```
# Cargue de Librerías básicas
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Importar tensorflow
import tensorflow as tf
print("TF version   : ", tf.__version__)

# Necesitaremos GPU
print("GPU available: ", tf.config.list_physical_devices('GPU'))

# keras version is 2.11.0
import keras
print("Keras version   : ", keras.__version__)


```

```
TF version   :  2.15.0
GPU available:  []
Keras version   :  2.15.0
```

```
#---------------------------------------------#
#       debido a que estoy usando COLAB       #
#---------------------------------------------#

from google.colab import drive
drive.mount('/content/drive') #/content/drive/MyDrive/pec2/data/xl.pickle
print("GPU available: ", tf.config.list_physical_devices('GPU'))
```

```
Mounted at /content/drive
GPU available:  []
```

```
import pandas as pd

home =  '/content/drive/MyDrive/TFM/'

file_path = home + "2017_2023DSTrabajo.xlsx"

dsXls = pd.read_excel(file_path)
dsXls.head(5)
dsXls.info()

```

```
####################################
# LIMPIEZA DE DATOS
####################################
#1. validar duplicados
dsXls.nunique()

#2. validar nulos, rellenar valores faltantes con la mediana
dsXls['Dist'].fillna(dsXls['Dist'].median(), inplace=True)
dsXls['Attendance'].fillna(dsXls['Attendance'].median(), inplace=True)
dsXls.isnull().sum()


####################################
# ESTADISTICAS
####################################
#dsXls.describe().T
dsXls.iloc[:,1:].describe()

```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4092 entries, 0 to 4091
Data columns (total 21 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   Date        4092 non-null   datetime64[ns]
 1   Round       4092 non-null   object
 2   Day         4092 non-null   object
 3   Venue       4092 non-null   object
 4   Result      4092 non-null   object
 5   GF          4092 non-null   float64
 6   GA          4092 non-null   float64
 7   Opponent    4092 non-null   object
 8   xG          4092 non-null   float64
 9   xGA         4092 non-null   float64
 10  Poss        4092 non-null   float64
 11  Attendance  3212 non-null   float64
 12  Season      4092 non-null   int64
 13  Team        4092 non-null   object
 14  Sh          4092 non-null   float64
 15  SoT         4092 non-null   float64
 16  Dist        4089 non-null   float64
 17  SCA         4092 non-null   float64
 18  KP          4092 non-null   float64
 19  PPA         4092 non-null   float64
 20  CrsPA       4092 non-null   float64
dtypes: datetime64[ns](1), float64(13), int64(1), object(6)
memory usage: 671.5+ KB
```

	GF	GA	xG	xGA	Poss	Attendance	
count	4092.000000	4092.000000	4092.000000	4092.000000	4092.000000	4092.000000	4(
mean	1.377810	1.377810	1.346163	1.346163	50.001222	36912.650049	2(
std	1.277631	1.277631	0.796551	0.796551	12.726702	15301.262664	
min	0.000000	0.000000	0.000000	0.000000	18.000000	2000.000000	2(
25%	0.000000	0.000000	0.700000	0.700000	41.000000	29296.000000	2(
50%	1.000000	1.000000	1.200000	1.200000	50.000000	32092.500000	2(
75%	2.000000	2.000000	1.800000	1.800000	59.000000	51237.000000	2(
max	9.000000	9.000000	5.900000	5.900000	82.000000	83222.000000	2(

```
from sklearn.model_selection import train_test_split
from sklearn.decomposition import PCA
```

```
from sklearn.preprocessing import StandardScaler, LabelEncoder
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.regularizers import l2
from tensorflow.keras.callbacks import EarlyStopping


# Cargar los datos
data = dsXls

# Asegurarse de que todas las columnas numéricas estén en el tipo de dato cor
data['Attendance'] = pd.to_numeric(data['Attendance'], errors='coerce')
data['Dist'] = pd.to_numeric(data['Dist'], errors='coerce')

# Imputar valores faltantes
data['Attendance'].fillna(data['Attendance'].median(), inplace=True)
data['Dist'].fillna(data['Dist'].median(), inplace=True)

# Convertir columnas de tipo string a variables numéricas usando Label Encodi
le = LabelEncoder()

# Separar características y variable objetivo. 'Date', 'Round', 'Day', 'Venue
X = data.drop(['Date', 'Round', 'Day', 'Venue', 'Result', 'Team', 'Opponent']
y = le.fit_transform(data['Result'])

# Asegurarse de que todas las características estén en el tipo de dato correc
X = X.apply(pd.to_numeric)

# Estandarizar las características
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Aplicar PCA
pca = PCA(n_components=0.95)  # Retener el 95% de la varianza
X_pca = pca.fit_transform(X_scaled)

