Time Series - Infosys Stock Price Predictions

Introduction

This is an attempt to predict Stock prices based on Stock prices of previous days. The stock market refers to the collection of markets and exchanges where regular activities of buying, selling, and issuance of shares of publicly-held companies take place.

This is a time series analysis and we will see different ways to predict the stock prices. The various models to be used are:

1. Avearage
2. Weighted Average
3. Moving Average
4. Weighted Moving Average
5. Linear Regression
6. Weighted Linear Regression
7. Lasso Regression
8. Moving Window Neural Network

```
# import necessary libraries:
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.metrics import mean_squared_error as mse

# original datasets:

original_data = pd.read_csv("infy_stock.csv")
original_data.head()
```

```
         Date Symbol Series  Prev Close     Open     High     Low     Last  \
0  2015-01-01   INFY     EQ     1972.55  1968.95  1982.00  1956.9  1971.00
1  2015-01-02   INFY     EQ     1974.40  1972.00  2019.05  1972.0  2017.95
2  2015-01-05   INFY     EQ     2013.20  2009.90  2030.00  1977.5  1996.00
3  2015-01-06   INFY     EQ     1995.90  1980.00  1985.00  1934.1  1965.10
4  2015-01-07   INFY     EQ     1954.20  1965.00  1974.75  1950.0  1966.05

     Close     VWAP    Volume      Turnover  Trades  Deliverable Volume  \
0  1974.40  1971.34   500691  9.870306e+13   14908              258080
1  2013.20  2003.25  1694580  3.394669e+14   54166             1249104
2  1995.90  2004.59  2484256  4.979911e+14   82694             1830962
3  1954.20  1954.82  2416829  4.724458e+14  108209             1772070
4  1963.55  1962.59  1812479  3.557162e+14   62463             1317720

   %Deliverble
0       0.5154
1       0.7371
2       0.7370
3       0.7332
4       0.7270
```

The Data:

The data we use for prediction would be for closing price of infosys in NSE (National Stock Exchange) for the business days in 2015. So we will import only the date column and closing price column.

```
df = pd.read_csv("infy_stock.csv", usecols=['Date', 'Close'], parse_dates=['Date'], index_col='Date')
df.head()
```

```
              Close
Date
2015-01-01  1974.40
2015-01-02  2013.20
2015-01-05  1995.90
2015-01-06  1954.20
2015-01-07  1963.55
```

```
df.shape

# we have data on working days only and so there are 248 data with start date as 01-01-2015 and end date as 31-12-2015.
```

```
(248, 1)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 248 entries, 2015-01-01 to 2015-12-31
Data columns (total 1 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   Close   248 non-null    float64
dtypes: float64(1)
memory usage: 3.9 KB
```

```python
# checking min & max value of data.
print("Min:", df.index.min())
print("Max:", df.index.max())
```

```
Min: 2015-01-01 00:00:00
Max: 2015-12-31 00:00:00
```

```python
plt.figure(figsize=(17,5))
df.Close.plot()
plt.title("Closing Price", fontsize=20)
plt.show()
```

Adjustment for split-up

There is a huge drop on 15/06/2015, this was the fifth split in Infosys Share Price. If we take this whole data, prediction might not be as expected as there is a split in between!

We have to either drop the data or adjust the values before split. Since the split is 2 for 1, we can normalize the data prior to split by dividing then by 2. (Old share are half that of today's share).

```python
# The Split
plt.figure(figsize=(17,5))
stock_price = pd.concat([df.Close[:'2015-06-12']/2, df.Close['2015-06-15':]]) # adjustment
plt.plot(stock_price)
plt.title('Closing Price Adjusted', fontsize=20)
plt.show()
```

And now we have an adjusted time series of Infosys stock prices.

Lets now Predict the Stock price based on various methods.

- We will predict the values on last 68 days in the series.
- We will use Mean squared error as a metrics to calculate the error in our prediction.
- We will compare the results of various methods at the end.

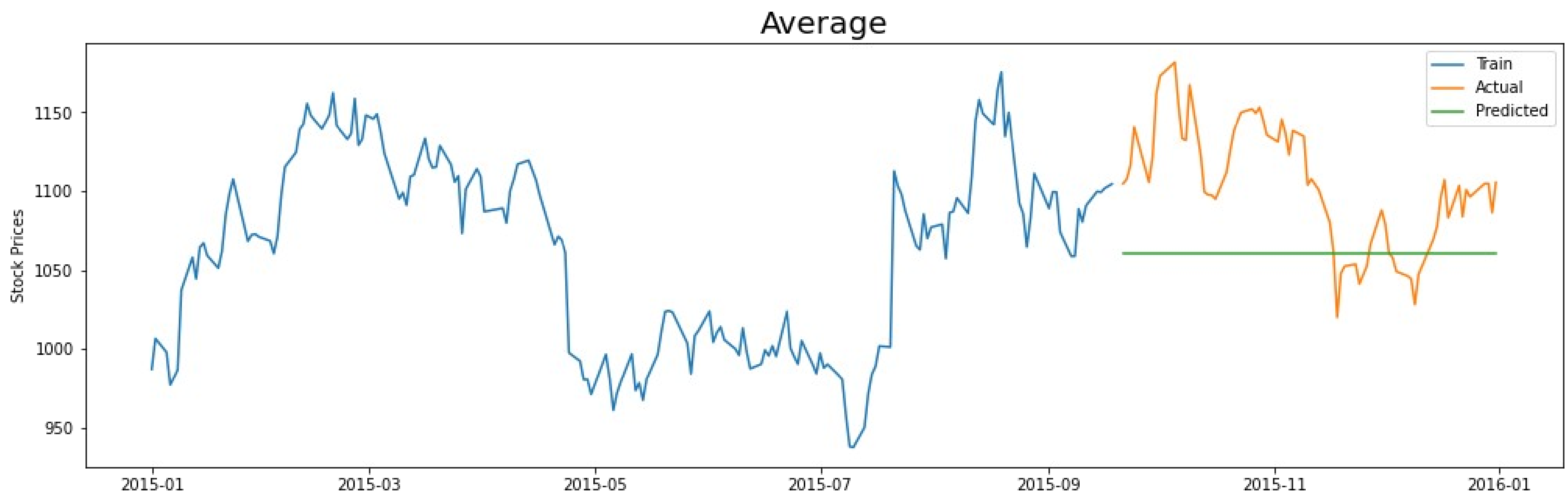
```python
#helper function to plot the stock prediction
prev_values = stock_price.iloc[:180] # training
y_test = stock_price.iloc[180:]   # test

def plot_pred(pred, title):
    plt.figure(figsize=(17,5))
    plt.plot(prev_values, label='Train')
    plt.plot(y_test, label='Actual')
    plt.plot(pred, label='Predicted')
    plt.ylabel("Stock Prices")
```

```
    plt.title(title, fontsize=20)
    plt.legend()
    plt.show()
```

1. Average

This is the simplest model. We will get as average of the previous values and predict it as the forecast.

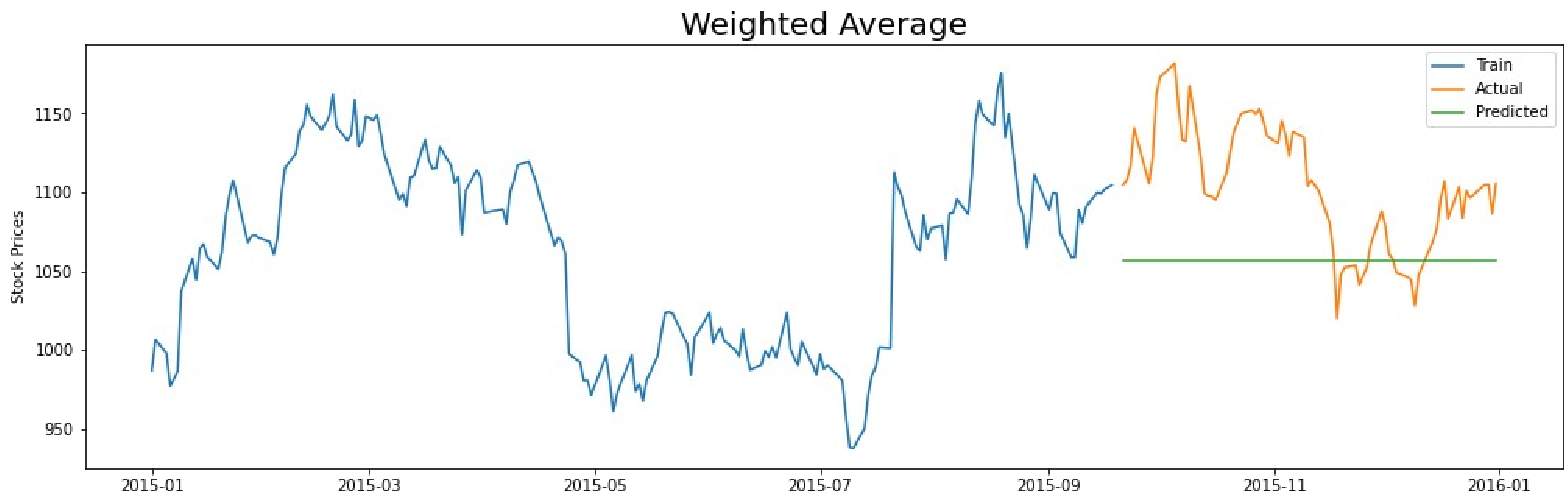
```
# Average of previous values
y_av = pd.Series(np.repeat(prev_values.mean(), 68), index=y_test.index)
mse(y_av, y_test)

3173.6356476000856

np.sqrt(mse(y_av, y_test))

56.33503037720035

plot_pred(y_av, "Average")
plt.show()
```



2. Weighted Mean

We shall give more weightage to the data which are close to the last day in training data, while calculating the mean. The last day in the training set will give a weightage of 1(=180/180) and the first day will get a weightage of 1/180.

```
weight = np.array(range(0,180))/180
weighted_train_data = np.multiply(prev_values, weight)

# weighted average is the sum of this weighted train data by the sum of the weight

weighted_average = sum(weighted_train_data)/sum(weight)
y_wa = pd.Series(np.repeat(weighted_average, 68), index=y_test.index)

print("MSE:", mse(y_wa, y_test))
print("MSE:", np.sqrt(mse(y_wa, y_test)))

MSE: 3496.475652551586
MSE: 59.1310041564625

plot_pred(y_wa, "Weighted Average")
plt.show()
```



For the other methods we will predict the value of stock price on a day based on the values of stock prices of 80 days prior to it. So in our series we will not consider the first eight days (since there previous eighty days is not in the series).

We have to test the last 68 values. This would be based on the last 80 days stock prices of each day in the test data.

