NNDL LAB

LAB 6

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In [21]:
```
import pandas as pd
from sklearn.preprocessing import MinMaxScaler

data = pd.read_csv('./HistoricalQuotes.csv')
data = data[[' Close/Last']]

data
```

Out[21]:

	Close/Last
0	$273.36
1	$273.52
2	$292.65
3	$288.08
4	$298.18
...	...
2513	$31.2786
2514	$30.1014
2515	$29.9043
2516	$29.8357
2517	$29.8557

2518 rows × 1 columns

- cleaned the Close/Last column by removing dollar signs and commas, converting it to a numeric format.
- applied Min-Max Scaling to normalize the Close prices between 0 and 1 for better model performance.
- extracted the normalized Close prices into a NumPy array for easy input into a model.

In [25]:
```
data['Close'] = data[' Close/Last'].replace('[\$,]', '', regex=True).astype(floa

scaler = MinMaxScaler(feature_range=(0, 1))
data['Close'] = scaler.fit_transform(data[['Close']])
```

```
close_prices = data['Close'].values
close_prices
```

Out[25]:
```
array([8.18942624e-01, 8.19480684e-01, 8.83812549e-01, ...,
       2.30693463e-04, 0.00000000e+00, 6.72575693e-05])
```

- split the data into training and testing sets, using 80% of the close_prices for training and the remaining 20% for testing.
- The training data consists of the first 80% of the close_prices, and the testing data includes the remaining 20%.
- assigned the first 80% of the close_prices to train_data and the rest to test_data for model evaluation.

In [26]:
```
train_size = int(len(close_prices) * 0.8)
train_data = close_prices[:train_size]
test_data = close_prices[train_size:]


train_size, train_data, test_data
```

Out[26]:
```
(2014,
 array([0.81894262, 0.81948068, 0.88381255, ..., 0.16123556, 0.16026033,
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8.93516807e-04, 2.30693463e-04, 0.00000000e+00, 6.72575693e-05]))
```

- defined a function create_sequences to transform the data into sequences: each sequence (x) is a window of sequence_length (default 60) previous values, with the following value as the target (y).
- applied this function to create x_train, y_train, x_test, and y_test by generating sequences from train_data and test_data, preparing the data for time-series modeling.
- Finally converted x_train, y_train, x_test, and y_test to float32 format for compatibility with neural networks.

In [27]:
```
import numpy as np

def create_sequences(data, sequence_length=60):
    x, y = [], []
    for i in range(sequence_length, len(data)):
        x.append(data[i-sequence_length:i])
        y.append(data[i])
    return np.array(x), np.array(y)

x_train, y_train = create_sequences(train_data)
x_test, y_test = create_sequences(test_data)


x_train = x_train.astype(np.float32)
y_train = y_train.astype(np.float32)
x_test = x_test.astype(np.float32)
y_test = y_test.astype(np.float32)


x_train, y_train,x_test, y_test
```

Out[27]:
```
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6.70931265e-02, 6.71519712e-02, 6.82711378e-02, 6.80212826e-02,
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7.22201690e-02, 7.11010024e-02, 6.99912533e-02, 7.17301965e-02,
7.03080371e-02, 6.87133595e-02, 6.61286488e-02, 6.46584034e-02,
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6.45480976e-02, 6.48554638e-02, 6.36784583e-02, 6.17807843e-02,
5.66261634e-02, 5.94893210e-02, 6.24486543e-02, 6.33182898e-02,
6.70796707e-02, 6.57345206e-02, 6.51292056e-02, 6.37938008e-02,
6.41852468e-02, 6.11418374e-02, 5.99937513e-02, 6.01235591e-02,
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5.39980754e-02, 5.35706542e-02, 5.35370260e-02, 5.41998483e-02,
5.36668338e-02, 5.32811098e-02, 5.38830645e-02, 5.25379144e-02,
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1.61656924e-02, 1.57429799e-02, 1.50993243e-02, 1.63533408e-02,
1.49311805e-02, 1.77512895e-02, 1.95958298e-02, 1.97111759e-02,
2.12436393e-02, 2.07153317e-02, 1.86350551e-02, 1.93365514e-02,
2.06289049e-02, 1.98601522e-02, 2.42897347e-02, 2.54136082e-02,
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2.18059123e-02, 2.06769947e-02, 1.76453590e-02, 1.97209287e-02,
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3.12266797e-02, 2.94588152e-02, 3.13342921e-02, 3.02756578e-02,
```

```
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 1.30288005e-02, 1.25627052e-02, 1.29686045e-02, 1.13090239e-02,
 1.05930669e-02, 8.55146348e-03, 9.85794235e-03, 9.37267859e-03,
 7.63844233e-03, 6.43755822e-03, 7.59035302e-03, 7.33578298e-03,
 7.49451108e-03, 7.20126787e-03, 8.52725096e-03, 7.99894240e-03,
 7.68182334e-03, 6.80747489e-03, 4.91451053e-03, 4.85229725e-03,
 8.93516815e-04, 2.30693462e-04, 0.00000000e+00, 6.72575698e-05],
dtype=float32))
```

