Set Device (GPU)

In [21]:
```
import torch
print("CUDA Available:", torch.cuda.is_available())
```

```
CUDA Available: True
```

Importing Libraries

In [1]:
```
import pandas as pd
import numpy as np
from sklearn.preprocessing import MinMaxScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, SimpleRNN
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.layers import LSTM
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.layers import GRU
import matplotlib.pyplot as plt
```

Loading GOOG Dataset

In [2]:
```
# Loading the dataset
data = pd.read_csv("D:\data\stock_market_data\sp500\csv\GOOG.csv")
data.head()
```

Out[2]:

	Date	Low	Open	Volume	High	Close	Adjusted Close
0	19-08-2004	2.390042	2.490664	897427216	2.591785	2.499133	2.499133
1	20-08-2004	2.503118	2.515820	458857488	2.716817	2.697639	2.697639
2	23-08-2004	2.716070	2.758411	366857939	2.826406	2.724787	2.724787
3	24-08-2004	2.579581	2.770615	306396159	2.779581	2.611960	2.611960
4	25-08-2004	2.587302	2.614201	184645512	2.689918	2.640104	2.640104

In [3]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4612 entries, 0 to 4611
Data columns (total 7 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   Date            4612 non-null   object 
 1   Low             4612 non-null   float64
 2   Open            4612 non-null   float64
 3   Volume          4612 non-null   int64  
 4   High            4612 non-null   float64
 5   Close           4612 non-null   float64
 6   Adjusted Close  4612 non-null   float64
dtypes: float64(5), int64(1), object(1)
memory usage: 252.3+ KB
```

In [4]:
```
data.describe()
```

Out[4]:

	Low	Open	Volume	High	Close	Adjusted Close
count	4612.000000	4612.000000	4.612000e+03	4612.000000	4612.000000	4612.000000
mean	37.088474	37.471847	1.238896e+08	37.856624	37.477273	37.477273
std	34.791176	35.163155	1.536223e+08	35.549294	35.170034	35.170034
min	2.390042	2.470490	1.584340e+05	2.534002	2.490913	2.490913
25%	12.401765	12.575302	2.992850e+07	12.697718	12.576174	12.576174
50%	22.808758	22.980115	6.869051e+07	23.098795	22.954461	22.954461
75%	52.975875	53.578501	1.549155e+08	54.106961	53.534375	53.534375
max	149.887497	151.863495	1.650833e+09	152.100006	150.709000	150.709000

In [5]:
```
# Convert 'Date' to DateTime format and encode as ordinal
data['Date'] = pd.to_datetime(data['Date'])
data['Date'] = data['Date'].map(pd.Timestamp.toordinal)

# Use past N days' data to predict the next M days as per the requirement
N = 30
M = 1

# Extracting the feature
features = ['Open', 'High', 'Low', 'Close', 'Volume']
data_values = data[features].values

X, y = [], []
for i in range(len(data_values) - N - M + 1):
    X.append(data_values[i:i+N])
    y.append(data_values[i+N:i+N+M, :])

X, y = np.array(X), np.array(y)
```

```
C:\Users\sanch\AppData\Local\Temp\ipykernel_15396\4147777905.py:2: UserWarning: P
arsing dates in %d-%m-%Y format when dayfirst=False (the default) was specified.
Pass `dayfirst=True` or specify a format to silence this warning.
  data['Date'] = pd.to_datetime(data['Date'])
```

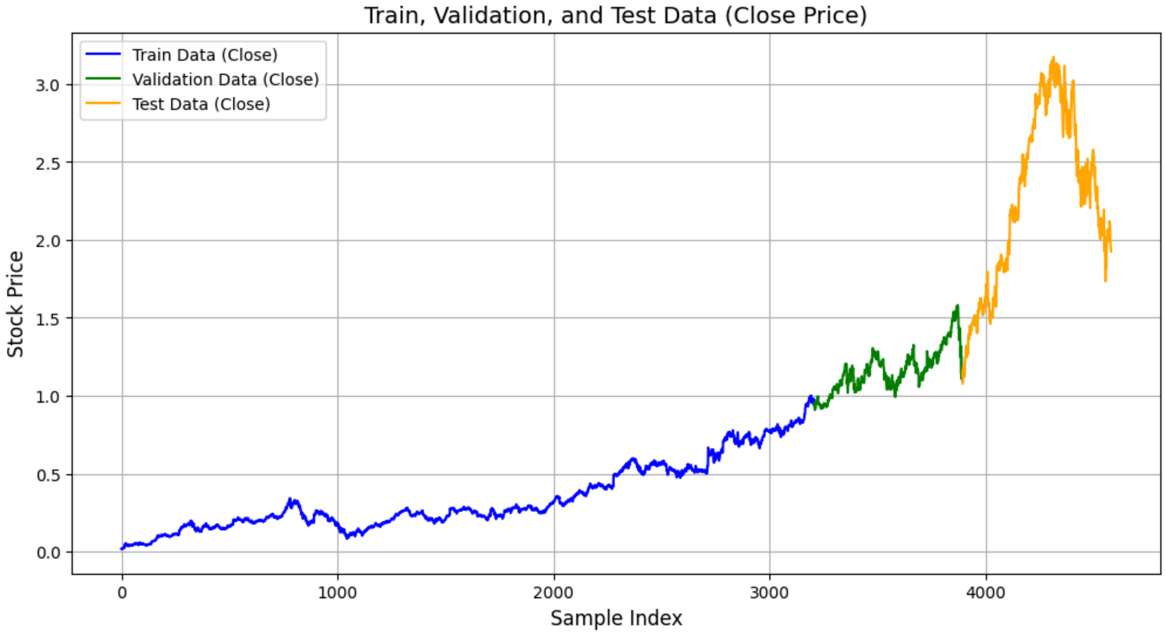
Train Test Split

In [6]:
```
# Split the dataset 70, 15, 15
train_size = int(0.7 * len(X))
val_size = int(0.15 * len(X))
X_train, X_val, X_test = X[:train_size], X[train_size:train_size+val_size], X[tr
y_train, y_val, y_test = y[:train_size], y[train_size:train_size+val_size], y[tr
```

Normalise Dataset

In [32]:
```
# Normalise the data
scaler = MinMaxScaler()
X_train = scaler.fit_transform(X_train.reshape(-1, X_train.shape[-1])).reshape(X
X_val = scaler.transform(X_val.reshape(-1, X_val.shape[-1])).reshape(X_val.shape
X_test = scaler.transform(X_test.reshape(-1, X_test.shape[-1])).reshape(X_test.s
y_train = scaler.transform(y_train.reshape(-1, y_train.shape[-1])).reshape(y_tra
y_val = scaler.transform(y_val.reshape(-1, y_val.shape[-1])).reshape(y_val.shape
y_test = scaler.transform(y_test.reshape(-1, y_test.shape[-1])).reshape(y_test.s
```

In [8]:
```
# Plotting the train, validation, and test data curves

