Experiment 1

Problem Statement:

To explore the basic features of Tensorflow and Keras packages.

Github & Google Colab Links:

GitHub Link: https://github.com/piyush-gambhir/ncu-lab-manual-and-end-semester-projects/blob/main/NCU-CSL312%20-%20DL%20-%20Lab%20Manual/Experiment%201/Experiment%201.ipynb

Google Colab Link:



Installing Dependencies:

```
In [ ]: ! pip install tensorflow-cpu numpy matplotlib keras
```

Code

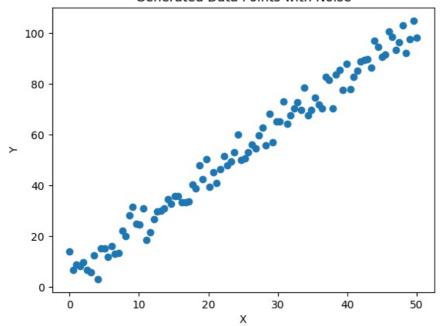
```
In []: import tensorflow as tf
        import numpy as np
        import matplotlib.pyplot as plt
        from tensorflow import keras
        # Constants and Variables
        x = tf.constant([[1., 2., 3.], [4., 5., 6.]])
        a = tf.constant([[1, 2], [3, 4]])
b = tf.constant([[1, 1], [1, 1]])
        c = tf.constant([[4.0, 5.0], [10.0, 1.0]])
        # Basic Tensor Operations
        print(x)
        print("Shape:", x.shape)
        print("DType:", x.dtype)
        print("Element-wise addition:", x + x)
print("Scalar multiplication:", 5 * x)
        # Concatenation and Mathematical Operations
        print("Concatenated:", tf.concat([x, x, x], axis=0))
        print("Softmax:", tf.nn.softmax(x, axis=-1))
        print("Sum:", tf.reduce_sum(x))
        # Element-wise and Matrix Operations
        print("Addition:\n", a + b)
        print("Element-wise Multiplication:\n", a * b)
        print("Matrix Multiplication:\n", tf.matmul(a, b))
        # Advanced Operations
        print("Max Value:", tf.reduce_max(c))
        print("Argmax:", tf.math.argmax(c))
        print("Softmax:\n", tf.nn.softmax(c))
        # Variable operations and Gradient Computation
        var = tf.Variable([0.0, 0.0, 0.0])
        var.assign([1, 2, 3])
        var.assign_add([1, 1, 1])
        x var = tf.Variable(1.0)
        with tf.GradientTape() as tape:
            y = x_var^{**}2 + 2 * x var - 5
        g_x = tape.gradient(y, x_var)
        print("Gradient dy/dx:", g_x.numpy())
        # tf.function for Graph Execution
        @tf.function
        def my func(x):
             return tf.reduce_sum(x)
```

```
print("tf.function example:", my_func(tf.constant([1, 2, 3])))
        # TensorFlow Module
        class MyModule(tf.Module):
            def __init__(self, value):
                super(MyModule, self). init ()
                self.weight = tf.Variable(value)
            @tf.function
            def multiply(self, x):
                return x * self.weight
        mod = MyModule(3)
        print("Module example:", mod.multiply(tf.constant([1, 2, 3])))
        # Simple Linear Model with Keras
        model = keras.Sequential([
            keras.layers.Dense(units=1, input_shape=[1])
        ])
        model.compile(optimizer='sgd', loss='mean_squared_error')
        xs = np.array([-1.0, 0.0, 1.0, 2.0, 3.0, 4.0], dtype=float)
        ys = np.array([-3.0, -1.0, 1.0, 3.0, 5.0, 7.0], dtype=float)
        model.fit(xs, ys, epochs=1000, verbose=0)
        # Convert the list [10.0] to a numpy array with shape (1, 1) for prediction
        x_predict = np.array([10.0]).reshape(-1, 1)
        predicted_value = model.predict(x_predict)
        print("Model prediction for x=10.0:", predicted value[0][0])
       tf.Tensor(
       [[1. 2. 3.]
        [4. 5. 6.]], shape=(2, 3), dtype=float32)
       Shape: (2, 3)
       DType: <dtype: 'float32'>
       Element-wise addition: tf.Tensor(
       [[ 2. 4. 6.] [ 8. 10. 12.]], shape=(2, 3), dtype=float32)
       Scalar multiplication: tf.Tensor(
       [[ 5. 10. 15.]
        [20. 25. 30.]], shape=(2, 3), dtype=float32)
       Concatenated: tf.Tensor(
       [[1. 2. 3.]
        [4. 5. 6.]
        [1. 2. 3.]
        [4. 5. 6.]
        [1. 2. 3.]
        [4. 5. 6.]], shape=(6, 3), dtype=float32)
       Softmax: tf.Tensor(
       [[0.09003057 0.24472848 0.6652409 ]
        [0.09003057 0.24472848 0.6652409 ]], shape=(2, 3), dtype=float32)
       Sum: tf.Tensor(21.0, shape=(), dtype=float32)
       Addition:
        tf.Tensor(
       [[2 3]
        [4 5]], shape=(2, 2), dtype=int32)
       Element-wise Multiplication:
       tf.Tensor(
       [[1 2]
        [3 4]], shape=(2, 2), dtype=int32)
       Matrix Multiplication:
        tf.Tensor(
        [7 7]], shape=(2, 2), dtype=int32)
       Max Value: tf.Tensor(10.0, shape=(), dtype=float32)
       Argmax: tf.Tensor([1 0], shape=(2,), dtype=int64)
        tf.Tensor(
       [[2.6894143e-01 7.3105854e-01]
        [9.9987662e-01 1.2339458e-04]], shape=(2, 2), dtype=float32)
       Gradient dy/dx: 4.0
       tf.function example: tf.Tensor(6, shape=(), dtype=int32)
       Module example: tf.Tensor([3 6 9], shape=(3,), dtype=int32)
                              - 0s 64ms/step
       Model prediction for x=10.0: 18.999922
In [ ]: import numpy as np
        import matplotlib.pyplot as plt
        import pandas as pd
        import seaborn as sns
```

