REGRESION - PRECIO DEL DIAMANTE

Integrantes de equipo:

- Julio César Choquehuayta Quenta 2018-119025
- Carlos Enrique Yufra Loza 2019-119051
- Pablo Moisés Aro Galindo 2019-119034
- Carlos Manuel Azañero Otoya 2015-119026
- Jose Angel Castro Caceres 2017-119054

DESCRIPCION DEL PROBLEMA

Cada diamante tiene una combinación única de atributos, como el peso en quilates, el corte, el color, la claridad y las dimensiones físicas (longitud, anchura y profundidad). Estos atributos influyen en el valor del diamante, y los compradores y vendedores de diamantes necesitan una forma precisa de determinar su precio.

Los joyeros y minoristas necesitan conocer el precio de compra y venta de los diamantes para establecer márgenes de beneficio adecuados. Los compradores de diamantes buscan información sobre el valor de un diamante específico para asegurarse de que están obteniendo un precio justo.

Por lo que se aplicara regresion con redes neuoranles para solucionar dicho problema, usando el conjunto de datos "Diamonds Prices" que nos proporciona una muestra grande y diversa de diamantes con sus respectivos precios y atributos.

Link del Dataset: https://www.kaggle.com/datasets/nancyalaswad90/diamonds-prices

ANALISIS EXPLORATORIO

Primero, nosotros necesitamos tener la dataset descargada y almacenada en una carpeta en drive para su proximo uso, ademas de importar las librerias necesarias.

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import tensorflow as tf
```

```
from tensorflow import keras
from tensorflow.keras import layers
```

```
#Cargamos la dataset
dataset_original = pd.read_csv('https://drive.google.com/uc?id=1f7l-r51EO6DhMbMotrijyke6xI
dataset_original
```

	Unnamed: 0	carat	cut	color	clarity	depth	table	price	x	y	z
0	1	0.23	Ideal	E	SI2	61.5	55.0	326	3.95	3.98	2.43
1	2	0.21	Premium	E	SI1	59.8	61.0	326	3.89	3.84	2.31
2	3	0.23	Good	E	VS1	56.9	65.0	327	4.05	4.07	2.31
3	4	0.29	Premium	I	VS2	62.4	58.0	334	4.20	4.23	2.63
4	5	0.31	Good	J	SI2	63.3	58.0	335	4.34	4.35	2.75
...	...	...	...	...	...	...	...	...	...	...	...
53938	53939	0.86	Premium	H	SI2	61.0	58.0	2757	6.15	6.12	3.74
53939	53940	0.75	Ideal	D	SI2	62.2	55.0	2757	5.83	5.87	3.64
53940	53941	0.71	Premium	E	SI1	60.5	55.0	2756	5.79	5.74	3.49
53941	53942	0.71	Premium	F	SI1	59.8	62.0	2756	5.74	5.73	3.43
53942	53943	0.70	Very Good	E	VS2	60.5	59.0	2757	5.71	5.76	3.47

53943 rows × 11 columns

Exploramos un poco la dataset a usar, usando alguans sentencias para visualizar mejor las columnas, tipos de datos y otros.

```
dataset_original.shape
```

```
(53943, 11)
```

```
dataset_original.isnull().sum()
```

```
Unnamed: 0    0
carat         0
cut           0
color         0
clarity       0
depth         0
table         0
price         0
x             0
y             0
```

```
z            0
dtype: int64
```

```
dataset_original.describe()
```

	Unnamed: 0	carat	depth	table	price	x
count	53943.000000	53943.000000	53943.000000	53943.000000	53943.000000	53943.000000
mean	26972.000000	0.797935	61.749322	57.457251	3932.734294	5.731158
std	15572.147122	0.473999	1.432626	2.234549	3989.338447	1.121730
min	1.000000	0.200000	43.000000	43.000000	326.000000	0.000000
25%	13486.500000	0.400000	61.000000	56.000000	950.000000	4.710000
50%	26972.000000	0.700000	61.800000	57.000000	2401.000000	5.700000
75%	40457.500000	1.040000	62.500000	59.000000	5324.000000	6.540000
max	53943.000000	5.010000	79.000000	95.000000	18823.000000	10.740000