- reshaped x_train and x_test to have three dimensions, where the last dimension is 1, making them suitable for LSTM and other neural network models that expect 3D input.
- The reshaping format is (samples, sequence_length, features), with 1 feature per timestep in each sequence.
- x_train and x_test are ready in 3D format, compatible with models like LSTM.

In [28]:
```
x_train = x_train.reshape((x_train.shape[0], x_train.shape[1], 1))
x_test = x_test.reshape((x_test.shape[0], x_test.shape[1], 1))

x_train, x_test
```

Out[28]:
```
(array([[[0.8189426 ],
         [0.81948066],
         [0.88381255],
         ...,
         [0.79277945],
         [0.779866  ],
         [0.772165  ]],

        [[0.81948066],
         [0.88381255],
         [0.8684442 ],
         ...,
         [0.779866  ],
         [0.772165  ],
         [0.78800416]],

        [[0.88381255],
         [0.8684442 ],
         [0.90240926],
         ...,
         [0.772165  ],
         [0.78800416],
         [0.79839545]],

        ...,

        [[0.16979644],
         [0.17125224],
         [0.17376934],
         ...,
         [0.15440892],
         [0.15580216],
         [0.16157655]],

        [[0.17125224],
         [0.17376934],
         [0.16724065],
         ...,
         [0.15580216],
         [0.16157655],
         [0.16123556]],

        [[0.17376934],
         [0.16724065],
         [0.16931118],
         ...,
         [0.16157655],
         [0.16123556],
         [0.16026032]]], dtype=float32),
 array([[[0.15224692],
         [0.15063779],
         [0.14774571],
         ...,
         [0.08688232],
         [0.08603218],
         [0.08327933]],

        [[0.15063779],
         [0.14774571],
         [0.14613624],
```

```
         ...,
         [0.08603218],
         [0.08327933],
         [0.07895568]],

        [[0.14774571],
         [0.14613624],
         [0.14700587],
         ...,
         [0.08327933],
         [0.07895568],
         [0.08035833]],

        ...,

        [[0.02137815],
         [0.01693882],
         [0.01747251],
         ...,
         [0.00491451],
         [0.0048523 ],
         [0.00089352]],

        [[0.01693882],
         [0.01747251],
         [0.01821234],
         ...,
         [0.0048523 ],
         [0.00089352],
         [0.00023069]],

        [[0.01747251],
         [0.01821234],
         [0.01607927],
         ...,
         [0.00089352],
         [0.00023069],
         [0.        ]]], dtype=float32))
```

- created a Sequential model with a SimpleRNN layer of 50 units and ReLU activation, suitable for time-series data processing.
- The input shape for the SimpleRNN layer is set to (sequence_length, 1), matching the shape of x_train.
- added a Dense layer with 1 unit as the output layer to predict a single value for each sequence.

In [29]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import SimpleRNN, Dense

model = Sequential([
    SimpleRNN(50, activation='relu', input_shape=(x_train.shape[1], 1)),
    Dense(1)
])
```

```
c:\Users\USER\AppData\Local\Programs\Python\Python311\Lib\site-packages\keras\src
\layers\rnn\rnn.py:204: UserWarning: Do not pass an `input_shape`/`input_dim` arg
ument to a layer. When using Sequential models, prefer using an `Input(shape)` ob
ject as the first layer in the model instead.
  super().__init__(**kwargs)
```

- compiled the model using the Adam optimizer, which adapts learning rates during training for efficient convergence.
- set the loss function to Mean Squared Error, ideal for regression tasks like time-series forecasting.

In [30]:
```
model.compile(optimizer='adam', loss='mean_squared_error')
```

- trained the model on x_train and y_train for 50 epochs, with a batch size of 32 to control updates per training batch.
- included validation_data as (x_test, y_test) to monitor the model's performance on unseen data after each epoch.
- This setup tracks training progress and helps prevent overfitting by using both training and validation data.

In [31]:
```
history = model.fit(x_train, y_train, epochs=50, batch_size=32, validation_data=
```