import tensorflow as tf

```
from tensorflow.keras.models import Sequential, load model
from tensorflow.keras.layers import Dense
from sklearn.model selection import train test split
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean absolute error, mean squared error
# Data Generation
np.random.seed(101)
x = np.linspace(0, 50, 100)
noise = np.random.normal(loc=0.0, scale=4.0, size=len(x))
y = 2 * x + 3 + noise # y = mx + b + noise
plt.scatter(x, y)
plt.title('Generated Data Points with Noise')
plt.xlabel('X')
plt.ylabel('Y')
plt.show()
# Neural Network Model for Regression
model = Sequential([
    Dense(4, input_dim=1, activation='relu'),
    Dense(4, activation='relu'),
    Dense(1, activation='linear')
])
model.compile(loss='mse', optimizer='adam')
model.fit(x, y, epochs=500, verbose=1)
model.summary()
# Predictions and Evaluation
x for predictions = np.linspace(0, 50, 1000)
y_predicted = model.predict(x_for_predictions)
predictions = model.predict(x).flatten()
mse = mean squared error(y, predictions)
mae = mean_absolute_error(y, predictions)
print(f"Mean Squared Error: {mse}")
print(f"Mean Absolute Error: {mae}")
plt.scatter(x, y, label='Original Data')
plt.plot(x_for_predictions, y_predicted, 'r', label='Line of Best Fit')
plt.title('Original Data and Predicted Line of Best Fit')
plt.xlabel('X')
plt.ylabel('Y')
plt.legend()
plt.show()
# Data Loading and Preparation
df = pd.read_csv('fake_reg.csv')
sns.pairplot(df)
plt.show()
X = df[['feature1', 'feature2']].values
y = df['price'].values
X_train, X_test, y_train, y_test = train_test_split(
   X, y, test_size=0.3, random_state=42)
scaler = MinMaxScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
# Model for Predicting Prices
price model = Sequential([
    Dense(4, input_shape=[2], activation='relu'),
    Dense(4, activation='relu'),
   Dense(1)
])
price_model.compile(optimizer='rmsprop', loss='mse')
# Fit the model and capture the history
history = price_model.fit(X_train_scaled, y_train, epochs=250, verbose=0)
# Model Evaluation
train loss = price model.evaluate(X train scaled, y train, verbose=0)
test loss = price model.evaluate(X test scaled, y test, verbose=0)
print(f"Training Loss: {train loss}")
print(f"Test Loss: {test_loss}")
# Plot Training Loss
loss = history.history['loss']
plt.plot(range(len(loss)), loss)
plt.title("Training Loss per Epoch")
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.show()
```

Generated Data Points with Noise



c:\Users\mainp\AppData\Local\Programs\Python\Python311\Lib\site-packages\keras\src\layers\core\dense.py:86: User
Warning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer usin
g an `Input(shape)` object as the first layer in the model instead.
 super().__init__(activity_regularizer=activity_regularizer, **kwargs)
Epoch 1/500

Epoch	1/500	26	5ms/step		1000	3816.8904
-, -	2/500		311137 3 CCP			301010304
4/4 —	3/500	0s	3ms/step	-	loss:	3675.2747
4/4 —	3/300	0s	3ms/step	-	loss:	3616.0183
Epoch	4/500	Ac	2ms/step	_	1000	3786.6235
Epoch	5/500		·			3700.0233
4/4 —	6/500	0s	2ms/step	-	loss:	3614.7380
4/4 —		0s	2ms/step	-	loss:	3600.3745
Epoch	7/500	As	2ms/step	_	1055.	3731.9346
Epoch	8/500					
4/4 — Enoch	9/500	0s	3ms/step	-	loss:	3544.4194
4/4 —		0s	2ms/step	-	loss:	3867.9727
Epoch 4/4 —	10/500	0s	3ms/step	_	loss:	3819.0059
Epoch	11/500		·			
4/4 — Epoch	12/500	0s	4ms/step	-	loss:	3638.5342
4/4 —	·	0s	2ms/step	-	loss:	3738.2158
Epoch 4/4 —	13/500	0s	2ms/step	_	loss:	3679.1357
	14/500		·			2700 2055
4/4 — Epoch	15/500	US	2ms/step	-	toss:	3789.3955
4/4 —	16 (500	0s	2ms/step	-	loss:	3729.8909
4/4 —	16/500	0s	2ms/step	-	loss:	3808.5630
Epoch	17/500	0.0	2ms/ston		10001	3720.5808
	18/500	0s	2ms/step	-	1055.	3720.3000
4/4 —	19/500	0s	2ms/step	-	loss:	3800.4888
4/4 —	137 300	0s	2ms/step	-	loss:	3922.3398
Epoch	20/500	As	2ms/step	_	1055.	3396.6860
Epoch	21/500	03	211137 3 сер		.055.	3330.0000
4/4 — Epoch	22/500	0s	2ms/step	-	loss:	3751.9087
4/4 —		0s	2ms/step	-	loss:	3722.5664
Epoch 4/4 —	23/500	0s	2ms/step	_	loss:	3788.3835
	24/500		·			2022 5667
4/4 — Epoch	25/500	0s	2ms/step	-	LOSS:	3823.5667
4/4 —	26 /500	0s	2ms/step	-	loss:	3814.0737
4/4 —	26/500	0s	2ms/step	-	loss:	3538.2739

