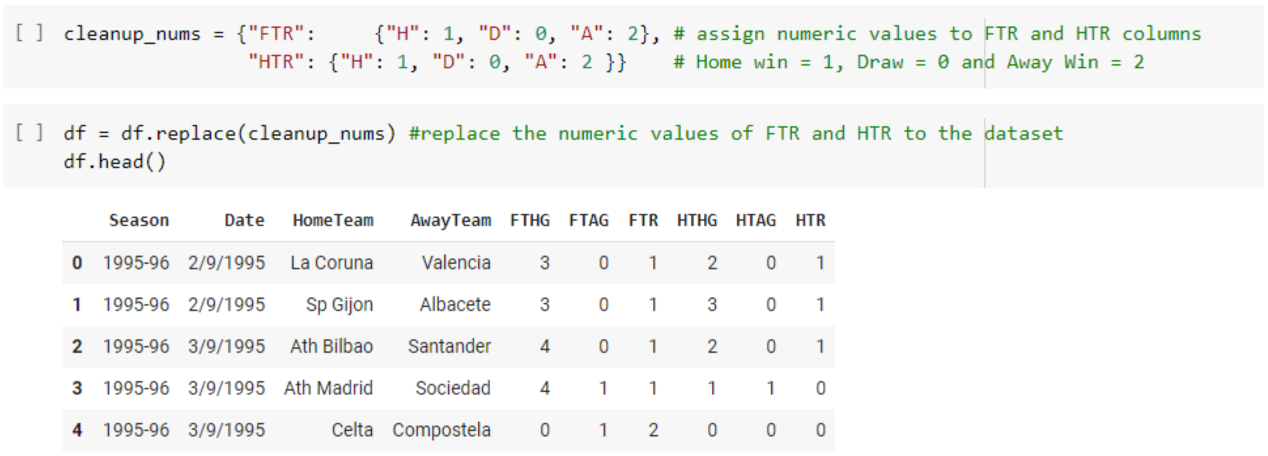


```
[ ] df.shape  #shape of the dataset- 9662 rows and 10 columns

    (9662, 10)

[ ] df.dtypes #types of the dataset features

    Season      object
    Date        object
    HomeTeam    object
    AwayTeam    object
    FTHG         int64
    FTAG         int64
    FTR         object
    HTHG         int64
    HTAG         int64
    HTR         object
    dtype: object
```

Fig. 3. Coding example of the data types of the values of each column.

Fig. 3 shows that the shape of the dataset is (9662, 10) where 9662 represents the rows and 10 represents the columns. The next segment of the code showing the output of the data type of values of each column. The output shows that among the 10 features six (6) have object data types and four (4) have int64 data types.

For this project, the targeted value/column which needs to be predicted is the FTR (Full Time Result) column. In the CSV file, this column has contains three (3) values- H (Home Team Win), A (Away Team Win), and D (Draw). So, these values are string types. To train the model, this value should be converted to numerical values. To do so, I have employed the find and replacing techniques of pandas which will reform the values of the FTR column into numerical values. Then, those values need to be replaced in the dataset. Similarly, the HTR column contains the same values, so, this column also needs to be converted. Fig. 4 shows the coding examples of the implementation of converting to numerical values.



```
[ ] cleanup_nums = {"FTR":     {"H": 1, "D": 0, "A": 2}, # assign numeric values to FTR and HTR columns
                    "HTR": {"H": 1, "D": 0, "A": 2 }}    # Home win = 1, Draw = 0 and Away Win = 2
```

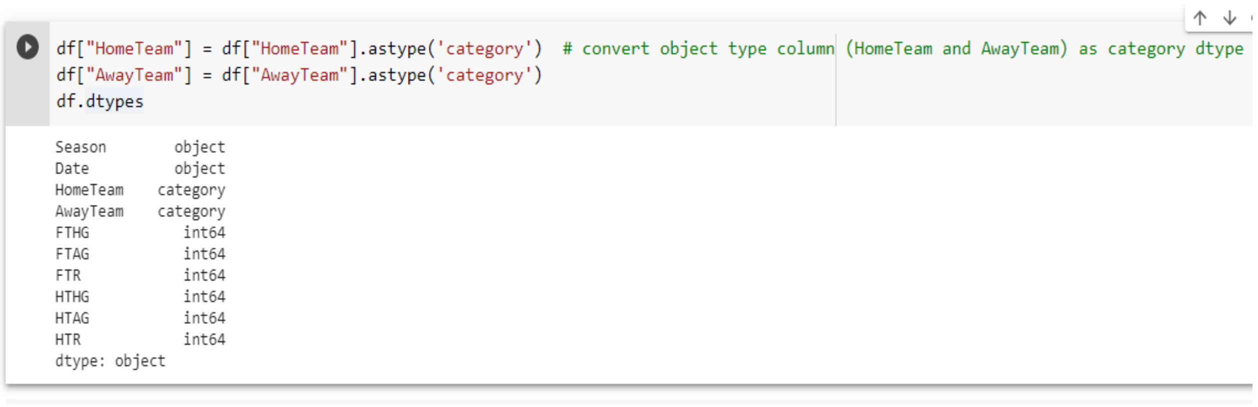
```
[ ] df = df.replace(cleanup_nums) #replace the numeric values of FTR and HTR to the dataset
    df.head()
```