Since we have neglected first 80 and last 68 in our test set, the train dataset will be between 80 and 180 (100 days).

```
y_train = stock_price[80:180]
y_test = stock_price[180:]
print("y_train:", y_train.shape, "\ny_test:", y_test.shape)
```

```
y_train: (100,)
y_test: (68,)
```

There are 100 days in training and 68 days in testing set. We will construct the festures, that is the last 68 days stock for each date in the y_train and y_test. This would be our target variable.

```
X_train = pd.DataFrame([list(stock_price[i:i+80]) for i in range(100)],
                      columns= range(80,0,-1), index=y_train.index)
X_test = pd.DataFrame([list(stock_price[i:i+80]) for i in range(100, 168)],
                      columns= range(80,0,-1), index=y_test.index)

X_train
```

```
                  80        79        78        77        76        75  \
Date
2015-04-30   987.200  1006.600   997.950   977.100   981.775   986.725
2015-05-04  1006.600   997.950   977.100   981.775   986.725  1037.225
2015-05-05   997.950   977.100   981.775   986.725  1037.225  1057.975
2015-05-06   977.100   981.775   986.725  1037.225  1057.975  1044.450
2015-05-07   981.775   986.725  1037.225  1057.975  1044.450  1064.325
...              ...       ...       ...       ...       ...       ...
2015-09-11  1023.225  1008.400  1003.650   984.250  1008.300  1011.575
2015-09-14  1008.400  1003.650   984.250  1008.300  1011.575  1023.900
2015-09-15  1003.650   984.250  1008.300  1011.575  1023.900  1004.325
2015-09-16   984.250  1008.300  1011.575  1023.900  1004.325  1010.450
2015-09-18  1008.300  1011.575  1023.900  1004.325  1010.450  1014.025

                  74        73        72        71  ...        10         9  \
Date                                                ...
2015-04-30  1037.225  1057.975  1044.450  1064.325  ...  1097.325  1089.625
2015-05-04  1057.975  1044.450  1064.325  1067.125  ...  1089.625  1066.075
2015-05-05  1044.450  1064.325  1067.125  1059.150  ...  1066.075  1071.300
2015-05-06  1064.325  1067.125  1059.150  1051.250  ...  1071.300  1068.850
2015-05-07  1067.125  1059.150  1051.250  1062.100  ...  1068.850  1061.000
...              ...       ...       ...       ...  ...       ...       ...
2015-09-11  1023.900  1004.325  1010.450  1014.025  ...  1111.050  1094.400
2015-09-14  1004.325  1010.450  1014.025  1005.825  ...  1094.400  1089.000
2015-09-15  1010.450  1014.025  1005.825  1000.025  ...  1089.000  1099.450
2015-09-16  1014.025  1005.825  1000.025   996.050  ...  1099.450  1099.350
2015-09-18  1005.825  1000.025   996.050  1013.250  ...  1099.350  1073.950

                   8         7         6         5         4         3  \
Date
2015-04-30  1066.075  1071.300  1068.850  1061.000   997.600   992.325
2015-05-04  1071.300  1068.850  1061.000   997.600   992.325   980.450
2015-05-05  1068.850  1061.000   997.600   992.325   980.450   980.575
2015-05-06  1061.000   997.600   992.325   980.450   980.575   971.125
2015-05-07   997.600   992.325   980.450   980.575   971.125   996.550
...              ...       ...       ...       ...       ...       ...
2015-09-11  1089.000  1099.450  1099.350  1073.950  1058.750  1058.800
2015-09-14  1099.450  1099.350  1073.950  1058.750  1058.800  1088.700
2015-09-15  1099.350  1073.950  1058.750  1058.800  1088.700  1080.450
2015-09-16  1073.950  1058.750  1058.800  1088.700  1080.450  1090.750
2015-09-18  1058.750  1058.800  1088.700  1080.450  1090.750  1099.750

                   2         1
Date
2015-04-30   980.450   980.575
2015-05-04   980.575   971.125
2015-05-05   971.125   996.550
2015-05-06   996.550   981.375
2015-05-07   981.375   961.025
...              ...       ...
2015-09-11  1088.700  1080.450
2015-09-14  1080.450  1090.750
2015-09-15  1090.750  1099.750
2015-09-16  1099.750  1099.200
2015-09-18  1099.200  1101.650

[100 rows x 80 columns]
```

X train is now a collection of 100 dates as index and a collection of stock prices of previous 80 days as features.

Similarlily, X_test is now a collection of 68 dates as index and a collection of stock prices of previous 80 days as features.

NOTE: Here 76 working days from '2015-05-04', the stock had a price of 986.725 and 77 working days from '2015-05-05', the stock has the same value. You can see the similarity of values along the diagonal. This is because consecutitive data will be similar to the previous except it drops the last value, shifts and has a new value.

We will use these values for stock price predictions in the other four methods.

3. Moving Average

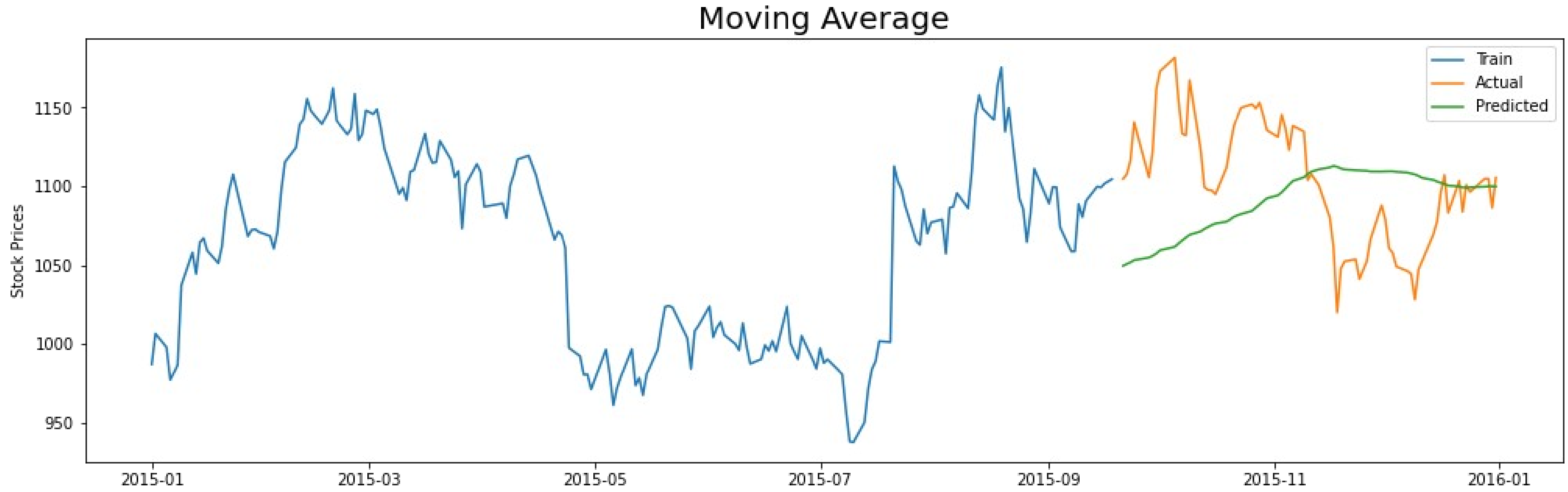
We have to predict the 68 values in data set and for each values we will get the average of previous 80 days.

This will be a simple mean of each column in the y_test.

```
y_ma = X_test.mean(axis=1)
print(" MSE:", mse(y_ma, y_test))
print("RMSE:",np.sqrt(mse(y_ma, y_test)))
```

```
 MSE: 2901.424183296478
RMSE: 53.86486965821488
```

```
plot_pred(y_ma, "Moving Average")
```



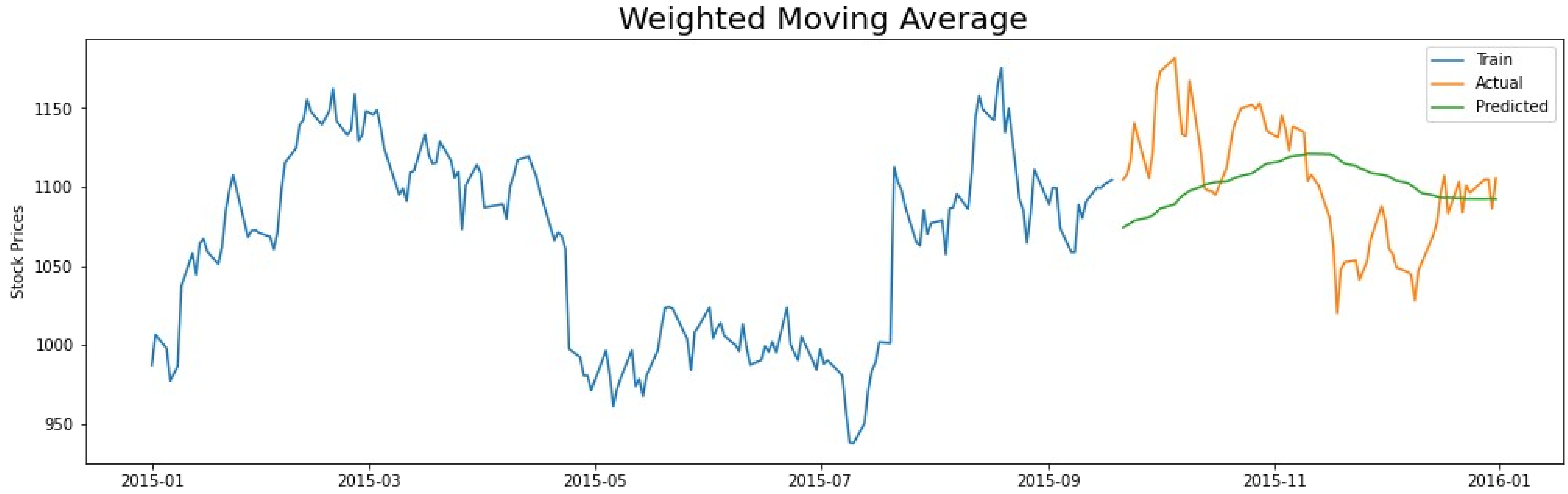
4. Weighted Moving Average

We will obtain the stock price on the test date by calculating the weighted mean of past 80 days. The last of the 80 day will have a weightage of 1(=80/80) and the first will have a weightage of 1/80.

```
weight = np.array(range(1,81))/80
# weighted moving average
y_wma = X_test@weight/sum(weight)
print(" MSE:", mse(y_wma, y_test))
print("RMSE:", np.sqrt(mse(y_wma, y_test)))
```

```
 MSE: 1769.433203930821
RMSE: 42.06463127059146
```

```
plot_pred(y_wma, "Weighted Moving Average")
```



5. Linear Regression

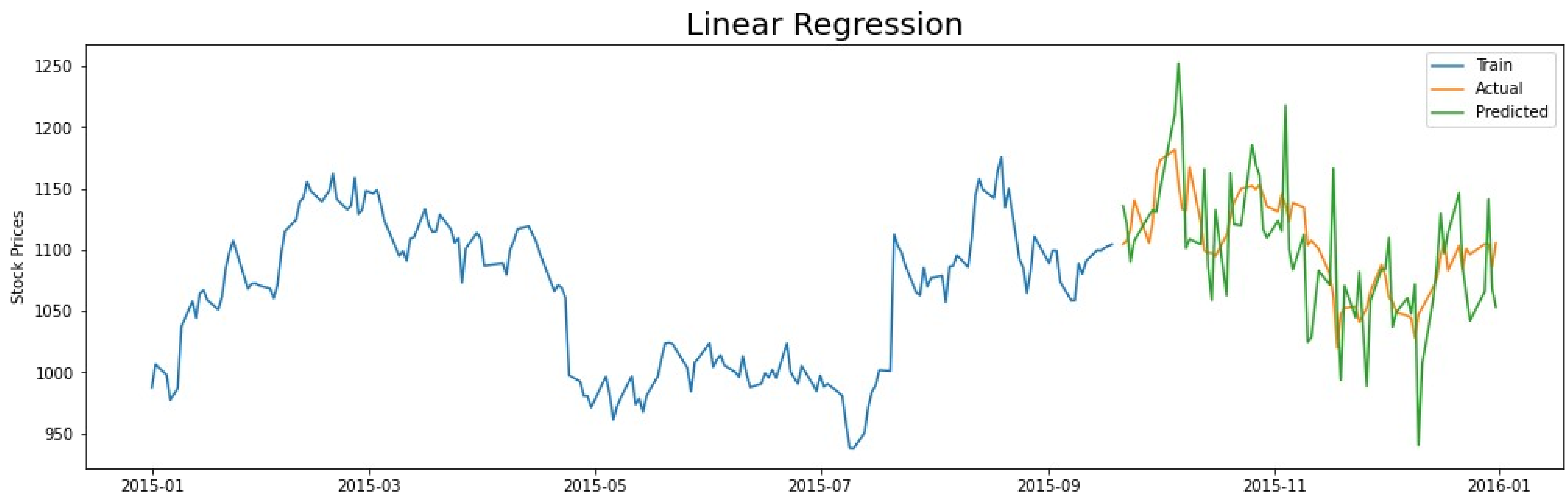
In this method, we will perform a linear regression on our dataset. The values will be predicted as a linear combination of the previous 80 days values.

```
from sklearn.linear_model import LinearRegression
lr = LinearRegression()

lr.fit(X_train, y_train)  # training the models
y_lr = lr.predict(X_test)
y_lr = pd.Series(y_lr, index=y_test.index)
```

```
print(" MSE:", mse(y_test, y_lr))
print("RMSE:", np.sqrt(mse(y_test, y_lr)))
```

```
 MSE: 1754.1645412925625
RMSE: 41.88274753753104
```

```
plot_pred(y_lr, "Linear Regression")
```



