experiment_12

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Course Name:	Deep Learning Lab
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Experiment:	12
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0.1 Question 1: Fit a Bi-directional LSTM model to predict the next day gold price given the gold price of 10 consecutive days. Use the dataset provided in Experiment 9. Now compare your results with the normal RNN model you have already fitted.

0.1.1 importing the necessary libraries

[8]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error, r2_score
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import SimpleRNN, LSTM, Bidirectional, Dense,␣
↪TimeDistributed
from tensorflow.keras.callbacks import EarlyStopping
import warnings
warnings.filterwarnings('ignore')
```

[9]:
```
np.random.seed(42)
```

0.1.2 Loading the dataset

[10]:
```
df = pd.read_csv("/kaggle/input/gold-price/gold_price.csv")
df
```

[10]:
```
        Date    Price
0    1833-01    18.93
1    1833-02    18.93
2    1833-03    18.93
```

```
3     1833-04    18.93
4     1833-05    18.93
…        …        …
2306  2025-03  2983.25
2307  2025-04  3217.64
2308  2025-05  3309.49
2309  2025-06  3352.66
2310  2025-07  3340.15

[2311 rows x 2 columns]
```

[11]:
```python
data = df['Price'].values.reshape(-1,1)
data
```

[11]:
```
array([[  18.93],
       [  18.93],
       [  18.93],
       …,
       [3309.49],
       [3352.66],
       [3340.15]])
```

0.1.3 Scaling the data

[12]:
```python
scaler = MinMaxScaler()
data_scaled = scaler.fit_transform(data)
```

0.1.4 Data Preparation

[13]:
```python
train_size = int(len(data_scaled)*0.8)
train_data = data_scaled[:train_size]
test_data = data_scaled[train_size:]
```

[14]:
```python
def create_sequences(data, input_length = 10, output_length = 10):
    x,y = [],[]
    for i in range(len(data)-input_length-output_length+1):
        x.append(data[i:i+input_length])
        y.append(data[i+input_length:i+input_length+output_length])
    return np.array(x), np.array(y)

input_length = 10
output_length = 10
x_train_full, y_train_full = create_sequences(train_data, input_length,␣
 ↪output_length)
x_test,y_test = create_sequences(test_data, input_length, output_length)
```

[15]:
```
val_fraction = 0.2
val_size = int(len(x_train_full)*val_fraction)

x_val = x_train_full[-val_size:]
y_val = y_train_full[-val_size:]

x_train = x_train_full[:-val_size]
y_train = y_train_full[:-val_size]
```

0.1.5 Building and evaluating by RNN model

[16]:
```
model = Sequential()
model.add(SimpleRNN(64, activation = 'tanh', return_sequences=True, input_shape␣
↪= (input_length,1)))
model.add(TimeDistributed(Dense(1)))

model.compile(optimizer='adam', loss = 'mean_squared_error')
model.summary()

early_stop = EarlyStopping(monitor = 'val_loss', patience = 10,␣
↪restore_best_weights=True, verbose=1)

history = model.fit(
    x_train,y_train,
    epochs = 500,
    batch_size = 16,
    validation_data = (x_val,y_val),
    verbose = 1,
    callbacks=[early_stop]
)
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
simple_rnn (SimpleRNN)	(None, 10, 64)	4,224
time_distributed (TimeDistributed)	(None, 10, 1)	65

Total params: 4,289 (16.75 KB)

Trainable params: 4,289 (16.75 KB)

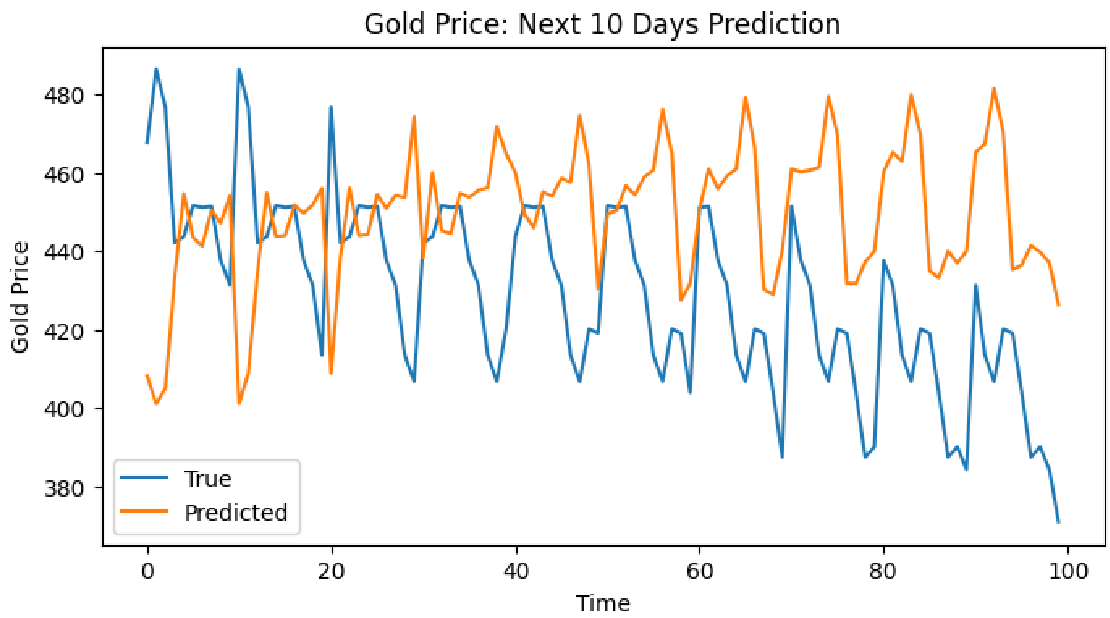
```
 Non-trainable params: 0 (0.00 B)

Epoch 1/500

WARNING: All log messages before absl::InitializeLog() is called are written to
STDERR
I0000 00:00:1761295987.279077     112 service.cc:148] XLA service 0x29e3e640
initialized for platform CUDA (this does not guarantee that XLA will be used).
Devices:
I0000 00:00:1761295987.280096     112 service.cc:156]   StreamExecutor device
(0): Tesla T4, Compute Capability 7.5
I0000 00:00:1761295987.280115     112 service.cc:156]   StreamExecutor device
(1): Tesla T4, Compute Capability 7.5
I0000 00:00:1761295987.558660     112 cuda_dnn.cc:529] Loaded cuDNN version
90300

63/92            0s 2ms/step - loss:
2.9922e-05

I0000 00:00:1761295988.718250     112 device_compiler.h:188] Compiled cluster
using XLA!  This line is logged at most once for the lifetime of the process.

92/92            6s 24ms/step -
loss: 2.3412e-05 - val_loss: 6.3514e-04
Epoch 2/500
92/92            0s 4ms/step - loss:
2.8970e-07 - val_loss: 5.2329e-04
Epoch 3/500
92/92            0s 4ms/step - loss:
2.1163e-07 - val_loss: 4.8959e-04
Epoch 4/500
92/92            0s 4ms/step - loss:
1.4307e-07 - val_loss: 4.7340e-04
Epoch 5/500
92/92            0s 4ms/step - loss:
1.4871e-07 - val_loss: 4.5697e-04
Epoch 6/500
92/92            0s 4ms/step - loss:
1.5850e-07 - val_loss: 4.4838e-04
Epoch 7/500
92/92            0s 4ms/step - loss:
1.2504e-07 - val_loss: 4.4195e-04
Epoch 8/500
92/92            0s 4ms/step - loss:
1.3084e-07 - val_loss: 4.3351e-04
Epoch 9/500
92/92            0s 4ms/step - loss:
1.5115e-07 - val_loss: 4.2935e-04
Epoch 10/500
```

```
92/92            0s 4ms/step - loss:
1.5966e-07 - val_loss: 4.2587e-04
Epoch 11/500
92/92            0s 4ms/step - loss:
1.4021e-07 - val_loss: 4.2291e-04
Epoch 12/500
92/92            0s 4ms/step - loss:
1.3425e-07 - val_loss: 4.2527e-04
Epoch 13/500
92/92            0s 4ms/step - loss:
1.2111e-07 - val_loss: 4.2202e-04
Epoch 14/500
92/92            0s 4ms/step - loss:
1.3579e-07 - val_loss: 4.2152e-04
Epoch 15/500
92/92            0s 4ms/step - loss:
1.0689e-07 - val_loss: 4.2098e-04
Epoch 16/500
92/92            0s 4ms/step - loss:
1.3036e-07 - val_loss: 4.2148e-04
Epoch 17/500
92/92            0s 4ms/step - loss:
1.5219e-07 - val_loss: 4.2154e-04
Epoch 18/500
92/92            0s 4ms/step - loss:
1.1955e-07 - val_loss: 4.1974e-04
Epoch 19/500
92/92            0s 4ms/step - loss:
1.4390e-07 - val_loss: 4.1823e-04
Epoch 20/500
92/92            0s 4ms/step - loss:
2.9235e-07 - val_loss: 4.2259e-04
Epoch 21/500
92/92            0s 4ms/step - loss:
1.2000e-07 - val_loss: 4.2321e-04
Epoch 22/500
92/92            0s 4ms/step - loss:
1.3220e-07 - val_loss: 4.2300e-04
Epoch 23/500
92/92            0s 4ms/step - loss:
2.2300e-07 - val_loss: 4.1949e-04
Epoch 24/500
92/92            0s 4ms/step - loss:
1.8356e-07 - val_loss: 4.2428e-04
Epoch 25/500
92/92            0s 4ms/step - loss:
2.0096e-07 - val_loss: 4.1890e-04
Epoch 26/500
```

```
92/92              0s 4ms/step - loss:
2.3200e-07 - val_loss: 4.2217e-04
Epoch 27/500
92/92              0s 4ms/step - loss:
6.9773e-08 - val_loss: 4.2140e-04
Epoch 28/500
92/92              0s 4ms/step - loss:
2.1022e-07 - val_loss: 4.2530e-04
Epoch 29/500
92/92              0s 4ms/step - loss:
1.3855e-07 - val_loss: 4.2069e-04
Epoch 29: early stopping
Restoring model weights from the end of the best epoch: 19.
```

[17]:
```
# Prediction
y_pred = model.predict(x_test)
y_pred_orig = scaler.inverse_transform(y_pred.reshape(-1,1))
y_test_orig = scaler.inverse_transform(y_test.reshape(-1,1))

# Evaluation
rmse = np.sqrt(mean_squared_error(y_test_orig, y_pred_orig))
r2 = r2_score(y_test_orig, y_pred_orig)

print("RMSE:", rmse)
print("R² Score:", r2)

# Plot results
plt.figure(figsize=(8,4))
plt.plot(y_test_orig[:100], label='True')
plt.plot(y_pred_orig[:100], label='Predicted')
plt.title("Gold Price: Next 10 Days Prediction")
plt.xlabel("Time")
plt.ylabel("Gold Price")
plt.legend()
plt.show()
```

```
14/14              1s 47ms/step
RMSE: 186.7050094694
R² Score: 0.9112067557553054
```



0.1.6 Using BILSTM model

[18]:
```
bi_lstm_model = Sequential()
bi_lstm_model.add(Bidirectional(
    LSTM(64,activation='tanh', return_sequences=True),
    input_shape = (input_length,1)
))
bi_lstm_model.add(TimeDistributed(Dense(1)))

bi_lstm_model.compile(optimizer = 'adam', loss = 'mean_squared_error')
bi_lstm_model.summary()

history_bi = bi_lstm_model.fit(
    x_train,y_train,
    epochs = 500,
    batch_size = 16,
    validation_data = (x_val,y_val),
    verbose = 1,
    callbacks = [early_stop]
)
```

```
Model: "sequential_2"


 Layer (type)                    Output Shape                  Param #
```

```
 bidirectional (Bidirectional)     (None, 10, 128)                 33,792

 time_distributed_1                (None, 10, 1)                      129
 (TimeDistributed)
```