# Dividir los datos en conjuntos de entrenamiento y prueba
X_train, X_test, y_train, y_test = train_test_split(X_pca, y, test_size=0.2,

# Convertir y_train y y_test a categorías
y_train = tf.keras.utils.to_categorical(y_train)
y_test = tf.keras.utils.to_categorical(y_test)

# Definir la red neuronal con regularización y dropout
```

```
model = Sequential()
model.add(Dense(128, input_dim=X_pca.shape[1], activation='relu', kernel_regu
model.add(Dropout(0.5))
model.add(Dense(64, activation='relu', kernel_regularizer=l2(0.01)))
model.add(Dropout(0.5))
model.add(Dense(y_train.shape[1], activation='softmax'))

# Compilar el modelo
model.compile(loss='categorical_crossentropy', optimizer=tf.keras.optimizers.

# Añadir EarlyStopping para evitar sobreentrenamiento
early_stopping = EarlyStopping(monitor='val_loss', patience=10, restore_best_

# Entrenar el modelo
history = model.fit(X_train, y_train, epochs=100, batch_size=32, validation_s

# Evaluar el modelo
loss, accuracy = model.evaluate(X_test, y_test)
print(f'Precisión del modelo: {accuracy:.2f}')
```

```
82/82 [==============================] - 0s 3ms/step - loss: 0.2572 - accura
Epoch 43/100
82/82 [==============================] - 0s 3ms/step - loss: 0.2581 - accura
Epoch 44/100
82/82 [==============================] - 0s 3ms/step - loss: 0.2507 - accura
Epoch 45/100
82/82 [==============================] - 0s 3ms/step - loss: 0.2503 - accura
Epoch 46/100
82/82 [==============================] - 0s 3ms/step - loss: 0.2541 - accura
Epoch 47/100
82/82 [==============================] - 0s 3ms/step - loss: 0.2528 - accura
Epoch 48/100
82/82 [==============================] - 0s 3ms/step - loss: 0.2509 - accura
Epoch 49/100
82/82 [==============================] - 0s 3ms/step - loss: 0.2446 - accura
Epoch 50/100
82/82 [==============================] - 0s 3ms/step - loss: 0.2453 - accura
Epoch 51/100
82/82 [==============================] - 0s 3ms/step - loss: 0.2562 - accura
Epoch 52/100
82/82 [==============================] - 0s 3ms/step - loss: 0.2465 - accura
Epoch 53/100
82/82 [==============================] - 0s 3ms/step - loss: 0.2572 - accura
Epoch 54/100
82/82 [==============================] - 0s 3ms/step - loss: 0.2472 - accura
Epoch 55/100
82/82 [==============================] - 0s 3ms/step - loss: 0.2509 - accura
Epoch 56/100
82/82 [==============================] - 0s 3ms/step - loss: 0.2399 - accura
```

```
Epoch 57/100
82/82 [==============================] - 0s 3ms/step - loss: 0.2495 - accura
Epoch 58/100
82/82 [==============================] - 0s 3ms/step - loss: 0.2537 - accura
Epoch 59/100
82/82 [==============================] - 0s 3ms/step - loss: 0.2504 - accura
Epoch 60/100
82/82 [==============================] - 0s 3ms/step - loss: 0.2461 - accura
Epoch 61/100
82/82 [==============================] - 0s 3ms/step - loss: 0.2382 - accura
Epoch 62/100
82/82 [==============================] - 0s 3ms/step - loss: 0.2382 - accura
Epoch 63/100
82/82 [==============================] - 0s 3ms/step - loss: 0.2461 - accura
Epoch 64/100
82/82 [==============================] - 0s 3ms/step - loss: 0.2375 - accura
Epoch 65/100
82/82 [==============================] - 0s 3ms/step - loss: 0.2452 - accura
Epoch 66/100
82/82 [==============================] - 0s 3ms/step - loss: 0.2416 - accura
Epoch 67/100
82/82 [==============================] - 0s 3ms/step - loss: 0.2305 - accura
Epoch 68/100
82/82 [==============================] - 0s 3ms/step - loss: 0.2340 - accura
Epoch 69/100
82/82 [==============================] - 0s 3ms/step - loss: 0.2425 - accura
Epoch 70/100
82/82 [==============================] - 0s 3ms/step - loss: 0.2326 - accura
Epoch 71/100
82/82 [==============================] - 0s 3ms/step - loss: 0.2422 - accura
```

```python
from sklearn.metrics import confusion_matrix, classification_report
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
from sklearn.model_selection import cross_val_score
import numpy as np

import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
#from tensorflow.keras.wrappers.scikit_learn import KerasClassifier
from tensorflow.keras.regularizers import l2