Epoch 27/500 4/4	0s	2ms/step	_	loss:	4052.5713
Epoch 28/500					3775.7695
Epoch 29/500 4/4	0s	2ms/step	_	loss:	3720.6047
Epoch 30/500 4/4	0s	2ms/step	_	loss:	3863.3772
Epoch 31/500 4/4	0s	2ms/step	_	loss:	3772.0359
Epoch 32/500 4/4					3683.1426
Epoch 33/500 4/4	0s	2ms/step	_	loss:	3871.5901
Epoch 34/500					3788.1516
Epoch 35/500 4/4	0s	2ms/step	_	loss:	3814.4290
Epoch 36/500 4/4	0s	1ms/step	_	loss:	3506.7356
Epoch 37/500 4/4	0s	2ms/step	_	loss:	3723.1694
Epoch 38/500 4/4	0s	2ms/step	_	loss:	3822.1555
Epoch 39/500 4/4	0s	2ms/step	_	loss:	3647.8518
Epoch 40/500 4/4	0s	2ms/step	_	loss:	3642.1448
Epoch 41/500 4/4	0s	2ms/step	_	loss:	3834.0903
Epoch 42/500 4/4	0s	2ms/step	_	loss:	3767.7690
Epoch 43/500 4/4	0s	2ms/step	_	loss:	3666.2305
Epoch 44/500 4/4	0s	1ms/step	_	loss:	3787.4944
Epoch 45/500 4/4	0s	2ms/step	_	loss:	3585.8687
Epoch 46/500 4/4	0s	2ms/step	_	loss:	3544.5134
Epoch 47/500 4/4 ———————————————————————————————————	0s	2ms/step	_	loss:	3781.7695
Epoch 48/500 4/4	0s	2ms/step	_	loss:	3680.3552
Epoch 49/500 4/4	0s	1ms/step	_	loss:	3668.9290
Epoch 50/500 4/4	0s	2ms/step	_	loss:	3537.4807
Epoch 51/500 4/4	0s	2ms/step	_	loss:	3689.3765
Epoch 52/500 4/4	0s	2ms/step	_	loss:	3855.9463
Epoch 53/500 4/4	0s	2ms/step	-	loss:	3758.1865
	0s	2ms/step	-	loss:	3819.4304
	0s	2ms/step	-	loss:	3773.0984
	0s	2ms/step	-	loss:	3617.3213
	0s	3ms/step	-	loss:	3531.2065
	0s	2ms/step	-	loss:	3621.2222
	0s	3ms/step	-	loss:	3594.0544
	0s	3ms/step	-	loss:	3549.4194
	0s	3ms/step	-	loss:	3401.9023
	0s	3ms/step	-	loss:	3801.1130
	0s	2ms/step	-	loss:	3791.5771
	0s	2ms/step	-	loss:	3904.9458
	0s	2ms/step	-	loss:	3530.1377
	0s	2ms/step	-	loss:	3497.6643
	0s	2ms/step	-	loss:	3849.0090
Epoch 68/500					

4/4 —	Θs	2ms/sten	_	lossi	3727 5684
Epoch 69/500					3599.6113
Epoch 70/500					3535.2051
Epoch 71/500		·			3587.6843
Epoch 72/500		·			3509.0911
Epoch 73/500		·			3870.8784
Epoch 74/500		·			3798.2300
Epoch 75/500					3791.4351
Epoch 76/500		·			3647.5059
Epoch 77/500		·			3563.2153
Epoch 78/500		·			3664.1831
Epoch 79/500		,			
Epoch 80/500		·			3700.1953
Epoch 81/500		·			3486.6387
Epoch 82/500		·			3876.1418
Epoch 83/500					3756.5974
Epoch 84/500					3595.6028
Epoch 85/500		·			3649.3088
Epoch 86/500		·			3601.9756
Epoch 87/500		·			3534.1589
Epoch 88/500		·			3663.2859
Epoch 89/500		·			3457.1731
Epoch 90/500					3707.9893
Epoch 91/500		,			3850.4265
Epoch 92/500					3573.3037
Epoch 93/500		·			3787.0315
Epoch 94/500		,			3530.4341
Epoch 95/500		·			3726.6323
Epoch 96/500		·			3707.8538 3675.9597
Epoch 97/500		,			
Epoch 98/500					3565.5083 3821.0054
Epoch 99/500					
Epoch 100/500		·			3659.5000 3803.7878
Epoch 101/500					
Epoch 102/500		·			3683.3623
Epoch 103/500					3575.9302 3881.7678
Epoch 104/500		·			
Epoch 105/500		·			3521.8792
Epoch 106/500		·			3663.3721
Epoch 107/500					3762.2756
Epoch 108/500		·			3466.2732
4/4 — Epoch 109/500		·			3778.4080
4/4 ————	υS	ziiis/step	-	1055:	3865.4961