Total params: 33,921 (132.50 KB)

Trainable params: 33,921 (132.50 KB)

Non-trainable params: 0 (0.00 B)

```
Epoch 1/500
92/92              5s 16ms/step -
loss: 1.0710e-05 - val_loss: 0.0015
Epoch 2/500
92/92              1s 7ms/step - loss:
1.0688e-06 - val_loss: 5.2557e-04
Epoch 3/500
92/92              1s 7ms/step - loss:
2.9227e-07 - val_loss: 3.9701e-04
Epoch 4/500
92/92              1s 7ms/step - loss:
2.0633e-07 - val_loss: 3.9914e-04
Epoch 5/500
92/92              1s 7ms/step - loss:
1.5224e-07 - val_loss: 3.9983e-04
Epoch 6/500
92/92              1s 7ms/step - loss:
1.4891e-07 - val_loss: 3.9675e-04
Epoch 7/500
92/92              1s 7ms/step - loss:
1.5273e-07 - val_loss: 3.9638e-04
Epoch 8/500
92/92              1s 7ms/step - loss:
1.8116e-07 - val_loss: 3.9759e-04
Epoch 9/500
92/92              1s 7ms/step - loss:
1.7967e-07 - val_loss: 3.9861e-04
Epoch 10/500
92/92              1s 7ms/step - loss:
2.8959e-07 - val_loss: 3.9980e-04
Epoch 11/500
92/92              1s 7ms/step - loss:
1.5154e-07 - val_loss: 3.9736e-04
Epoch 12/500
```

```
92/92              1s 7ms/step - loss:
1.2115e-07 - val_loss: 4.0076e-04
Epoch 13/500
92/92              1s 7ms/step - loss:
2.0046e-07 - val_loss: 3.9604e-04
Epoch 14/500
92/92              1s 7ms/step - loss:
2.0586e-07 - val_loss: 3.9899e-04
Epoch 15/500
92/92              1s 7ms/step - loss:
1.7687e-07 - val_loss: 3.9823e-04
Epoch 16/500
92/92              1s 7ms/step - loss:
1.8910e-07 - val_loss: 3.9699e-04
Epoch 17/500
92/92              1s 7ms/step - loss:
1.3568e-07 - val_loss: 3.9636e-04
Epoch 18/500
92/92              1s 7ms/step - loss:
1.8496e-07 - val_loss: 3.9764e-04
Epoch 19/500
92/92              1s 7ms/step - loss:
1.5573e-07 - val_loss: 3.9528e-04
Epoch 20/500
92/92              1s 7ms/step - loss:
3.5770e-07 - val_loss: 3.9545e-04
Epoch 21/500
92/92              1s 7ms/step - loss:
1.2461e-07 - val_loss: 3.9392e-04
Epoch 22/500
92/92              1s 7ms/step - loss:
1.7862e-07 - val_loss: 3.9504e-04
Epoch 23/500
92/92              1s 7ms/step - loss:
1.3434e-07 - val_loss: 3.9399e-04
Epoch 24/500
92/92              1s 7ms/step - loss:
1.8069e-07 - val_loss: 3.9545e-04
Epoch 25/500
92/92              1s 7ms/step - loss:
1.7114e-07 - val_loss: 3.9163e-04
Epoch 26/500
92/92              1s 7ms/step - loss:
1.5392e-07 - val_loss: 3.9266e-04
Epoch 27/500
92/92              1s 7ms/step - loss:
1.7987e-07 - val_loss: 3.9154e-04
Epoch 28/500
```

```
92/92            1s 7ms/step - loss:
1.4647e-07 - val_loss: 3.9217e-04
Epoch 29/500
92/92            1s 7ms/step - loss:
1.4289e-07 - val_loss: 3.9165e-04
Epoch 30/500
92/92            1s 7ms/step - loss:
1.8981e-07 - val_loss: 3.9075e-04
Epoch 31/500
92/92            1s 7ms/step - loss:
1.8342e-07 - val_loss: 3.9176e-04
Epoch 32/500
92/92            1s 7ms/step - loss:
1.8744e-07 - val_loss: 3.8595e-04
Epoch 33/500
92/92            1s 7ms/step - loss:
1.4892e-07 - val_loss: 3.8678e-04
Epoch 34/500
92/92            1s 7ms/step - loss:
1.0678e-07 - val_loss: 3.8459e-04
Epoch 35/500
92/92            1s 7ms/step - loss:
3.0573e-07 - val_loss: 3.8596e-04
Epoch 36/500
92/92            1s 7ms/step - loss:
1.2692e-07 - val_loss: 3.8467e-04
Epoch 37/500
92/92            1s 7ms/step - loss:
1.3147e-07 - val_loss: 3.8366e-04
Epoch 38/500
92/92            1s 7ms/step - loss:
1.3421e-07 - val_loss: 3.8134e-04
Epoch 39/500
92/92            1s 7ms/step - loss:
1.1967e-07 - val_loss: 3.8438e-04
Epoch 40/500
92/92            1s 7ms/step - loss:
1.9595e-07 - val_loss: 3.7835e-04
Epoch 41/500
92/92            1s 7ms/step - loss:
1.4387e-07 - val_loss: 3.7935e-04
Epoch 42/500
92/92            1s 7ms/step - loss:
2.1298e-07 - val_loss: 3.7809e-04
Epoch 43/500
92/92            1s 7ms/step - loss:
1.1347e-07 - val_loss: 3.7753e-04
Epoch 44/500
```

```
92/92            1s 7ms/step - loss:
1.2188e-07 - val_loss: 3.7717e-04
Epoch 45/500
92/92            1s 7ms/step - loss:
1.0146e-07 - val_loss: 3.7515e-04
Epoch 46/500
92/92            1s 7ms/step - loss:
1.1224e-07 - val_loss: 3.7476e-04
Epoch 47/500
92/92            1s 7ms/step - loss:
1.2226e-07 - val_loss: 3.7410e-04
Epoch 48/500
92/92            1s 7ms/step - loss:
1.5474e-07 - val_loss: 3.7248e-04
Epoch 49/500
92/92            1s 7ms/step - loss:
1.1321e-07 - val_loss: 3.7601e-04
Epoch 50/500
92/92            1s 7ms/step - loss:
1.2579e-07 - val_loss: 3.6973e-04
Epoch 51/500
92/92            1s 7ms/step - loss:
1.6851e-07 - val_loss: 3.7596e-04
Epoch 52/500
92/92            1s 7ms/step - loss:
1.9137e-07 - val_loss: 3.7216e-04
Epoch 53/500
92/92            1s 7ms/step - loss:
1.2570e-07 - val_loss: 3.6932e-04
Epoch 54/500
92/92            1s 7ms/step - loss:
9.2349e-08 - val_loss: 3.7010e-04
Epoch 55/500
92/92            1s 7ms/step - loss:
1.0150e-07 - val_loss: 3.6872e-04
Epoch 56/500
92/92            1s 7ms/step - loss:
2.1384e-07 - val_loss: 3.7768e-04
Epoch 57/500
92/92            1s 7ms/step - loss:
1.1757e-07 - val_loss: 3.7302e-04
Epoch 58/500
92/92            1s 7ms/step - loss:
1.4827e-07 - val_loss: 3.7008e-04
Epoch 59/500
92/92            1s 7ms/step - loss:
1.6573e-07 - val_loss: 3.6915e-04
Epoch 60/500
```

```
92/92              1s 7ms/step - loss:
1.3518e-07 - val_loss: 3.6574e-04
Epoch 61/500
92/92              1s 7ms/step - loss:
1.2757e-07 - val_loss: 3.6593e-04
Epoch 62/500
92/92              1s 7ms/step - loss:
1.1473e-07 - val_loss: 3.7203e-04
Epoch 63/500
92/92              1s 7ms/step - loss:
1.3397e-07 - val_loss: 3.6386e-04
Epoch 64/500
92/92              1s 7ms/step - loss:
1.3648e-07 - val_loss: 3.7098e-04
Epoch 65/500
92/92              1s 7ms/step - loss:
1.0484e-07 - val_loss: 3.6444e-04
Epoch 66/500
92/92              1s 7ms/step - loss:
1.0648e-07 - val_loss: 3.6441e-04
Epoch 67/500
92/92              1s 7ms/step - loss:
1.1889e-07 - val_loss: 3.6512e-04
Epoch 68/500
92/92              1s 7ms/step - loss:
8.4904e-08 - val_loss: 3.6223e-04
Epoch 69/500
92/92              1s 7ms/step - loss:
9.8827e-08 - val_loss: 3.6328e-04
Epoch 70/500
92/92              1s 7ms/step - loss:
1.2392e-07 - val_loss: 3.6106e-04
Epoch 71/500
92/92              1s 7ms/step - loss:
1.1559e-07 - val_loss: 3.6352e-04
Epoch 72/500
92/92              1s 7ms/step - loss:
1.8298e-07 - val_loss: 3.5981e-04
Epoch 73/500
92/92              1s 7ms/step - loss:
1.3921e-07 - val_loss: 3.6111e-04
Epoch 74/500
92/92              1s 7ms/step - loss:
1.8179e-07 - val_loss: 3.6311e-04
Epoch 75/500
92/92              1s 7ms/step - loss:
1.2298e-07 - val_loss: 3.6648e-04
Epoch 76/500
```

```
92/92            1s 7ms/step - loss:
1.0086e-07 - val_loss: 3.6320e-04
Epoch 77/500
92/92            1s 7ms/step - loss:
1.9350e-07 - val_loss: 3.7138e-04
Epoch 78/500
92/92            1s 7ms/step - loss:
1.0791e-07 - val_loss: 3.6154e-04
Epoch 79/500
92/92            1s 7ms/step - loss:
1.3756e-07 - val_loss: 3.5857e-04
Epoch 80/500
92/92            1s 7ms/step - loss:
1.3152e-07 - val_loss: 3.6630e-04
Epoch 81/500
92/92            1s 7ms/step - loss:
1.4106e-07 - val_loss: 3.6482e-04
Epoch 82/500
92/92            1s 7ms/step - loss:
2.0275e-07 - val_loss: 3.6789e-04
Epoch 83/500
92/92            1s 7ms/step - loss:
1.5904e-07 - val_loss: 3.6566e-04
Epoch 84/500
92/92            1s 7ms/step - loss:
1.6535e-07 - val_loss: 3.5773e-04
Epoch 85/500
92/92            1s 7ms/step - loss:
1.4168e-07 - val_loss: 3.6708e-04
Epoch 86/500
92/92            1s 7ms/step - loss:
1.0750e-07 - val_loss: 3.6001e-04
Epoch 87/500
92/92            1s 7ms/step - loss:
1.2099e-07 - val_loss: 3.5650e-04
Epoch 88/500
92/92            1s 7ms/step - loss:
1.1119e-07 - val_loss: 3.5940e-04
Epoch 89/500
92/92            1s 7ms/step - loss:
1.4038e-07 - val_loss: 3.5629e-04
Epoch 90/500
92/92            1s 7ms/step - loss:
9.7647e-08 - val_loss: 3.5902e-04
Epoch 91/500
92/92            1s 7ms/step - loss:
9.1289e-08 - val_loss: 3.6504e-04
Epoch 92/500
```

```
92/92            1s 7ms/step - loss:
1.2399e-07 - val_loss: 3.6095e-04
Epoch 93/500
92/92            1s 7ms/step - loss:
9.6766e-08 - val_loss: 3.5526e-04
Epoch 94/500
92/92            1s 7ms/step - loss:
1.5958e-07 - val_loss: 3.6885e-04
Epoch 95/500
92/92            1s 7ms/step - loss:
1.8195e-07 - val_loss: 3.5615e-04
Epoch 96/500
92/92            1s 7ms/step - loss:
1.3906e-07 - val_loss: 3.5612e-04
Epoch 97/500
92/92            1s 7ms/step - loss:
1.3914e-07 - val_loss: 3.5631e-04
Epoch 98/500
92/92            1s 7ms/step - loss:
1.3634e-07 - val_loss: 3.5990e-04
Epoch 99/500
92/92            1s 7ms/step - loss:
9.8214e-08 - val_loss: 3.6002e-04
Epoch 100/500
92/92            1s 7ms/step - loss:
1.1996e-07 - val_loss: 3.6439e-04
Epoch 101/500
92/92            1s 7ms/step - loss:
1.3461e-07 - val_loss: 3.5482e-04
Epoch 102/500
92/92            1s 7ms/step - loss:
8.2685e-08 - val_loss: 3.5869e-04
Epoch 103/500
92/92            1s 7ms/step - loss:
1.3302e-07 - val_loss: 3.5459e-04
Epoch 104/500
92/92            1s 7ms/step - loss:
1.2693e-07 - val_loss: 3.5580e-04
Epoch 105/500
92/92            1s 7ms/step - loss:
1.7274e-07 - val_loss: 3.5584e-04
Epoch 106/500
92/92            1s 7ms/step - loss:
1.2302e-07 - val_loss: 3.5318e-04
Epoch 107/500
92/92            1s 7ms/step - loss:
9.5606e-08 - val_loss: 3.6031e-04
Epoch 108/500
```

```
92/92 1s 7ms/step - loss:
1.1034e-07 - val_loss: 3.5679e-04
Epoch 109/500
92/92 1s 7ms/step - loss:
1.1884e-07 - val_loss: 3.6418e-04
Epoch 110/500
92/92 1s 7ms/step - loss:
1.2954e-07 - val_loss: 3.6281e-04
Epoch 111/500
92/92 1s 7ms/step - loss:
1.2139e-07 - val_loss: 3.5991e-04
Epoch 112/500
92/92 1s 7ms/step - loss:
1.0097e-07 - val_loss: 3.5521e-04
Epoch 113/500
92/92 1s 7ms/step - loss:
1.1657e-07 - val_loss: 3.5269e-04
Epoch 114/500
92/92 1s 7ms/step - loss:
1.2303e-07 - val_loss: 3.5919e-04
Epoch 115/500
92/92 1s 7ms/step - loss:
1.1162e-07 - val_loss: 3.5857e-04
Epoch 116/500
92/92 1s 7ms/step - loss:
1.1750e-07 - val_loss: 3.6253e-04
Epoch 117/500
92/92 1s 7ms/step - loss:
1.3116e-07 - val_loss: 3.5005e-04
Epoch 118/500
92/92 1s 7ms/step - loss:
8.1851e-08 - val_loss: 3.6008e-04
Epoch 119/500
92/92 1s 7ms/step - loss:
1.2547e-07 - val_loss: 3.5062e-04
Epoch 120/500
92/92 1s 7ms/step - loss:
1.2040e-07 - val_loss: 3.5415e-04
Epoch 121/500
92/92 1s 7ms/step - loss:
1.1192e-07 - val_loss: 3.5339e-04
Epoch 122/500
92/92 1s 7ms/step - loss:
1.2573e-07 - val_loss: 3.5383e-04
Epoch 123/500
92/92 1s 7ms/step - loss:
1.0293e-07 - val_loss: 3.6419e-04
Epoch 124/500
```