```
Epoch 1/50
62/62 ━━━━━━━━━━━━━━━━━━━━ 4s 15ms/step - loss: 0.0228 - val_loss: 9.7903e-04
Epoch 2/50
62/62 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - loss: 1.7303e-04 - val_loss: 2.0708e-05
Epoch 3/50
62/62 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - loss: 9.0496e-05 - val_loss: 1.2874e-05
Epoch 4/50
62/62 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - loss: 8.1938e-05 - val_loss: 1.3887e-05
Epoch 5/50
62/62 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - loss: 8.0532e-05 - val_loss: 1.6519e-05
Epoch 6/50
62/62 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - loss: 8.5846e-05 - val_loss: 1.2287e-05
Epoch 7/50
62/62 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - loss: 9.3494e-05 - val_loss: 1.3019e-05
Epoch 8/50
62/62 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 8.7416e-05 - val_loss: 1.2226e-05
Epoch 9/50
62/62 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 8.4403e-05 - val_loss: 1.3889e-05
Epoch 10/50
62/62 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - loss: 8.6141e-05 - val_loss: 3.0730e-05
Epoch 11/50
62/62 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - loss: 8.7487e-05 - val_loss: 1.2913e-05
Epoch 12/50
62/62 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - loss: 8.1956e-05 - val_loss: 1.3215e-05
Epoch 13/50
62/62 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 8.2626e-05 - val_loss: 1.3142e-05
Epoch 14/50
62/62 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 8.3668e-05 - val_loss: 2.2998e-05
Epoch 15/50
62/62 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 1.4629e-04 - val_loss: 1.6313e-05
Epoch 16/50
62/62 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 7.9700e-05 - val_loss: 1.5791e-05
Epoch 17/50
62/62 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - loss: 8.3285e-05 - val_loss: 1.7922e-05
Epoch 18/50
62/62 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 1.1074e-04 - val_loss: 1.7821e-05
Epoch 19/50
62/62 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - loss: 8.0629e-05 - val_loss: 5.1676e-05
Epoch 20/50
62/62 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - loss: 7.7448e-05 - val_loss: 3.0262e-05
Epoch 21/50
62/62 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - loss: 1.0741e-04 - val_loss: 3.0158e-05
Epoch 22/50
62/62 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - loss: 9.2536e-05 - val_loss: 7.8522e-05
Epoch 23/50
62/62 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - loss: 7.9803e-05 - val_loss: 9.2827e-05
Epoch 24/50
62/62 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - loss: 1.0139e-04 - val_loss: 4.7734e-05
Epoch 25/50
62/62 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 8.2084e-05 - val_loss: 5.6436e-05
Epoch 26/50
62/62 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 7.5303e-05 - val_loss: 7.0249e-05
Epoch 27/50
62/62 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - loss: 9.2960e-05 - val_loss: 4.1804e-05
Epoch 28/50
62/62 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - loss: 7.2981e-05 - val_loss: 6.2996e-05
Epoch 29/50
62/62 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - loss: 7.8299e-05 - val_loss: 1.3634e-04
Epoch 30/50
62/62 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - loss: 7.6190e-05 - val_loss: 4.4956e-05
```