# Extracting "Close" price data from y_train, y_val, and y_test
y_train_close = y_train[:, :, 3].reshape(-1)
y_val_close = y_val[:, :, 3].reshape(-1)
y_test_close = y_test[:, :, 3].reshape(-1)
train_indices = range(len(y_train_close))
val_indices = range(len(y_train_close), len(y_train_close) + len(y_val_close))
test_indices = range(len(y_train_close) + len(y_val_close), len(y_train_close) +

# Plot the curves
plt.figure(figsize=(12, 6))
plt.plot(train_indices, y_train_close, label='Train Data (Close)', color='blue',
plt.plot(val_indices, y_val_close, label='Validation Data (Close)', color='green
plt.plot(test_indices, y_test_close, label='Test Data (Close)', color='orange',
plt.title('Train, Validation, and Test Data (Close Price)', fontsize=14)
plt.xlabel('Sample Index', fontsize=12)
plt.ylabel('Stock Price', fontsize=12)
plt.legend()
plt.grid(True)
plt.show()
```



In [9]:
```
# Displaying dimensions of the split dataset
print("Training data dimensions:")
print(f"X_train: {X_train.shape}, y_train: {y_train.shape}")

print("Validation data dimensions:")
print(f"X_val: {X_val.shape}, y_val: {y_val.shape}")

print("Test data dimensions:")
print(f"X_test: {X_test.shape}, y_test: {y_test.shape}")
```

```
Training data dimensions:
X_train: (3207, 30, 5), y_train: (3207, 1, 5)
Validation data dimensions:
X_val: (687, 30, 5), y_val: (687, 1, 5)
Test data dimensions:
X_test: (688, 30, 5), y_test: (688, 1, 5)
```

Baseline RNN Model

In [10]:
```
# Build the baseline Simple RNN model
baseline_rnn = Sequential([
    SimpleRNN(10, activation='relu', input_shape=(N, len(features))),
    Dense(M * len(features))
])

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

# Train the model
baseline_history = baseline_rnn.fit(X_train, y_train.reshape(y_train.shape[0], -
                                    validation_data=(X_val, y_val.reshape(y_val.
                                    epochs=20, batch_size=32, verbose=1)

# Evaluate on test data
baseline_test_loss, baseline_test_mae = baseline_rnn.evaluate(X_test, y_test.res
print(f"Baseline Test Loss: {baseline_test_loss}, Test MAE: {baseline_test_mae}"

# Predict
y_test_pred_baseline = baseline_rnn.predict(X_test)
```

```
# Inverse transform for comparison
y_test_actual_baseline = scaler.inverse_transform(y_test.reshape(-1, y_test.shap
y_test_pred_baseline = scaler.inverse_transform(y_test_pred_baseline.reshape(-1,