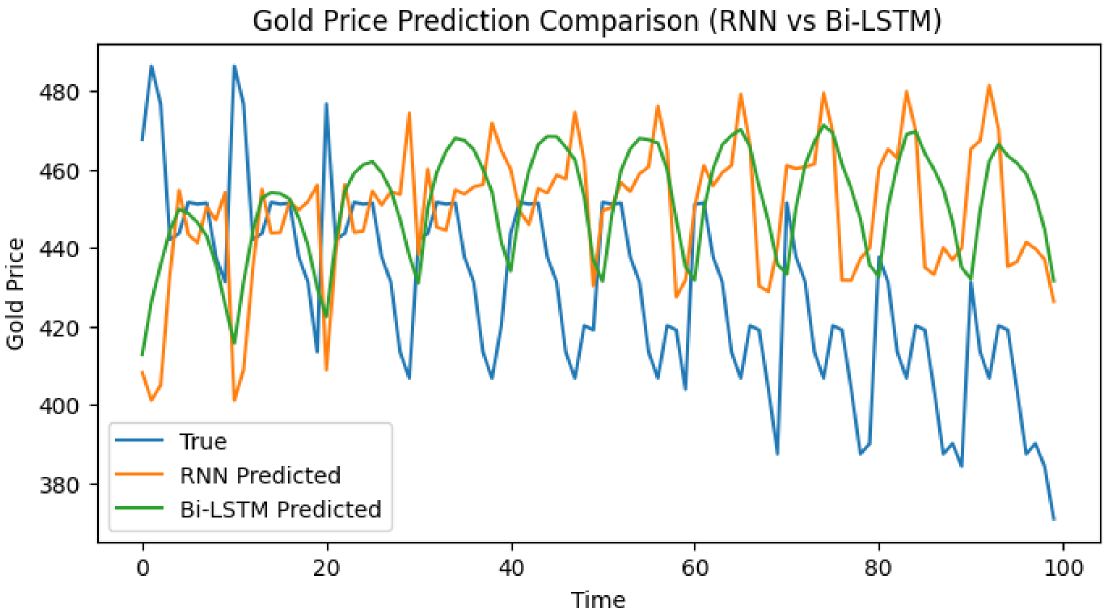
```
92/92            1s 7ms/step - loss:
1.5610e-07 - val_loss: 3.5208e-04
Epoch 125/500
92/92            1s 7ms/step - loss:
1.2532e-07 - val_loss: 3.7049e-04
Epoch 126/500
92/92            1s 7ms/step - loss:
1.5244e-07 - val_loss: 3.5420e-04
Epoch 127/500
92/92            1s 7ms/step - loss:
1.2222e-07 - val_loss: 3.5829e-04
Epoch 127: early stopping
Restoring model weights from the end of the best epoch: 117.
```

[19]:

```
# Prediction
y_pred_bi = bi_lstm_model.predict(x_test)
y_pred_bi_orig = scaler.inverse_transform(y_pred_bi.reshape(-1,1))
y_test_orig = scaler.inverse_transform(y_test.reshape(-1,1))

# Evaluation
rmse_bi = np.sqrt(mean_squared_error(y_test_orig, y_pred_bi_orig))
r2_bi = r2_score(y_test_orig, y_pred_bi_orig)

print("\nBi-LSTM Results")
print("RMSE:", rmse_bi)
print("R² Score:", r2_bi)

# Compare with Simple RNN
print("\nComparison")
print(f"Simple RNN -> RMSE: {rmse:.4f}, R²: {r2:.4f}")
print(f"Bi-LSTM     -> RMSE: {rmse_bi:.4f}, R²: {r2_bi:.4f}")

# Plot comparison
plt.figure(figsize=(8,4))
plt.plot(y_test_orig[:100], label='True')
plt.plot(y_pred_orig[:100], label='RNN Predicted')
plt.plot(y_pred_bi_orig[:100], label='Bi-LSTM Predicted')
plt.title("Gold Price Prediction Comparison (RNN vs Bi-LSTM)")
plt.xlabel("Time")
plt.ylabel("Gold Price")
plt.legend()
plt.show()
```

```
14/14            1s 28ms/step

Bi-LSTM Results
RMSE: 372.3040884351593
R² Score: 0.6469277430632671
```

```
Comparison
Simple RNN -> RMSE: 186.7050, R²: 0.9112
Bi-LSTM     -> RMSE: 372.3041, R²: 0.6469
```