	Season	Date	HomeTeam	AwayTeam	FTHG	FTAG	FTR	HTHG	HTAG	HTR
0	1995-96	2/9/1995	La Coruna	Valencia	3	0	1	2	0	1
1	1995-96	2/9/1995	Sp Gijon	Albacete	3	0	1	3	0	1
2	1995-96	3/9/1995	Ath Bilbao	Santander	4	0	1	2	0	1
3	1995-96	3/9/1995	Ath Madrid	Sociedad	4	1	1	1	1	0
4	1995-96	3/9/1995	Celta	Compostela	0	1	2	0	0	0

Fig. 4. Coding examples of label encoding of the FTR and HTR columns.

Fig. 4 showing the implementation of the converting and replacing the converted value to the main dataset. The ‘H’ value converted as 1, ‘D’ value converted as 0, and the ‘A’ value converted as 2. The same procedure has been followed in the HTR column also.

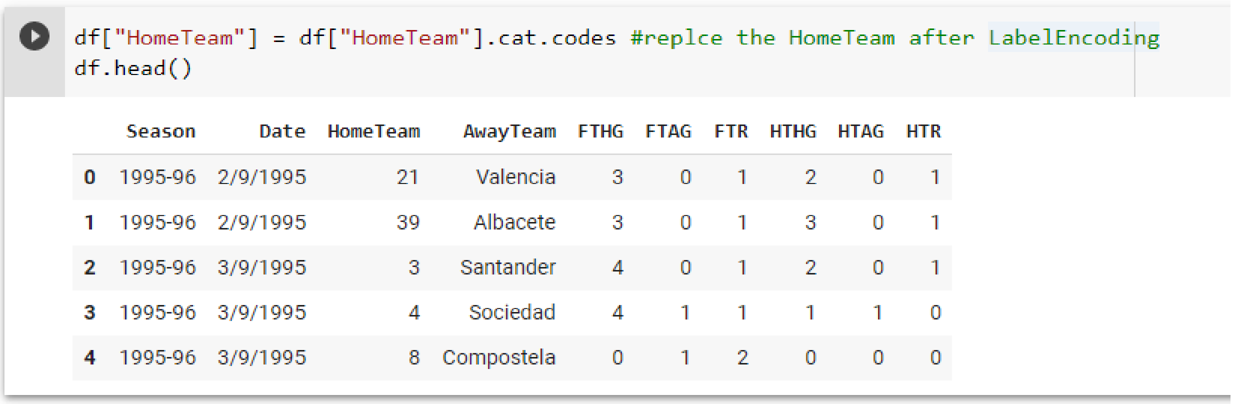
From fig. 3, there are also two columns named- HomeTeam and AwayTeam, these two columns are the object data types. These are categorical variables. So, these two columns need to be converted to the numerical value. For this, at first, the values need to be converted as the category data types. Then, the Label Encoder needs to be employed to encode these values. By doing so, each value of these two columns will contains a unique number. As this column contains the team names, so, each team will have different numerical numbers. The fig. 5 and 6 show the coding representation of the label encoder.



```
df["HomeTeam"] = df["HomeTeam"].astype('category')  # convert object type column (HomeTeam and AwayTeam) as category dtype
df["AwayTeam"] = df["AwayTeam"].astype('category')
df.dtypes
```

```
Season        object
Date          object
HomeTeam    category
AwayTeam    category
FTHG           int64
FTAG           int64
FTR            int64
HTHG           int64
HTAG           int64
HTR            int64
dtype: object
```

Fig. 5. Coding example of converting the object data type to category data type.