```
dataset_original.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 53943 entries, 0 to 53942
Data columns (total 11 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   Unnamed: 0  53943 non-null  int64  
 1   carat       53943 non-null  float64
 2   cut         53943 non-null  object 
 3   color       53943 non-null  object 
 4   clarity     53943 non-null  object 
 5   depth       53943 non-null  float64
 6   table       53943 non-null  float64
 7   price       53943 non-null  int64  
 8   x           53943 non-null  float64
 9   y           53943 non-null  float64
 10  z           53943 non-null  float64
dtypes: float64(6), int64(2), object(3)
memory usage: 4.5+ MB
```

```
#Aplicamos un backup y eliminamos la columna innecesaria
dataset_copia = dataset_original.copy()
columns_to_drop = ['Unnamed: 0']
dataset_copia.drop(columns=columns_to_drop, inplace=True)
```

Convertimos los datos categoricos a numericos

```
cut_mapping = {'Fair': 0, 'Good': 1, 'Very Good': 2,'Premium':3,'Ideal':4}
color_mapping = {'D': 6, 'E': 5, 'F': 4,'G' : 3, 'H' : 2, 'I' : 1, 'J' : 0}
clarity_mapping = {'I1' : 0, 'SI2':1, 'SI1':2,'VS2':3,'VS1':4,'VVS2':5,'VVS1':6,'IF':7}
dataset_copia['cut_numerica'] = dataset_copia['cut'].map(cut_mapping)
dataset_copia['color_numerica'] = dataset_copia['color'].map(color_mapping)
dataset_copia['clarity_numerica'] = dataset_copia['clarity'].map(clarity_mapping)
```

```
print(dataset_copia)
print("Dimensiones del dataset_original:", dataset_original.shape)
print("Dimensiones del dataset_copia:", dataset_copia.shape)
print(dataset_copia.info())
```

```
       carat        cut color clarity  depth  table  price     x     y     z  \
0       0.23      Ideal     E     SI2   61.5   55.0    326  3.95  3.98  2.43
1       0.21    Premium     E     SI1   59.8   61.0    326  3.89  3.84  2.31
2       0.23       Good     E     VS1   56.9   65.0    327  4.05  4.07  2.31
3       0.29    Premium     I     VS2   62.4   58.0    334  4.20  4.23  2.63
4       0.31       Good     J     SI2   63.3   58.0    335  4.34  4.35  2.75
...      ...        ...   ...     ...    ...    ...    ...   ...   ...   ...
53938   0.86    Premium     H     SI2   61.0   58.0   2757  6.15  6.12  3.74
53939   0.75      Ideal     D     SI2   62.2   55.0   2757  5.83  5.87  3.64
53940   0.71    Premium     E     SI1   60.5   55.0   2756  5.79  5.74  3.49
53941   0.71    Premium     F     SI1   59.8   62.0   2756  5.74  5.73  3.43
53942   0.70  Very Good     E     VS2   60.5   59.0   2757  5.71  5.76  3.47

       cut_numerica  color_numerica  clarity_numerica
0                 4               5                 1
1                 3               5                 2
2                 1               5                 4
3                 3               1                 3
4                 1               0                 1
...             ...             ...               ...
53938             3               2                 1
53939             4               6                 1
53940             3               5                 2
53941             3               4                 2
53942             2               5                 3

[53943 rows x 13 columns]
Dimensiones del dataset_original: (53943, 11)
Dimensiones del dataset_copia: (53943, 13)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 53943 entries, 0 to 53942
Data columns (total 13 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   carat             53943 non-null  float64
 1   cut               53943 non-null  object
 2   color             53943 non-null  object
 3   clarity           53943 non-null  object
 4   depth             53943 non-null  float64
 5   table             53943 non-null  float64
 6   price             53943 non-null  int64
 7   x                 53943 non-null  float64
```

```
 8   y                  53943 non-null  float64
 9   z                  53943 non-null  float64
 10  cut_numerica       53943 non-null  int64
 11  color_numerica     53943 non-null  int64
 12  clarity_numerica   53943 non-null  int64
dtypes: float64(6), int64(4), object(3)
memory usage: 5.4+ MB
None
```

```
columns_to_drop = ['cut','color','clarity']
dataset_copia.drop(columns=columns_to_drop, inplace=True)
```