0.2 Question 2: Further fit a Bi-directional GRU model for the same problem and verify the results

[20]:
```
from tensorflow.keras.layers import GRU, Bidirectional, Dense

model_bi_gru = Sequential([
    Bidirectional(GRU(128, activation='tanh', return_sequences=True),␣
 ↪input_shape=(input_length, 1)),
    GRU(64, activation='tanh', return_sequences=True),
    TimeDistributed(Dense(1))
])

model_bi_gru.compile(optimizer='adam', loss='mse', metrics=['mae'])
model_bi_gru.summary()

history_bi_gru = model_bi_gru.fit(
    x_train, y_train,
    validation_data=(x_val, y_val),
    epochs=300,
    batch_size=32,
    verbose=1,
```

```
    callbacks = [early_stop]
)
```

```
Model: "sequential_3"


 Layer (type)                   Output Shape                Param #

 bidirectional_1 (Bidirectional)  (None, 10, 256)          100,608

 gru_1 (GRU)                    (None, 10, 64)              61,824

 time_distributed_2             (None, 10, 1)                   65
 (TimeDistributed)


 Total params: 162,497 (634.75 KB)

 Trainable params: 162,497 (634.75 KB)

 Non-trainable params: 0 (0.00 B)

Epoch 1/300
46/46             5s 22ms/step -
loss: 2.1960e-04 - mae: 0.0105 - val_loss: 0.0032 - val_mae: 0.0352
Epoch 2/300
46/46             0s 9ms/step - loss:
3.2220e-06 - mae: 0.0013 - val_loss: 0.0027 - val_mae: 0.0320
Epoch 3/300
46/46             0s 9ms/step - loss:
2.1868e-06 - mae: 0.0011 - val_loss: 0.0021 - val_mae: 0.0277
Epoch 4/300
46/46             0s 9ms/step - loss:
1.4954e-06 - mae: 9.0845e-04 - val_loss: 0.0015 - val_mae: 0.0223
Epoch 5/300
46/46             0s 9ms/step - loss:
1.0564e-06 - mae: 7.8649e-04 - val_loss: 9.9463e-04 - val_mae: 0.0172
Epoch 6/300
46/46             0s 9ms/step - loss:
5.7561e-07 - mae: 5.5285e-04 - val_loss: 7.0374e-04 - val_mae: 0.0132
Epoch 7/300
46/46             0s 9ms/step - loss:
3.8566e-07 - mae: 4.1654e-04 - val_loss: 5.7977e-04 - val_mae: 0.0117
Epoch 8/300
46/46             0s 9ms/step - loss:
```

```
2.4982e-07 - mae: 2.8545e-04 - val_loss: 5.4596e-04 - val_mae: 0.0114
Epoch 9/300
46/46            0s 9ms/step - loss:
2.1459e-07 - mae: 2.5976e-04 - val_loss: 5.3664e-04 - val_mae: 0.0113
Epoch 10/300
46/46            0s 9ms/step - loss:
2.0915e-07 - mae: 2.6218e-04 - val_loss: 5.3093e-04 - val_mae: 0.0113
Epoch 11/300
46/46            0s 9ms/step - loss:
1.8803e-07 - mae: 2.4524e-04 - val_loss: 5.2697e-04 - val_mae: 0.0113
Epoch 12/300
46/46            0s 9ms/step - loss:
2.5848e-07 - mae: 3.3178e-04 - val_loss: 5.2190e-04 - val_mae: 0.0112
Epoch 13/300
46/46            0s 9ms/step - loss:
1.9476e-07 - mae: 2.6432e-04 - val_loss: 5.1609e-04 - val_mae: 0.0111
Epoch 14/300
46/46            0s 9ms/step - loss:
1.8444e-07 - mae: 2.3574e-04 - val_loss: 5.1107e-04 - val_mae: 0.0111
Epoch 15/300
46/46            0s 9ms/step - loss:
2.1947e-07 - mae: 2.8283e-04 - val_loss: 5.0832e-04 - val_mae: 0.0110
Epoch 16/300
46/46            0s 9ms/step - loss:
2.4763e-07 - mae: 3.2747e-04 - val_loss: 5.0199e-04 - val_mae: 0.0109
Epoch 17/300
46/46            0s 9ms/step - loss:
2.0366e-07 - mae: 2.7391e-04 - val_loss: 4.9930e-04 - val_mae: 0.0109
Epoch 18/300
46/46            0s 9ms/step - loss:
1.9560e-07 - mae: 2.5955e-04 - val_loss: 4.9499e-04 - val_mae: 0.0109
Epoch 19/300
46/46            0s 9ms/step - loss:
1.8243e-07 - mae: 2.5151e-04 - val_loss: 4.9220e-04 - val_mae: 0.0108
Epoch 20/300
46/46            0s 9ms/step - loss:
2.2575e-07 - mae: 3.0466e-04 - val_loss: 4.8938e-04 - val_mae: 0.0108
Epoch 21/300
46/46            0s 9ms/step - loss:
1.8140e-07 - mae: 2.6931e-04 - val_loss: 4.8766e-04 - val_mae: 0.0108
Epoch 22/300
46/46            0s 9ms/step - loss:
1.9538e-07 - mae: 2.8804e-04 - val_loss: 4.8264e-04 - val_mae: 0.0107
Epoch 23/300
46/46            0s 9ms/step - loss:
2.4056e-07 - mae: 3.3312e-04 - val_loss: 4.8206e-04 - val_mae: 0.0107
Epoch 24/300
46/46            0s 9ms/step - loss:
```

```
2.3873e-07 - mae: 3.2049e-04 - val_loss: 4.7908e-04 - val_mae: 0.0107
Epoch 25/300
46/46            0s 9ms/step - loss:
1.9723e-07 - mae: 2.9129e-04 - val_loss: 4.7484e-04 - val_mae: 0.0106
Epoch 26/300
46/46            0s 9ms/step - loss:
2.3289e-07 - mae: 3.2491e-04 - val_loss: 4.7649e-04 - val_mae: 0.0107
Epoch 27/300
46/46            0s 9ms/step - loss:
1.9443e-07 - mae: 2.8274e-04 - val_loss: 4.7423e-04 - val_mae: 0.0106
Epoch 28/300
46/46            0s 9ms/step - loss:
2.3540e-07 - mae: 3.4790e-04 - val_loss: 4.7166e-04 - val_mae: 0.0106
Epoch 29/300
46/46            0s 9ms/step - loss:
1.6880e-07 - mae: 2.5057e-04 - val_loss: 4.7008e-04 - val_mae: 0.0105
Epoch 30/300
46/46            0s 9ms/step - loss:
1.8579e-07 - mae: 2.7926e-04 - val_loss: 4.6944e-04 - val_mae: 0.0105
Epoch 31/300
46/46            0s 9ms/step - loss:
1.8288e-07 - mae: 2.5605e-04 - val_loss: 4.6864e-04 - val_mae: 0.0105
Epoch 32/300
46/46            0s 9ms/step - loss:
1.8072e-07 - mae: 2.7378e-04 - val_loss: 4.6729e-04 - val_mae: 0.0105
Epoch 33/300
46/46            0s 9ms/step - loss:
1.8149e-07 - mae: 2.7130e-04 - val_loss: 4.6397e-04 - val_mae: 0.0105
Epoch 34/300
46/46            0s 9ms/step - loss:
2.1230e-07 - mae: 3.2007e-04 - val_loss: 4.6383e-04 - val_mae: 0.0105
Epoch 35/300
46/46            0s 9ms/step - loss:
1.6220e-07 - mae: 2.5847e-04 - val_loss: 4.6302e-04 - val_mae: 0.0105
Epoch 36/300
46/46            0s 9ms/step - loss:
1.7194e-07 - mae: 2.6140e-04 - val_loss: 4.6122e-04 - val_mae: 0.0104
Epoch 37/300
46/46            0s 9ms/step - loss:
1.8362e-07 - mae: 2.8006e-04 - val_loss: 4.6015e-04 - val_mae: 0.0104
Epoch 38/300
46/46            0s 9ms/step - loss:
1.7966e-07 - mae: 2.8382e-04 - val_loss: 4.5995e-04 - val_mae: 0.0104
Epoch 39/300
46/46            0s 9ms/step - loss:
1.8320e-07 - mae: 2.8476e-04 - val_loss: 4.5966e-04 - val_mae: 0.0104
Epoch 40/300
46/46            0s 9ms/step - loss:
```

```
2.0529e-07 - mae: 3.1467e-04 - val_loss: 4.5699e-04 - val_mae: 0.0104
Epoch 41/300
46/46            0s 9ms/step - loss:
1.5513e-07 - mae: 2.4262e-04 - val_loss: 4.5495e-04 - val_mae: 0.0104
Epoch 42/300
46/46            0s 9ms/step - loss:
1.8028e-07 - mae: 2.8374e-04 - val_loss: 4.5297e-04 - val_mae: 0.0103
Epoch 43/300
46/46            0s 9ms/step - loss:
2.6502e-07 - mae: 3.8754e-04 - val_loss: 4.5476e-04 - val_mae: 0.0103
Epoch 44/300
46/46            0s 9ms/step - loss:
1.7377e-07 - mae: 2.5939e-04 - val_loss: 4.5440e-04 - val_mae: 0.0103
Epoch 45/300
46/46            0s 9ms/step - loss:
1.8170e-07 - mae: 2.8728e-04 - val_loss: 4.5158e-04 - val_mae: 0.0103
Epoch 46/300
46/46            0s 9ms/step - loss:
1.6436e-07 - mae: 2.8513e-04 - val_loss: 4.5401e-04 - val_mae: 0.0103
Epoch 47/300
46/46            0s 9ms/step - loss:
1.6452e-07 - mae: 2.6197e-04 - val_loss: 4.5191e-04 - val_mae: 0.0103
Epoch 48/300
46/46            0s 9ms/step - loss:
2.5020e-07 - mae: 3.6326e-04 - val_loss: 4.5018e-04 - val_mae: 0.0102
Epoch 49/300
46/46            0s 9ms/step - loss:
1.7150e-07 - mae: 2.5528e-04 - val_loss: 4.4914e-04 - val_mae: 0.0102
Epoch 50/300
46/46            0s 9ms/step - loss:
1.6175e-07 - mae: 2.6855e-04 - val_loss: 4.5220e-04 - val_mae: 0.0104
Epoch 51/300
46/46            0s 9ms/step - loss:
3.0631e-07 - mae: 4.3748e-04 - val_loss: 4.4503e-04 - val_mae: 0.0101
Epoch 52/300
46/46            0s 9ms/step - loss:
2.5118e-07 - mae: 3.6231e-04 - val_loss: 4.5292e-04 - val_mae: 0.0103
Epoch 53/300
46/46            0s 9ms/step - loss:
5.3410e-07 - mae: 5.8283e-04 - val_loss: 4.4268e-04 - val_mae: 0.0101
Epoch 54/300
46/46            0s 9ms/step - loss:
2.6111e-07 - mae: 3.9745e-04 - val_loss: 4.4042e-04 - val_mae: 0.0101
Epoch 55/300
46/46            0s 9ms/step - loss:
2.6434e-07 - mae: 3.8021e-04 - val_loss: 4.4352e-04 - val_mae: 0.0101
Epoch 56/300
46/46            0s 9ms/step - loss:
```

```
2.4606e-07 - mae: 3.4561e-04 - val_loss: 4.4470e-04 - val_mae: 0.0102
Epoch 57/300
46/46            0s 9ms/step - loss:
1.9125e-07 - mae: 2.9335e-04 - val_loss: 4.4274e-04 - val_mae: 0.0101
Epoch 58/300
46/46            0s 9ms/step - loss:
1.3726e-07 - mae: 2.3193e-04 - val_loss: 4.4172e-04 - val_mae: 0.0101
Epoch 59/300
46/46            0s 9ms/step - loss:
1.7820e-07 - mae: 2.9587e-04 - val_loss: 4.3614e-04 - val_mae: 0.0101
Epoch 60/300
46/46            0s 9ms/step - loss:
2.8236e-07 - mae: 3.8552e-04 - val_loss: 4.4061e-04 - val_mae: 0.0101
Epoch 61/300
46/46            0s 9ms/step - loss:
1.8847e-07 - mae: 2.9694e-04 - val_loss: 4.4131e-04 - val_mae: 0.0102
Epoch 62/300
46/46            0s 9ms/step - loss:
2.1957e-07 - mae: 3.2891e-04 - val_loss: 4.3372e-04 - val_mae: 0.0100
Epoch 63/300
46/46            0s 9ms/step - loss:
2.9544e-07 - mae: 4.4697e-04 - val_loss: 4.3150e-04 - val_mae: 0.0100
Epoch 64/300
46/46            0s 9ms/step - loss:
3.1299e-07 - mae: 4.2969e-04 - val_loss: 4.3034e-04 - val_mae: 0.0100
Epoch 65/300
46/46            0s 9ms/step - loss:
3.4859e-07 - mae: 4.8454e-04 - val_loss: 4.3039e-04 - val_mae: 0.0100
Epoch 66/300
46/46            0s 9ms/step - loss:
2.3129e-07 - mae: 3.4534e-04 - val_loss: 4.3211e-04 - val_mae: 0.0099
Epoch 67/300
46/46            0s 9ms/step - loss:
2.0648e-07 - mae: 3.1983e-04 - val_loss: 4.3416e-04 - val_mae: 0.0100
Epoch 68/300
46/46            0s 9ms/step - loss:
1.8723e-07 - mae: 2.7685e-04 - val_loss: 4.3230e-04 - val_mae: 0.0099
Epoch 69/300
46/46            0s 9ms/step - loss:
2.2451e-07 - mae: 3.3981e-04 - val_loss: 4.3136e-04 - val_mae: 0.0099
Epoch 70/300
46/46            0s 9ms/step - loss:
2.4862e-07 - mae: 3.6927e-04 - val_loss: 4.3011e-04 - val_mae: 0.0099
Epoch 71/300
46/46            0s 9ms/step - loss:
1.6267e-07 - mae: 2.5472e-04 - val_loss: 4.2877e-04 - val_mae: 0.0099
Epoch 72/300
46/46            0s 9ms/step - loss:
```

```
1.8678e-07 - mae: 3.0790e-04 - val_loss: 4.2911e-04 - val_mae: 0.0099
Epoch 73/300
46/46            0s 9ms/step - loss:
1.6384e-07 - mae: 2.3431e-04 - val_loss: 4.2476e-04 - val_mae: 0.0098
Epoch 74/300
46/46            0s 9ms/step - loss:
2.3205e-07 - mae: 3.7415e-04 - val_loss: 4.2908e-04 - val_mae: 0.0100
Epoch 75/300
46/46            0s 9ms/step - loss:
2.1190e-07 - mae: 3.6357e-04 - val_loss: 4.3533e-04 - val_mae: 0.0103
Epoch 76/300
46/46            0s 9ms/step - loss:
5.6783e-07 - mae: 5.9472e-04 - val_loss: 4.2704e-04 - val_mae: 0.0099
Epoch 77/300
46/46            0s 9ms/step - loss:
2.1302e-07 - mae: 3.2577e-04 - val_loss: 4.2340e-04 - val_mae: 0.0098
Epoch 78/300
46/46            0s 9ms/step - loss:
1.9668e-07 - mae: 3.1046e-04 - val_loss: 4.2263e-04 - val_mae: 0.0097
Epoch 79/300
46/46            0s 9ms/step - loss:
3.6671e-07 - mae: 4.8037e-04 - val_loss: 4.2027e-04 - val_mae: 0.0097
Epoch 80/300
46/46            0s 9ms/step - loss:
3.1282e-07 - mae: 4.1899e-04 - val_loss: 4.2444e-04 - val_mae: 0.0098
Epoch 81/300
46/46            0s 9ms/step - loss:
2.5830e-07 - mae: 3.8839e-04 - val_loss: 4.2440e-04 - val_mae: 0.0100
Epoch 82/300
46/46            0s 9ms/step - loss:
3.0870e-07 - mae: 4.6022e-04 - val_loss: 4.2386e-04 - val_mae: 0.0097
Epoch 83/300
46/46            0s 9ms/step - loss:
1.8935e-07 - mae: 2.9357e-04 - val_loss: 4.2107e-04 - val_mae: 0.0098
Epoch 84/300
46/46            0s 9ms/step - loss:
1.7058e-07 - mae: 2.5400e-04 - val_loss: 4.2423e-04 - val_mae: 0.0097
Epoch 85/300
46/46            0s 9ms/step - loss:
4.3083e-07 - mae: 5.4710e-04 - val_loss: 4.2178e-04 - val_mae: 0.0099
Epoch 86/300
46/46            0s 9ms/step - loss:
2.2214e-07 - mae: 3.6107e-04 - val_loss: 4.1688e-04 - val_mae: 0.0098
Epoch 87/300
46/46            0s 9ms/step - loss:
2.3340e-07 - mae: 3.8152e-04 - val_loss: 4.2168e-04 - val_mae: 0.0099
Epoch 88/300
46/46            0s 9ms/step - loss:
```

```
1.9714e-07 - mae: 3.1977e-04 - val_loss: 4.1716e-04 - val_mae: 0.0097
Epoch 89/300
46/46            0s 9ms/step - loss:
2.3158e-07 - mae: 3.7269e-04 - val_loss: 4.1768e-04 - val_mae: 0.0097
Epoch 90/300
46/46            0s 9ms/step - loss:
2.3476e-07 - mae: 3.3402e-04 - val_loss: 4.1752e-04 - val_mae: 0.0097
Epoch 91/300
46/46            0s 9ms/step - loss:
1.6109e-07 - mae: 2.9943e-04 - val_loss: 4.1653e-04 - val_mae: 0.0097
Epoch 92/300
46/46            0s 9ms/step - loss:
1.6750e-07 - mae: 3.0411e-04 - val_loss: 4.1387e-04 - val_mae: 0.0096
Epoch 93/300
46/46            0s 9ms/step - loss:
4.3593e-07 - mae: 5.3108e-04 - val_loss: 4.1650e-04 - val_mae: 0.0098
Epoch 94/300
46/46            0s 9ms/step - loss:
2.0367e-07 - mae: 3.2063e-04 - val_loss: 4.1797e-04 - val_mae: 0.0100
Epoch 95/300
46/46            0s 9ms/step - loss:
3.2600e-07 - mae: 4.5597e-04 - val_loss: 4.1554e-04 - val_mae: 0.0098
Epoch 96/300
46/46            0s 9ms/step - loss:
3.0701e-07 - mae: 4.4865e-04 - val_loss: 4.0990e-04 - val_mae: 0.0097
Epoch 97/300
46/46            0s 9ms/step - loss:
2.3217e-07 - mae: 3.6762e-04 - val_loss: 4.1179e-04 - val_mae: 0.0096
Epoch 98/300
46/46            0s 9ms/step - loss:
2.5072e-07 - mae: 4.0004e-04 - val_loss: 4.0962e-04 - val_mae: 0.0097
Epoch 99/300
46/46            0s 9ms/step - loss:
3.1804e-07 - mae: 4.7343e-04 - val_loss: 4.1106e-04 - val_mae: 0.0096
Epoch 100/300
46/46            0s 9ms/step - loss:
1.7672e-07 - mae: 2.8659e-04 - val_loss: 4.1179e-04 - val_mae: 0.0096
Epoch 101/300
46/46            0s 9ms/step - loss:
2.0958e-07 - mae: 3.3946e-04 - val_loss: 4.0913e-04 - val_mae: 0.0096
Epoch 102/300
46/46            0s 9ms/step - loss:
1.3828e-07 - mae: 2.3610e-04 - val_loss: 4.1050e-04 - val_mae: 0.0096
Epoch 103/300
46/46            0s 9ms/step - loss:
1.4638e-07 - mae: 2.2900e-04 - val_loss: 4.0905e-04 - val_mae: 0.0095
Epoch 104/300
46/46            0s 9ms/step - loss:
```

```
3.5192e-07 - mae: 4.6750e-04 - val_loss: 4.0865e-04 - val_mae: 0.0095
Epoch 105/300
46/46             0s 9ms/step - loss:
2.1334e-07 - mae: 3.0232e-04 - val_loss: 4.1513e-04 - val_mae: 0.0097
Epoch 106/300
46/46             0s 9ms/step - loss:
4.8425e-07 - mae: 5.7513e-04 - val_loss: 4.1155e-04 - val_mae: 0.0098
Epoch 107/300
46/46             0s 9ms/step - loss:
1.9049e-07 - mae: 3.2610e-04 - val_loss: 4.0473e-04 - val_mae: 0.0095
Epoch 108/300
46/46             0s 9ms/step - loss:
2.7342e-07 - mae: 4.0446e-04 - val_loss: 4.1064e-04 - val_mae: 0.0096
Epoch 109/300
46/46             0s 9ms/step - loss:
2.6860e-07 - mae: 3.6357e-04 - val_loss: 4.1095e-04 - val_mae: 0.0097
Epoch 110/300
46/46             0s 9ms/step - loss:
2.6286e-07 - mae: 3.7719e-04 - val_loss: 4.0891e-04 - val_mae: 0.0096
Epoch 111/300
46/46             0s 9ms/step - loss:
2.0030e-07 - mae: 3.1382e-04 - val_loss: 4.1039e-04 - val_mae: 0.0096
Epoch 112/300
46/46             0s 9ms/step - loss:
1.2257e-07 - mae: 2.0158e-04 - val_loss: 4.0860e-04 - val_mae: 0.0096
Epoch 113/300
46/46             0s 9ms/step - loss:
2.4703e-07 - mae: 3.6486e-04 - val_loss: 4.0487e-04 - val_mae: 0.0095
Epoch 114/300
46/46             0s 9ms/step - loss:
2.0257e-07 - mae: 3.1618e-04 - val_loss: 4.0429e-04 - val_mae: 0.0095
Epoch 115/300
46/46             0s 9ms/step - loss:
2.0488e-07 - mae: 3.4157e-04 - val_loss: 4.0960e-04 - val_mae: 0.0098
Epoch 116/300
46/46             0s 9ms/step - loss:
1.8012e-07 - mae: 3.0050e-04 - val_loss: 4.0868e-04 - val_mae: 0.0096
Epoch 117/300
46/46             0s 9ms/step - loss:
2.4437e-07 - mae: 3.7986e-04 - val_loss: 4.0421e-04 - val_mae: 0.0096
Epoch 118/300
46/46             0s 9ms/step - loss:
2.7755e-07 - mae: 4.1390e-04 - val_loss: 4.0452e-04 - val_mae: 0.0094
Epoch 119/300
46/46             0s 9ms/step - loss:
1.7031e-07 - mae: 2.8399e-04 - val_loss: 4.0744e-04 - val_mae: 0.0095
Epoch 120/300
46/46             0s 9ms/step - loss:
```

```
2.3416e-07 - mae: 3.7235e-04 - val_loss: 4.0683e-04 - val_mae: 0.0096
Epoch 121/300
46/46              0s 9ms/step - loss:
2.0283e-07 - mae: 3.0802e-04 - val_loss: 4.0610e-04 - val_mae: 0.0095
Epoch 122/300
46/46              0s 9ms/step - loss:
2.0553e-07 - mae: 3.1012e-04 - val_loss: 4.0592e-04 - val_mae: 0.0095
Epoch 123/300
46/46              0s 9ms/step - loss:
2.9221e-07 - mae: 3.8149e-04 - val_loss: 4.0842e-04 - val_mae: 0.0096
Epoch 124/300
46/46              0s 9ms/step - loss:
1.7277e-07 - mae: 3.0790e-04 - val_loss: 4.0836e-04 - val_mae: 0.0097
Epoch 125/300
46/46              0s 9ms/step - loss:
2.4435e-07 - mae: 3.7951e-04 - val_loss: 4.0439e-04 - val_mae: 0.0095
Epoch 126/300
46/46              0s 9ms/step - loss:
9.3621e-08 - mae: 1.6555e-04 - val_loss: 4.0616e-04 - val_mae: 0.0095
Epoch 127/300
46/46              0s 9ms/step - loss:
2.5296e-07 - mae: 3.5764e-04 - val_loss: 4.0494e-04 - val_mae: 0.0094
Epoch 127: early stopping
Restoring model weights from the end of the best epoch: 117.
```