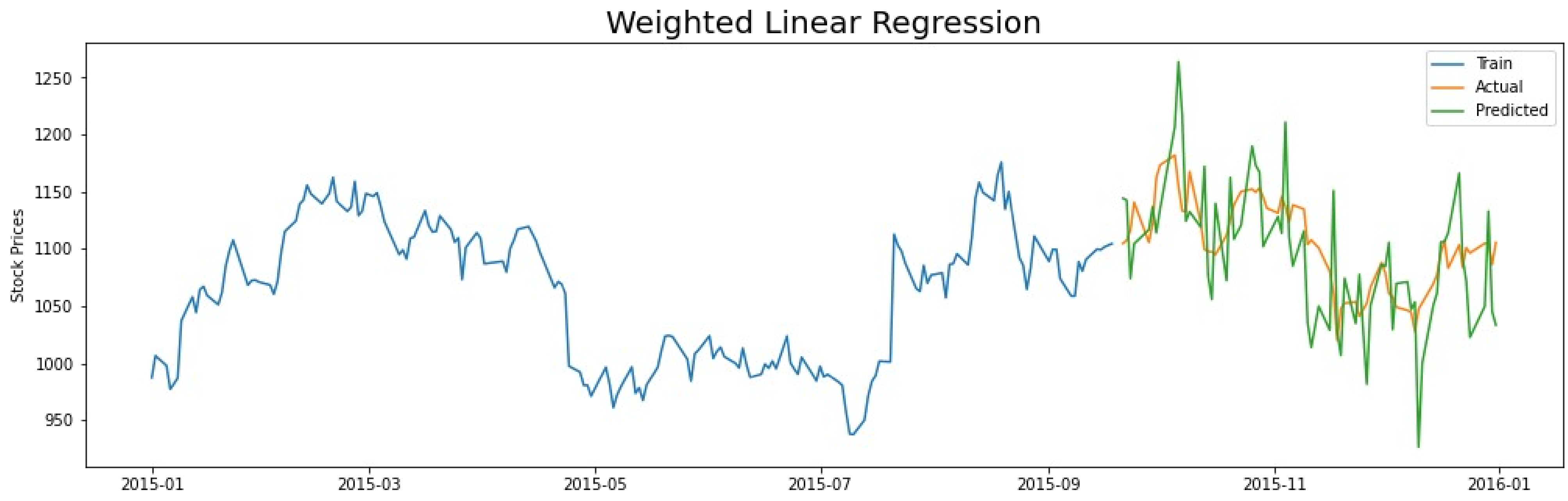
6. Weighted Linear Regression

We provide weighted to our input data rather than the features.

```
weight = np.array(range(1,101))/100

from sklearn.linear_model import LinearRegression
wlr = LinearRegression()

wlr.fit(X_train, y_train, weight)  # training the models
y_wlr = wlr.predict(X_test)
y_wlr = pd.Series(y_wlr, index=y_test.index)

print(" MSE:", mse(y_test, y_wlr))
print("RMSE:", np.sqrt(mse(y_test, y_wlr)))
```

```
 MSE: 2054.3614078787446
RMSE: 45.325063793432705
```

```
plot_pred(y_wlr, "Weighted Linear Regression")
```



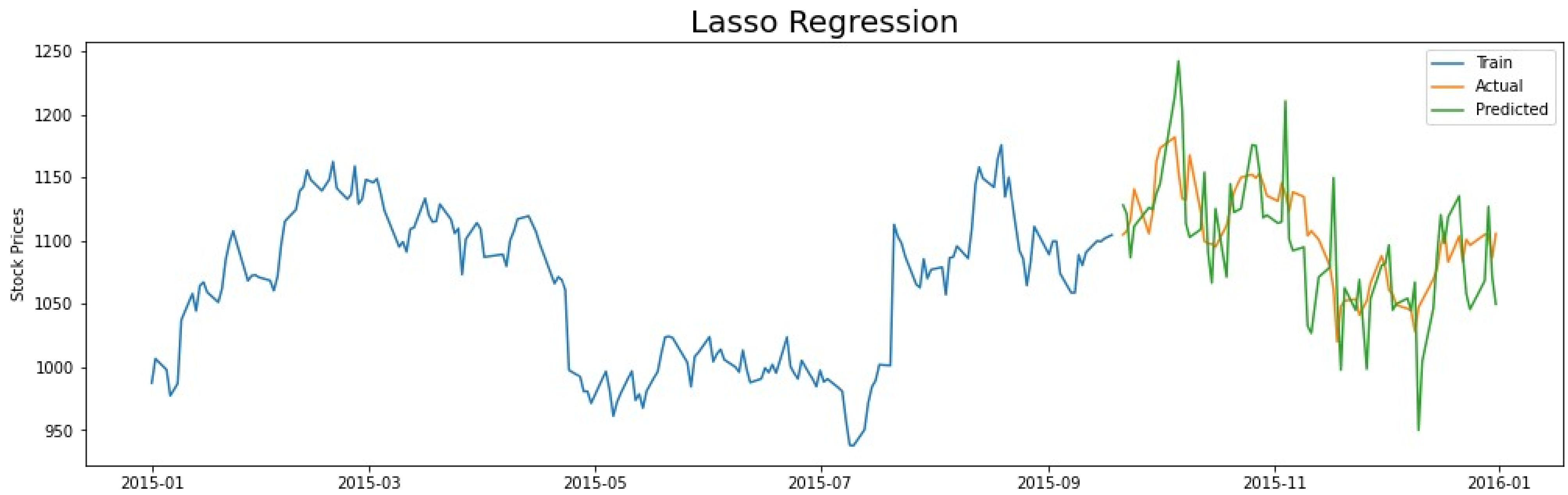
7. Lasso Regression

Linear regression with L1 regualtions.

```
from sklearn.linear_model import Lasso
lasso = Lasso()

las = lasso.fit(X_train, y_train)
y_las = las.predict(X_test)
y_las = pd.Series(y_las, index=y_test.index)

print(" MSE:", mse(y_test, y_las))
print("RMSE:", np.sqrt(mse(y_test, y_las)))
```

```
 MSE: 1467.3338646133786
RMSE: 38.305794138920795
```

```
/usr/local/lib/python3.10/site-packages/sklearn/linear_model/_coordinate_descent.py:628: ConvergenceWarning: Objective did not converge. You might want to increase the number of iterations, check the scale of the features or consider increasing regularisation. Duality gap: 5.020e+02, tolerance: 3.391e+01
  model = cd_fast.enet_coordinate_descent(

plot_pred(y_las, "Lasso Regression")
```