```
dataset_copia.sample(10)
```

	carat	depth	table	price	x	y	z	cut_numerica	color_numerica	clarit
8771	1.01	64.6	59.0	4468	6.23	6.30	4.05	1	6	
26726	0.32	61.2	56.0	645	4.39	4.43	2.70	4	3	
25837	1.71	59.1	58.0	14882	7.76	7.80	4.60	3	5	
51612	0.73	62.1	58.0	2395	5.75	5.81	3.59	2	5	
36359	0.40	62.2	55.0	939	4.72	4.76	2.95	4	1	
7823	1.00	60.8	60.0	4295	6.45	6.41	3.91	3	6	
34137	0.32	61.6	55.0	854	4.42	4.44	2.73	4	4	
29111	0.34	63.2	55.0	689	4.50	4.46	2.83	2	2	
35932	0.35	61.9	61.0	919	4.54	4.50	2.80	3	5	
14920	1.50	64.9	58.0	6006	7.09	7.03	4.58	0	0	

```
# Dividir el conjunto de datos en conjuntos de entrenamiento y prueba
train_dataset = dataset_copia.sample(frac=0.8, random_state=0)
test_dataset = dataset_copia.drop(train_dataset.index)
```

```
# Separe la variable objetivo (precio) de las características
train_features = train_dataset.drop("price", axis=1)
train_labels = train_dataset["price"]
test_features = test_dataset.drop("price", axis=1)
test_labels = test_dataset["price"]
```

```
train_features
```

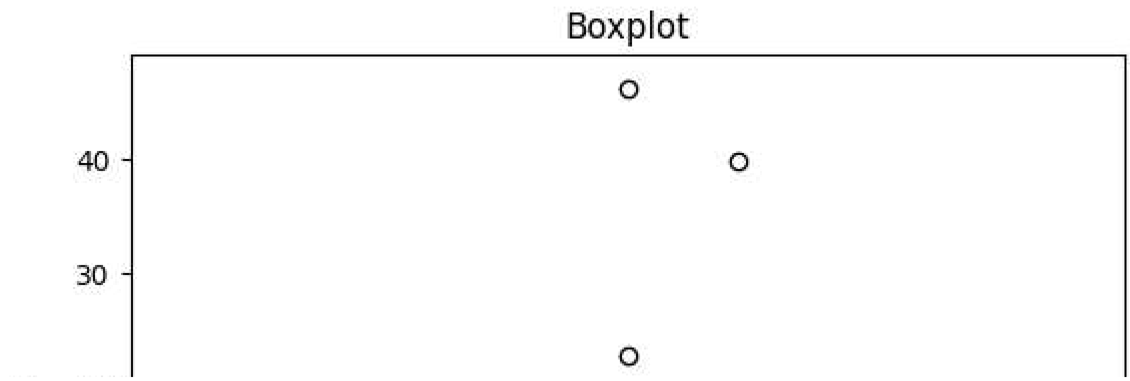
	carat	depth	table	x	y	z	cut_numerica	color_numerica	clarity_numer
34665	0.31	61.7	56.0	4.35	4.31	2.67	4	5	
36941	0.34	60.6	58.0	4.55	4.57	2.76	2	4	
14973	1.57	59.6	56.0	7.59	7.50	4.50	3	0	
19891	1.20	62.3	56.0	6.77	6.82	4.23	4	3	
41070	0.46	62.2	55.0	4.94	4.97	3.08	4	1	
...	...	...	...	...	...	...	...	...	
22623	1.63	62.6	53.0	7.55	7.49	4.71	4	3	
11095	1.10	62.0	59.0	6.62	6.60	4.10	3	4	
10092	0.90	63.6	55.0	6.15	6.12	3.90	1	4	
26364	0.32	63.0	55.0	4.35	4.38	2.75	2	3	

```
# Normalizamos las caracteristicas
train_mean = train_features.mean()
train_std = train_features.std()
train_features = (train_features - train_mean) / train_std
test_features = (test_features - train_mean) / train_std
```

```
# Crear el boxplot
plt.boxplot(train_features.values)

# Agregar etiquetas y título
plt.xlabel("Variable")
plt.ylabel("Valores")
plt.title("Boxplot")

# Mostrar el gráfico
plt.show()
```




```python
# Definimos el modelo de red neuronal
model = keras.Sequential([
    layers.Dense(1024, activation="relu", input_shape=[len(train_features.keys())]),
    layers.Dense(512, activation="relu"),
    layers.Dense(128, activation="relu"),
    layers.Dense(64, activation="relu"),
    layers.Dense(32, activation="relu"),
    layers.Dense(1)
])
```