# Predict on validation data using the baseline model
y_val_pred_baseline = baseline_rnn.predict(X_val)

# Inverse transform the predictions
y_val_actual_baseline = scaler.inverse_transform(y_val.reshape(-1, y_val.shape[-
y_val_pred_baseline = scaler.inverse_transform(y_val_pred_baseline.reshape(-1, y
```

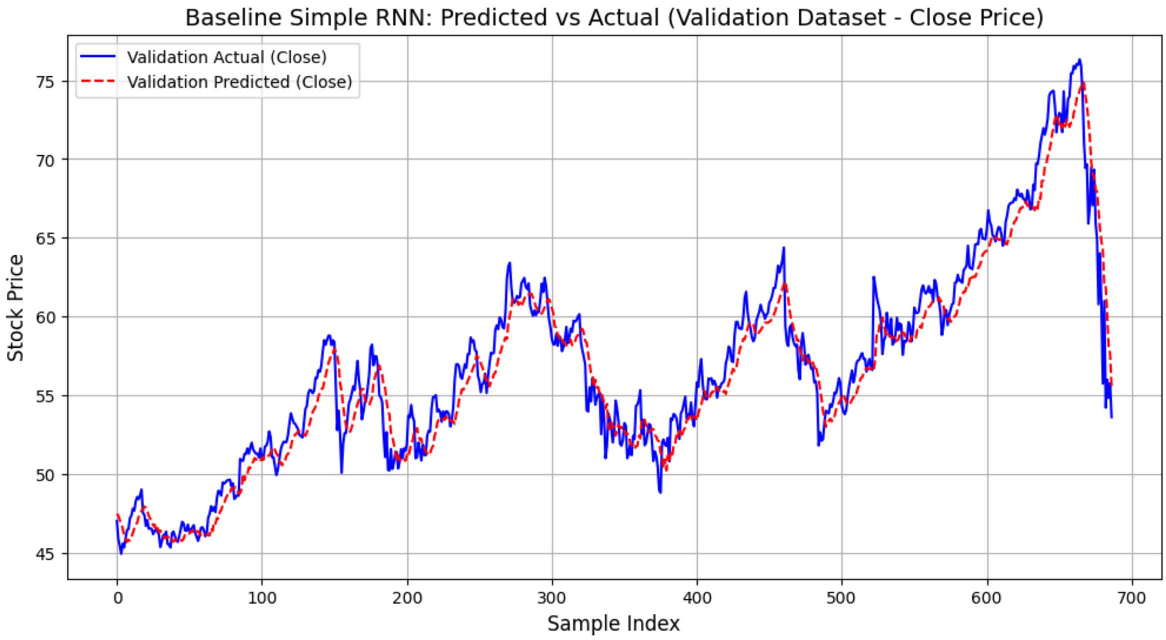
```
Epoch 1/20
```

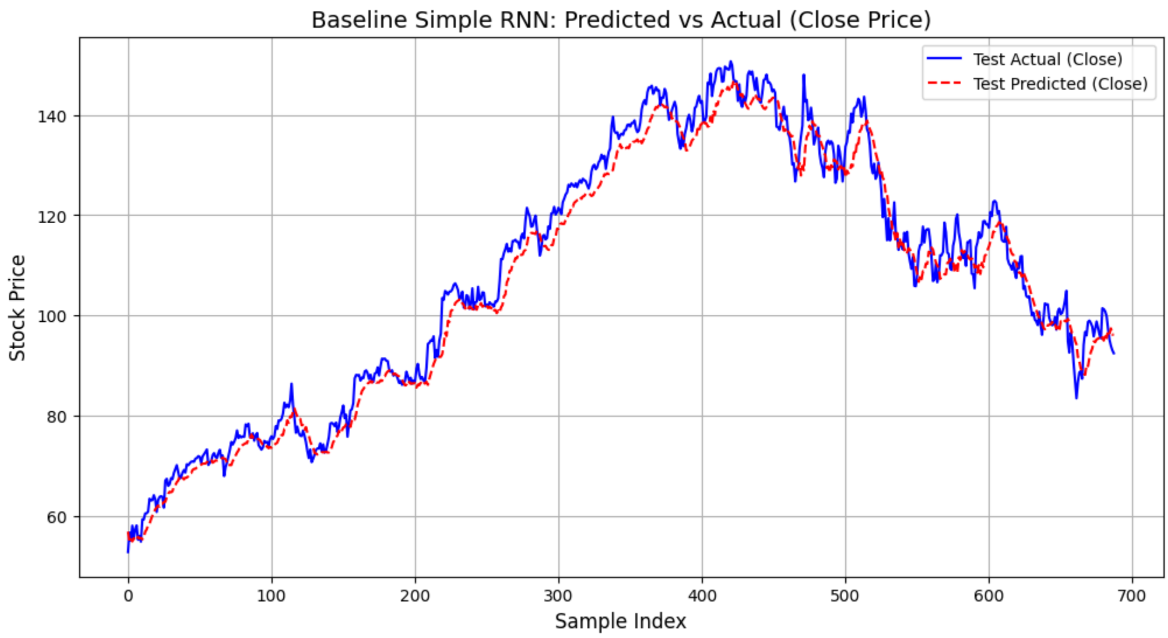
```
E:\Codes_data\try\envs\ai\lib\site-packages\keras\src\layers\rnn\rnn.py:200: User
Warning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using
Sequential models, prefer using an `Input(shape)` object as the first layer in th
e model instead.
  super().__init__(**kwargs)
```