Epoch 110/500 4/4	0s	2ms/step	_	loss:	3657.7354
Epoch 111/500 4/4	0s	3ms/step	_	loss:	3577.7549
Epoch 112/500 4/4	0s	3ms/step	_	loss:	3555.4988
Epoch 113/500 4/4					3402.5037
Epoch 114/500 4/4					3601.8081
Epoch 115/500					3877.0283
Epoch 116/500					3460.6855
Epoch 117/500					3695.4744
Epoch 118/500					3547.4724
Epoch 119/500					3823.6931
Epoch 120/500					3749.3816
Epoch 121/500		·			3551.9087
Epoch 122/500					3708.9658
Epoch 123/500					
Epoch 124/500					3624.6333
Epoch 125/500					3543.9485
4/4 Epoch 126/500					3637.2446
4/4 Epoch 127/500					3528.6948
4/4 Epoch 128/500					3726.1416
Epoch 129/500					3561.2117
4/4 Epoch 130/500		·			3685.8352
4/4 Epoch 131/500					3792.5557
4/4 Epoch 132/500					3508.3396
Epoch 133/500					3611.1714
Epoch 134/500					3676.2795
Epoch 135/500		·			3486.2947
Epoch 136/500					3752.9761
Epoch 137/500					3597.2219
Epoch 138/500					3823.5085
Epoch 139/500		·			3442.4275
Epoch 140/500					3827.8149
Epoch 141/500					3535.0696
Epoch 142/500		·			3582.6538
Epoch 143/500					3740.8047
Epoch 144/500					3583.7705
Epoch 145/500		·			3692.0676
Epoch 146/500		·			3339.5420
Epoch 147/500					3575.7456
Epoch 148/500					3555.1521
Epoch 149/500		•			3795.9875
Epoch 150/500					3550.7166
4/4 Epoch 151/500	0s	2ms/step	-	loss:	3612.2913

4/4	0.5	2mc/ston		10001	3668.6956
Epoch 152/500					
Epoch 153/500					3428.4895
Epoch 154/500		·			3717.8928
Epoch 155/500					3665.3367
Epoch 156/500		·			3798.4753
Epoch 157/500		·			3694.0249
Epoch 158/500	0s	3ms/step	-	loss:	3592.8997
Epoch 159/500	0s	3ms/step	-	loss:	3570.4670
4/4 Epoch 160/500	0s	2ms/step	-	loss:	3610.2344
Epoch 161/500	0s	2ms/step	-	loss:	3646.8958
4/4 Epoch 162/500	0s	2ms/step	-	loss:	3790.3738
4/4 Epoch 163/500	0s	2ms/step	-	loss:	3686.1350
4/4 Epoch 164/500	0s	2ms/step	-	loss:	3595.1726
4/4 Epoch 165/500	0s	3ms/step	-	loss:	3685.2866
4/4 Epoch 166/500	0s	3ms/step	-	loss:	3610.4939
4/4 — Epoch 167/500	0s	2ms/step	-	loss:	3759.0813
4/4 — Epoch 168/500	0s	3ms/step	-	loss:	3503.3552
4/4 — Epoch 169/500	0s	2ms/step	-	loss:	3902.9788
•	0s	3ms/step	-	loss:	3749.9226
4/4 — Epoch 171/500	0s	3ms/step	-	loss:	3570.8782
•	0s	2ms/step	-	loss:	3676.9365
-	0s	2ms/step	-	loss:	3787.3030
	0s	2ms/step	-	loss:	3285.4719
•	0s	2ms/step	-	loss:	3738.2148
-	0s	2ms/step	-	loss:	3722.9512
•	0s	3ms/step	-	loss:	3859.4263
4/4 — Epoch 178/500	0s	3ms/step	-	loss:	3531.3284
•	0s	2ms/step	-	loss:	3542.4065
•	0s	2ms/step	-	loss:	3951.8823
•	0s	2ms/step	-	loss:	3601.0166
•	0s	2ms/step	-	loss:	3665.3298
•	0s	2ms/step	-	loss:	3785.4243
•	0s	2ms/step	-	loss:	3615.0276
•	0s	2ms/step	-	loss:	3578.2012
•	0s	2ms/step	-	loss:	3547.1123
•	0s	3ms/step	-	loss:	3948.3577
-	0s	3ms/step	-	loss:	3787.9390
•	0s	2ms/step	-	loss:	3595.8418
•	0s	3ms/step	-	loss:	3734.6472
•	0s	2ms/step	-	loss:	3612.0278
4/4	0s	3ms/step	-	loss:	3693.4551
Epoch 192/500 4/4	0s	2ms/step	-	loss:	3711.5449