8. Moving Window Neural Network

We construct a simple feed forward network taking 80 features as our input.

```
from keras.models import Sequential
from keras.layers import Dense

# moving average neural network
ma_nn = Sequential([Dense(64, input_shape=(80,), activation='relu'),
                   Dense(32, activation='linear'), Dense(1)])

ma_nn.compile(loss='mse', optimizer='rmsprop', metrics=['mae','mse'])

history = ma_nn.fit(X_train, y_train, epochs=250, batch_size=32, validation_split=0.25)

2024-01-03 06:39:39.835707: I tensorflow/core/util/port.cc:110] oneDNN custom operations are on. You may see slightly different numerical results due to floating-point round-off errors from different computation orders. To turn them off, set the environment variable `TF_ENABLE_ONEDNN_OPTS=0`.
2024-01-03 06:39:39.875836: I tensorflow/core/platform/cpu_feature_guard.cc:182] This TensorFlow binary is optimized to use available CPU instructions in performance-critical operations.
To enable the following instructions: AVX2 AVX512F AVX512_VNNI FMA, in other operations, rebuild TensorFlow with the appropriate compiler flags.

VOC-NOTICE: GPU memory for this assignment is capped at 1024MiB

2024-01-03 06:39:41.812402: E tensorflow/compiler/xla/stream_executor/cuda/cuda_driver.cc:268] failed call to cuInit: CUDA_ERROR_NO_DEVICE: no CUDA-capable device is detected

Epoch 1/250
3/3 [==============================] - 1s 80ms/step - loss: 755490.1250 - mae: 825.1856 - mse: 755490.1250 - val_loss: 3872.0312 - val_mae: 50.2578 - val_mse: 3872.0312
Epoch 2/250
3/3 [==============================] - 0s 10ms/step - loss: 19333.9375 - mae: 111.0158 - mse: 19333.9375 - val_loss: 45329.6406 - val_mae: 204.2789 - val_mse: 45329.6406
Epoch 3/250
3/3 [==============================] - 0s 10ms/step - loss: 9933.1670 - mae: 76.3690 - mse: 9933.1670 - val_loss: 6155.5718 - val_mae: 65.9540 - val_mse: 6155.5718
Epoch 4/250
3/3 [==============================] - 0s 10ms/step - loss: 20811.0234 - mae: 121.8267 - mse: 20811.0234 - val_loss: 48063.3203 - val_mae: 210.9165 - val_mse: 48063.3203
Epoch 5/250
3/3 [==============================] - 0s 9ms/step - loss: 12008.7021 - mae: 89.7113 - mse: 12008.7021 - val_loss: 53281.1211 - val_mae: 222.9886 - val_mse: 53281.1211
Epoch 6/250
3/3 [==============================] - 0s 10ms/step - loss: 35986.2539 - mae: 158.6639 - mse: 35986.2539 - val_loss: 52799.6602 - val_mae: 221.0602 - val_mse: 52799.6602
Epoch 7/250
3/3 [==============================] - 0s 10ms/step - loss: 194532.9688 - mae: 427.0182 - mse: 194532.9688 - val_loss: 309652.8438 - val_mae: 553.5629 - val_mse: 309652.8438
Epoch 8/250
3/3 [==============================] - 0s 10ms/step - loss: 115174.7891 - mae: 314.7294 - mse: 115174.7891 - val_loss: 3716.5916 - val_mae: 49.2822 - val_mse: 3716.5916
Epoch 9/250
3/3 [==============================] - 0s 10ms/step - loss: 34478.9727 - mae: 161.8132 - mse: 34478.9727 - val_loss: 177244.9062 - val_mae: 417.0781 - val_mse: 177244.9062
Epoch 10/250
3/3 [==============================] - 0s 10ms/step - loss: 59520.2930 - mae: 223.5652 - mse: 59520.2930 - val_loss: 5293.4561 - val_mae: 60.7888 - val_mse: 5293.4561
Epoch 11/250
```

```
3/3 [==============================] - 0s 9ms/step - loss: 56579.1055 - mae: 216.5438 - mse: 56579.1055 -
val_loss: 233922.8438 - val_mae: 480.3403 - val_mse: 233922.8438
Epoch 12/250
3/3 [==============================] - 0s 9ms/step - loss: 125646.6797 - mae: 341.8745 - mse: 125646.6797 -
val_loss: 11911.1504 - val_mae: 92.5677 - val_mse: 11911.1504
Epoch 13/250
3/3 [==============================] - 0s 10ms/step - loss: 44308.5156 - mae: 185.8236 - mse: 44308.5156 -
val_loss: 65875.7656 - val_mae: 250.0622 - val_mse: 65875.7656
Epoch 14/250
3/3 [==============================] - 0s 9ms/step - loss: 31628.5195 - mae: 153.1725 - mse: 31628.5195 -
val_loss: 11414.1064 - val_mae: 90.3253 - val_mse: 11414.1064
Epoch 15/250
3/3 [==============================] - 0s 9ms/step - loss: 96479.8906 - mae: 294.5144 - mse: 96479.8906 -
val_loss: 219501.2656 - val_mae: 465.1562 - val_mse: 219501.2656
Epoch 16/250
3/3 [==============================] - 0s 9ms/step - loss: 106204.5859 - mae: 313.2326 - mse: 106204.5859 -
val_loss: 16439.3008 - val_mae: 113.3109 - val_mse: 16439.3008
Epoch 17/250
3/3 [==============================] - 0s 9ms/step - loss: 62888.5000 - mae: 231.4918 - mse: 62888.5000 -
val_loss: 66716.0234 - val_mae: 251.8970 - val_mse: 66716.0234
Epoch 18/250
3/3 [==============================] - 0s 10ms/step - loss: 20100.2812 - mae: 117.3676 - mse: 20100.2812 -
val_loss: 3470.8955 - val_mae: 47.1291 - val_mse: 3470.8955
Epoch 19/250
3/3 [==============================] - 0s 9ms/step - loss: 36040.8320 - mae: 168.3422 - mse: 36040.8320 -
val_loss: 185942.3750 - val_mae: 427.6024 - val_mse: 185942.3750
Epoch 20/250
3/3 [==============================] - 0s 9ms/step - loss: 120357.8516 - mae: 334.1165 - mse: 120357.8516 -
val_loss: 33348.5820 - val_mae: 172.5002 - val_mse: 33348.5820
Epoch 21/250
3/3 [==============================] - 0s 9ms/step - loss: 66534.7031 - mae: 237.0806 - mse: 66534.7031 -
val_loss: 91343.9922 - val_mae: 296.9472 - val_mse: 91343.9922
Epoch 22/250
3/3 [==============================] - 0s 10ms/step - loss: 25706.5176 - mae: 137.2344 - mse: 25706.5176 -
val_loss: 5309.8481 - val_mae: 60.3609 - val_mse: 5309.8481
Epoch 23/250
3/3 [==============================] - 0s 10ms/step - loss: 30354.5605 - mae: 155.1786 - mse: 30354.5605 -
val_loss: 99095.8281 - val_mae: 309.7658 - val_mse: 99095.8281
Epoch 24/250
3/3 [==============================] - 0s 9ms/step - loss: 60324.7070 - mae: 224.6804 - mse: 60324.7070 -
val_loss: 44885.0469 - val_mae: 203.2577 - val_mse: 44885.0469
Epoch 25/250
3/3 [==============================] - 0s 9ms/step - loss: 108739.9844 - mae: 315.7075 - mse: 108739.9844 -
val_loss: 121819.1797 - val_mae: 344.5912 - val_mse: 121819.1797
Epoch 26/250
3/3 [==============================] - 0s 9ms/step - loss: 36096.1484 - mae: 164.7327 - mse: 36096.1484 -
val_loss: 16173.3633 - val_mae: 113.6308 - val_mse: 16173.3633
Epoch 27/250
3/3 [==============================] - 0s 10ms/step - loss: 11318.7041 - mae: 87.0778 - mse: 11318.7041 -
val_loss: 105877.3281 - val_mae: 320.6253 - val_mse: 105877.3281
Epoch 28/250
3/3 [==============================] - 0s 9ms/step - loss: 64800.6914 - mae: 235.0586 - mse: 64800.6914 -
val_loss: 39101.2383 - val_mae: 188.6752 - val_mse: 39101.2383
Epoch 29/250
3/3 [==============================] - 0s 10ms/step - loss: 111920.5625 - mae: 322.1611 - mse: 111920.5625 -
val_loss: 146420.0312 - val_mae: 378.7253 - val_mse: 146420.0312
Epoch 30/250
3/3 [==============================] - 0s 10ms/step - loss: 44252.5703 - mae: 186.4310 - mse: 44252.5703 -
val_loss: 9620.3242 - val_mae: 83.0016 - val_mse: 9620.3242
Epoch 31/250
3/3 [==============================] - 0s 9ms/step - loss: 11907.4570 - mae: 93.3839 - mse: 11907.4570 - val_loss:
67253.3125 - val_mae: 253.3394 - val_mse: 67253.3125
Epoch 32/250
3/3 [==============================] - 0s 10ms/step - loss: 26630.7090 - mae: 140.9517 - mse: 26630.7090 -
val_loss: 3363.8943 - val_mae: 47.3232 - val_mse: 3363.8943
Epoch 33/250
3/3 [==============================] - 0s 9ms/step - loss: 47261.9453 - mae: 196.1258 - mse: 47261.9453 -
val_loss: 228839.5781 - val_mae: 475.3630 - val_mse: 228839.5781
Epoch 34/250
3/3 [==============================] - 0s 9ms/step - loss: 117816.5859 - mae: 332.8687 - mse: 117816.5859 -
val_loss: 20113.5469 - val_mae: 129.4240 - val_mse: 20113.5469
Epoch 35/250
3/3 [==============================] - 0s 9ms/step - loss: 66143.5859 - mae: 238.0274 - mse: 66143.5859 -
val_loss: 52043.4219 - val_mae: 221.3751 - val_mse: 52043.4219
Epoch 36/250
3/3 [==============================] - 0s 9ms/step - loss: 17270.6855 - mae: 109.3623 - mse: 17270.6855 -
val_loss: 3432.3062 - val_mae: 48.4705 - val_mse: 3432.3062
Epoch 37/250
3/3 [==============================] - 0s 9ms/step - loss: 28454.3672 - mae: 146.8175 - mse: 28454.3672 -
val_loss: 117883.6406 - val_mae: 339.0704 - val_mse: 117883.6406
Epoch 38/250
3/3 [==============================] - 0s 9ms/step - loss: 68709.6797 - mae: 246.7551 - mse: 68709.6797 -
val_loss: 24858.8809 - val_mae: 146.7733 - val_mse: 24858.8809
Epoch 39/250
3/3 [==============================] - 0s 9ms/step - loss: 78401.4062 - mae: 264.4094 - mse: 78401.4062 -
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val_loss: 74528.5547 - val_mae: 267.5588 - val_mse: 74528.5547
Epoch 40/250
3/3 [==============================] - 0s 10ms/step - loss: 18913.0371 - mae: 117.1264 - mse: 18913.0371 -
val_loss: 4375.6680 - val_mae: 53.4275 - val_mse: 4375.6680
Epoch 41/250
3/3 [==============================] - 0s 10ms/step - loss: 24120.3633 - mae: 132.8995 - mse: 24120.3633 -
val_loss: 183217.8750 - val_mae: 424.7684 - val_mse: 183217.8750
Epoch 42/250
3/3 [==============================] - 0s 9ms/step - loss: 87608.3281 - mae: 283.4946 - mse: 87608.3281 -
val_loss: 7011.4082 - val_mae: 71.4462 - val_mse: 7011.4082
Epoch 43/250
3/3 [==============================] - 0s 9ms/step - loss: 37739.2148 - mae: 174.9896 - mse: 37739.2148 -
val_loss: 101689.6797 - val_mae: 314.3726 - val_mse: 101689.6797
Epoch 44/250
3/3 [==============================] - 0s 10ms/step - loss: 42703.0938 - mae: 188.9442 - mse: 42703.0938 -
val_loss: 12377.4111 - val_mae: 96.4034 - val_mse: 12377.4111
Epoch 45/250