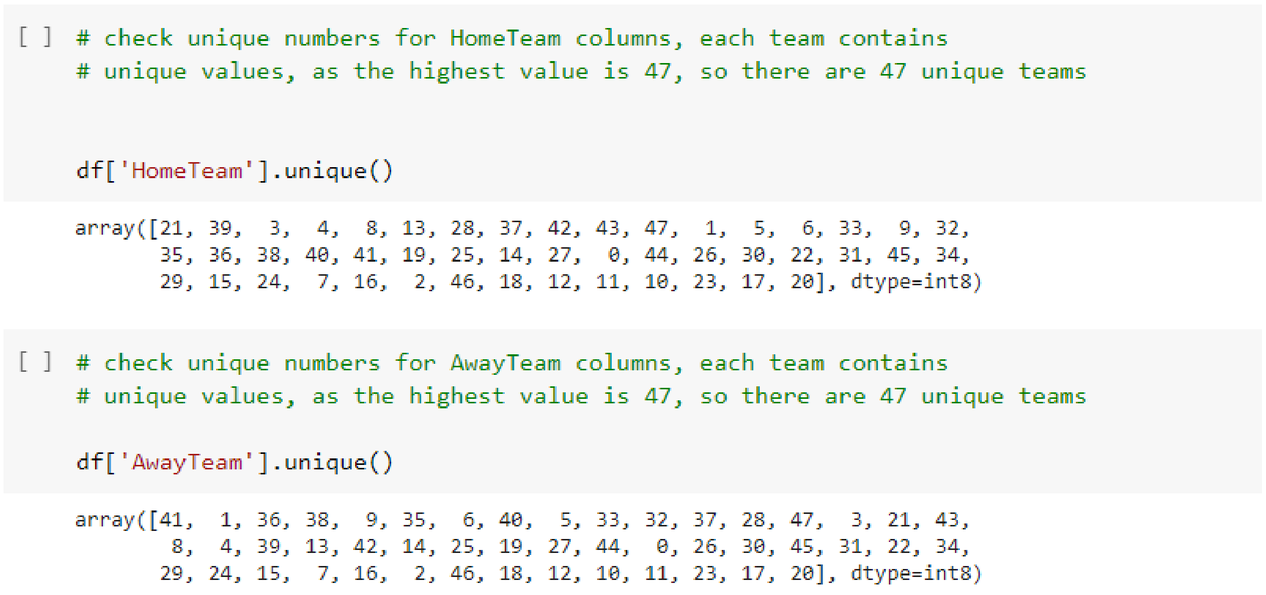


```
df["HomeTeam"] = df["HomeTeam"].cat.codes #replce the HomeTeam after LabelEncoding
df.head()
```

	Season	Date	HomeTeam	AwayTeam	FTHG	FTAG	FTR	HTHG	HTAG	HTR
0	1995-96	2/9/1995	21	Valencia	3	0	1	2	0	1
1	1995-96	2/9/1995	39	Albacete	3	0	1	3	0	1
2	1995-96	3/9/1995	3	Santander	4	0	1	2	0	1
3	1995-96	3/9/1995	4	Sociedad	4	1	1	1	1	0
4	1995-96	3/9/1995	8	Compostela	0	1	2	0	0	0

Fig. 6. Coding example of label encoding of the HomeTeam columns

From fig. 6, the values of HomeTeam column is changed from string to integer type and each values are unique, as the team names are unique. Fig. 7 shows the all the unique numbers of the HomeTeam and AwayTeam column.



```
# check unique numbers for HomeTeam columns, each team contains
# unique values, as the highest value is 47, so there are 47 unique teams


df['HomeTeam'].unique()
```