[21]:

```python
y_pred = model_bi_gru.predict(x_test)
y_test_flat = y_test.reshape(-1, 1)
y_pred_flat = y_pred.reshape(-1, 1)

y_test_inv = scaler.inverse_transform(y_test_flat)
y_pred_inv = scaler.inverse_transform(y_pred_flat)

mse_inv = mean_squared_error(y_test_inv, y_pred_inv)
r2_inv = r2_score(y_test_inv, y_pred_inv)

print(f"Results -> MSE: {mse_inv:.4f}, R²: {r2_inv:.4f}")
```

```
14/14              1s 32ms/step
Results -> MSE: 29558.9640, R²: 0.9247
```

0.3 Questions 3: Next, we will try to attempt the sentence completion task mentioned in lab experiment 11. Think how you can create a simple model with an RNN to predict the next word once you give a sentence to the model. Try to create one such model that can do this task. Use the same IMDb dataset for the task. (Hint: Try to first prepare the sequences for training just like we did in gold price prediction, Sequences in which we have say 10 words as inputs and the next word as output. And we can plan, like, in our model, the final layer with a vocabulary size number of neurons. So that you can run with a softmax activation function in the final layer.

[22]:
```
import numpy as np
from tensorflow.keras.datasets import imdb
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, SimpleRNN, Dense
from tensorflow.keras.utils import to_categorical
```

[23]:
```
vocab_size = 5000
sequence_length = 10

(x_train,_),(_,_) = imdb.load_data(num_words = vocab_size)

all_words = [word for review in x_train for word in review]

sequences = []
next_words = []

for i in range(len(all_words) - sequence_length):
    seq = all_words[i:i+sequence_length]
    next_word = all_words[i+sequence_length]
    sequences.append(seq)
    next_words.append(next_word)

sequences = np.array(sequences)
next_words = to_categorical(next_words, num_classes = vocab_size)

print("Input shape:", sequences.shape)
print("Output shape:", next_words.shape)
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-
datasets/imdb.npz
17464789/17464789          0s
0us/step
Input shape: (5967831, 10)
Output shape: (5967831, 5000)
```

[24]:

```
model = Sequential()
model.add(Embedding(input_dim=vocab_size, output_dim=50,
    input_shape=(sequence_length,)))
model.add(SimpleRNN(128))
model.add(Dense(vocab_size, activation='softmax'))

model.compile(loss='categorical_crossentropy', optimizer='adam',
    metrics=['accuracy'])
model.summary()
```

Model: "sequential_4"

Layer (type)	Output Shape	Param #
embedding (Embedding)	(None, 10, 50)	250,000
simple_rnn_1 (SimpleRNN)	(None, 128)	22,912
dense_3 (Dense)	(None, 5000)	645,000

Total params: 917,912 (3.50 MB)

Trainable params: 917,912 (3.50 MB)

Non-trainable params: 0 (0.00 B)