Epoch 193/500 4/4	0s	2ms/step	_	loss:	3581.8889
Epoch 194/500 4/4	0s	5ms/step	_	loss:	3506.9919
Epoch 195/500 4/4	0s	2ms/step	_	loss:	3611.2136
Epoch 196/500		·			3627.6519
Epoch 197/500		·			3451.8752
Epoch 198/500		·			3718.3813
Epoch 199/500		·			3618.7676
Epoch 200/500		·			3684.1008
Epoch 201/500		·			3488.1860
Epoch 202/500		·			3566.0291
Epoch 203/500		·			3641.5952
Epoch 204/500		·			3890.7412
Epoch 205/500		·			3665.7502
Epoch 206/500		·			
Epoch 207/500					3487.6699
Epoch 208/500		·			3779.0593
Epoch 209/500		·			3736.5266
4/4 Epoch 210/500		·			3628.9646
4/4 Epoch 211/500		·			3792.7427
Epoch 212/500		·			3514.5664
4/4 Epoch 213/500		·			3654.5886
4/4 — Epoch 214/500		·			3823.3696
4/4 — Epoch 215/500		·			3664.6343
Epoch 216/500		•			3659.7388
Epoch 217/500					3665.6597
Epoch 218/500					3681.1626
Epoch 219/500					3714.9773
Epoch 220/500		·			3735.9863
Epoch 221/500		·			3583.6680
Epoch 222/500					3386.2151
Epoch 223/500		·			3663.6296
Epoch 224/500		·			3582.3069
Epoch 225/500		·			3695.7581
Epoch 226/500					3746.1292
Epoch 227/500		·			3752.8557
Epoch 228/500		·			3622.3643
Epoch 229/500		·			3698.0437
Epoch 230/500					3506.3298
Epoch 231/500		·			3529.7114
Epoch 232/500					3594.5698
Epoch 233/500		·			3718.9463
4/4 Epoch 234/500	0s	2ms/step	-	loss:	3647.6880

4/4	0.5	2mc/cton		10001	3669.1826
Epoch 235/500					
Epoch 236/500					3814.9971
Epoch 237/500		·			3625.0571
Epoch 238/500		·			3615.2637
Epoch 239/500		·			3697.3149
Epoch 240/500		·			3550.8381
Epoch 241/500	0s	2ms/step	-	loss:	3699.4607
Epoch 242/500	0s	2ms/step	-	loss:	3607.7410
4/4 Epoch 243/500	0s	2ms/step	-	loss:	3568.6294
4/4 Epoch 244/500	0s	2ms/step	-	loss:	3595.2551
4/4 Epoch 245/500	0s	2ms/step	-	loss:	3672.4287
4/4 Epoch 246/500	0s	2ms/step	-	loss:	3741.0073
4/4 Epoch 247/500	0s	3ms/step	-	loss:	3550.4480
	0s	2ms/step	-	loss:	3858.6042
•	0s	2ms/step	-	loss:	3607.4082
•	0s	2ms/step	-	loss:	3713.8374
•	0s	2ms/step	-	loss:	3493.0554
-	0s	2ms/step	-	loss:	3716.6240
•	0s	3ms/step	-	loss:	3494.5198
4/4 ———————————————————————————————————	0s	2ms/step	-	loss:	3503.6211
•	0s	3ms/step	-	loss:	3549.8018
•	0s	2ms/step	-	loss:	3619.2717
•	0s	2ms/step	-	loss:	3425.4307
4/4 ————	0s	2ms/step	-	loss:	3591.0955
-	0s	2ms/step	-	loss:	3617.0510
	0s	3ms/step	-	loss:	3730.2864
Epoch 260/500 4/4	0s	3ms/step	-	loss:	3760.6926
•	0s	2ms/step	-	loss:	3480.3313
	0s	2ms/step	-	loss:	3680.2073
	0s	3ms/step	-	loss:	3577.4744
	0s	2ms/step	-	loss:	3598.9878
	0s	3ms/step	-	loss:	3557.6548
	0s	2ms/step	-	loss:	3580.0815
	0s	2ms/step	-	loss:	3443.1519
	0s	2ms/step	-	loss:	3607.0271
	0s	2ms/step	-	loss:	3751.3823
	0s	2ms/step	-	loss:	3598.9592
	0s	2ms/step	-	loss:	3370.8289
	0s	2ms/step	-	loss:	3749.4119
	0s	2ms/step	-	loss:	3765.1172
	0s	2ms/step	-	loss:	3753.7019
Epoch 275/500 4/4	0s	2ms/step	-	loss:	3530.5029

Epoch 276/500					
•	0s	2ms/step	-	loss:	3762.7134
4/4 —	0s	3ms/step	-	loss:	3647.8623
Epoch 278/500 4/4 ———————————————————————————————————	0s	2ms/step	-	loss:	3965.6323
Epoch 279/500 4/4	0s	2ms/step	-	loss:	3584.4011
Epoch 280/500 4/4	0s	2ms/step	-	loss:	3809.0718
Epoch 281/500 4/4	0s	2ms/step	-	loss:	3662.9648
Epoch 282/500 4/4	0s	3ms/step	-	loss:	3645.3472
	0s	2ms/step	-	loss:	3657.3889
Epoch 284/500 4/4	0s	2ms/step	-	loss:	3481.8865
Epoch 285/500 4/4	0s	2ms/step	-	loss:	3731.1421
Epoch 286/500 4/4	0s	2ms/step	-	loss:	3430.5081
Epoch 287/500 4/4	0s	3ms/step	-	loss:	3649.5869
Epoch 288/500 4/4	0s	2ms/step	-	loss:	3413.8455
Epoch 289/500 4/4	0s	3ms/step	-	loss:	3618.4810
Epoch 290/500 4/4	0s	3ms/step	-	loss:	3416.5496
Epoch 291/500 4/4	0s	2ms/step	-	loss:	3460.8340
Epoch 292/500 4/4	0s	2ms/step	-	loss:	3669.0669
Epoch 293/500 4/4	0s	2ms/step	-	loss:	3797.7305
Epoch 294/500 4/4	0s	2ms/step	-	loss:	3699.3115
Epoch 295/500 4/4	0s	2ms/step	-	loss:	3474.9795
Epoch 296/500 4/4	0s	2ms/step	_	loss:	3598.8396
Epoch 297/500 4/4	0s	3ms/step	_	loss:	3687.4304
Epoch 298/500 4/4	0s	2ms/step	_	loss:	3549.9939
Epoch 299/500 4/4	0s	2ms/step	_	loss:	3672.8447
Epoch 300/500					3427.4580
Epoch 301/500 4/4	0s	3ms/step	_	loss:	3588.5837
Epoch 302/500 4/4	0s	3ms/step	_	loss:	3783.2983
Epoch 303/500 4/4	0s	2ms/step	_	loss:	3646.0210
Epoch 304/500 4/4	0s	2ms/step	_	loss:	3685.8931
Epoch 305/500		·			3611.5291
Epoch 306/500		·			3509.1682
Epoch 307/500 4/4	0s	2ms/step	_	loss:	3665.7490
Epoch 308/500					3691.6858
Epoch 309/500					3461.4661
Epoch 310/500		·			3729.0508
Epoch 311/500		·			3452.7273
Epoch 312/500					3438.2395
Epoch 313/500					3399.6455
Epoch 314/500		·			3382.0073
Epoch 315/500		·			3629.9778
Epoch 316/500		·			3454.3887
Epoch 317/500	- -	-, στορ			