```
101/101 ━━━━━━━━━━━━━━━━━━━━ 2s 6ms/step - loss: 0.1856 - mae: 0.2978 - val_loss:
0.3124 - val_mae: 0.4347
Epoch 2/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0156 - mae: 0.0805 - val_loss:
0.0145 - val_mae: 0.0890
Epoch 3/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 0.0031 - mae: 0.0360 - val_loss:
0.0052 - val_mae: 0.0602
Epoch 4/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0018 - mae: 0.0268 - val_loss:
0.0022 - val_mae: 0.0398
Epoch 5/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - loss: 0.0015 - mae: 0.0227 - val_loss:
0.0023 - val_mae: 0.0388
Epoch 6/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 0.0012 - mae: 0.0196 - val_loss:
0.0018 - val_mae: 0.0335
Epoch 7/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 0.0012 - mae: 0.0193 - val_loss:
0.0020 - val_mae: 0.0363
Epoch 8/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 0.0010 - mae: 0.0185 - val_loss:
0.0020 - val_mae: 0.0362
Epoch 9/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 0.0012 - mae: 0.0185 - val_loss:
0.0014 - val_mae: 0.0305
Epoch 10/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - loss: 0.0012 - mae: 0.0183 - val_loss:
0.0014 - val_mae: 0.0298
Epoch 11/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0011 - mae: 0.0172 - val_loss:
0.0015 - val_mae: 0.0298
Epoch 12/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0011 - mae: 0.0169 - val_loss:
0.0019 - val_mae: 0.0336
Epoch 13/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - loss: 9.3504e-04 - mae: 0.0164 - val_l
oss: 0.0013 - val_mae: 0.0281
Epoch 14/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 8.8960e-04 - mae: 0.0157 - val_l
oss: 0.0012 - val_mae: 0.0270
Epoch 15/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 9.6224e-04 - mae: 0.0152 - val_l
oss: 0.0014 - val_mae: 0.0295
Epoch 16/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 9.1985e-04 - mae: 0.0151 - val_l
oss: 9.8719e-04 - val_mae: 0.0235
Epoch 17/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - loss: 8.6993e-04 - mae: 0.0149 - val_l
oss: 9.9554e-04 - val_mae: 0.0239
Epoch 18/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 7.9107e-04 - mae: 0.0144 - val_l
oss: 0.0018 - val_mae: 0.0296
Epoch 19/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 7.2477e-04 - mae: 0.0141 - val_l
oss: 0.0011 - val_mae: 0.0243
Epoch 20/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 8.0498e-04 - mae: 0.0139 - val_l
oss: 0.0012 - val_mae: 0.0253
22/22 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0050 - mae: 0.0526
```

```
Baseline Test Loss: 0.0076013486832380295, Test MAE: 0.06658827513456345
22/22 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step
22/22 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step
```

In [11]:
```
# Plot baseline validation results
plt.figure(figsize=(12, 6))
plt.plot(y_val_actual_baseline[:, 0, 3], label='Validation Actual (Close)', colo
plt.plot(y_val_pred_baseline[:, 0, 3], label='Validation Predicted (Close)', col
plt.title('Baseline Simple RNN: Predicted vs Actual (Validation Dataset - Close 
plt.xlabel('Sample Index', fontsize=12)
plt.ylabel('Stock Price', fontsize=12)
plt.legend()
plt.grid(True)
plt.show()

# Plot baseline test data results
plt.figure(figsize=(12, 6))
plt.plot(y_test_actual_baseline[:, 0, 3], label='Test Actual (Close)', color='bl
plt.plot(y_test_pred_baseline[:, 0, 3], label='Test Predicted (Close)', color='r
plt.title('Baseline Simple RNN: Predicted vs Actual (Close Price)', fontsize=14)
plt.xlabel('Sample Index', fontsize=12)
plt.ylabel('Stock Price', fontsize=12)
plt.legend()
plt.grid(True)
plt.show()
```





Optimise RNN Hyperparameters

In [12]:
```
# Define function for optimisation
def build_and_evaluate(units, learning_rate, batch_size, epochs):
    model = Sequential([
        SimpleRNN(units, activation='relu', input_shape=(N, len(features))),
        Dense(M * len(features))
    ])
    model.compile(optimizer=Adam(learning_rate=learning_rate), loss='mse', metri
    history = model.fit(X_train, y_train.reshape(y_train.shape[0], -1),
                        validation_data=(X_val, y_val.reshape(y_val.shape[0], -1
                        epochs=epochs, batch_size=batch_size, verbose=1)
    test_loss, test_mae = model.evaluate(X_test, y_test.reshape(y_test.shape[0],
    print(f"Units: {units}, Learning Rate: {learning_rate}, Batch Size: {batch_s
    print(f"Test Loss: {test_loss}, Test MAE: {test_mae}")
    return model, history, test_loss, test_mae

# Optimise tuning
results = []
for units in [50]:
    for lr in [0.001]:
        for batch in [32]:
            for epoch in [20]:
                opt_model, opt_history, opt_test_loss, opt_test_mae = build_and_
                results.append((units, lr, batch, epoch, opt_test_loss, opt_test

# Display results
results_df = pd.DataFrame(results, columns=['Units', 'Learning Rate', 'Batch Siz
print("\nOptimized RNN Results:")
print(results_df)

# Predict on test data using optimised model
y_test_pred_optimized = opt_model.predict(X_test)

# Inverse transform
y_test_actual_optimized = scaler.inverse_transform(y_test.reshape(-1, y_test.sha
y_test_pred_optimized = scaler.inverse_transform(y_test_pred_optimized.reshape(-
```

```
# Predict on validation data using the optimised model
y_val_pred_optimized = opt_model.predict(X_val)

# Inverse transform the predictions
y_val_actual_optimized = scaler.inverse_transform(y_val.reshape(-1, y_val.shape[
y_val_pred_optimized = scaler.inverse_transform(y_val_pred_optimized.reshape(-1,
```