[29]:

```
es = EarlyStopping(monitor='val_loss', patience=5, restore_best_weights=True,
    verbose=1)
model.fit(sequences[:50000], next_words[:50000], epochs=300, batch_size=128,
    callbacks = [es], verbose = 1)
```

```
Epoch 1/300
391/391                2s 4ms/step -
accuracy: 0.7552 - loss: 1.1056
Epoch 2/300
391/391                1s 4ms/step -
accuracy: 0.7543 - loss: 1.0969
Epoch 3/300
391/391                1s 4ms/step -
accuracy: 0.7623 - loss: 1.0668
Epoch 4/300
391/391                1s 4ms/step -
accuracy: 0.7680 - loss: 1.0392
```

```
Epoch 5/300
391/391              1s 4ms/step -
accuracy: 0.7739 - loss: 1.0230
Epoch 6/300
391/391              1s 4ms/step -
accuracy: 0.7798 - loss: 1.0004
Epoch 7/300
391/391              1s 4ms/step -
accuracy: 0.7810 - loss: 0.9762
Epoch 8/300
391/391              1s 4ms/step -
accuracy: 0.7865 - loss: 0.9520
Epoch 9/300
391/391              1s 4ms/step -
accuracy: 0.7933 - loss: 0.9319
Epoch 10/300
391/391              1s 4ms/step -
accuracy: 0.7936 - loss: 0.9202
Epoch 11/300
391/391              1s 4ms/step -
accuracy: 0.7964 - loss: 0.9118
Epoch 12/300
391/391              1s 4ms/step -
accuracy: 0.8002 - loss: 0.8900
Epoch 13/300
391/391              1s 4ms/step -
accuracy: 0.8067 - loss: 0.8673
Epoch 14/300
391/391              1s 4ms/step -
accuracy: 0.8039 - loss: 0.8662
Epoch 15/300
391/391              1s 4ms/step -
accuracy: 0.8123 - loss: 0.8337
Epoch 16/300
391/391              1s 4ms/step -
accuracy: 0.8156 - loss: 0.8266
Epoch 17/300
391/391              1s 4ms/step -
accuracy: 0.8166 - loss: 0.8140
Epoch 18/300
391/391              1s 4ms/step -
accuracy: 0.8232 - loss: 0.7895
Epoch 19/300
391/391              1s 4ms/step -
accuracy: 0.8231 - loss: 0.7808
Epoch 20/300
391/391              1s 4ms/step -
accuracy: 0.8285 - loss: 0.7698
```

```
Epoch 21/300
391/391            1s 4ms/step -
accuracy: 0.8295 - loss: 0.7585
Epoch 22/300
391/391            1s 4ms/step -
accuracy: 0.8278 - loss: 0.7599
Epoch 23/300
391/391            1s 4ms/step -
accuracy: 0.8314 - loss: 0.7503
Epoch 24/300
391/391            1s 4ms/step -
accuracy: 0.8329 - loss: 0.7349
Epoch 25/300
391/391            1s 4ms/step -
accuracy: 0.8306 - loss: 0.7349
Epoch 26/300
391/391            1s 4ms/step -
accuracy: 0.8329 - loss: 0.7279
Epoch 27/300
391/391            1s 4ms/step -
accuracy: 0.8390 - loss: 0.7041
Epoch 28/300
391/391            1s 4ms/step -
accuracy: 0.8425 - loss: 0.6942
Epoch 29/300
391/391            1s 4ms/step -
accuracy: 0.8452 - loss: 0.6778
Epoch 30/300
391/391            1s 4ms/step -
accuracy: 0.8446 - loss: 0.6761
Epoch 31/300
391/391            1s 4ms/step -
accuracy: 0.8467 - loss: 0.6695
Epoch 32/300
391/391            1s 4ms/step -
accuracy: 0.8464 - loss: 0.6649
Epoch 33/300
391/391            1s 4ms/step -
accuracy: 0.8464 - loss: 0.6658
Epoch 34/300
391/391            1s 4ms/step -
accuracy: 0.8467 - loss: 0.6610
Epoch 35/300
391/391            1s 4ms/step -
accuracy: 0.8544 - loss: 0.6342
Epoch 36/300
391/391            1s 4ms/step -
accuracy: 0.8616 - loss: 0.6119
```

```
Epoch 37/300
391/391            1s 4ms/step -
accuracy: 0.8559 - loss: 0.6219
Epoch 38/300
391/391            1s 4ms/step -
accuracy: 0.8585 - loss: 0.6126
Epoch 39/300
391/391            1s 4ms/step -
accuracy: 0.8593 - loss: 0.6101
Epoch 40/300
391/391            1s 4ms/step -
accuracy: 0.8597 - loss: 0.6153
Epoch 41/300
391/391            1s 4ms/step -
accuracy: 0.8663 - loss: 0.5877
Epoch 42/300
391/391            1s 4ms/step -
accuracy: 0.8664 - loss: 0.5806
Epoch 43/300
391/391            1s 4ms/step -
accuracy: 0.8631 - loss: 0.5888
Epoch 44/300
391/391            1s 4ms/step -
accuracy: 0.8670 - loss: 0.5718
Epoch 45/300
391/391            1s 4ms/step -
accuracy: 0.8726 - loss: 0.5639
Epoch 46/300
391/391            1s 4ms/step -
accuracy: 0.8651 - loss: 0.5739
Epoch 47/300
391/391            1s 4ms/step -
accuracy: 0.8714 - loss: 0.5581
Epoch 48/300
391/391            1s 4ms/step -
accuracy: 0.8754 - loss: 0.5453
Epoch 49/300
391/391            1s 4ms/step -
accuracy: 0.8750 - loss: 0.5403
Epoch 50/300
391/391            1s 4ms/step -
accuracy: 0.8707 - loss: 0.5593
Epoch 51/300
391/391            1s 4ms/step -
accuracy: 0.8683 - loss: 0.5603
Epoch 52/300
391/391            2s 4ms/step -
accuracy: 0.8699 - loss: 0.5543
```

```
Epoch 53/300
391/391            1s 4ms/step -
accuracy: 0.8778 - loss: 0.5323
Epoch 54/300
391/391            1s 4ms/step -
accuracy: 0.8828 - loss: 0.5127
Epoch 55/300
391/391            1s 4ms/step -
accuracy: 0.8779 - loss: 0.5219
Epoch 56/300
391/391            1s 4ms/step -
accuracy: 0.8764 - loss: 0.5350
Epoch 57/300
391/391            1s 4ms/step -
accuracy: 0.8825 - loss: 0.5046
Epoch 58/300
391/391            1s 4ms/step -
accuracy: 0.8848 - loss: 0.4902
Epoch 59/300
391/391            1s 4ms/step -
accuracy: 0.8819 - loss: 0.5028
Epoch 60/300
391/391            1s 4ms/step -
accuracy: 0.8805 - loss: 0.5044
Epoch 61/300
391/391            1s 4ms/step -
accuracy: 0.8843 - loss: 0.4978
Epoch 62/300
391/391            1s 4ms/step -
accuracy: 0.8780 - loss: 0.5033
Epoch 63/300
391/391            1s 4ms/step -
accuracy: 0.8811 - loss: 0.5045
Epoch 64/300
391/391            1s 4ms/step -
accuracy: 0.8848 - loss: 0.4919
Epoch 65/300
391/391            1s 4ms/step -
accuracy: 0.8827 - loss: 0.4959
Epoch 66/300
391/391            1s 4ms/step -
accuracy: 0.8838 - loss: 0.4892
Epoch 67/300
391/391            1s 4ms/step -
accuracy: 0.8900 - loss: 0.4663
Epoch 68/300
391/391            1s 4ms/step -
accuracy: 0.8905 - loss: 0.4654
```

```
Epoch 69/300
391/391              1s 4ms/step -
accuracy: 0.8929 - loss: 0.4565
Epoch 70/300
391/391              1s 4ms/step -
accuracy: 0.8860 - loss: 0.4707
Epoch 71/300
391/391              1s 4ms/step -
accuracy: 0.8901 - loss: 0.4645
Epoch 72/300
391/391              1s 4ms/step -
accuracy: 0.8879 - loss: 0.4708
Epoch 73/300
391/391              1s 4ms/step -
accuracy: 0.8880 - loss: 0.4682
Epoch 74/300
391/391              1s 4ms/step -
accuracy: 0.8904 - loss: 0.4633
Epoch 75/300
391/391              1s 4ms/step -
accuracy: 0.8886 - loss: 0.4653
Epoch 76/300
391/391              1s 4ms/step -
accuracy: 0.8925 - loss: 0.4493
Epoch 77/300
391/391              1s 4ms/step -
accuracy: 0.8979 - loss: 0.4365
Epoch 78/300
391/391              1s 4ms/step -
accuracy: 0.8970 - loss: 0.4358
Epoch 79/300
391/391              1s 4ms/step -
accuracy: 0.8916 - loss: 0.4500
Epoch 80/300
391/391              1s 4ms/step -
accuracy: 0.8866 - loss: 0.4654
Epoch 81/300
391/391              1s 4ms/step -
accuracy: 0.8902 - loss: 0.4495
Epoch 82/300
391/391              1s 4ms/step -
accuracy: 0.8944 - loss: 0.4385
Epoch 83/300
391/391              1s 4ms/step -
accuracy: 0.8959 - loss: 0.4291
Epoch 84/300
391/391              1s 4ms/step -
accuracy: 0.9011 - loss: 0.4199
```

```
Epoch 85/300
391/391              1s 4ms/step -
accuracy: 0.8987 - loss: 0.4259
Epoch 86/300
391/391              1s 4ms/step -
accuracy: 0.8991 - loss: 0.4240
Epoch 87/300
391/391              1s 4ms/step -
accuracy: 0.8896 - loss: 0.4468
Epoch 88/300
391/391              1s 4ms/step -
accuracy: 0.8971 - loss: 0.4256
Epoch 89/300
391/391              1s 4ms/step -
accuracy: 0.9052 - loss: 0.4003
Epoch 90/300
391/391              1s 4ms/step -
accuracy: 0.9078 - loss: 0.3895
Epoch 91/300
391/391              1s 4ms/step -
accuracy: 0.9006 - loss: 0.4136
Epoch 92/300
391/391              1s 4ms/step -
accuracy: 0.8941 - loss: 0.4265
Epoch 93/300
391/391              1s 4ms/step -
accuracy: 0.8947 - loss: 0.4255
Epoch 94/300
391/391              1s 4ms/step -
accuracy: 0.8998 - loss: 0.4124
Epoch 95/300
391/391              1s 4ms/step -
accuracy: 0.8930 - loss: 0.4314
Epoch 96/300
391/391              1s 4ms/step -
accuracy: 0.9029 - loss: 0.3957
Epoch 97/300
391/391              1s 4ms/step -
accuracy: 0.9098 - loss: 0.3759
Epoch 98/300
391/391              1s 4ms/step -
accuracy: 0.9072 - loss: 0.3869
Epoch 99/300
391/391              1s 4ms/step -
accuracy: 0.8895 - loss: 0.4433
Epoch 100/300
391/391              1s 4ms/step -
accuracy: 0.8989 - loss: 0.4048
```

```
Epoch 101/300
391/391            1s 4ms/step -
accuracy: 0.9088 - loss: 0.3797
Epoch 102/300
391/391            2s 4ms/step -
accuracy: 0.9047 - loss: 0.3905
Epoch 103/300
391/391            1s 4ms/step -
accuracy: 0.9031 - loss: 0.3921
Epoch 104/300
391/391            1s 4ms/step -
accuracy: 0.9056 - loss: 0.3850
Epoch 105/300
391/391            1s 4ms/step -
accuracy: 0.8979 - loss: 0.4052
Epoch 106/300
391/391            1s 4ms/step -
accuracy: 0.9025 - loss: 0.3933
Epoch 107/300
391/391            1s 4ms/step -
accuracy: 0.9146 - loss: 0.3573
Epoch 108/300
391/391            1s 4ms/step -
accuracy: 0.9104 - loss: 0.3667
Epoch 109/300
391/391            1s 4ms/step -
accuracy: 0.9056 - loss: 0.3770
Epoch 110/300
391/391            1s 4ms/step -
accuracy: 0.8956 - loss: 0.4183
Epoch 111/300
391/391            1s 4ms/step -
accuracy: 0.9043 - loss: 0.3872
Epoch 112/300
391/391            1s 4ms/step -
accuracy: 0.9089 - loss: 0.3710
Epoch 113/300
391/391            1s 4ms/step -
accuracy: 0.9115 - loss: 0.3662
Epoch 114/300
391/391            1s 4ms/step -
accuracy: 0.9111 - loss: 0.3676
Epoch 115/300
391/391            1s 4ms/step -
accuracy: 0.9105 - loss: 0.3598
Epoch 116/300
391/391            1s 4ms/step -
accuracy: 0.9022 - loss: 0.3911
```

```
Epoch 117/300
391/391             1s 4ms/step -
accuracy: 0.9044 - loss: 0.3792
Epoch 118/300
391/391             1s 4ms/step -
accuracy: 0.9089 - loss: 0.3707
Epoch 119/300
391/391             1s 4ms/step -
accuracy: 0.9153 - loss: 0.3542
Epoch 120/300
391/391             1s 4ms/step -
accuracy: 0.9175 - loss: 0.3442
Epoch 121/300
391/391             1s 4ms/step -
accuracy: 0.9121 - loss: 0.3560
Epoch 122/300
391/391             1s 4ms/step -
accuracy: 0.9106 - loss: 0.3629
Epoch 123/300
391/391             1s 4ms/step -
accuracy: 0.9092 - loss: 0.3640
Epoch 124/300
391/391             1s 4ms/step -
accuracy: 0.9119 - loss: 0.3567
Epoch 125/300
391/391             1s 4ms/step -
accuracy: 0.9165 - loss: 0.3470
Epoch 126/300
391/391             1s 4ms/step -
accuracy: 0.9067 - loss: 0.3663
Epoch 127/300
391/391             1s 4ms/step -
accuracy: 0.9079 - loss: 0.3633
Epoch 128/300
391/391             1s 4ms/step -
accuracy: 0.9102 - loss: 0.3619
Epoch 129/300
391/391             1s 4ms/step -
accuracy: 0.9170 - loss: 0.3370
Epoch 130/300
391/391             1s 4ms/step -
accuracy: 0.9067 - loss: 0.3634
Epoch 131/300
391/391             1s 4ms/step -
accuracy: 0.9109 - loss: 0.3582
Epoch 132/300
391/391             1s 4ms/step -
accuracy: 0.9124 - loss: 0.3536
```

```
Epoch 133/300
391/391            1s 4ms/step -
accuracy: 0.9112 - loss: 0.3535
Epoch 134/300
391/391            1s 4ms/step -
accuracy: 0.9168 - loss: 0.3363
Epoch 135/300
391/391            1s 4ms/step -
accuracy: 0.9115 - loss: 0.3580
Epoch 136/300
391/391            2s 4ms/step -
accuracy: 0.9123 - loss: 0.3528
Epoch 137/300
391/391            1s 4ms/step -
accuracy: 0.9129 - loss: 0.3449
Epoch 138/300
391/391            1s 4ms/step -
accuracy: 0.9209 - loss: 0.3180
Epoch 139/300
391/391            2s 4ms/step -
accuracy: 0.9222 - loss: 0.3147
Epoch 140/300
391/391            1s 4ms/step -
accuracy: 0.9135 - loss: 0.3462
Epoch 141/300
391/391            1s 4ms/step -
accuracy: 0.9088 - loss: 0.3614
Epoch 142/300
391/391            1s 4ms/step -
accuracy: 0.9082 - loss: 0.3575
Epoch 143/300
391/391            1s 4ms/step -
accuracy: 0.9151 - loss: 0.3357
Epoch 144/300
391/391            1s 4ms/step -
accuracy: 0.9178 - loss: 0.3259
Epoch 145/300
391/391            1s 4ms/step -
accuracy: 0.9146 - loss: 0.3362
Epoch 146/300
391/391            1s 4ms/step -
accuracy: 0.9110 - loss: 0.3492
Epoch 147/300
391/391            1s 4ms/step -
accuracy: 0.9134 - loss: 0.3444
Epoch 148/300
391/391            1s 4ms/step -
accuracy: 0.9206 - loss: 0.3158
```

```
Epoch 149/300
391/391            1s 4ms/step -
accuracy: 0.9262 - loss: 0.3022
Epoch 150/300