```python
model.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_12 (Dense)            (None, 1024)              10240

 dense_13 (Dense)            (None, 512)               524800

 dense_14 (Dense)            (None, 128)               65664

 dense_15 (Dense)            (None, 64)                8256

 dense_16 (Dense)            (None, 32)                2080

 dense_17 (Dense)            (None, 1)                 33

=================================================================
Total params: 611,073
Trainable params: 611,073
Non-trainable params: 0
_________________________________________________________________
```

```python
# Compilamos el modelo
model.compile(loss="mse", optimizer='adam', metrics=["mae", "mse"])
```

```python
# Entrenamos el modelo
history = model.fit(train_features, train_labels, epochs=50, validation_data=(test_feature
```

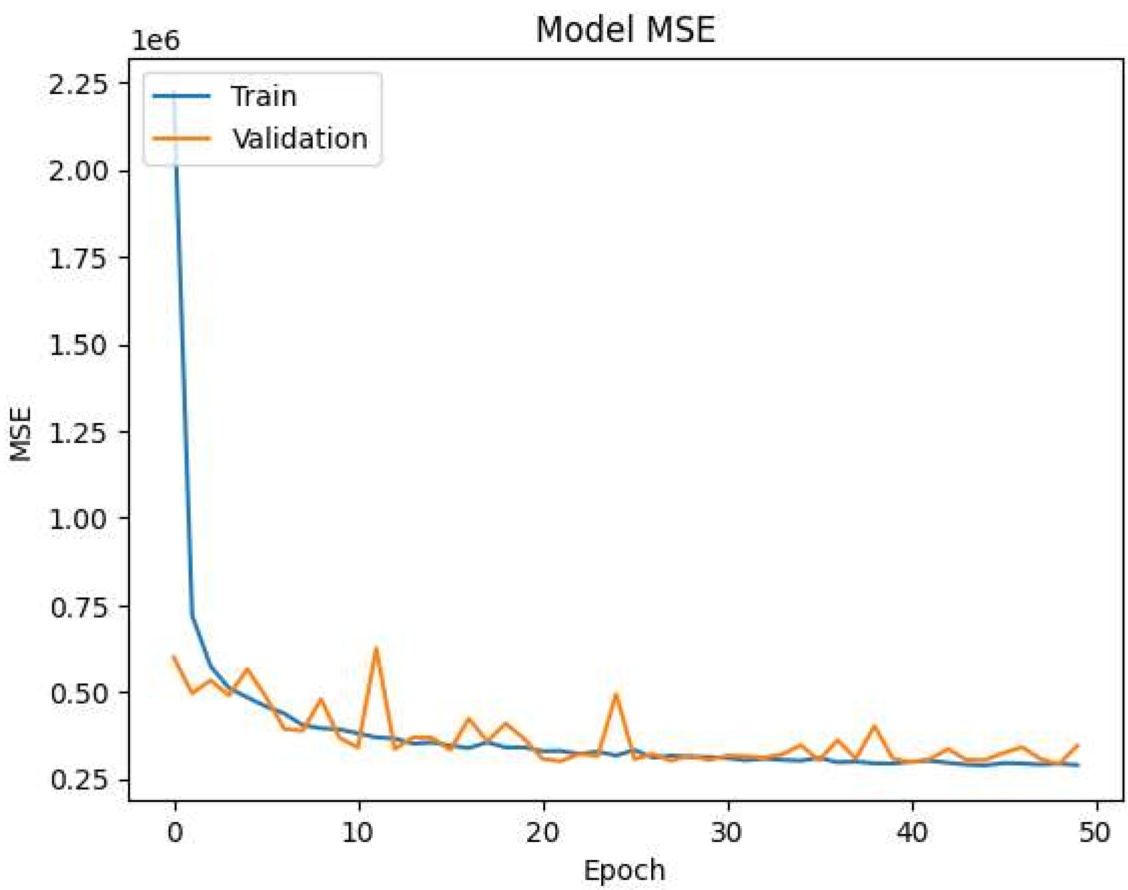
```
Epoch 1/50
1349/1349 [==============================] - 25s 17ms/step - loss: 2223022.7500 - mae
Epoch 2/50
1349/1349 [==============================] - 23s 17ms/step - loss: 720341.0000 - mae:
Epoch 3/50
1349/1349 [==============================] - 23s 17ms/step - loss: 574371.8125 - mae:
Epoch 4/50
1349/1349 [==============================] - 24s 18ms/step - loss: 511529.0625 - mae:
Epoch 5/50
1349/1349 [==============================] - 22s 16ms/step - loss: 484186.2188 - mae:
Epoch 6/50
1349/1349 [==============================] - 22s 16ms/step - loss: 458560.1250 - mae:
Epoch 7/50
1349/1349 [==============================] - 23s 17ms/step - loss: 437975.5625 - mae:
Epoch 8/50
1349/1349 [==============================] - 24s 18ms/step - loss: 404645.1562 - mae:
Epoch 9/50
1349/1349 [==============================] - 23s 17ms/step - loss: 395504.4375 - mae:
Epoch 10/50