```
Epoch 31/50
62/62 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 7.4526e-05 - val_loss: 9.1757e-05
Epoch 32/50
62/62 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - loss: 8.0900e-05 - val_loss: 4.4539e-05
Epoch 33/50
62/62 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - loss: 6.9766e-05 - val_loss: 4.4009e-05
Epoch 34/50
62/62 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - loss: 9.4020e-05 - val_loss: 9.8293e-05
Epoch 35/50
62/62 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - loss: 7.8226e-05 - val_loss: 4.5018e-05
Epoch 36/50
62/62 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 8.3395e-05 - val_loss: 7.2891e-05
Epoch 37/50
62/62 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 7.8704e-05 - val_loss: 3.9896e-05
Epoch 38/50
62/62 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - loss: 8.2200e-05 - val_loss: 8.5654e-05
Epoch 39/50
62/62 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - loss: 8.1440e-05 - val_loss: 9.4426e-05
Epoch 40/50
62/62 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - loss: 8.0268e-05 - val_loss: 6.6794e-05
Epoch 41/50
62/62 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 8.0337e-05 - val_loss: 9.9476e-05
Epoch 42/50
62/62 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - loss: 7.2974e-05 - val_loss: 7.0504e-05
Epoch 43/50
62/62 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - loss: 7.5203e-05 - val_loss: 4.9368e-05
Epoch 44/50
62/62 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - loss: 8.7591e-05 - val_loss: 6.1487e-05
Epoch 45/50
62/62 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - loss: 7.8586e-05 - val_loss: 7.7440e-05
Epoch 46/50
62/62 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - loss: 6.4162e-05 - val_loss: 4.4111e-05
Epoch 47/50
62/62 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 6.8256e-05 - val_loss: 5.5714e-05
Epoch 48/50
62/62 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - loss: 6.7018e-05 - val_loss: 3.3207e-05
Epoch 49/50
62/62 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - loss: 6.3396e-05 - val_loss: 1.7134e-05
Epoch 50/50
62/62 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - loss: 6.6380e-05 - val_loss: 4.5663e-05
```

- generated predictions on the x_test data using the trained model.
- used scaler.inverse_transform to convert the predictions back to their original scale, making them comparable to the actual prices.
- Similarly, transformed y_test back to the original scale, providing the true values for comparison with the predictions.

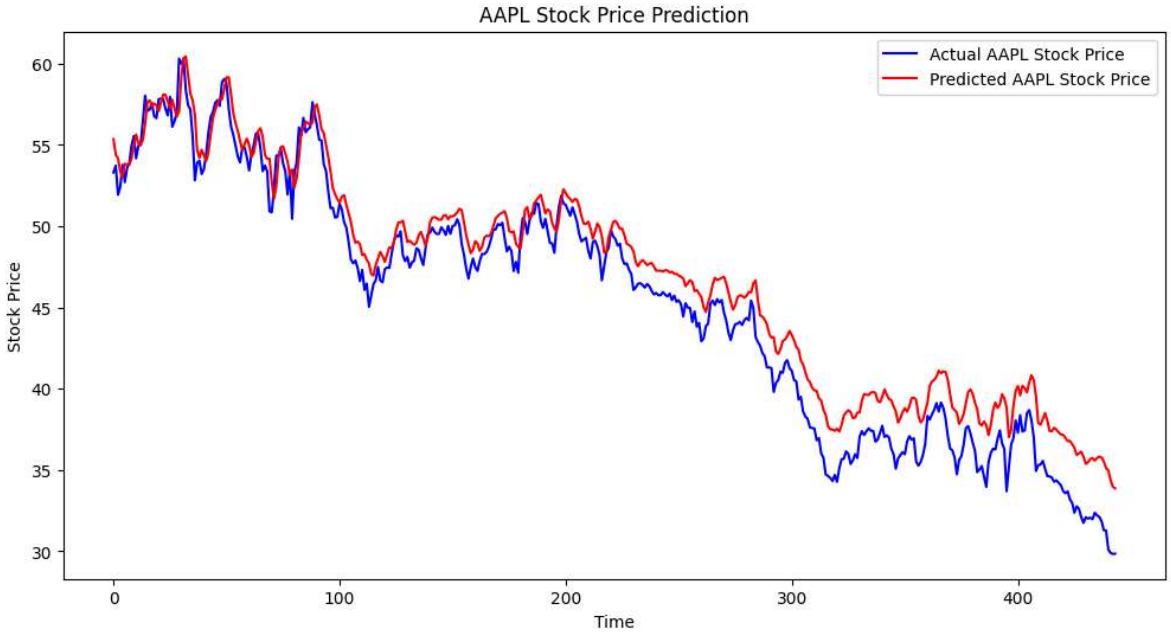
In [32]:
```
predictions = model.predict(x_test)
predictions = scaler.inverse_transform(predictions)
actual_prices = scaler.inverse_transform(y_test.reshape(-1, 1))
```

```
14/14 ━━━━━━━━━━━━━━━━━━━━ 1s 23ms/step
```

In [33]:
```
import matplotlib.pyplot as plt

plt.figure(figsize=(12, 6))
plt.plot(actual_prices, color='blue', label='Actual AAPL Stock Price')
plt.plot(predictions, color='red', label='Predicted AAPL Stock Price')
```

```
plt.title('AAPL Stock Price Prediction')
plt.xlabel('Time')
plt.ylabel('Stock Price')
plt.legend()
plt.show()
```



- evaluated the model's performance by calculating Mean Absolute Error (MAE), which measures the average absolute difference between predicted and actual prices.
- calculated Root Mean Squared Error (RMSE) by taking the square root of Mean Squared Error, providing insight into the model's prediction accuracy.

In [34]:
```
from sklearn.metrics import mean_absolute_error, mean_squared_error
import numpy as np

mae = mean_absolute_error(actual_prices, predictions)
rmse = np.sqrt(mean_squared_error(actual_prices, predictions))

print(f"MAE: {mae}")
print(f"RMSE: {rmse}")
```

```
MAE: 1.7192814350128174
RMSE: 2.009431838989258
```