```
Epoch 1/20
```

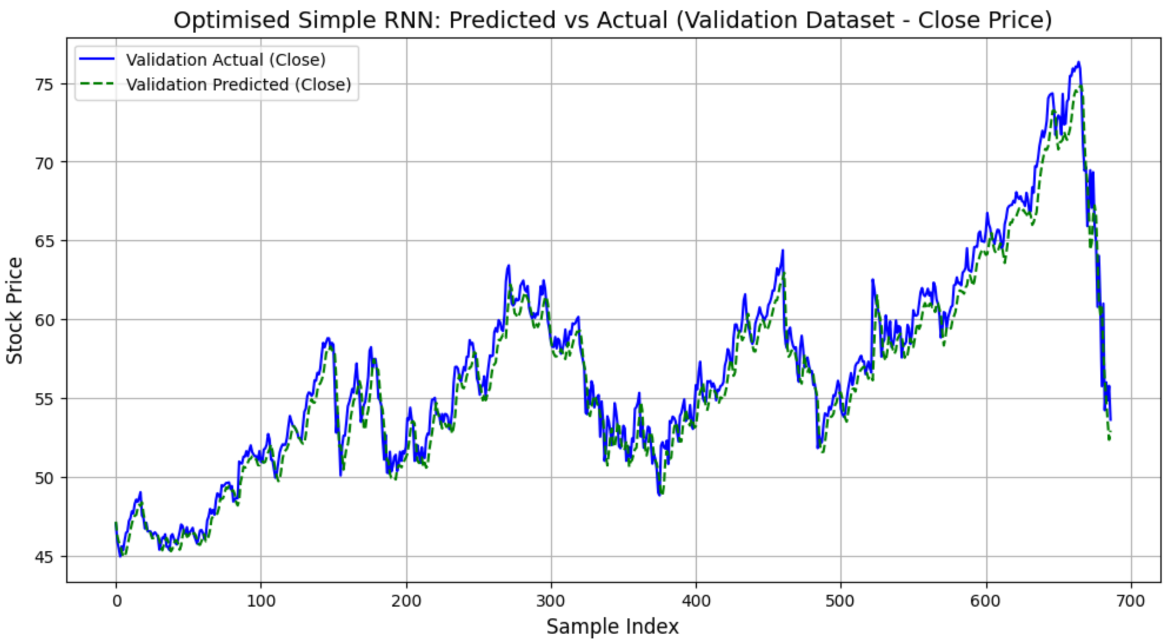
```
E:\Codes_data\try\envs\ai\lib\site-packages\keras\src\layers\rnn\rnn.py:200: User
Warning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using
Sequential models, prefer using an `Input(shape)` object as the first layer in th
e model instead.
  super().__init__(**kwargs)
```

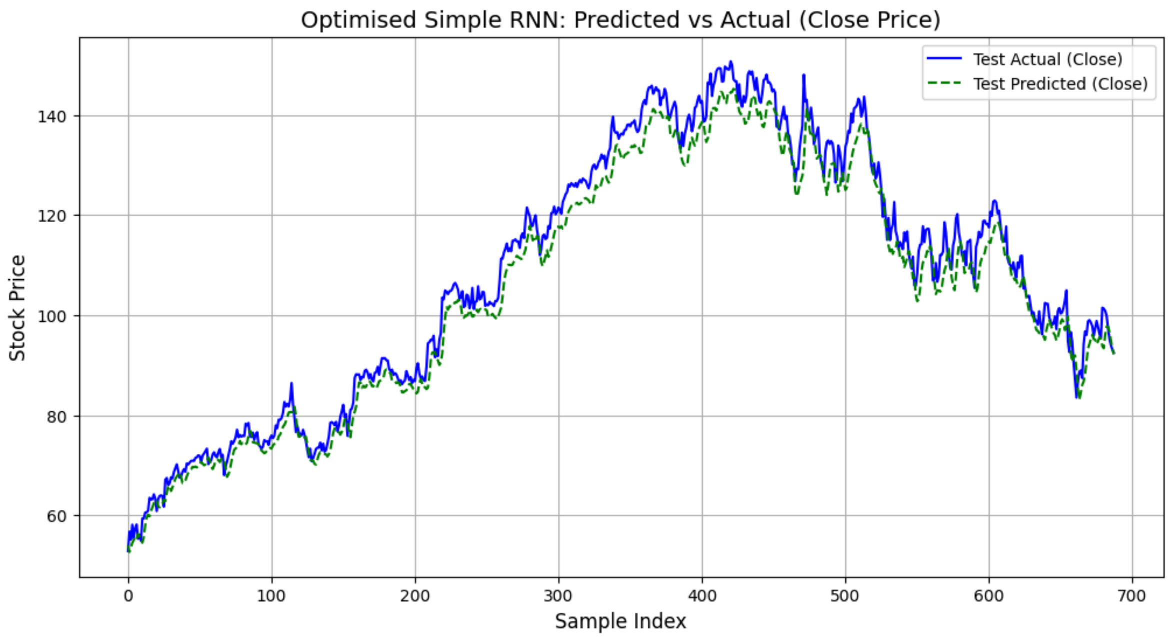
```
101/101 ━━━━━━━━━━━━━━━━━━━━ 2s 7ms/step - loss: 0.0748 - mae: 0.1642 - val_loss: 
0.0024 - val_mae: 0.0406
Epoch 2/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 9.8004e-04 - mae: 0.0165 - val_l
oss: 0.0011 - val_mae: 0.0264
Epoch 3/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 9.0754e-04 - mae: 0.0145 - val_l
oss: 0.0011 - val_mae: 0.0249
Epoch 4/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 7.0094e-04 - mae: 0.0134 - val_l
oss: 8.9475e-04 - val_mae: 0.0216
Epoch 5/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 6.9500e-04 - mae: 0.0128 - val_l
oss: 6.9041e-04 - val_mae: 0.0191
Epoch 6/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 7.0986e-04 - mae: 0.0127 - val_l
oss: 6.9501e-04 - val_mae: 0.0190
Epoch 7/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 7.2279e-04 - mae: 0.0124 - val_l
oss: 8.2567e-04 - val_mae: 0.0206
Epoch 8/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - loss: 7.1828e-04 - mae: 0.0119 - val_l
oss: 7.3479e-04 - val_mae: 0.0208
Epoch 9/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - loss: 7.4938e-04 - mae: 0.0122 - val_l
oss: 8.0316e-04 - val_mae: 0.0222
Epoch 10/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 6.9156e-04 - mae: 0.0119 - val_l
oss: 6.1070e-04 - val_mae: 0.0181
Epoch 11/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 7.6640e-04 - mae: 0.0120 - val_l
oss: 6.4558e-04 - val_mae: 0.0191
Epoch 12/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 7.1598e-04 - mae: 0.0115 - val_l
oss: 7.7490e-04 - val_mae: 0.0222
Epoch 13/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - loss: 7.0460e-04 - mae: 0.0115 - val_l
oss: 4.8661e-04 - val_mae: 0.0157
Epoch 14/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - loss: 7.0875e-04 - mae: 0.0112 - val_l
oss: 5.5674e-04 - val_mae: 0.0176
Epoch 15/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - loss: 6.8318e-04 - mae: 0.0110 - val_l
oss: 5.7575e-04 - val_mae: 0.0174
Epoch 16/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 5.9962e-04 - mae: 0.0107 - val_l
oss: 4.9983e-04 - val_mae: 0.0156
Epoch 17/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 7.4784e-04 - mae: 0.0111 - val_l
oss: 6.2443e-04 - val_mae: 0.0191
Epoch 18/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 6.9669e-04 - mae: 0.0109 - val_l
oss: 4.6996e-04 - val_mae: 0.0150
Epoch 19/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 7.7199e-04 - mae: 0.0110 - val_l
oss: 5.3096e-04 - val_mae: 0.0172
Epoch 20/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 7.2645e-04 - mae: 0.0107 - val_l
oss: 4.3712e-04 - val_mae: 0.0145
Units: 50, Learning Rate: 0.001, Batch Size: 32, Epochs: 20
```