1349/1349 [==============================] - 22s 16ms/step - loss: 392049.4688 - mae:
Epoch 11/50
1349/1349 [==============================] - 24s 18ms/step - loss: 381148.6250 - mae:
Epoch 12/50
1349/1349 [==============================] - 23s 17ms/step - loss: 369030.1875 - mae:
Epoch 13/50
1349/1349 [==============================] - 23s 17ms/step - loss: 365957.0938 - mae:
Epoch 14/50
1349/1349 [==============================] - 22s 16ms/step - loss: 350917.3125 - mae:
Epoch 15/50
1349/1349 [==============================] - 23s 17ms/step - loss: 354675.0625 - mae:
Epoch 16/50
1349/1349 [==============================] - 23s 17ms/step - loss: 345779.9688 - mae:
Epoch 17/50
1349/1349 [==============================] - 24s 18ms/step - loss: 338441.4062 - mae:
Epoch 18/50
1349/1349 [==============================] - 22s 16ms/step - loss: 355027.9062 - mae:
Epoch 19/50
1349/1349 [==============================] - 23s 17ms/step - loss: 340290.0312 - mae:
Epoch 20/50
1349/1349 [==============================] - 23s 17ms/step - loss: 340347.5938 - mae:
Epoch 21/50
1349/1349 [==============================] - 22s 17ms/step - loss: 329559.9062 - mae:
Epoch 22/50
1349/1349 [==============================] - 21s 16ms/step - loss: 330078.3125 - mae:
Epoch 23/50
1349/1349 [==============================] - 24s 18ms/step - loss: 321663.7812 - mae:
Epoch 24/50
1349/1349 [==============================] - 23s 17ms/step - loss: 327938.6875 - mae:
Epoch 25/50
1349/1349 [==============================] - 23s 17ms/step - loss: 316874.0312 - mae:
Epoch 26/50
1349/1349 [==============================] - 22s 16ms/step - loss: 332375.6875 - mae:
Epoch 27/50
1349/1349 [==============================] - 23s 17ms/step - loss: 310980.9062 - mae:
Epoch 28/50
1349/1349 [==============================] - 23s 17ms/step - loss: 316696.4062 - mae:
```