3/3 [==============================] - 0s 10ms/step - loss: 42646.3320 - mae: 188.1387 - mse: 42646.3320 -
val_loss: 90438.0469 - val_mae: 295.9465 - val_mse: 90438.0469
Epoch 46/250
3/3 [==============================] - 0s 10ms/step - loss: 42948.2031 - mae: 189.1167 - mse: 42948.2031 -
val_loss: 9644.5146 - val_mae: 83.4630 - val_mse: 9644.5146
Epoch 47/250
3/3 [==============================] - 0s 9ms/step - loss: 50099.1719 - mae: 207.1008 - mse: 50099.1719 -
val_loss: 104717.5781 - val_mae: 319.2468 - val_mse: 104717.5781
Epoch 48/250
3/3 [==============================] - 0s 9ms/step - loss: 41669.2188 - mae: 186.6076 - mse: 41669.2188 -
val_loss: 7966.0249 - val_mae: 75.9521 - val_mse: 7966.0249
Epoch 49/250
3/3 [==============================] - 0s 9ms/step - loss: 44461.3945 - mae: 193.3555 - mse: 44461.3945 -
val_loss: 74042.0625 - val_mae: 266.9039 - val_mse: 74042.0625
Epoch 50/250
3/3 [==============================] - 0s 9ms/step - loss: 29147.2227 - mae: 149.3586 - mse: 29147.2227 -
val_loss: 8922.7910 - val_mae: 80.1483 - val_mse: 8922.7910
Epoch 51/250
3/3 [==============================] - 0s 10ms/step - loss: 55315.4766 - mae: 219.8755 - mse: 55315.4766 -
val_loss: 94983.5312 - val_mae: 303.6967 - val_mse: 94983.5312
Epoch 52/250
3/3 [==============================] - 0s 9ms/step - loss: 21998.5039 - mae: 126.6420 - mse: 21998.5039 -
val_loss: 4057.4177 - val_mae: 50.8768 - val_mse: 4057.4177
Epoch 53/250
3/3 [==============================] - 0s 9ms/step - loss: 27025.4590 - mae: 146.6560 - mse: 27025.4590 -
val_loss: 144947.4062 - val_mae: 377.2099 - val_mse: 144947.4062
Epoch 54/250
3/3 [==============================] - 0s 9ms/step - loss: 66418.1484 - mae: 243.8085 - mse: 66418.1484 -
val_loss: 7336.0640 - val_mae: 73.2275 - val_mse: 7336.0640
Epoch 55/250
3/3 [==============================] - 0s 9ms/step - loss: 39194.7812 - mae: 179.2718 - mse: 39194.7812 -
val_loss: 69603.1094 - val_mae: 258.6349 - val_mse: 69603.1094
Epoch 56/250
3/3 [==============================] - 0s 9ms/step - loss: 14474.6084 - mae: 104.5745 - mse: 14474.6084 -
val_loss: 2942.8247 - val_mae: 43.9063 - val_mse: 2942.8247
Epoch 57/250
3/3 [==============================] - 0s 10ms/step - loss: 34857.8203 - mae: 167.5617 - mse: 34857.8203 -
val_loss: 163261.5469 - val_mae: 400.8730 - val_mse: 163261.5469
Epoch 58/250
3/3 [==============================] - 0s 9ms/step - loss: 66197.3828 - mae: 241.9226 - mse: 66197.3828 -
val_loss: 3086.9707 - val_mae: 46.1743 - val_mse: 3086.9707
Epoch 59/250
3/3 [==============================] - 0s 9ms/step - loss: 11702.5244 - mae: 80.8518 - mse: 11702.5244 - val_loss:
46906.2500 - val_mae: 210.2861 - val_mse: 46906.2500
Epoch 60/250
3/3 [==============================] - 0s 9ms/step - loss: 28306.6660 - mae: 147.4392 - mse: 28306.6660 -
val_loss: 9036.2881 - val_mae: 81.1034 - val_mse: 9036.2881
Epoch 61/250
3/3 [==============================] - 0s 9ms/step - loss: 50432.1758 - mae: 208.1436 - mse: 50432.1758 -
val_loss: 50345.5781 - val_mae: 218.4049 - val_mse: 50345.5781
Epoch 62/250
3/3 [==============================] - 0s 9ms/step - loss: 16097.1445 - mae: 105.5573 - mse: 16097.1445 -
val_loss: 3004.0908 - val_mae: 43.3781 - val_mse: 3004.0908
Epoch 63/250
3/3 [==============================] - 0s 9ms/step - loss: 28546.0527 - mae: 151.2113 - mse: 28546.0527 -
val_loss: 144769.8281 - val_mae: 377.1649 - val_mse: 144769.8281
Epoch 64/250
3/3 [==============================] - 0s 9ms/step - loss: 63883.0586 - mae: 238.7981 - mse: 63883.0586 -
val_loss: 4340.8853 - val_mae: 56.9114 - val_mse: 4340.8853
Epoch 65/250
3/3 [==============================] - 0s 9ms/step - loss: 36084.6016 - mae: 169.1965 - mse: 36084.6016 -
val_loss: 41202.9766 - val_mae: 196.3811 - val_mse: 41202.9766
Epoch 66/250
3/3 [==============================] - 0s 9ms/step - loss: 10744.3213 - mae: 85.8535 - mse: 10744.3213 - val_loss:
7519.8774 - val_mae: 72.7046 - val_mse: 7519.8774
Epoch 67/250
3/3 [==============================] - 0s 9ms/step - loss: 7127.0898 - mae: 71.2640 - mse: 7127.0898 - val_loss:
27007.3301 - val_mae: 156.2900 - val_mse: 27007.3301
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Epoch 68/250
3/3 [==============================] - 0s 9ms/step - loss: 8451.3584 - mae: 76.1924 - mse: 8451.3584 - val_loss:
8986.1904 - val_mae: 81.2229 - val_mse: 8986.1904
Epoch 69/250
3/3 [==============================] - 0s 9ms/step - loss: 77489.7500 - mae: 258.6219 - mse: 77489.7500 -
val_loss: 193287.9219 - val_mae: 436.8393 - val_mse: 193287.9219
Epoch 70/250
3/3 [==============================] - 0s 9ms/step - loss: 54588.9805 - mae: 199.2880 - mse: 54588.9805 -
val_loss: 6892.7437 - val_mae: 68.8343 - val_mse: 6892.7437
Epoch 71/250
3/3 [==============================] - 0s 10ms/step - loss: 6983.3145 - mae: 69.6313 - mse: 6983.3145 - val_loss:
32210.5391 - val_mae: 172.3527 - val_mse: 32210.5391
Epoch 72/250
3/3 [==============================] - 0s 9ms/step - loss: 8442.8682 - mae: 73.8131 - mse: 8442.8682 - val_loss:
11652.5479 - val_mae: 95.4117 - val_mse: 11652.5479
Epoch 73/250
3/3 [==============================] - 0s 10ms/step - loss: 6854.7949 - mae: 68.6732 - mse: 6854.7949 - val_loss:
55530.7656 - val_mae: 230.4351 - val_mse: 55530.7656
Epoch 74/250
3/3 [==============================] - 0s 10ms/step - loss: 29421.5938 - mae: 147.0938 - mse: 29421.5938 -
val_loss: 39264.2109 - val_mae: 191.0810 - val_mse: 39264.2109
Epoch 75/250
3/3 [==============================] - 0s 10ms/step - loss: 74162.2969 - mae: 258.5461 - mse: 74162.2969 -
val_loss: 78839.0547 - val_mae: 276.3202 - val_mse: 78839.0547
Epoch 76/250
3/3 [==============================] - 0s 9ms/step - loss: 23825.7852 - mae: 131.0356 - mse: 23825.7852 -
val_loss: 11676.8711 - val_mae: 95.6871 - val_mse: 11676.8711
Epoch 77/250
3/3 [==============================] - 0s 10ms/step - loss: 6968.5391 - mae: 66.6097 - mse: 6968.5391 - val_loss:
22065.5176 - val_mae: 140.1234 - val_mse: 22065.5176
Epoch 78/250
3/3 [==============================] - 0s 11ms/step - loss: 7923.6626 - mae: 70.5680 - mse: 7923.6626 - val_loss:
5095.0327 - val_mae: 62.1966 - val_mse: 5095.0327
Epoch 79/250
3/3 [==============================] - 0s 9ms/step - loss: 51458.6016 - mae: 209.6964 - mse: 51458.6016 -
val_loss: 129067.9609 - val_mae: 355.9691 - val_mse: 129067.9609
Epoch 80/250
3/3 [==============================] - 0s 9ms/step - loss: 37276.4141 - mae: 171.5417 - mse: 37276.4141 -
val_loss: 2505.8293 - val_mae: 39.5196 - val_mse: 2505.8293
Epoch 81/250
3/3 [==============================] - 0s 9ms/step - loss: 16797.3457 - mae: 111.8021 - mse: 16797.3457 -
val_loss: 35540.8320 - val_mae: 182.2093 - val_mse: 35540.8320
Epoch 82/250
3/3 [==============================] - 0s 9ms/step - loss: 11798.2129 - mae: 91.2273 - mse: 11798.2129 - val_loss:
2742.2678 - val_mae: 41.0137 - val_mse: 2742.2678
Epoch 83/250
3/3 [==============================] - 0s 9ms/step - loss: 12693.4258 - mae: 93.0110 - mse: 12693.4258 - val_loss:
73792.6094 - val_mae: 267.4775 - val_mse: 73792.6094
Epoch 84/250
3/3 [==============================] - 0s 9ms/step - loss: 49144.3711 - mae: 205.9135 - mse: 49144.3711 -
val_loss: 12553.8711 - val_mae: 100.1941 - val_mse: 12553.8711
Epoch 85/250
3/3 [==============================] - 0s 9ms/step - loss: 27797.8027 - mae: 143.8603 - mse: 27797.8027 -
val_loss: 44766.6641 - val_mae: 206.0394 - val_mse: 44766.6641
Epoch 86/250
3/3 [==============================] - 0s 9ms/step - loss: 12231.7783 - mae: 91.0940 - mse: 12231.7783 - val_loss:
4915.3110 - val_mae: 56.9983 - val_mse: 4915.3110
Epoch 87/250
3/3 [==============================] - 0s 9ms/step - loss: 8778.3633 - mae: 79.2323 - mse: 8778.3633 - val_loss:
32338.2656 - val_mae: 173.4480 - val_mse: 32338.2656
Epoch 88/250
3/3 [==============================] - 0s 9ms/step - loss: 12317.4502 - mae: 91.8735 - mse: 12317.4502 - val_loss:
25515.4805 - val_mae: 151.7733 - val_mse: 25515.4805
Epoch 89/250
3/3 [==============================] - 0s 9ms/step - loss: 64749.0273 - mae: 242.8339 - mse: 64749.0273 -
val_loss: 68918.2188 - val_mae: 258.2932 - val_mse: 68918.2188
Epoch 90/250
3/3 [==============================] - 0s 9ms/step - loss: 17714.9707 - mae: 112.4165 - mse: 17714.9707 -
val_loss: 3916.1082 - val_mae: 49.5256 - val_mse: 3916.1082
Epoch 91/250
3/3 [==============================] - 0s 9ms/step - loss: 7597.5439 - mae: 73.6837 - mse: 7597.5439 - val_loss:
20374.2383 - val_mae: 134.7654 - val_mse: 20374.2383
Epoch 92/250
3/3 [==============================] - 0s 9ms/step - loss: 7263.1084 - mae: 69.5825 - mse: 7263.1084 - val_loss:
2342.9287 - val_mae: 38.1184 - val_mse: 2342.9287
Epoch 93/250
3/3 [==============================] - 0s 9ms/step - loss: 28223.6738 - mae: 148.6670 - mse: 28223.6738 -
val_loss: 119878.3672 - val_mae: 343.1863 - val_mse: 119878.3672
Epoch 94/250
3/3 [==============================] - 0s 9ms/step - loss: 57475.1875 - mae: 224.7966 - mse: 57475.1875 -
val_loss: 6114.9761 - val_mae: 64.6662 - val_mse: 6114.9761
Epoch 95/250
3/3 [==============================] - 0s 9ms/step - loss: 7199.0142 - mae: 69.8963 - mse: 7199.0142 - val_loss:
24553.8027 - val_mae: 149.6626 - val_mse: 24553.8027
Epoch 96/250
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3/3 [==============================] - 0s 9ms/step - loss: 6377.8110 - mae: 65.0789 - mse: 6377.8110 - val_loss: 24154.3281 - val_mae: 148.4293 - val_mse: 24154.3281