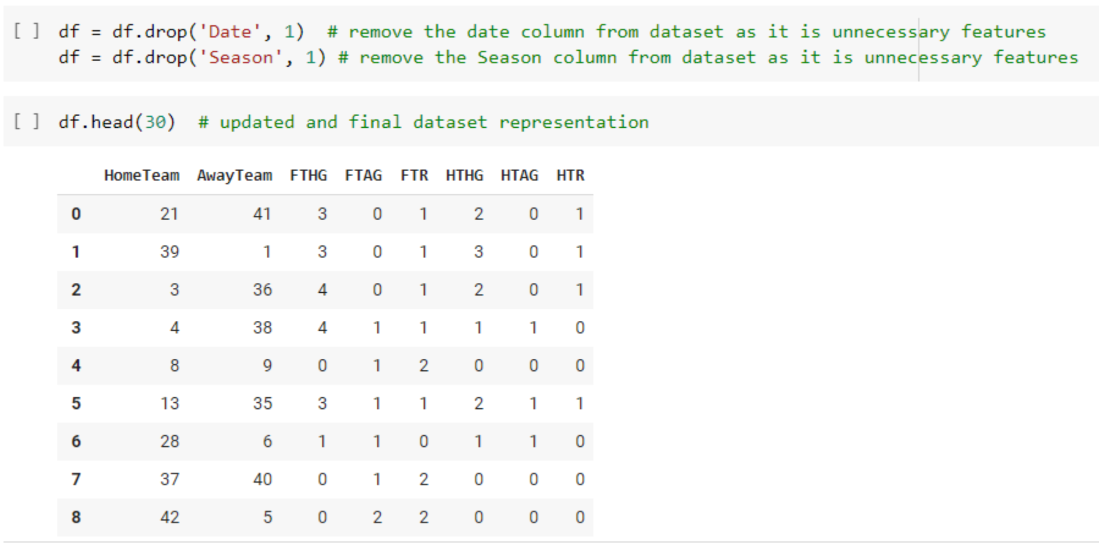
```
array([21, 39,  3,  4,  8, 13, 28, 37, 42, 43, 47,  1,  5,  6, 33,  9, 32,
       35, 36, 38, 40, 41, 19, 25, 14, 27,  0, 44, 26, 30, 22, 31, 45, 34,
       29, 15, 24,  7, 16,  2, 46, 18, 12, 11, 10, 23, 17, 20], dtype=int8)
```

```
# check unique numbers for AwayTeam columns, each team contains
# unique values, as the highest value is 47, so there are 47 unique teams

df['AwayTeam'].unique()
```

```
array([41,  1, 36, 38,  9, 35,  6, 40,  5, 33, 32, 37, 28, 47,  3, 21, 43,
        8,  4, 39, 13, 42, 14, 25, 19, 27, 44,  0, 26, 30, 45, 31, 22, 34,
       29, 24, 15,  7, 16,  2, 46, 18, 12, 10, 11, 23, 17, 20], dtype=int8)
```

Fig. 7. Output numbers of HomeTeam and AwayTeam Columns.

Now, in the dataset, there are two columns which are not important to predict the match outcome which are Date and Season column. So, these two columns need to be removed from the dataset. To do that, the fig. 8 shows the coding example of removing. Also, the fig. contains the updated and final representation of the dataset.



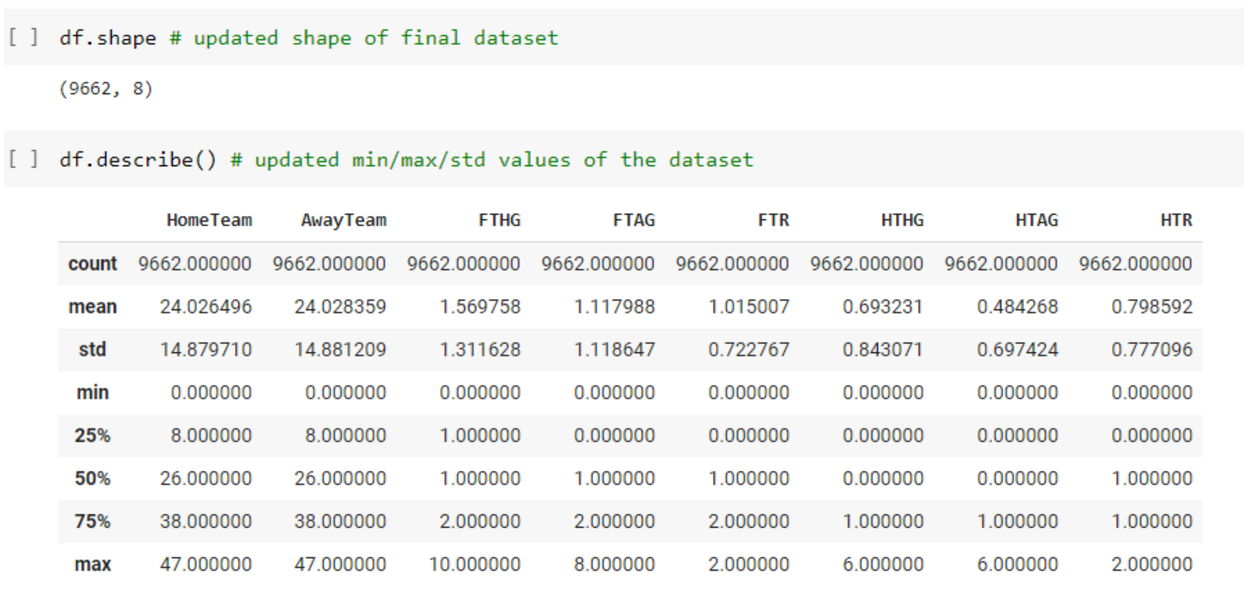
```
[ ] df = df.drop('Date', 1)  # remove the date column from dataset as it is unnecessary features
    df = df.drop('Season', 1) # remove the Season column from dataset as it is unnecessary features
```

```
[ ] df.head(30)  # updated and final dataset representation
```