```
Test Loss: 0.003099022200331092, Test MAE: 0.038996994495391846

Optimized RNN Results:
   Units  Learning Rate  Batch Size  Epochs  Test Loss  Test MAE
0     50          0.001          32      20   0.003099  0.038997
22/22 ━━━━━━━━━━━━━━━━━━━━ 0s 13ms/step
22/22 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step
```

In [ ]:

In [13]:
```python
# Plot optimised validation results
plt.figure(figsize=(12, 6))
plt.plot(y_val_actual_optimized[:, 0, 3], label='Validation Actual (Close)', col
plt.plot(y_val_pred_optimized[:, 0, 3], label='Validation Predicted (Close)', cc
plt.title('Optimised Simple RNN: Predicted vs Actual (Validation Dataset - Close
plt.xlabel('Sample Index', fontsize=12)
plt.ylabel('Stock Price', fontsize=12)
plt.legend()
plt.grid(True)
plt.show()

# Plot optimised results
plt.figure(figsize=(12, 6))
plt.plot(y_test_actual_optimized[:, 0, 3], label='Test Actual (Close)', color='b
plt.plot(y_test_pred_optimized[:, 0, 3], label='Test Predicted (Close)', color='
plt.title('Optimised Simple RNN: Predicted vs Actual (Close Price)', fontsize=14
plt.xlabel('Sample Index', fontsize=12)
plt.ylabel('Stock Price', fontsize=12)
plt.legend()
plt.grid(True)
plt.show()
```





In [ ]:

Baseline LSTM Model

In [14]:

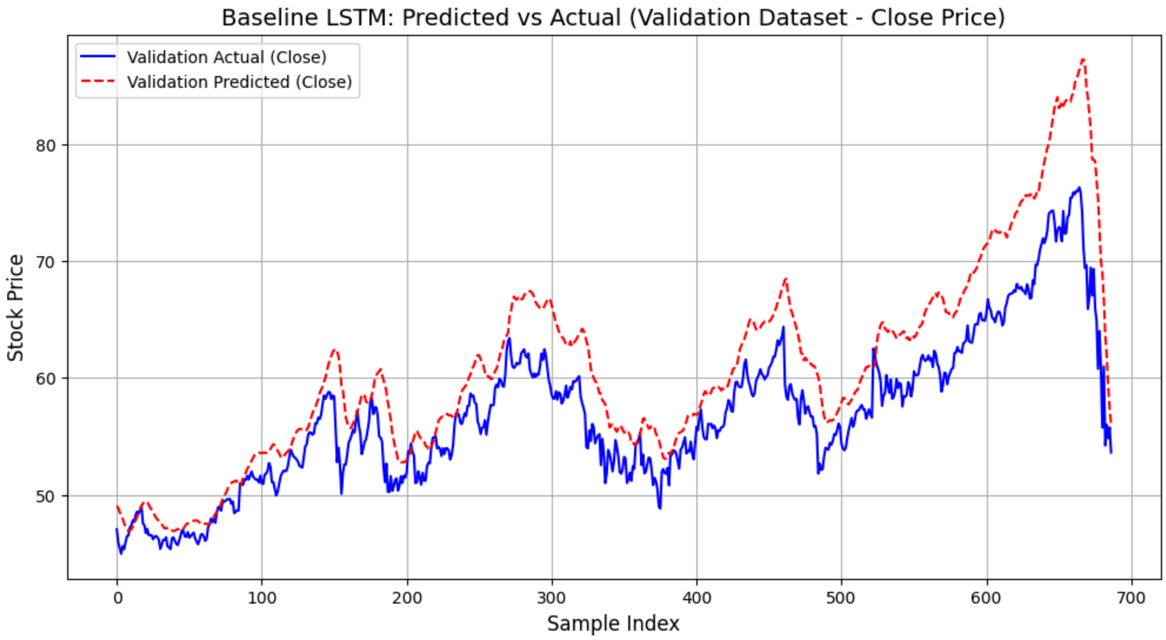
```
# Build LSTM baseline model
baseline_lstm = Sequential([
    LSTM(10, activation='relu', input_shape=(N, len(features))),
    Dense(M * len(features))
])