4/4	As	2ms/sten	_	1055.	3618.9810
Epoch 318/500					3439.9214
Epoch 319/500					
Epoch 320/500		·			3635.2361
Epoch 321/500		·			3800.1772
Epoch 322/500		·			3781.1365
Epoch 323/500					3579.1440
Epoch 324/500		·			3678.7109
Epoch 325/500		·			3768.5339
Epoch 326/500		·			3632.6880
Epoch 327/500		·			3634.0393
Epoch 328/500	0s	2ms/step	-	loss:	3466.8225
4/4 Epoch 329/500	0s	2ms/step	-	loss:	3790.4399
Epoch 330/500	0s	2ms/step	-	loss:	3560.4646
4/4 Epoch 331/500	0s	2ms/step	-	loss:	3512.8240
4/4 Epoch 332/500	0s	2ms/step	-	loss:	3444.1353
4/4 Epoch 333/500	0s	3ms/step	-	loss:	3560.3945
4/4 Epoch 334/500	0s	2ms/step	-	loss:	3759.6860
4/4 — Epoch 335/500	0s	2ms/step	-	loss:	3587.9236
4/4 — Epoch 336/500	0s	3ms/step	-	loss:	3354.6216
4/4 — Epoch 337/500	0s	2ms/step	-	loss:	3655.8999
4/4 — Epoch 338/500	0s	2ms/step	-	loss:	3842.3271
-	0s	2ms/step	-	loss:	3597.5894
	0s	2ms/step	-	loss:	3623.5762
-	0s	2ms/step	-	loss:	3700.5781
-	0s	2ms/step	-	loss:	3661.3533
•	0s	2ms/step	-	loss:	3481.2271
•	0s	2ms/step	-	loss:	3695.5081
•	0s	3ms/step	-	loss:	3361.4939
4/4 — Epoch 346/500	0s	3ms/step	-	loss:	3602.6375
•	0s	3ms/step	-	loss:	3356.3799
•	0s	3ms/step	-	loss:	3488.1899
	0s	2ms/step	-	loss:	3624.3035
•	0s	2ms/step	-	loss:	3441.5093
•	0s	2ms/step	-	loss:	3568.8315
-	0s	2ms/step	-	loss:	3781.4521
•	0s	2ms/step	-	loss:	3520.7346
-	0s	2ms/step	-	loss:	3391.4167
•	0s	3ms/step	-	loss:	3540.0449
-	0s	2ms/step	-	loss:	3607.8835
	0s	2ms/step	-	loss:	3780.1013
4/4	0s	2ms/step	-	loss:	3523.0718
Epoch 358/500 4/4	0s	2ms/step	-	loss:	3481.7930

Frach 250/500					
	0s	2ms/step	-	loss:	3504.8594
Epoch 360/500 4/4	0s	2ms/step	-	loss:	3634.7908
Epoch 361/500 4/4	0s	2ms/step	_	loss:	3379.5002
Epoch 362/500 4/4	0s	2ms/step	_	loss:	3667.7012
Epoch 363/500 4/4	0s	2ms/step	_	loss:	3579.1216
Epoch 364/500 4/4		•			3443.5920
Epoch 365/500		·			3610.8706
Epoch 366/500		•			3620.2825
Epoch 367/500		•			3428.5823
Epoch 368/500 4/4		•			3645.2622
Epoch 369/500		·			3346.5510
Epoch 370/500		•			
Epoch 371/500		•			3419.8677
4/4 Epoch 372/500					3613.5229
Epoch 373/500		·			3432.3372
Epoch 374/500		•			3686.5540
Epoch 375/500					3697.0808
4/4 — Epoch 376/500		·			3509.4854
4/4 — Epoch 377/500		•			3482.5789
Epoch 378/500		•			3927.1260
4/4 Epoch 379/500					3488.9758
4/4 Epoch 380/500	0s	2ms/step	-	loss:	3431.9539
4/4 Epoch 381/500	0s	2ms/step	-	loss:	3522.4609
Epoch 382/500		•			3542.3809
4/4 Epoch 383/500	0s	2ms/step	-	loss:	3497.3472
4/4 Epoch 384/500	0s	3ms/step	-	loss:	3804.5195
4/4 Epoch 385/500	0s	2ms/step	-	loss:	3419.8145
4/4 Epoch 386/500	0s	10ms/step	ο .	- loss	: 3566.4260
4/4 Epoch 387/500	0s	2ms/step	-	loss:	3688.1892
4/4 Epoch 388/500	0s	2ms/step	-	loss:	3496.9563
4/4 Epoch 389/500	0s	3ms/step	-	loss:	3615.3118
4/4 Epoch 390/500	0s	3ms/step	-	loss:	3472.7603
4/4 ———————————————————————————————————	0s	2ms/step	-	loss:	3523.1501
4/4 — Epoch 392/500	0s	2ms/step	-	loss:	3315.7944
4/4 — Epoch 393/500	0s	2ms/step	-	loss:	3538.7412
•	0s	2ms/step	-	loss:	3736.2139
•	0s	2ms/step	-	loss:	3532.7183
•	0s	3ms/step	-	loss:	3445.5337
•	0s	2ms/step	-	loss:	3695.7170
•	0s	3ms/step	-	loss:	3613.5110
•	0s	3ms/step	-	loss:	3468.6104
4/4 —	0s	2ms/step	-	loss:	3463.7615
Epoch 400/500					