# Evaluar el modelo
loss, accuracy = model.evaluate(X_test, y_test)
print(f'Precisión del modelo: {accuracy:.2f}')

```

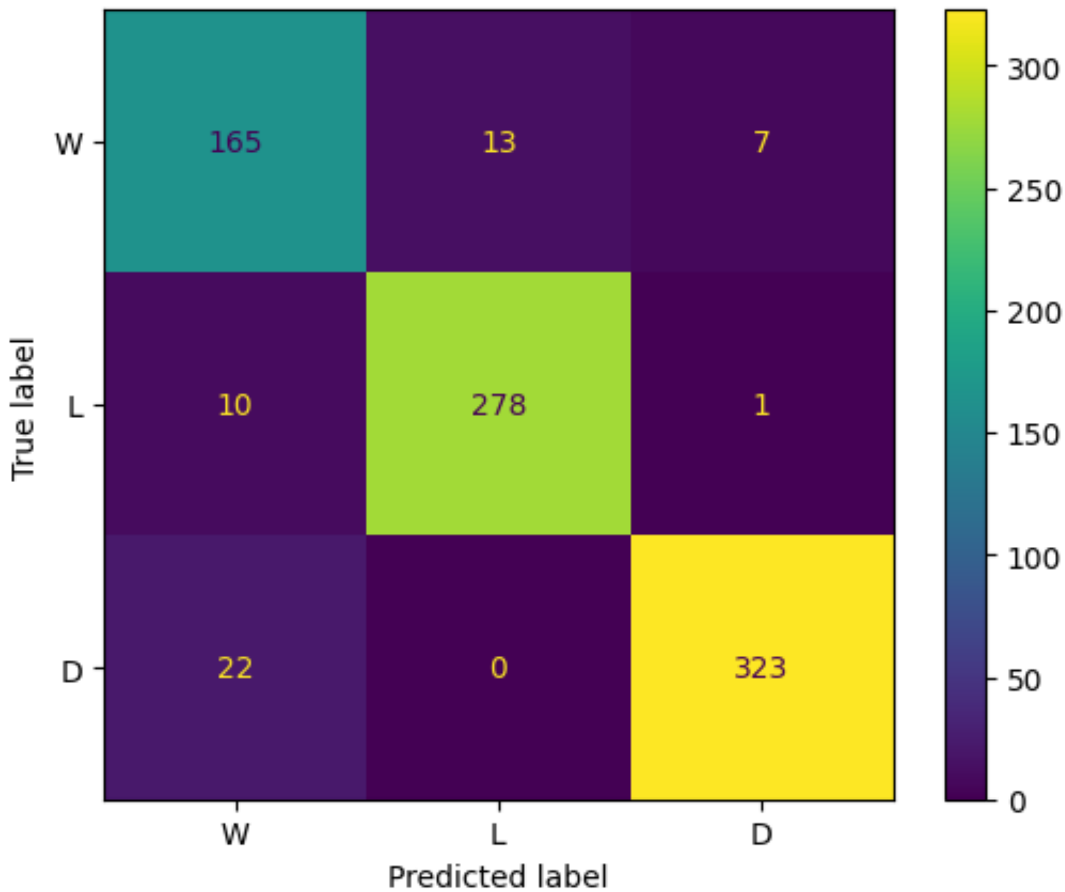
```
# Obtener predicciones
y_pred_cat = model.predict(X_test)
y_pred = np.argmax(y_pred_cat, axis=1)
y_true = np.argmax(y_test, axis=1)

# Calcular la matriz de confusión
conf_matrix = confusion_matrix(y_true, y_pred)
print("Matriz de Confusión:")
print(conf_matrix)
disp = ConfusionMatrixDisplay(confusion_matrix=conf_matrix, display_labels=['W
disp.plot()
plt.show()


# Obtener el reporte de clasificación
class_report = classification_report(y_true, y_pred)
print("Reporte de Clasificación:")
print(class_report)


```

```
26/26 [==============================] - 0s 2ms/step - loss: 0.2197 - accuracy
Precisión del modelo: 0.94
26/26 [==============================] - 0s 1ms/step
Matriz de Confusión:
[[165  13   7]
 [ 10 278   1]
 [ 22   0 323]]
```




```
Reporte de Clasificación:
              precision    recall  f1-score   support

           0       0.84      0.89      0.86       185
           1       0.96      0.96      0.96       289
           2       0.98      0.94      0.96       345

    accuracy                           0.94       819
   macro avg       0.92      0.93      0.93       819
weighted avg       0.94      0.94      0.94       819
```