Epoch 97/250
3/3 [==============================] - 0s 9ms/step - loss: 6546.9570 - mae: 67.2645 - mse: 6546.9570 - val_loss: 2796.9431 - val_mae: 40.8966 - val_mse: 2796.9431
Epoch 98/250
3/3 [==============================] - 0s 9ms/step - loss: 27054.8125 - mae: 144.3217 - mse: 27054.8125 - val_loss: 139800.6094 - val_mae: 371.1845 - val_mse: 139800.6094
Epoch 99/250
3/3 [==============================] - 0s 9ms/step - loss: 47984.3281 - mae: 200.0758 - mse: 47984.3281 - val_loss: 2804.9556 - val_mae: 46.2975 - val_mse: 2804.9556
Epoch 100/250
3/3 [==============================] - 0s 9ms/step - loss: 18813.3359 - mae: 119.3473 - mse: 18813.3359 - val_loss: 35707.4766 - val_mae: 183.5383 - val_mse: 35707.4766
Epoch 101/250
3/3 [==============================] - 0s 9ms/step - loss: 13209.7852 - mae: 97.6626 - mse: 13209.7852 - val_loss: 2120.7603 - val_mae: 36.2162 - val_mse: 2120.7603
Epoch 102/250
3/3 [==============================] - 0s 9ms/step - loss: 13580.3525 - mae: 102.1064 - mse: 13580.3525 - val_loss: 43973.3711 - val_mae: 205.0517 - val_mse: 43973.3711
Epoch 103/250
3/3 [==============================] - 0s 9ms/step - loss: 25391.9570 - mae: 143.9439 - mse: 25391.9570 - val_loss: 6924.5117 - val_mae: 71.9832 - val_mse: 6924.5117
Epoch 104/250
3/3 [==============================] - 0s 9ms/step - loss: 17936.9512 - mae: 113.3144 - mse: 17936.9512 - val_loss: 18927.3203 - val_mae: 130.2809 - val_mse: 18927.3203
Epoch 105/250
3/3 [==============================] - 0s 9ms/step - loss: 5649.1196 - mae: 58.5567 - mse: 5649.1196 - val_loss: 18569.0234 - val_mae: 128.9358 - val_mse: 18569.0234
Epoch 106/250
3/3 [==============================] - 0s 9ms/step - loss: 5100.9585 - mae: 56.9421 - mse: 5100.9585 - val_loss: 7669.5752 - val_mae: 75.5158 - val_mse: 7669.5752
Epoch 107/250
3/3 [==============================] - 0s 9ms/step - loss: 4339.9170 - mae: 52.2729 - mse: 4339.9170 - val_loss: 12784.6279 - val_mae: 104.1992 - val_mse: 12784.6279
Epoch 108/250
3/3 [==============================] - 0s 9ms/step - loss: 4205.6270 - mae: 52.0154 - mse: 4205.6270 - val_loss: 11049.9102 - val_mae: 95.5610 - val_mse: 11049.9102
Epoch 109/250
3/3 [==============================] - 0s 9ms/step - loss: 4297.4341 - mae: 50.6303 - mse: 4297.4341 - val_loss: 41403.4805 - val_mae: 198.9510 - val_mse: 41403.4805
Epoch 110/250
3/3 [==============================] - 0s 9ms/step - loss: 66089.3828 - mae: 226.3300 - mse: 66089.3828 - val_loss: 9825.1660 - val_mae: 88.2797 - val_mse: 9825.1660
Epoch 111/250
3/3 [==============================] - 0s 9ms/step - loss: 18917.7305 - mae: 115.8000 - mse: 18917.7305 - val_loss: 16001.7979 - val_mae: 118.8786 - val_mse: 16001.7979
Epoch 112/250
3/3 [==============================] - 0s 10ms/step - loss: 4514.4976 - mae: 51.8923 - mse: 4514.4976 - val_loss: 3145.5735 - val_mae: 43.5331 - val_mse: 3145.5735
Epoch 113/250
3/3 [==============================] - 0s 9ms/step - loss: 4340.4395 - mae: 54.5673 - mse: 4340.4395 - val_loss: 30288.3359 - val_mae: 168.7291 - val_mse: 30288.3359
Epoch 114/250
3/3 [==============================] - 0s 9ms/step - loss: 10453.8428 - mae: 86.2868 - mse: 10453.8428 - val_loss: 2565.6384 - val_mae: 44.6684 - val_mse: 2565.6384
Epoch 115/250
3/3 [==============================] - 0s 9ms/step - loss: 16552.8457 - mae: 113.1693 - mse: 16552.8457 - val_loss: 65018.1016 - val_mae: 251.5057 - val_mse: 65018.1016
Epoch 116/250
3/3 [==============================] - 0s 9ms/step - loss: 27568.2207 - mae: 153.2928 - mse: 27568.2207 - val_loss: 12034.9160 - val_mae: 100.1254 - val_mse: 12034.9160
Epoch 117/250
3/3 [==============================] - 0s 9ms/step - loss: 28974.6270 - mae: 153.8845 - mse: 28974.6270 - val_loss: 10876.1328 - val_mae: 94.9411 - val_mse: 10876.1328
Epoch 118/250
3/3 [==============================] - 0s 10ms/step - loss: 4398.5649 - mae: 52.2378 - mse: 4398.5649 - val_loss: 24331.1270 - val_mae: 150.0777 - val_mse: 24331.1270
Epoch 119/250
3/3 [==============================] - 0s 10ms/step - loss: 5624.1270 - mae: 61.0063 - mse: 5624.1270 - val_loss: 2317.2598 - val_mae: 36.4921 - val_mse: 2317.2598
Epoch 120/250
3/3 [==============================] - 0s 10ms/step - loss: 6924.5654 - mae: 70.7302 - mse: 6924.5659 - val_loss: 47258.9492 - val_mae: 213.3394 - val_mse: 47258.9492
Epoch 121/250
3/3 [==============================] - 0s 10ms/step - loss: 33385.7344 - mae: 170.7119 - mse: 33385.7344 - val_loss: 1971.5593 - val_mae: 35.8359 - val_mse: 1971.5593
Epoch 122/250
3/3 [==============================] - 0s 10ms/step - loss: 12867.1182 - mae: 97.7302 - mse: 12867.1182 - val_loss: 46646.2891 - val_mae: 211.9010 - val_mse: 46646.2891
Epoch 123/250
3/3 [==============================] - 0s 9ms/step - loss: 18857.1191 - mae: 121.7809 - mse: 18857.1191 - val_loss: 2068.8110 - val_mae: 34.7511 - val_mse: 2068.8110
Epoch 124/250
3/3 [==============================] - 0s 9ms/step - loss: 8299.6562 - mae: 78.5908 - mse: 8299.6562 - val_loss:
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22704.4746 - val_mae: 144.6409 - val_mse: 22704.4746
Epoch 125/250
3/3 [==============================] - 0s 9ms/step - loss: 5444.5947 - mae: 60.9519 - mse: 5444.5947 - val_loss:
5798.9487 - val_mae: 63.5136 - val_mse: 5798.9487
Epoch 126/250
3/3 [==============================] - 0s 9ms/step - loss: 3710.4753 - mae: 49.4302 - mse: 3710.4753 - val_loss:
2118.4094 - val_mae: 34.7451 - val_mse: 2118.4094
Epoch 127/250
3/3 [==============================] - 0s 9ms/step - loss: 11817.5615 - mae: 92.8637 - mse: 11817.5615 - val_loss:
75982.5078 - val_mae: 272.5498 - val_mse: 75982.5078
Epoch 128/250
3/3 [==============================] - 0s 9ms/step - loss: 30644.9727 - mae: 161.8365 - mse: 30644.9727 -
val_loss: 2051.6230 - val_mae: 36.0498 - val_mse: 2051.6230
Epoch 129/250
3/3 [==============================] - 0s 9ms/step - loss: 7481.4033 - mae: 71.1073 - mse: 7481.4033 - val_loss:
2863.7380 - val_mae: 40.6418 - val_mse: 2863.7380
Epoch 130/250
3/3 [==============================] - 0s 9ms/step - loss: 9471.9863 - mae: 84.8422 - mse: 9471.9863 - val_loss:
31161.2617 - val_mae: 171.5866 - val_mse: 31161.2617
Epoch 131/250
3/3 [==============================] - 0s 9ms/step - loss: 15140.7451 - mae: 108.2338 - mse: 15140.7451 -
val_loss: 2311.2593 - val_mae: 42.7671 - val_mse: 2311.2593
Epoch 132/250
3/3 [==============================] - 0s 9ms/step - loss: 17402.2012 - mae: 117.3299 - mse: 17402.2012 -
val_loss: 22482.8379 - val_mae: 143.4903 - val_mse: 22482.8379
Epoch 133/250
3/3 [==============================] - 0s 9ms/step - loss: 6079.2847 - mae: 63.1499 - mse: 6079.2847 - val_loss:
2116.5757 - val_mae: 34.3811 - val_mse: 2116.5757
Epoch 134/250
3/3 [==============================] - 0s 9ms/step - loss: 12102.9004 - mae: 95.0543 - mse: 12102.9004 - val_loss:
70791.1094 - val_mae: 262.6898 - val_mse: 70791.1094
Epoch 135/250
3/3 [==============================] - 0s 9ms/step - loss: 33841.7227 - mae: 171.3734 - mse: 33841.7227 -
val_loss: 1887.2976 - val_mae: 35.8296 - val_mse: 1887.2976
Epoch 136/250
3/3 [==============================] - 0s 9ms/step - loss: 10413.6416 - mae: 88.5886 - mse: 10413.6416 - val_loss:
26179.5176 - val_mae: 156.4412 - val_mse: 26179.5176
Epoch 137/250
3/3 [==============================] - 0s 9ms/step - loss: 8918.2822 - mae: 82.0459 - mse: 8918.2822 - val_loss:
1830.6685 - val_mae: 34.5697 - val_mse: 1830.6685
Epoch 138/250
3/3 [==============================] - 0s 9ms/step - loss: 6173.5591 - mae: 65.0873 - mse: 6173.5591 - val_loss:
17190.7188 - val_mae: 124.5302 - val_mse: 17190.7188
Epoch 139/250
3/3 [==============================] - 0s 9ms/step - loss: 4639.0171 - mae: 54.9178 - mse: 4639.0171 - val_loss:
1852.2527 - val_mae: 35.8526 - val_mse: 1852.2527
Epoch 140/250
3/3 [==============================] - 0s 9ms/step - loss: 14170.1152 - mae: 105.0219 - mse: 14170.1152 -
val_loss: 79339.3984 - val_mae: 278.6845 - val_mse: 79339.3984
Epoch 141/250
3/3 [==============================] - 0s 10ms/step - loss: 31652.2109 - mae: 161.6367 - mse: 31652.2109 -
val_loss: 2708.3193 - val_mae: 39.2115 - val_mse: 2708.3193
Epoch 142/250
3/3 [==============================] - 0s 10ms/step - loss: 6315.1743 - mae: 64.6700 - mse: 6315.1743 - val_loss:
30313.1074 - val_mae: 169.3572 - val_mse: 30313.1074
Epoch 143/250
3/3 [==============================] - 0s 10ms/step - loss: 9014.7949 - mae: 81.3877 - mse: 9014.7949 - val_loss:
3491.0803 - val_mae: 53.4706 - val_mse: 3491.0803
Epoch 144/250
3/3 [==============================] - 0s 9ms/step - loss: 17138.5078 - mae: 116.9757 - mse: 17138.5078 -
val_loss: 25415.1074 - val_mae: 154.1197 - val_mse: 25415.1074
Epoch 145/250
3/3 [==============================] - 0s 9ms/step - loss: 7488.2456 - mae: 71.7179 - mse: 7488.2456 - val_loss:
2089.3079 - val_mae: 33.7712 - val_mse: 2089.3079
Epoch 146/250
3/3 [==============================] - 0s 9ms/step - loss: 4175.2114 - mae: 52.0643 - mse: 4175.2114 - val_loss:
3287.2195 - val_mae: 44.7660 - val_mse: 3287.2195
Epoch 147/250
3/3 [==============================] - 0s 9ms/step - loss: 5184.8286 - mae: 59.5240 - mse: 5184.8286 - val_loss:
42223.2109 - val_mae: 201.6613 - val_mse: 42223.2109
Epoch 148/250
3/3 [==============================] - 0s 9ms/step - loss: 19625.1113 - mae: 128.3850 - mse: 19625.1113 -
val_loss: 1920.8057 - val_mae: 32.7110 - val_mse: 1920.8057
Epoch 149/250