	HomeTeam	AwayTeam	FTHG	FTAG	FTR	HTHG	HTAG	HTR
0	21	41	3	0	1	2	0	1
1	39	1	3	0	1	3	0	1
2	3	36	4	0	1	2	0	1
3	4	38	4	1	1	1	1	0
4	8	9	0	1	2	0	0	0
5	13	35	3	1	1	2	1	1
6	28	6	1	1	0	1	1	0
7	37	40	0	1	2	0	0	0
8	42	5	0	2	2	0	0	0

Fig. 8. Removing Date and Season column and representation of updated dataset.

Now, the dataset are fully ready for further operation. Let's have a look to the updated shape of the dataset and statistics.



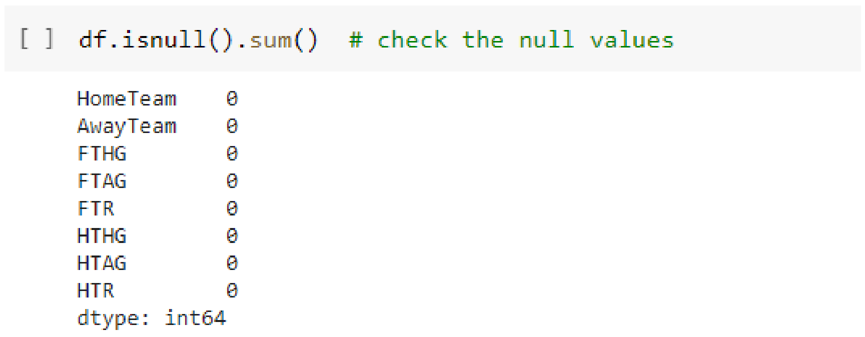
```
[ ] df.shape # updated shape of final dataset

    (9662, 8)
```

```
[ ] df.describe() # updated min/max/std values of the dataset
```

	HomeTeam	AwayTeam	FTHG	FTAG	FTR	HTHG	HTAG	HTR
count	9662.000000	9662.000000	9662.000000	9662.000000	9662.000000	9662.000000	9662.000000	9662.000000
mean	24.026496	24.028359	1.569758	1.117988	1.015007	0.693231	0.484268	0.798592
std	14.879710	14.881209	1.311628	1.118647	0.722767	0.843071	0.697424	0.777096
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	8.000000	8.000000	1.000000	0.000000	0.000000	0.000000	0.000000	0.000000
50%	26.000000	26.000000	1.000000	1.000000	1.000000	0.000000	0.000000	1.000000
75%	38.000000	38.000000	2.000000	2.000000	2.000000	1.000000	1.000000	1.000000
max	47.000000	47.000000	10.000000	8.000000	2.000000	6.000000	6.000000	2.000000

Fig. 9. Coding examples of updated shape and statistics of the final dataset.

Before doing any further approach, let's check the dataset, if there any null values in any column. Fig. 10 shows the code examples of checking null values.



```
[ ] df.isnull().sum()  # check the null values

    HomeTeam    0
    AwayTeam    0
    FTHG        0
    FTAG        0
    FTR         0
    HTHG        0
    HTAG        0
    HTR         0
    dtype: int64
```

Fig. 10. Coding example for checking null/missing values.

So, from the figure, we can observe that there are no missing values in any column of the dataset. Now, the dataset are ready for training and testing purpose.

Explore the Dataset

Before moving to the training, let's have a look at the target column (FTR) and HTR column by observing the pie chart. Fig. 11 and 12 show the pie chart of the HTR and FTR columns respectively.

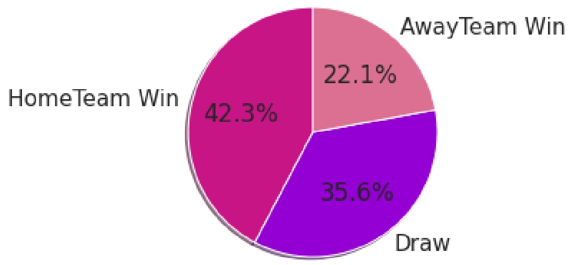


Fig. 11. Pie chart of the HTR column.