391/391            1s 4ms/step -
accuracy: 0.9213 - loss: 0.3216
Epoch 151/300
391/391            1s 4ms/step -
accuracy: 0.9167 - loss: 0.3316
Epoch 152/300
391/391            1s 4ms/step -
accuracy: 0.9083 - loss: 0.3593
Epoch 153/300
391/391            1s 4ms/step -
accuracy: 0.9089 - loss: 0.3487
Epoch 154/300
391/391            1s 4ms/step -
accuracy: 0.9128 - loss: 0.3419
Epoch 155/300
391/391            1s 4ms/step -
accuracy: 0.9246 - loss: 0.3043
Epoch 156/300
391/391            1s 4ms/step -
accuracy: 0.9205 - loss: 0.3192
Epoch 157/300
391/391            1s 4ms/step -
accuracy: 0.9254 - loss: 0.2996
Epoch 158/300
391/391            1s 4ms/step -
accuracy: 0.9243 - loss: 0.3045
Epoch 159/300
391/391            1s 4ms/step -
accuracy: 0.9201 - loss: 0.3179
Epoch 160/300
391/391            1s 4ms/step -
accuracy: 0.9170 - loss: 0.3227
Epoch 161/300
391/391            1s 4ms/step -
accuracy: 0.9150 - loss: 0.3318
Epoch 162/300
391/391            2s 4ms/step -
accuracy: 0.9185 - loss: 0.3197
Epoch 163/300
391/391            1s 4ms/step -
accuracy: 0.9163 - loss: 0.3259
Epoch 164/300
391/391            1s 4ms/step -
accuracy: 0.9236 - loss: 0.3063
```

```
Epoch 165/300
391/391              1s 4ms/step -
accuracy: 0.9183 - loss: 0.3209
Epoch 166/300
391/391              1s 4ms/step -
accuracy: 0.9214 - loss: 0.3076
Epoch 167/300
391/391              1s 4ms/step -
accuracy: 0.9199 - loss: 0.3171
Epoch 168/300
391/391              1s 4ms/step -
accuracy: 0.9292 - loss: 0.2823
Epoch 169/300
391/391              1s 4ms/step -
accuracy: 0.9199 - loss: 0.3117
Epoch 170/300
391/391              1s 4ms/step -
accuracy: 0.9166 - loss: 0.3215
Epoch 171/300
391/391              1s 4ms/step -
accuracy: 0.9162 - loss: 0.3266
Epoch 172/300
391/391              1s 4ms/step -
accuracy: 0.9152 - loss: 0.3273
Epoch 173/300
391/391              1s 4ms/step -
accuracy: 0.9204 - loss: 0.3111
Epoch 174/300
391/391              1s 4ms/step -
accuracy: 0.9266 - loss: 0.2872
Epoch 175/300
391/391              1s 4ms/step -
accuracy: 0.9294 - loss: 0.2776
Epoch 176/300
391/391              1s 4ms/step -
accuracy: 0.9326 - loss: 0.2785
Epoch 177/300
391/391              1s 4ms/step -
accuracy: 0.9230 - loss: 0.2995
Epoch 178/300
391/391              1s 4ms/step -
accuracy: 0.9083 - loss: 0.3433
Epoch 179/300
391/391              1s 4ms/step -
accuracy: 0.9091 - loss: 0.3496
Epoch 180/300
391/391              1s 4ms/step -
accuracy: 0.9231 - loss: 0.2979
```

```
Epoch 181/300
391/391            1s 4ms/step -
accuracy: 0.9269 - loss: 0.2884
Epoch 182/300
391/391            1s 4ms/step -
accuracy: 0.9333 - loss: 0.2654
Epoch 183/300
391/391            1s 4ms/step -
accuracy: 0.9269 - loss: 0.2877
Epoch 184/300
391/391            1s 4ms/step -
accuracy: 0.9232 - loss: 0.2950
Epoch 185/300
391/391            1s 4ms/step -
accuracy: 0.9178 - loss: 0.3140
Epoch 186/300
391/391            1s 4ms/step -
accuracy: 0.9220 - loss: 0.3085
Epoch 187/300
391/391            1s 4ms/step -
accuracy: 0.9311 - loss: 0.2703
Epoch 188/300
391/391            1s 4ms/step -
accuracy: 0.9250 - loss: 0.2927
Epoch 189/300
391/391            1s 4ms/step -
accuracy: 0.9158 - loss: 0.3193
Epoch 190/300
391/391            1s 4ms/step -
accuracy: 0.9246 - loss: 0.2914
Epoch 191/300
391/391            1s 4ms/step -
accuracy: 0.9248 - loss: 0.2904
Epoch 192/300
391/391            1s 4ms/step -
accuracy: 0.9316 - loss: 0.2718
Epoch 193/300
391/391            1s 4ms/step -
accuracy: 0.9309 - loss: 0.2677
Epoch 194/300
391/391            1s 4ms/step -
accuracy: 0.9311 - loss: 0.2712
Epoch 195/300
391/391            1s 4ms/step -
accuracy: 0.9254 - loss: 0.2942
Epoch 196/300
391/391            1s 4ms/step -
accuracy: 0.9201 - loss: 0.3113
```

```
Epoch 197/300
391/391             1s 4ms/step -
accuracy: 0.9222 - loss: 0.2927
Epoch 198/300
391/391             1s 4ms/step -
accuracy: 0.9277 - loss: 0.2794
Epoch 199/300
391/391             1s 4ms/step -
accuracy: 0.9230 - loss: 0.2958
Epoch 200/300
391/391             1s 4ms/step -
accuracy: 0.9260 - loss: 0.2780
Epoch 201/300
391/391             1s 4ms/step -
accuracy: 0.9332 - loss: 0.2673
Epoch 202/300
391/391             1s 4ms/step -
accuracy: 0.9194 - loss: 0.3068
Epoch 203/300
391/391             1s 4ms/step -
accuracy: 0.9258 - loss: 0.2817
Epoch 204/300
391/391             2s 4ms/step -
accuracy: 0.9222 - loss: 0.2929
Epoch 205/300
391/391             2s 4ms/step -
accuracy: 0.9219 - loss: 0.2985
Epoch 206/300
391/391             2s 4ms/step -
accuracy: 0.9175 - loss: 0.3153
Epoch 207/300
391/391             2s 4ms/step -
accuracy: 0.9277 - loss: 0.2772
Epoch 208/300
391/391             2s 4ms/step -
accuracy: 0.9321 - loss: 0.2605
Epoch 209/300
391/391             2s 4ms/step -
accuracy: 0.9363 - loss: 0.2557
Epoch 210/300
391/391             2s 4ms/step -
accuracy: 0.9343 - loss: 0.2651
Epoch 211/300
391/391             2s 4ms/step -
accuracy: 0.9245 - loss: 0.2906
Epoch 212/300
391/391             1s 4ms/step -
accuracy: 0.9119 - loss: 0.3239
```

```
Epoch 213/300
391/391            1s 4ms/step -
accuracy: 0.9167 - loss: 0.3136
Epoch 214/300
391/391            1s 4ms/step -
accuracy: 0.9321 - loss: 0.2688
Epoch 215/300
391/391            1s 4ms/step -
accuracy: 0.9412 - loss: 0.2387
Epoch 216/300
391/391            1s 4ms/step -
accuracy: 0.9286 - loss: 0.2738
Epoch 217/300
391/391            1s 4ms/step -
accuracy: 0.9330 - loss: 0.2563
Epoch 218/300
391/391            1s 4ms/step -
accuracy: 0.9228 - loss: 0.2945
Epoch 219/300
391/391            1s 4ms/step -
accuracy: 0.9330 - loss: 0.2597
Epoch 220/300
391/391            1s 4ms/step -
accuracy: 0.9253 - loss: 0.2878
Epoch 221/300
391/391            1s 4ms/step -
accuracy: 0.9235 - loss: 0.2949
Epoch 222/300
391/391            1s 4ms/step -
accuracy: 0.9242 - loss: 0.2878
Epoch 223/300
391/391            1s 4ms/step -
accuracy: 0.9378 - loss: 0.2506
Epoch 224/300
391/391            1s 4ms/step -
accuracy: 0.9394 - loss: 0.2375
Epoch 225/300
391/391            1s 4ms/step -
accuracy: 0.9247 - loss: 0.2839
Epoch 226/300
391/391            1s 4ms/step -
accuracy: 0.9291 - loss: 0.2710
Epoch 227/300
391/391            1s 4ms/step -
accuracy: 0.9315 - loss: 0.2661
Epoch 228/300
391/391            1s 4ms/step -
accuracy: 0.9268 - loss: 0.2762
```

```
Epoch 229/300
391/391             1s 4ms/step -
accuracy: 0.9332 - loss: 0.2523
Epoch 230/300
391/391             1s 4ms/step -
accuracy: 0.9272 - loss: 0.2768
Epoch 231/300
391/391             1s 4ms/step -
accuracy: 0.9352 - loss: 0.2536
Epoch 232/300
391/391             1s 4ms/step -
accuracy: 0.9314 - loss: 0.2614
Epoch 233/300
391/391             1s 4ms/step -
accuracy: 0.9205 - loss: 0.2951
Epoch 234/300
391/391             1s 4ms/step -
accuracy: 0.9185 - loss: 0.3060
Epoch 235/300
391/391             1s 4ms/step -
accuracy: 0.9341 - loss: 0.2603
Epoch 236/300
391/391             1s 4ms/step -
accuracy: 0.9385 - loss: 0.2500
Epoch 237/300
391/391             1s 4ms/step -
accuracy: 0.9422 - loss: 0.2268
Epoch 238/300
391/391             1s 4ms/step -
accuracy: 0.9384 - loss: 0.2390
Epoch 239/300
391/391             1s 4ms/step -
accuracy: 0.9346 - loss: 0.2508
Epoch 240/300
391/391             1s 4ms/step -
accuracy: 0.9298 - loss: 0.2698
Epoch 241/300
391/391             1s 4ms/step -
accuracy: 0.9256 - loss: 0.2807
Epoch 242/300
391/391             1s 4ms/step -
accuracy: 0.9274 - loss: 0.2715
Epoch 243/300
391/391             1s 4ms/step -
accuracy: 0.9308 - loss: 0.2590
Epoch 244/300
391/391             1s 4ms/step -
accuracy: 0.9378 - loss: 0.2369
```

```
Epoch 245/300
391/391              1s 4ms/step -
accuracy: 0.9337 - loss: 0.2522
Epoch 246/300
391/391              1s 4ms/step -
accuracy: 0.9358 - loss: 0.2491
Epoch 247/300
391/391              1s 4ms/step -
accuracy: 0.9334 - loss: 0.2564
Epoch 248/300
391/391              1s 4ms/step -
accuracy: 0.9372 - loss: 0.2422
Epoch 249/300
391/391              1s 4ms/step -
accuracy: 0.9372 - loss: 0.2476
Epoch 250/300
391/391              1s 4ms/step -
accuracy: 0.9258 - loss: 0.2698
Epoch 251/300
391/391              1s 4ms/step -
accuracy: 0.9256 - loss: 0.2799
Epoch 252/300
391/391              1s 4ms/step -
accuracy: 0.9198 - loss: 0.2993
Epoch 253/300
391/391              1s 4ms/step -
accuracy: 0.9201 - loss: 0.2903
Epoch 254/300
391/391              1s 4ms/step -
accuracy: 0.9387 - loss: 0.2350
Epoch 255/300
391/391              1s 4ms/step -
accuracy: 0.9475 - loss: 0.2143
Epoch 256/300
391/391              1s 4ms/step -
accuracy: 0.9417 - loss: 0.2292
Epoch 257/300
391/391              1s 4ms/step -
accuracy: 0.9302 - loss: 0.2607
Epoch 258/300
391/391              1s 4ms/step -
accuracy: 0.9243 - loss: 0.2828
Epoch 259/300
391/391              1s 4ms/step -
accuracy: 0.9299 - loss: 0.2650
Epoch 260/300
391/391              1s 4ms/step -
accuracy: 0.9287 - loss: 0.2685
```

```
Epoch 261/300
391/391             1s 4ms/step -
accuracy: 0.9374 - loss: 0.2441
Epoch 262/300
391/391             1s 4ms/step -
accuracy: 0.9358 - loss: 0.2455
Epoch 263/300
391/391             1s 4ms/step -
accuracy: 0.9363 - loss: 0.2454
Epoch 264/300
391/391             1s 4ms/step -
accuracy: 0.9374 - loss: 0.2429
Epoch 265/300
391/391             1s 4ms/step -
accuracy: 0.9330 - loss: 0.2497
Epoch 266/300
391/391             1s 4ms/step -
accuracy: 0.9429 - loss: 0.2306
Epoch 267/300
391/391             1s 4ms/step -
accuracy: 0.9352 - loss: 0.2453
Epoch 268/300
391/391             1s 4ms/step -
accuracy: 0.9334 - loss: 0.2525
Epoch 269/300
391/391             1s 4ms/step -
accuracy: 0.9244 - loss: 0.2828
Epoch 270/300
391/391             1s 4ms/step -
accuracy: 0.9323 - loss: 0.2544
Epoch 271/300
391/391             1s 4ms/step -
accuracy: 0.9352 - loss: 0.2445
Epoch 272/300
391/391             1s 4ms/step -
accuracy: 0.9384 - loss: 0.2311
Epoch 273/300
391/391             1s 4ms/step -
accuracy: 0.9321 - loss: 0.2559
Epoch 274/300
391/391             1s 4ms/step -
accuracy: 0.9365 - loss: 0.2490
Epoch 275/300
391/391             1s 4ms/step -
accuracy: 0.9382 - loss: 0.2358
Epoch 276/300
391/391             1s 4ms/step -
accuracy: 0.9341 - loss: 0.2496
```

```
Epoch 277/300
391/391              1s 4ms/step -
accuracy: 0.9424 - loss: 0.2230
Epoch 278/300
391/391              1s 4ms/step -
accuracy: 0.9290 - loss: 0.2607
Epoch 279/300
391/391              1s 4ms/step -
accuracy: 0.9241 - loss: 0.2802
Epoch 280/300
391/391              1s 4ms/step -
accuracy: 0.9328 - loss: 0.2538
Epoch 281/300
391/391              1s 4ms/step -
accuracy: 0.9401 - loss: 0.2309
Epoch 282/300
391/391              1s 4ms/step -
accuracy: 0.9464 - loss: 0.2096
Epoch 283/300
391/391              1s 4ms/step -
accuracy: 0.9375 - loss: 0.2368
Epoch 284/300
391/391              1s 4ms/step -
accuracy: 0.9369 - loss: 0.2362
Epoch 285/300
391/391              1s 4ms/step -
accuracy: 0.9376 - loss: 0.2342
Epoch 286/300
391/391              1s 4ms/step -
accuracy: 0.9381 - loss: 0.2352
Epoch 287/300
391/391              1s 4ms/step -
accuracy: 0.9342 - loss: 0.2499
Epoch 288/300
391/391              1s 4ms/step -
accuracy: 0.9255 - loss: 0.2706
Epoch 289/300
391/391              1s 4ms/step -
accuracy: 0.9323 - loss: 0.2561
Epoch 290/300
391/391              1s 4ms/step -
accuracy: 0.9384 - loss: 0.2351
Epoch 291/300
391/391              1s 4ms/step -
accuracy: 0.9394 - loss: 0.2283
Epoch 292/300
391/391              1s 4ms/step -
accuracy: 0.9457 - loss: 0.2085
```

```
Epoch 293/300
391/391            1s 4ms/step -
accuracy: 0.9465 - loss: 0.2148
Epoch 294/300
391/391            1s 4ms/step -
accuracy: 0.9337 - loss: 0.2458
Epoch 295/300
391/391            1s 4ms/step -
accuracy: 0.9255 - loss: 0.2798
Epoch 296/300
391/391            1s 4ms/step -
accuracy: 0.9353 - loss: 0.2456
Epoch 297/300
391/391            1s 4ms/step -
accuracy: 0.9451 - loss: 0.2121
Epoch 298/300
391/391            1s 4ms/step -
accuracy: 0.9447 - loss: 0.2107
Epoch 299/300
391/391            1s 4ms/step -
accuracy: 0.9307 - loss: 0.2487
Epoch 300/300
391/391            1s 4ms/step -
accuracy: 0.9345 - loss: 0.2427
```