3/3 [==============================] - 0s 9ms/step - loss: 6630.5776 - mae: 65.9462 - mse: 6630.5776 - val_loss:
10085.3848 - val_mae: 91.8400 - val_mse: 10085.3848
Epoch 150/250
3/3 [==============================] - 0s 10ms/step - loss: 3366.4099 - mae: 42.1062 - mse: 3366.4099 - val_loss:
2186.6897 - val_mae: 34.4958 - val_mse: 2186.6897
Epoch 151/250
3/3 [==============================] - 0s 9ms/step - loss: 7787.9502 - mae: 74.1262 - mse: 7787.9502 - val_loss:
72160.0312 - val_mae: 265.7798 - val_mse: 72160.0312
Epoch 152/250
3/3 [==============================] - 0s 9ms/step - loss: 32753.7832 - mae: 169.1131 - mse: 32753.7832 -
val_loss: 1821.9663 - val_mae: 31.6420 - val_mse: 1821.9663
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Epoch 153/250
3/3 [==============================] - 0s 9ms/step - loss: 6328.2412 - mae: 64.6225 - mse: 6328.2412 - val_loss:
16945.8906 - val_mae: 123.9740 - val_mse: 16945.8906
Epoch 154/250
3/3 [==============================] - 0s 10ms/step - loss: 4599.6255 - mae: 55.4584 - mse: 4599.6255 - val_loss:
5763.1504 - val_mae: 64.5173 - val_mse: 5763.1504
Epoch 155/250
3/3 [==============================] - 0s 10ms/step - loss: 3431.3660 - mae: 48.8440 - mse: 3431.3660 - val_loss:
2368.2480 - val_mae: 36.1221 - val_mse: 2368.2480
Epoch 156/250
3/3 [==============================] - 0s 9ms/step - loss: 3159.5513 - mae: 46.8547 - mse: 3159.5513 - val_loss:
25552.7754 - val_mae: 155.0079 - val_mse: 25552.7754
Epoch 157/250
3/3 [==============================] - 0s 9ms/step - loss: 26262.0762 - mae: 145.9372 - mse: 26262.0762 -
val_loss: 2698.5332 - val_mae: 47.3053 - val_mse: 2698.5332
Epoch 158/250
3/3 [==============================] - 0s 9ms/step - loss: 11972.3438 - mae: 96.3415 - mse: 11972.3438 - val_loss:
31442.8652 - val_mae: 173.0811 - val_mse: 31442.8652
Epoch 159/250
3/3 [==============================] - 0s 9ms/step - loss: 8693.7715 - mae: 79.0429 - mse: 8693.7715 - val_loss:
1814.7516 - val_mae: 31.0630 - val_mse: 1814.7516
Epoch 160/250
3/3 [==============================] - 0s 9ms/step - loss: 6371.9727 - mae: 66.8708 - mse: 6371.9727 - val_loss:
15859.8398 - val_mae: 119.7740 - val_mse: 15859.8398
Epoch 161/250
3/3 [==============================] - 0s 9ms/step - loss: 8287.3428 - mae: 75.3837 - mse: 8287.3428 - val_loss:
1721.2533 - val_mae: 35.5496 - val_mse: 1721.2533
Epoch 162/250
3/3 [==============================] - 0s 9ms/step - loss: 11454.0898 - mae: 91.7797 - mse: 11454.0898 - val_loss:
25577.9180 - val_mae: 155.2166 - val_mse: 25577.9180
Epoch 163/250
3/3 [==============================] - 0s 9ms/step - loss: 6708.6118 - mae: 68.1074 - mse: 6708.6118 - val_loss:
5083.4141 - val_mae: 59.4079 - val_mse: 5083.4141
Epoch 164/250
3/3 [==============================] - 0s 9ms/step - loss: 3310.7578 - mae: 47.1031 - mse: 3310.7578 - val_loss:
1991.7627 - val_mae: 32.5403 - val_mse: 1991.7627
Epoch 165/250
3/3 [==============================] - 0s 9ms/step - loss: 9631.7334 - mae: 84.8697 - mse: 9631.7334 - val_loss:
64441.0195 - val_mae: 251.0848 - val_mse: 64441.0195
Epoch 166/250
3/3 [==============================] - 0s 9ms/step - loss: 22004.7324 - mae: 132.1139 - mse: 22004.7324 -
val_loss: 1583.9080 - val_mae: 30.6891 - val_mse: 1583.9080
Epoch 167/250
3/3 [==============================] - 0s 9ms/step - loss: 5332.8970 - mae: 58.9835 - mse: 5332.8970 - val_loss:
16008.0986 - val_mae: 120.5118 - val_mse: 16008.0986
Epoch 168/250
3/3 [==============================] - 0s 9ms/step - loss: 7756.4224 - mae: 73.2941 - mse: 7756.4224 - val_loss:
3934.7446 - val_mae: 50.3248 - val_mse: 3934.7446
Epoch 169/250
3/3 [==============================] - 0s 9ms/step - loss: 3463.5520 - mae: 46.9129 - mse: 3463.5518 - val_loss:
5457.1938 - val_mae: 62.7608 - val_mse: 5457.1938
Epoch 170/250
3/3 [==============================] - 0s 9ms/step - loss: 4137.9482 - mae: 48.5712 - mse: 4137.9482 - val_loss:
37618.0664 - val_mae: 190.2611 - val_mse: 37618.0664
Epoch 171/250
3/3 [==============================] - 0s 9ms/step - loss: 19927.3125 - mae: 129.4845 - mse: 19927.3125 -
val_loss: 2189.9382 - val_mae: 42.8511 - val_mse: 2189.9382
Epoch 172/250
3/3 [==============================] - 0s 9ms/step - loss: 8414.2402 - mae: 78.1124 - mse: 8414.2402 - val_loss:
15183.5996 - val_mae: 117.0921 - val_mse: 15183.5996
Epoch 173/250
3/3 [==============================] - 0s 9ms/step - loss: 6466.4561 - mae: 67.2633 - mse: 6466.4561 - val_loss:
1811.3286 - val_mae: 38.0303 - val_mse: 1811.3286
Epoch 174/250
3/3 [==============================] - 0s 9ms/step - loss: 8422.9287 - mae: 77.2751 - mse: 8422.9287 - val_loss:
21302.1934 - val_mae: 140.8875 - val_mse: 21302.1934
Epoch 175/250
3/3 [==============================] - 0s 9ms/step - loss: 9932.2021 - mae: 84.7637 - mse: 9932.2021 - val_loss:
2967.4790 - val_mae: 42.0133 - val_mse: 2967.4790
Epoch 176/250
3/3 [==============================] - 0s 9ms/step - loss: 4795.3755 - mae: 57.5466 - mse: 4795.3755 - val_loss:
13617.1396 - val_mae: 110.2513 - val_mse: 13617.1396
Epoch 177/250
3/3 [==============================] - 0s 9ms/step - loss: 6052.7231 - mae: 66.4766 - mse: 6052.7231 - val_loss:
1784.9978 - val_mae: 37.0673 - val_mse: 1784.9978
Epoch 178/250
3/3 [==============================] - 0s 9ms/step - loss: 10660.8662 - mae: 90.1744 - mse: 10660.8662 - val_loss:
11950.0889 - val_mae: 101.8209 - val_mse: 11950.0889
Epoch 179/250
3/3 [==============================] - 0s 9ms/step - loss: 7565.4219 - mae: 73.0218 - mse: 7565.4219 - val_loss:
2045.4094 - val_mae: 41.2547 - val_mse: 2045.4094
Epoch 180/250
3/3 [==============================] - 0s 9ms/step - loss: 9660.0918 - mae: 83.6804 - mse: 9660.0918 - val_loss:
24257.6797 - val_mae: 150.8701 - val_mse: 24257.6797
Epoch 181/250
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3/3 [==============================] - 0s 9ms/step - loss: 4704.3140 - mae: 57.2266 - mse: 4704.3140 - val_loss: 12743.3623 - val_mae: 106.2797 - val_mse: 12743.3623
Epoch 182/250
3/3 [==============================] - 0s 9ms/step - loss: 5771.2676 - mae: 63.5176 - mse: 5771.2676 - val_loss: 3149.2969 - val_mae: 51.8439 - val_mse: 3149.2969
Epoch 183/250
3/3 [==============================] - 0s 9ms/step - loss: 11472.1689 - mae: 93.4574 - mse: 11472.1689 - val_loss: 11363.9775 - val_mae: 99.6622 - val_mse: 11363.9775
Epoch 184/250
3/3 [==============================] - 0s 9ms/step - loss: 3957.6646 - mae: 51.0067 - mse: 3957.6646 - val_loss: 2395.4897 - val_mae: 36.5602 - val_mse: 2395.4897
Epoch 185/250
3/3 [==============================] - 0s 9ms/step - loss: 3993.8843 - mae: 51.1501 - mse: 3993.8838 - val_loss: 17033.6602 - val_mae: 125.0629 - val_mse: 17033.6602
Epoch 186/250
3/3 [==============================] - 0s 9ms/step - loss: 9462.0068 - mae: 80.3715 - mse: 9462.0068 - val_loss: 7087.3711 - val_mae: 75.1373 - val_mse: 7087.3711
Epoch 187/250
3/3 [==============================] - 0s 9ms/step - loss: 21064.6602 - mae: 132.8810 - mse: 21064.6602 - val_loss: 14757.4834 - val_mae: 114.5699 - val_mse: 14757.4834
Epoch 188/250
3/3 [==============================] - 0s 9ms/step - loss: 5614.3086 - mae: 65.2096 - mse: 5614.3086 - val_loss: 2011.3627 - val_mae: 30.2877 - val_mse: 2011.3627
Epoch 189/250
3/3 [==============================] - 0s 9ms/step - loss: 3386.6443 - mae: 49.0021 - mse: 3386.6443 - val_loss: 3675.3022 - val_mae: 46.3926 - val_mse: 3675.3022
Epoch 190/250
3/3 [==============================] - 0s 9ms/step - loss: 3676.9617 - mae: 49.3848 - mse: 3676.9617 - val_loss: 1945.1360 - val_mae: 39.9875 - val_mse: 1945.1360
Epoch 191/250
3/3 [==============================] - 0s 9ms/step - loss: 5679.4263 - mae: 63.4909 - mse: 5679.4263 - val_loss: 42673.3047 - val_mae: 202.8187 - val_mse: 42673.3047
Epoch 192/250
3/3 [==============================] - 0s 9ms/step - loss: 16971.6387 - mae: 115.4642 - mse: 16971.6387 - val_loss: 1701.3064 - val_mae: 31.6832 - val_mse: 1701.3064
Epoch 193/250
3/3 [==============================] - 0s 9ms/step - loss: 4599.4717 - mae: 57.6423 - mse: 4599.4717 - val_loss: 10739.3486 - val_mae: 95.5421 - val_mse: 10739.3486
Epoch 194/250
3/3 [==============================] - 0s 9ms/step - loss: 4076.1355 - mae: 50.3188 - mse: 4076.1355 - val_loss: 2478.4917 - val_mae: 46.3997 - val_mse: 2478.4917
Epoch 195/250
3/3 [==============================] - 0s 9ms/step - loss: 9321.4932 - mae: 83.0573 - mse: 9321.4932 - val_loss: 11656.7090 - val_mae: 100.2778 - val_mse: 11656.7090
Epoch 196/250
3/3 [==============================] - 0s 10ms/step - loss: 4559.0957 - mae: 55.8098 - mse: 4559.0957 - val_loss: 1717.8849 - val_mae: 35.2940 - val_mse: 1717.8849
Epoch 197/250
3/3 [==============================] - 0s 10ms/step - loss: 7435.9434 - mae: 73.8295 - mse: 7435.9434 - val_loss: 37295.1328 - val_mae: 189.1445 - val_mse: 37295.1328
Epoch 198/250
3/3 [==============================] - 0s 10ms/step - loss: 18980.3379 - mae: 125.2888 - mse: 18980.3379 - val_loss: 3553.3870 - val_mae: 45.5681 - val_mse: 3553.3870
Epoch 199/250
3/3 [==============================] - 0s 9ms/step - loss: 3966.2725 - mae: 49.6642 - mse: 3966.2725 - val_loss: 12604.5127 - val_mae: 105.0197 - val_mse: 12604.5127
Epoch 200/250
3/3 [==============================] - 0s 9ms/step - loss: 5097.2090 - mae: 59.2091 - mse: 5097.2090 - val_loss: 1937.0563 - val_mae: 29.6768 - val_mse: 1937.0563
Epoch 201/250