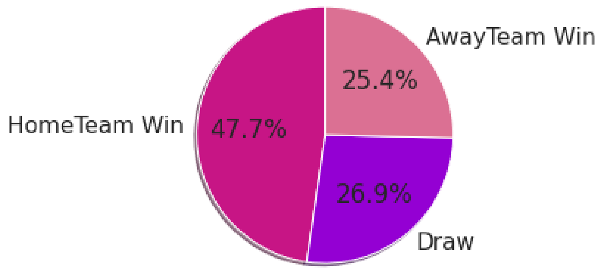
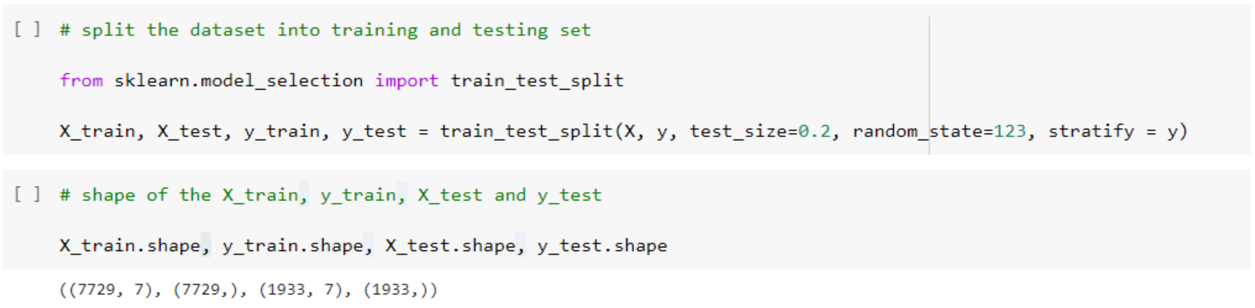


Fig. 12. Pie chart of FTR column.

From these figures, in the HTR column, the winning percentage of the Home team is 42.3% and in the FTR column is 47.7%. Where the winning percentage of the HTR and FTR column of the Away team is 35.6% and 26.9% respectively. So, the winning percentage of the Home team is much higher than the Away team. Also, to mention the draw percentage of these two columns is 22.1% in HTR and 25.4% in FTR columns.

Spilt the Dataset

Before training the model, the dataset needs to be split into train and test sets. Here, I have split the dataset by keeping 80% of the data for training and 20% data for testing purposes. Fig. 13 shows the code implementation of the train and test set to split.



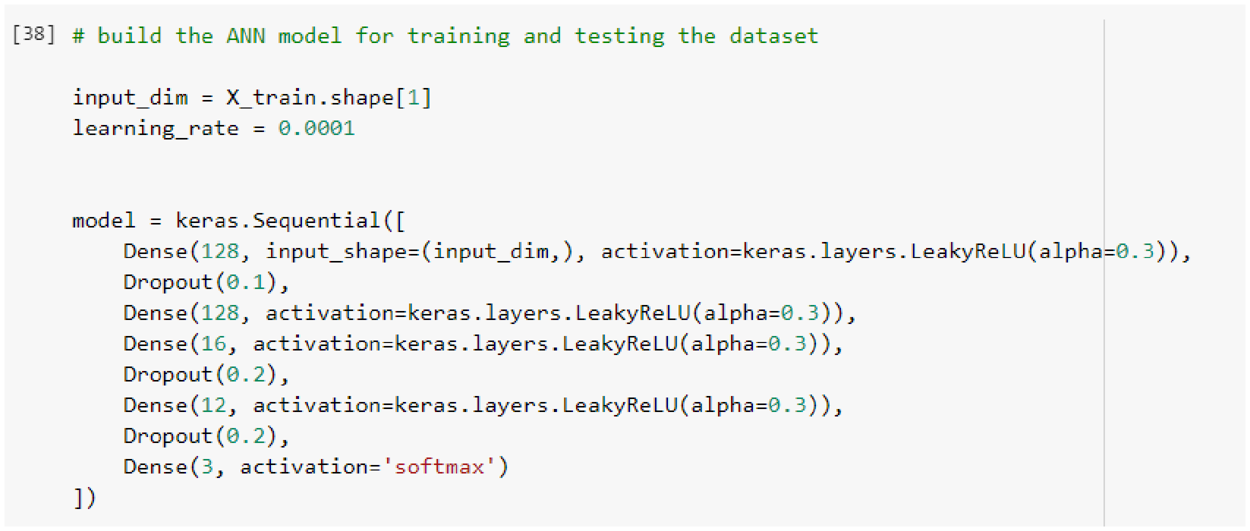
```
[ ] # split the dataset into training and testing set

    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=123, stratify = y)

[ ] # shape of the X_train, y_train, X_test and y_test

    X_train.shape, y_train.shape, X_test.shape, y_test.shape

    ((7729, 7), (7729,), (1933, 7), (1933,))
```