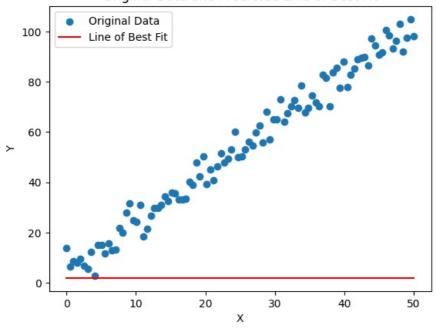
4/4	0.5	2mc/ston		10001	2650 0005
Epoch 401/500					3650.0085
Epoch 402/500					3731.3623
Epoch 403/500		·			3431.4224
Epoch 404/500		·			3700.9255
Epoch 405/500		·			3497.9287
Epoch 406/500		·			3666.8196
Epoch 407/500		·			3664.5974
Epoch 408/500	0s	2ms/step	-	loss:	3716.5508
4/4 Epoch 409/500	0s	2ms/step	-	loss:	3601.4985
Epoch 410/500	0s	2ms/step	-	loss:	3406.0740
4/4 Epoch 411/500	0s	2ms/step	-	loss:	3599.0664
4/4 Epoch 412/500	0s	2ms/step	-	loss:	3616.6870
4/4 Epoch 413/500	0s	2ms/step	-	loss:	3700.8440
4/4 Epoch 414/500	0s	3ms/step	-	loss:	3593.4841
4/4 — Epoch 415/500	0s	2ms/step	-	loss:	3603.2903
4/4 — Epoch 416/500	0s	3ms/step	-	loss:	3427.0139
4/4 — Epoch 417/500	0s	2ms/step	-	loss:	3426.0276
-	0s	2ms/step	-	loss:	3498.4465
•	0s	2ms/step	-	loss:	3407.2537
4/4 — Epoch 420/500	0s	2ms/step	-	loss:	3585.5059
•	0s	2ms/step	-	loss:	3606.3254
•	0s	2ms/step	-	loss:	3434.1121
•	0s	2ms/step	-	loss:	3425.1160
•	0s	2ms/step	-	loss:	3527.1877
-	0s	2ms/step	-	loss:	3420.0227
•	0s	3ms/step	-	loss:	3597.9490
4/4 Epoch 427/500	0s	3ms/step	-	loss:	3586.9204
•	0s	3ms/step	-	loss:	3462.8303
•	0s	2ms/step	-	loss:	3628.2527
•	0s	2ms/step	-	loss:	3614.9878
•	0s	3ms/step	-	loss:	3508.2495
•	0s	2ms/step	-	loss:	3546.2881
-	0s	3ms/step	-	loss:	3644.9766
•	0s	2ms/step	-	loss:	3596.0020
•	0s	2ms/step	-	loss:	3566.9639
•	0s	2ms/step	-	loss:	3566.3191
•	0s	3ms/step	-	loss:	3641.2190
4/4 ————	0s	2ms/step	-	loss:	3493.6919
	0s	2ms/step	-	loss:	3596.1484
	0s	2ms/step	-	loss:	3431.0552
	0s	2ms/step	-	loss:	3769.8232
Epoch 441/500 4/4	0s	2ms/step	-	loss:	3681.7207