[29]:
```
<keras.src.callbacks.history.History at 0x7a8c15de0b50>
```

[30]:
```
word_index = imdb.get_word_index()

index_word = {index + 3: word for word, index in word_index.items() if index+3␣
 ↪< vocab_size}
index_word[0] = '<PAD>'
index_word[1] = '<START>'
index_word[2] = '<UNK>'
```

[31]:
```
def predict_next_word(model, seed_seq, index_word, sequence_length=10):

    seq_input = pad_sequences([seed_seq], maxlen=sequence_length)

    pred_probs = model.predict(seq_input, verbose=0)[0]

    next_word_index = np.argmax(pred_probs)

    next_word = index_word.get(next_word_index, '<UNK>')

    return next_word
```

[32]:
```python
num_samples = 5  # number of sequences to test
seed_sequences = [all_words[i:i+sequence_length] for i in range(num_samples)]

# Convert seed sequences to actual words for display
seed_words_list = [[index_word.get(idx, '<UNK>') for idx in seq] for seq in␣
↪seed_sequences]


predicted_next_words = []

for seq in seed_sequences:
    next_word = predict_next_word(model, seq, index_word,␣
↪sequence_length=sequence_length)
    predicted_next_words.append(next_word)


for i in range(num_samples):
    print(f"Seed sequence {i+1}: {' '.join(seed_words_list[i])}")
    print(f"Predicted next word: {predicted_next_words[i]}")
    print("-" * 50)
```

```
Seed sequence 1: <START> this film was just brilliant casting location scenery
story
Predicted next word: direction
--------------------------------------------------
Seed sequence 2: this film was just brilliant casting location scenery story
direction
Predicted next word: everyone's
--------------------------------------------------
Seed sequence 3: film was just brilliant casting location scenery story
direction everyone's
Predicted next word: really
--------------------------------------------------
Seed sequence 4: was just brilliant casting location scenery story direction
everyone's really
Predicted next word: suited
--------------------------------------------------
Seed sequence 5: just brilliant casting location scenery story direction
everyone's really suited
Predicted next word: the
--------------------------------------------------
```