3/3 [==============================] - 0s 9ms/step - loss: 3301.1016 - mae: 46.9720 - mse: 3301.1016 - val_loss: 14157.6328 - val_mae: 112.2589 - val_mse: 14157.6328
Epoch 202/250
3/3 [==============================] - 0s 10ms/step - loss: 9047.4414 - mae: 79.7239 - mse: 9047.4414 - val_loss: 4427.6904 - val_mae: 60.6730 - val_mse: 4427.6904
Epoch 203/250
3/3 [==============================] - 0s 10ms/step - loss: 12091.8564 - mae: 96.6998 - mse: 12091.8564 - val_loss: 3990.6309 - val_mae: 49.7674 - val_mse: 3990.6309
Epoch 204/250
3/3 [==============================] - 0s 11ms/step - loss: 3024.6367 - mae: 42.3534 - mse: 3024.6367 - val_loss: 11708.2949 - val_mae: 100.8007 - val_mse: 11708.2949
Epoch 205/250
3/3 [==============================] - 0s 9ms/step - loss: 8507.0459 - mae: 77.9200 - mse: 8507.0459 - val_loss: 5144.4946 - val_mae: 64.4722 - val_mse: 5144.4946
Epoch 206/250
3/3 [==============================] - 0s 10ms/step - loss: 13024.4678 - mae: 101.0205 - mse: 13024.4678 - val_loss: 18288.8398 - val_mae: 129.4960 - val_mse: 18288.8398
Epoch 207/250
3/3 [==============================] - 0s 9ms/step - loss: 6245.2817 - mae: 66.4916 - mse: 6245.2817 - val_loss: 2601.1750 - val_mae: 47.4305 - val_mse: 2601.1750
Epoch 208/250
3/3 [==============================] - 0s 9ms/step - loss: 3945.9175 - mae: 48.3059 - mse: 3945.9175 - val_loss: 5395.4399 - val_mae: 61.9431 - val_mse: 5395.4399
Epoch 209/250
3/3 [==============================] - 0s 9ms/step - loss: 3726.6108 - mae: 49.4730 - mse: 3726.6108 - val_loss:
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3210.9297 - val_mae: 42.6550 - val_mse: 3210.9297
Epoch 210/250
3/3 [==============================] - 0s 9ms/step - loss: 2783.6892 - mae: 42.5142 - mse: 2783.6892 - val_loss:
1714.9822 - val_mae: 29.1310 - val_mse: 1714.9822
Epoch 211/250
3/3 [==============================] - 0s 9ms/step - loss: 2817.2053 - mae: 42.7183 - mse: 2817.2053 - val_loss:
4828.3237 - val_mae: 57.3366 - val_mse: 4828.3237
Epoch 212/250
3/3 [==============================] - 0s 9ms/step - loss: 5376.2017 - mae: 60.7791 - mse: 5376.2017 - val_loss:
3687.1821 - val_mae: 55.9229 - val_mse: 3687.1821
Epoch 213/250
3/3 [==============================] - 0s 10ms/step - loss: 9837.9443 - mae: 84.2783 - mse: 9837.9443 - val_loss:
16453.6602 - val_mae: 122.3063 - val_mse: 16453.6602
Epoch 214/250
3/3 [==============================] - 0s 10ms/step - loss: 6534.6558 - mae: 66.8352 - mse: 6534.6558 - val_loss:
4484.1494 - val_mae: 60.7097 - val_mse: 4484.1494
Epoch 215/250
3/3 [==============================] - 0s 9ms/step - loss: 14549.3721 - mae: 107.4526 - mse: 14549.3721 -
val_loss: 20543.7930 - val_mae: 138.0966 - val_mse: 20543.7930
Epoch 216/250
3/3 [==============================] - 0s 9ms/step - loss: 6215.8784 - mae: 62.1448 - mse: 6215.8784 - val_loss:
2489.4304 - val_mae: 35.5206 - val_mse: 2489.4304
Epoch 217/250
3/3 [==============================] - 0s 9ms/step - loss: 3659.7891 - mae: 48.1250 - mse: 3659.7891 - val_loss:
7992.9517 - val_mae: 80.5541 - val_mse: 7992.9517
Epoch 218/250
3/3 [==============================] - 0s 9ms/step - loss: 4402.9561 - mae: 52.0720 - mse: 4402.9561 - val_loss:
11140.5391 - val_mae: 97.5416 - val_mse: 11140.5391
Epoch 219/250
3/3 [==============================] - 0s 9ms/step - loss: 24123.4961 - mae: 142.9810 - mse: 24123.4961 -
val_loss: 8545.4033 - val_mae: 83.9872 - val_mse: 8545.4033
Epoch 220/250
3/3 [==============================] - 0s 9ms/step - loss: 4296.3027 - mae: 52.6853 - mse: 4296.3027 - val_loss:
1636.3911 - val_mae: 35.1613 - val_mse: 1636.3911
Epoch 221/250
3/3 [==============================] - 0s 9ms/step - loss: 5679.2441 - mae: 61.7845 - mse: 5679.2441 - val_loss:
14095.8350 - val_mae: 112.3946 - val_mse: 14095.8350
Epoch 222/250
3/3 [==============================] - 0s 9ms/step - loss: 3024.9431 - mae: 45.8957 - mse: 3024.9431 - val_loss:
3192.3848 - val_mae: 42.9713 - val_mse: 3192.3848
Epoch 223/250
3/3 [==============================] - 0s 9ms/step - loss: 2445.0513 - mae: 39.2925 - mse: 2445.0513 - val_loss:
1699.6447 - val_mae: 36.5662 - val_mse: 1699.6447
Epoch 224/250
3/3 [==============================] - 0s 9ms/step - loss: 11553.4316 - mae: 93.9565 - mse: 11553.4316 - val_loss:
38956.9883 - val_mae: 193.8085 - val_mse: 38956.9883
Epoch 225/250
3/3 [==============================] - 0s 9ms/step - loss: 12094.1182 - mae: 94.6153 - mse: 12094.1182 - val_loss:
2828.7231 - val_mae: 39.2234 - val_mse: 2828.7231
Epoch 226/250
3/3 [==============================] - 0s 9ms/step - loss: 2490.7004 - mae: 39.9938 - mse: 2490.7002 - val_loss:
4705.0073 - val_mae: 56.7555 - val_mse: 4705.0073
Epoch 227/250
3/3 [==============================] - 0s 9ms/step - loss: 2382.5154 - mae: 39.9303 - mse: 2382.5154 - val_loss:
2181.4324 - val_mae: 32.4291 - val_mse: 2181.4324
Epoch 228/250
3/3 [==============================] - 0s 9ms/step - loss: 2340.3037 - mae: 38.2259 - mse: 2340.3037 - val_loss:
1998.1489 - val_mae: 40.9279 - val_mse: 1998.1489
Epoch 229/250
3/3 [==============================] - 0s 9ms/step - loss: 12812.9180 - mae: 98.0248 - mse: 12812.9180 - val_loss:
44430.1016 - val_mae: 207.5163 - val_mse: 44430.1016
Epoch 230/250
3/3 [==============================] - 0s 9ms/step - loss: 14093.0303 - mae: 97.9516 - mse: 14093.0303 - val_loss:
1513.1425 - val_mae: 31.8558 - val_mse: 1513.1425
Epoch 231/250
3/3 [==============================] - 0s 9ms/step - loss: 3894.9363 - mae: 51.7210 - mse: 3894.9363 - val_loss:
10913.6562 - val_mae: 97.3553 - val_mse: 10913.6562
Epoch 232/250
3/3 [==============================] - 0s 9ms/step - loss: 6266.2114 - mae: 65.1356 - mse: 6266.2114 - val_loss:
1588.7292 - val_mae: 28.9826 - val_mse: 1588.7292
Epoch 233/250
3/3 [==============================] - 0s 9ms/step - loss: 4493.2393 - mae: 54.0866 - mse: 4493.2393 - val_loss:
16113.3896 - val_mae: 121.2713 - val_mse: 16113.3896
Epoch 234/250
3/3 [==============================] - 0s 9ms/step - loss: 7155.1782 - mae: 73.9420 - mse: 7155.1782 - val_loss:
2275.1743 - val_mae: 44.0674 - val_mse: 2275.1743
Epoch 235/250
3/3 [==============================] - 0s 9ms/step - loss: 7838.7407 - mae: 76.6327 - mse: 7838.7407 - val_loss:
12392.7871 - val_mae: 104.8144 - val_mse: 12392.7871
Epoch 236/250
3/3 [==============================] - 0s 9ms/step - loss: 5292.8203 - mae: 60.0512 - mse: 5292.8203 - val_loss:
1709.8539 - val_mae: 28.3297 - val_mse: 1709.8539
Epoch 237/250
3/3 [==============================] - 0s 9ms/step - loss: 3349.9495 - mae: 46.2004 - mse: 3349.9495 - val_loss:
7977.9824 - val_mae: 81.0277 - val_mse: 7977.9824
```
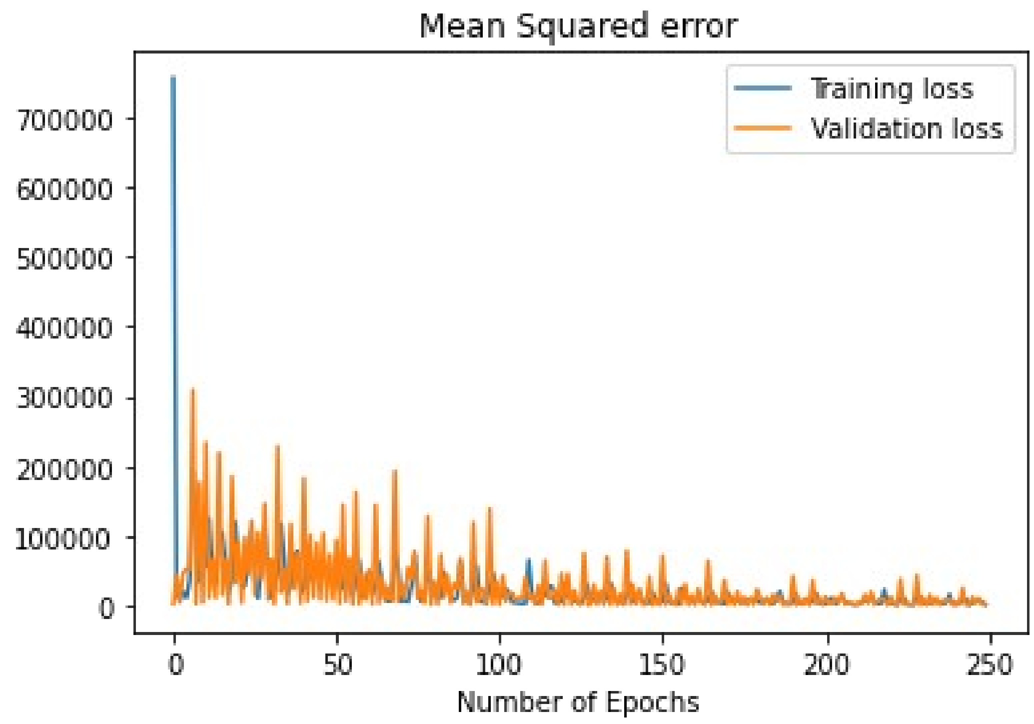

```
Epoch 238/250
3/3 [==============================] - 0s 9ms/step - loss: 5395.0142 - mae: 59.2095 - mse: 5395.0142 - val_loss: 8172.2324 - val_mae: 81.6563 - val_mse: 8172.2324
Epoch 239/250
3/3 [==============================] - 0s 9ms/step - loss: 17151.6152 - mae: 119.8718 - mse: 17151.6152 - val_loss: 10493.2227 - val_mae: 95.4267 - val_mse: 10493.2227
Epoch 240/250
3/3 [==============================] - 0s 9ms/step - loss: 3806.7500 - mae: 48.7789 - mse: 3806.7500 - val_loss: 1956.1312 - val_mae: 30.2968 - val_mse: 1956.1312
Epoch 241/250
3/3 [==============================] - 0s 9ms/step - loss: 2386.2891 - mae: 38.7940 - mse: 2386.2891 - val_loss: 5740.3618 - val_mae: 65.8986 - val_mse: 5740.3618
Epoch 242/250
3/3 [==============================] - 0s 9ms/step - loss: 3834.6604 - mae: 49.1923 - mse: 3834.6604 - val_loss: 3127.2847 - val_mae: 51.4616 - val_mse: 3127.2847
Epoch 243/250
3/3 [==============================] - 0s 9ms/step - loss: 11479.0938 - mae: 97.0973 - mse: 11479.0938 - val_loss: 26289.9609 - val_mae: 157.9575 - val_mse: 26289.9609
Epoch 244/250
3/3 [==============================] - 0s 9ms/step - loss: 9913.9453 - mae: 86.1181 - mse: 9913.9453 - val_loss: 1989.1382 - val_mae: 30.6191 - val_mse: 1989.1382
Epoch 245/250
3/3 [==============================] - 0s 9ms/step - loss: 2437.7236 - mae: 39.7978 - mse: 2437.7236 - val_loss: 1454.2183 - val_mae: 32.2939 - val_mse: 1454.2183
Epoch 246/250
3/3 [==============================] - 0s 9ms/step - loss: 4767.9727 - mae: 56.8373 - mse: 4767.9727 - val_loss: 13197.9883 - val_mae: 108.7755 - val_mse: 13197.9883
Epoch 247/250
3/3 [==============================] - 0s 9ms/step - loss: 7906.0151 - mae: 76.3573 - mse: 7906.0151 - val_loss: 4662.6011 - val_mae: 61.1221 - val_mse: 4662.6011
Epoch 248/250
3/3 [==============================] - 0s 9ms/step - loss: 7448.2173 - mae: 73.8236 - mse: 7448.2173 - val_loss: 11741.7559 - val_mae: 101.8281 - val_mse: 11741.7559
Epoch 249/250
3/3 [==============================] - 0s 10ms/step - loss: 5666.8110 - mae: 64.0682 - mse: 5666.8110 - val_loss: 3125.4998 - val_mae: 43.0151 - val_mse: 3125.4998
Epoch 250/250
3/3 [==============================] - 0s 9ms/step - loss: 2703.7754 - mae: 40.8860 - mse: 2703.7754 - val_loss: 1887.0824 - val_mae: 39.4918 - val_mse: 1887.0824

plt.plot(history.history['mse'],label='Training loss')
plt.plot(history.history['val_mse'], label='Validation loss')
plt.title("Mean Squared error")
plt.xlabel("Number of Epochs")
plt.legend()
plt.show()
```




```
loss_nn,mae_nn,mse_nn = ma_nn.evaluate(X_test,y_test)
print("\nloss:",loss_nn,"\nmae:",mae_nn,"\nmse:",mse_nn)

3/3 [==============================] - 0s 2ms/step - loss: 3224.0562 - mae: 43.2840 - mse: 3224.0562

loss: 3224.05615234375
mae: 43.284000396728516
mse: 3224.05615234375
```