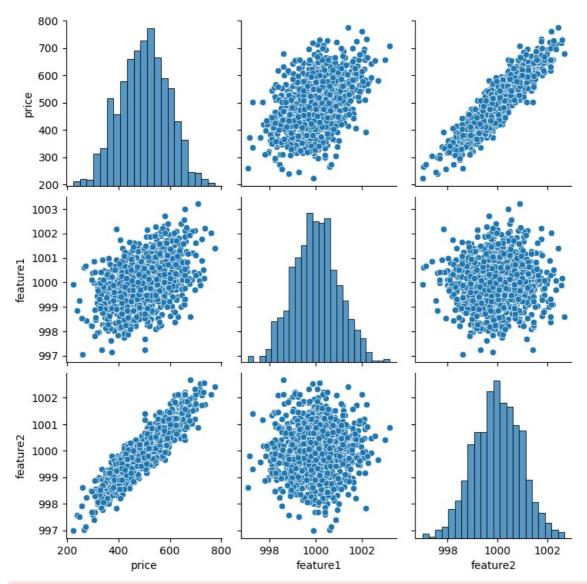
F b. 442 /F00			
	s 3ms/st	ep - loss:	3621.2769
	s 2ms/st	ep - loss:	3625.0840
Epoch 444/500 4/4	s 2ms/st	ep - loss:	3457.6482
Epoch 445/500 4/4 ———————————————————————————————————	s 2ms/st	ep - loss:	3390.5500
Epoch 446/500 4/4)s 2ms/st	ep - loss:	3546.9133
Epoch 447/500 4/4)s 2ms/st	ep - loss:	3669.8533
Epoch 448/500 4/4)s 2ms/st	ep - loss:	3533.9375
Epoch 449/500		ep - loss:	
Epoch 450/500		ep - loss:	
Epoch 451/500		ep - loss:	
Epoch 452/500		ep - loss:	
Epoch 453/500		ep - loss:	
Epoch 454/500		ep - loss:	
Epoch 455/500			
Epoch 456/500		ep - loss:	
Epoch 457/500		ep - loss:	
Epoch 458/500		ep - loss:	
Epoch 459/500		ep - loss:	
Epoch 460/500		ep - loss: -	
Epoch 461/500		ep - loss:	
Epoch 462/500		ep - loss:	
4/4 Epoch 463/500)s 3ms/st	ep - loss:	3383.3713
4/4 Epoch 464/500	s 2ms/st	ep - loss:	3594.3408
Epoch 465/500		ep - loss:	
4/4 Epoch 466/500)s 13ms/s	tep - loss	: 3400.2600
4/4 Epoch 467/500	s 2ms/st	ep - loss:	3360.4033
4/4 Epoch 468/500	s 2ms/st	ep - loss:	3369.3276
4/4 Epoch 469/500	s 2ms/st	ep - loss:	3486.7615
4/4 Epoch 470/500	s 2ms/st	ep - loss:	3643.2195
4/4 Epoch 471/500	s 2ms/st	ep - loss:	3667.7383
4/4 Epoch 472/500	s 2ms/st	ep - loss:	3483.6396
4/4 Epoch 473/500	s 2ms/st	ep - loss:	3817.4968
4/4 Epoch 474/500	s 2ms/st	ep - loss:	3278.1777
4/4 — Epoch 475/500	s 2ms/st	ep - loss:	3666.5107
4/4 — Epoch 476/500	s 2ms/st	ep - loss:	3512.7146
•	s 2ms/st	ep - loss:	3425.8547
•	s 3ms/st	ep - loss:	3667.4707
•	s 2ms/st	ep - loss:	3402.9075
•	s 2ms/st	ep - loss:	3575.8669
•	s 2ms/st	ep - loss:	3597.7974
4/4 ————	s 2ms/st	ep - loss:	3645.1619
	s 2ms/st	ep - loss:	3564.3828
Epoch 483/500			

4/4	– 0s	2ms/step	-	loss:	3410.9966
Epoch 484/500 4/4	– 0s	2ms/step	_	loss:	3389.3645
Epoch 485/500 4/4	0c	2mc/stan		1000	3746 4028
Epoch 486/500		-			
4/4 Epoch 487/500		-			
4/4 — Epoch 488/500	– 0s	3ms/step	-	loss:	3426.7507
4/4	– 0s	2ms/step	-	loss:	3501.9563
Epoch 489/500 4/4	– 0s	2ms/step	-	loss:	3576.9556
Epoch 490/500 4/4	- 0s	2ms/sten	_	loss:	3598.8433
Epoch 491/500 4/4					
Epoch 492/500					
4/4 — Epoch 493/500	– 0s	2ms/step	-	loss:	3300.2268
4/4	– 0s	2ms/step	-	loss:	3499.2441
Epoch 494/500 4/4	– 0s	2ms/step	-	loss:	3603.8699
Epoch 495/500 4/4	– 0s	2ms/step	_	loss:	3428.2437
Epoch 496/500 4/4					
Epoch 497/500					
4/4 — Epoch 498/500					
4/4 — Epoch 499/500	– 0s	2ms/step	-	loss:	3356.8669
4/4	— 0s	2ms/step	-	loss:	3345.0784
Epoch 500/500 4/4	– 0s	2ms/step	_	loss:	3525.1396
Model: "sequential"					

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 4)	8
dense_1 (Dense)	(None, 4)	20
dense_2 (Dense)	(None, 1)	5

Original Data and Predicted Line of Best Fit

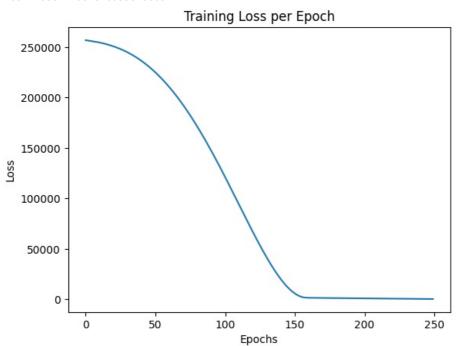




c:\Users\mainp\AppData\Local\Programs\Python\Python311\Lib\site-packages\keras\src\layers\core\dense.py:86: User
Warning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer usin
g an `Input(shape)` object as the first layer in the model instead.

super().__init__(activity_regularizer=activity_regularizer, **kwargs)

Training Loss: 419.9224548339844 Test Loss: 408.3269958496094



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