Fig. 13. Coding examples of train-test spilt of the dataset.

From the following figure, after split the dataset, the X_train and y_train contain a total of 7729 data, and X_test and y_test contain a total of 1933 data from the dataset.

Build an ANN model

To train the model, at first, I have built an ANN model from scratch. The model will be used for the training and testing of the dataset. Here, I have used one (1) input layer, three (3) hidden layers, and one (1) output layer. The detailed representation of the model is shown in fig. 14.



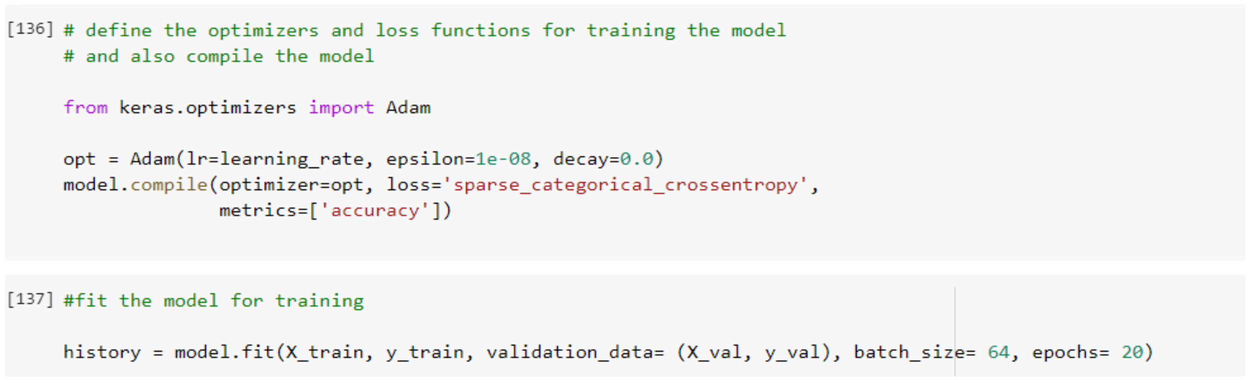
```
[38] # build the ANN model for training and testing the dataset

     input_dim = X_train.shape[1]
     learning_rate = 0.0001


     model = keras.Sequential([
         Dense(128, input_shape=(input_dim,), activation=keras.layers.LeakyReLU(alpha=0.3)),
         Dropout(0.1),
         Dense(128, activation=keras.layers.LeakyReLU(alpha=0.3)),
         Dense(16, activation=keras.layers.LeakyReLU(alpha=0.3)),
         Dropout(0.2),
         Dense(12, activation=keras.layers.LeakyReLU(alpha=0.3)),
         Dropout(0.2),
         Dense(3, activation='softmax')
     ])
```

Fig. 14. Representation of the ANN model.

The figure shows that the input layer has nodes of 128 and the activation function is LeakyReLU. After the input layer, there are three dense layers or hidden layers with different nodes but the same activation function (LeakyReLU). Also, there is one output layer with 3 nodes for 3 output classes (HomeTeam win, Draw, or AwayTeam win). The softmax activation function is used in the output layer as this is a multiclass classification problem. To reduce the over-fitting and underfitting issues, the DropOut function is also used. Thus, the model is ready for training and testing.

Compile and Fit the Model

After building the ANN model, the model needs to be compiled by employing optimizers and loss function. Here, I have used Adam optimizer and for calculating the loss, the sparse categorical cross-entropy is used. For training the model, I have set the batch size to 64 and a learning rate of 0.0001 with only 20 epochs. Fig. 15 shows the detailed view of compile and fitting the model.



```
[136] # define the optimizers and loss functions for training the model
      # and also compile the model

      from keras.optimizers import Adam

      opt = Adam(lr=learning_rate, epsilon=1e-08, decay=0.0)
      model.compile(optimizer=opt, loss='sparse_categorical_crossentropy',
                    metrics=['accuracy'])
```

```
[137] #fit the model for training

      history = model.fit(X_train, y_train, validation_data= (X_val, y_val), batch_size= 64, epochs= 20)
```

Fig. 15. Coding examples of compile and fitting the ANN model.