```
Epoch 29/50
```

```
# Evaluar el modelo en el conjunto de prueba
test_loss, test_mae, test_mse = model.evaluate(test_features, test_labels)
```

```
338/338 [==============================] - 1s 4ms/step - loss: 345592.5625 - mae: 323.89
```

```
plt.plot(history.history["mse"])
plt.plot(history.history["val_mse"])
plt.title("Model MSE")
plt.ylabel("MSE")
plt.xlabel("Epoch")
plt.legend(["Train", "Validation"], loc="upper left")
plt.show()
```

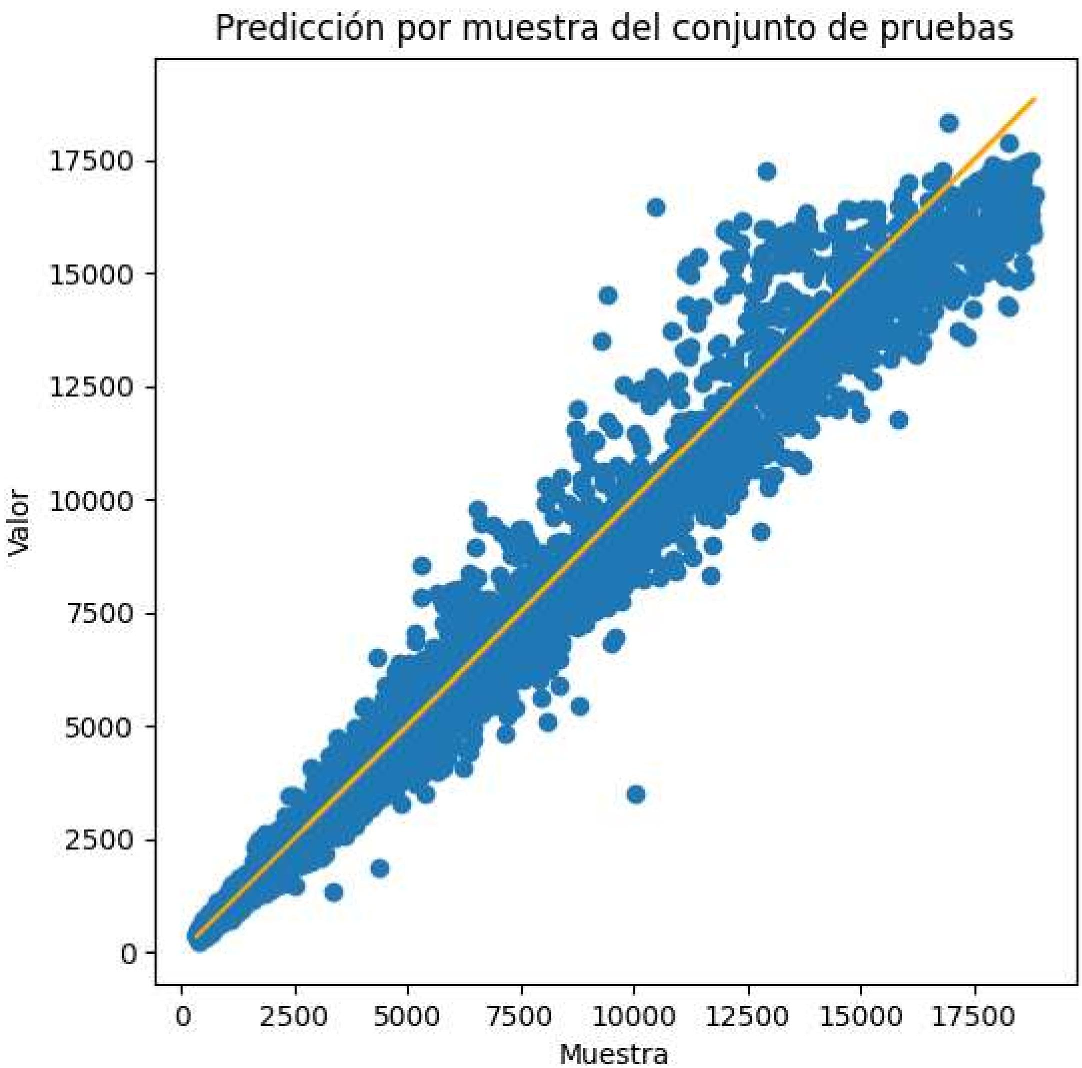



```
# Make predictions on new data
new_data = np.array([[0.23,61.5,55,3.95,3.98,2.43,4,5,1]])
new_data = (new_data - train_mean.values.reshape(1, -1)) / train_std.values.reshape(1, -1)
prediction = model.predict(new_data)
print("Predicción del precio:", prediction[0][0])
```