# Compile the model
baseline_lstm.compile(optimizer=Adam(learning_rate=0.001), loss='mse', metrics=[

# Train the LSTM baseline model
baseline_lstm_history = baseline_lstm.fit(X_train, y_train.reshape(y_train.shape
                                          validation_data=(X_val, y_val.reshape(
                                          epochs=20, batch_size=32, verbose=1)

# Evaluate on test data
baseline_lstm_test_loss, baseline_lstm_test_mae = baseline_lstm.evaluate(X_test,
print(f"Baseline LSTM Test Loss: {baseline_lstm_test_loss}, Test MAE: {baseline_

# Predict on validation and test data
y_val_pred_baseline_lstm = baseline_lstm.predict(X_val)
y_test_pred_baseline_lstm = baseline_lstm.predict(X_test)

# Inverse transform the predictions
y_val_actual_baseline_lstm = scaler.inverse_transform(y_val.reshape(-1, y_val.sh
y_val_pred_baseline_lstm = scaler.inverse_transform(y_val_pred_baseline_lstm.res
y_test_actual_baseline_lstm = scaler.inverse_transform(y_test.reshape(-1, y_test
y_test_pred_baseline_lstm = scaler.inverse_transform(y_test_pred_baseline_lstm.r
```

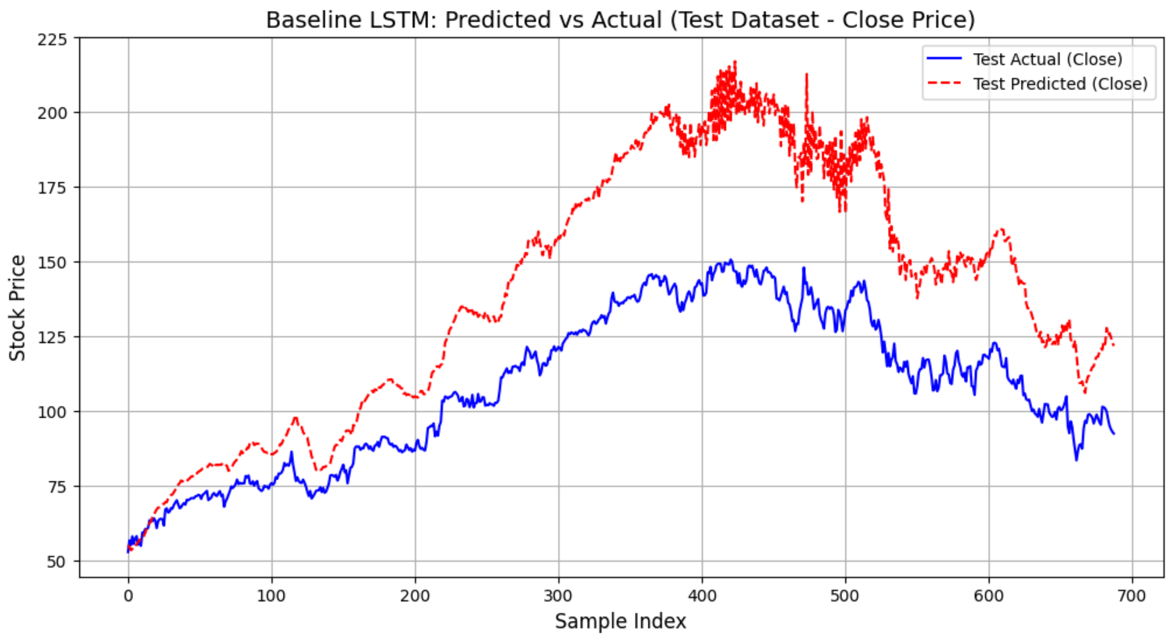
```
Epoch 1/20
E:\Codes_data\try\envs\ai\lib\site-packages\keras\src\layers\rnn\rnn.py:200: User
Warning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using
Sequential models, prefer using an `Input(shape)` object as the first layer in th
e model instead.
  super().__init__(**kwargs)
```