Performance Analysis

To analyze the performance of the training and testing, I have considered accuracy, precision, recall, and F1 score. After training the model with 64 batch sizes and 20 epochs, the model has been achieved a satisfactory result. The result of these four (4) metrics has been shown in Table I.

Table I. Analysis of various metrics sore

Parameters/ Metrics	**Accuracy**	**Recall**	**Precision**	**F1 Score**	**Test Accuracy**
Draw	98.93%	98%	100%	99%	99.38%
Home Team		100%	99%	100%	
Away Team		100%	99%	100%	

The performance table shows that the overall training accuracy is 99.93%. Where the overall test accuracy is 99.38%. These two scores indicating the good performance of the ANN model to predict or classify the football dataset. Also, the recall, precision, and f1 score performances are very satisfactory in each class. In draw class, the precision achieved 100% accuracy, whereas in Home and Away class, recall and f1 score achieved 100% accuracy. So, the model has been performed well to predict the football outcomes.

Confusion Matrix

The confusion matrix is an important method to measure the prediction accuracy of the ANN model. It plots actual or true labels concerning the predicted label for each class. Fig. 16 shows the detailed view of the confusion matrix of this ANN model.

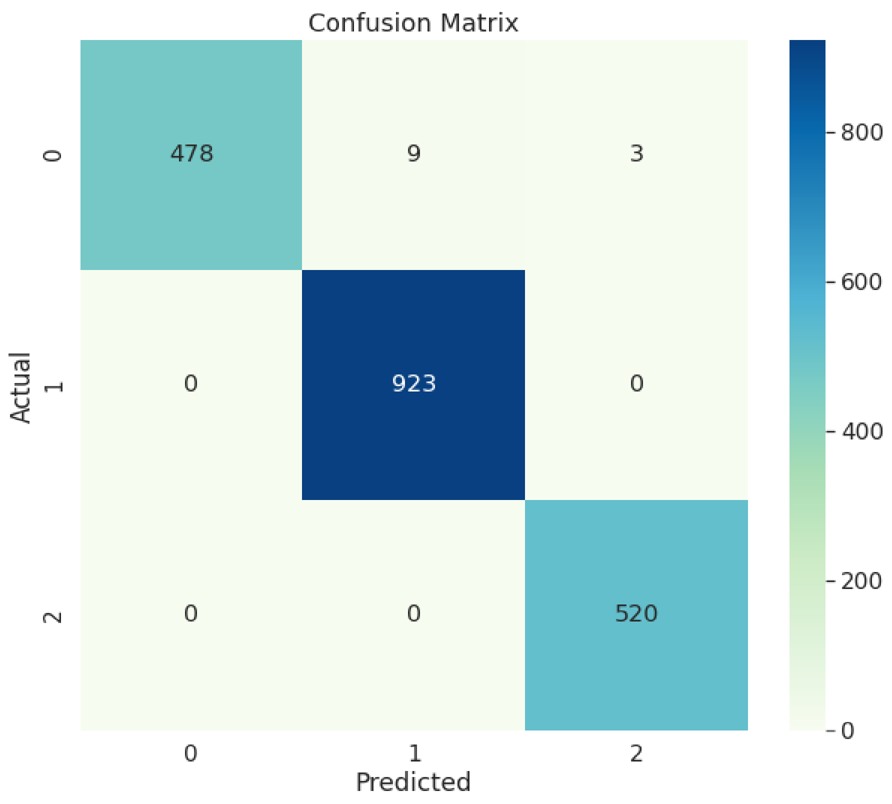


Fig. 16. Confusion matrix.

The confusion matrix shows the prediction of each three class with respect to the actual label. There are three classes where ‘0’ represents the ‘Draw’, ‘1’ represents the ‘HomeTeam Win’, and ‘2’ represents the ‘Away Team Win’. In actual label, draw class has 490 values and the ANN model predicted 478 values, so, it miss-predict the 12 values as other class. Whereas in the other classes (Home and Away team win), the model successfully predicted all the values as a true label. In other words, the model hasn’t done any miss-prediction to predict the Home and Away team win classes. Thus, it can be said that the ANN model has shown a very satisfactory performance to predict the outcomes of the given football match dataset.