```
1/1 [==============================] - 0s 25ms/step
Predicción del precio: 328.2354
```

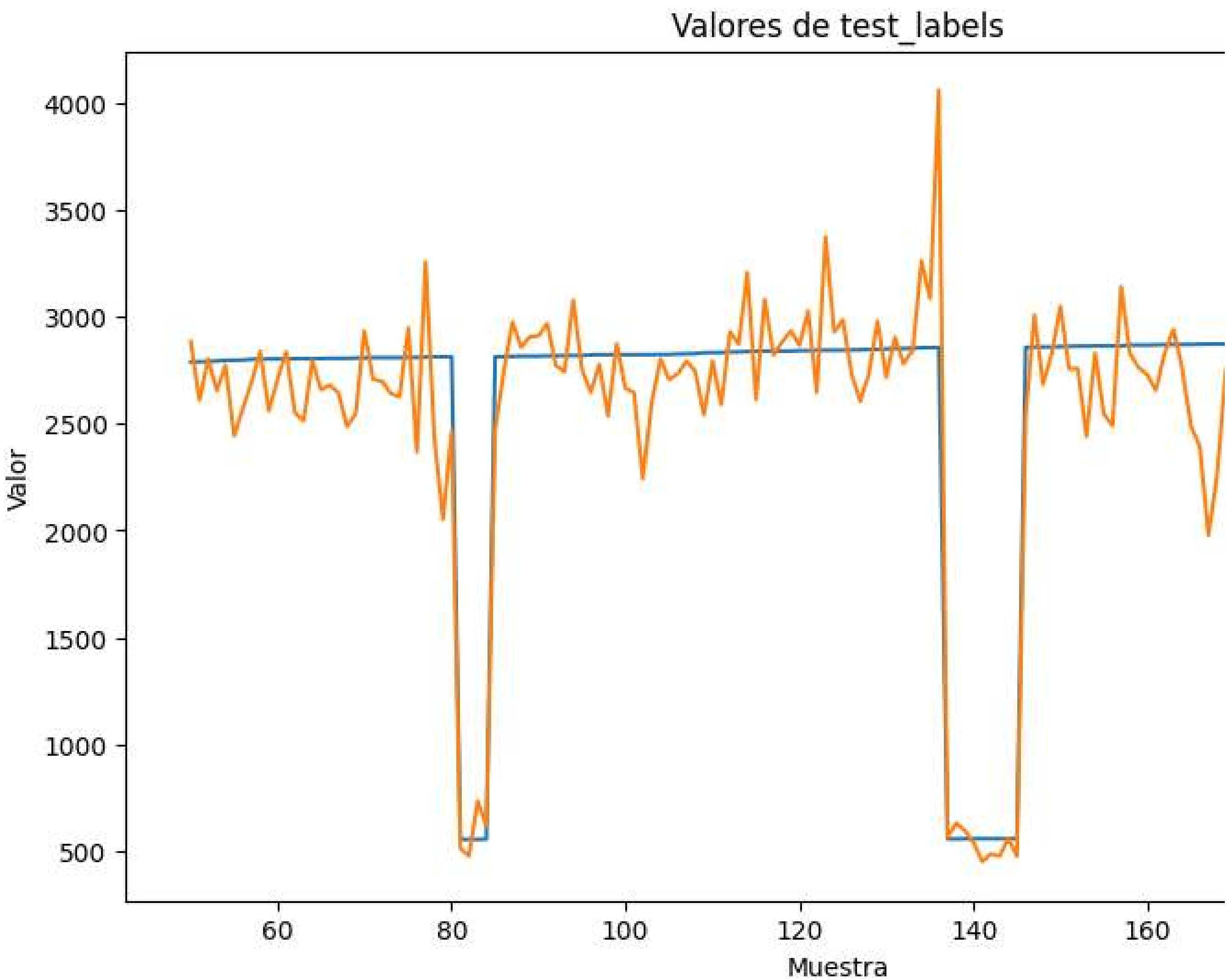
```
predicciones = model.predict(test_features)
inicio = 50
fin=200
# Crear la gráfica de predicción por muestra
plt.figure(figsize=(10, 6))
a=plt.axes(aspect='equal')
plt.scatter(test_labels,predicciones)
plt.xlabel('Muestra')
plt.ylabel('Valor')
plt.title('Predicción por muestra del conjunto de pruebas')
_=plt.plot(test_labels,test_labels,color='orange')
plt.show()
```

```
338/338 [==============================] - 1s 4ms/step
```




```
plt.figure(figsize=(10, 6))
plt.plot(range(inicio,fin), test_labels[inicio:fin])
plt.plot(range(inicio,fin), predicciones[inicio:fin])
plt.xlabel('Muestra')
plt.ylabel('Valor')
```

```
plt.title('Valores de test_labels')
plt.show()
```




```
# Plot each feature along with the predicted values
fig, axs = plt.subplots(3, 4, figsize=(15, 10))
axs = axs.flatten()

for i, column in enumerate(train_features.columns):
    axs[i].scatter(train_features[column], train_labels, s=2, color='black')
    #axs[i].scatter(test_features[column], test_labels, s=2, color='red')
    axs[i].scatter(train_features[column], model.predict(train_features), s=2, color='red'
    #axs[i].plot(test_features[column], model.predict(test_features), linewidth=1)
```

```
1349/1349 [==============================] - 6s 4ms/step
1349/1349 [==============================] - 6s 4ms/step
1349/1349 [==============================] - 5s 4ms/step
1349/1349 [==============================] - 5s 4ms/step
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1349/1349 [==============================] - 6s 4ms/step
```