```
101/101 ━━━━━━━━━━━━━━━━━━━━ 3s 10ms/step - loss: 0.1151 - mae: 0.2613 - val_los
s: 0.5027 - val_mae: 0.5636
Epoch 2/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - loss: 0.0183 - mae: 0.0848 - val_loss:
0.5132 - val_mae: 0.5375
Epoch 3/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - loss: 0.0029 - mae: 0.0353 - val_loss:
0.1448 - val_mae: 0.3047
Epoch 4/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - loss: 0.0017 - mae: 0.0244 - val_loss:
0.0879 - val_mae: 0.1945
Epoch 5/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - loss: 0.0013 - mae: 0.0212 - val_loss:
0.0730 - val_mae: 0.1602
Epoch 6/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - loss: 0.0015 - mae: 0.0206 - val_loss:
0.0646 - val_mae: 0.1513
Epoch 7/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - loss: 0.0012 - mae: 0.0193 - val_loss:
0.0604 - val_mae: 0.1475
Epoch 8/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - loss: 0.0011 - mae: 0.0184 - val_loss:
0.0517 - val_mae: 0.1448
Epoch 9/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - loss: 0.0011 - mae: 0.0174 - val_loss:
0.0416 - val_mae: 0.1320
Epoch 10/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - loss: 9.2682e-04 - mae: 0.0167 - val_l
oss: 0.0272 - val_mae: 0.1036
Epoch 11/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - loss: 8.6577e-04 - mae: 0.0156 - val_l
oss: 0.0298 - val_mae: 0.1147
Epoch 12/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - loss: 8.8172e-04 - mae: 0.0152 - val_l
oss: 0.0215 - val_mae: 0.0973
Epoch 13/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - loss: 9.1625e-04 - mae: 0.0143 - val_l
oss: 0.0164 - val_mae: 0.0863
Epoch 14/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - loss: 8.7829e-04 - mae: 0.0136 - val_l
oss: 0.0177 - val_mae: 0.0919
Epoch 15/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - loss: 7.8475e-04 - mae: 0.0134 - val_l
oss: 0.0145 - val_mae: 0.0841
Epoch 16/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - loss: 7.8699e-04 - mae: 0.0130 - val_l
oss: 0.0117 - val_mae: 0.0751
Epoch 17/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - loss: 7.7639e-04 - mae: 0.0127 - val_l
oss: 0.0100 - val_mae: 0.0672
Epoch 18/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - loss: 7.7015e-04 - mae: 0.0130 - val_l
oss: 0.0087 - val_mae: 0.0643
Epoch 19/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - loss: 8.5276e-04 - mae: 0.0126 - val_l
oss: 0.0083 - val_mae: 0.0640
Epoch 20/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - loss: 8.4055e-04 - mae: 0.0124 - val_l
oss: 0.0060 - val_mae: 0.0542
22/22 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.3239 - mae: 0.4239
```

```
Baseline LSTM Test Loss: 0.5862671732902527, Test MAE: 0.6585427522659302
22/22 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step
22/22 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
```

In [15]:
```
# Plot validation dataset results for baseline LSTM
plt.figure(figsize=(12, 6))
plt.plot(y_val_actual_baseline_lstm[:, 0, 3], label='Validation Actual (Close)',
plt.plot(y_val_pred_baseline_lstm[:, 0, 3], label='Validation Predicted (Close)'
plt.title('Baseline LSTM: Predicted vs Actual (Validation Dataset - Close Price)
plt.xlabel('Sample Index', fontsize=12)
plt.ylabel('Stock Price', fontsize=12)
plt.legend()
plt.grid(True)
plt.show()

# Plot test dataset results for baseline LSTM
plt.figure(figsize=(12, 6))
plt.plot(y_test_actual_baseline_lstm[:, 0, 3], label='Test Actual (Close)', colo
plt.plot(y_test_pred_baseline_lstm[:, 0, 3], label='Test Predicted (Close)', col
plt.title('Baseline LSTM: Predicted vs Actual (Test Dataset - Close Price)', fon
plt.xlabel('Sample Index', fontsize=12)
plt.ylabel('Stock Price', fontsize=12)
plt.legend()
plt.grid(True)
plt.show()
```





Optimise LSTM Hyperparameters

In [16]:
```
# Function to build and evaluate LSTM model with different hyperparameters
def build_and_evaluate_lstm(units, batch_size):
    model = Sequential([
        LSTM(units, activation='relu', input_shape=(N, len(features))),
        Dense(M * len(features))
    ])
    model.compile(optimizer=Adam(learning_rate=0.001), loss='mse', metrics=['mae
    history = model.fit(X_train, y_train.reshape(y_train.shape[0], -1),
                        validation_data=(X_val, y_val.reshape(y_val.shape[0], -1
                        epochs=20, batch_size=batch_size, verbose=1)
    test_loss, test_mae = model.evaluate(X_test, y_test.reshape(y_test.shape[0],
    return test_loss, test_mae, model, history

# Test different hyperparameter combinations for LSTM
lstm_results = []
for units in [50]:
    for batch_size in [32]:
        test_loss, test_mae, lstm_model, lstm_history = build_and_evaluate_lstm(
        lstm_results.append((units, batch_size, test_loss, test_mae))

# Display results
lstm_results_df = pd.DataFrame(lstm_results, columns=['Units', 'Batch Size', 'Te
print("\nOptimised LSTM Results:")
print(lstm_results_df)

# Ensure input shapes are consistent for prediction
X_val_corrected = X_val.reshape(X_val.shape[0], X_val.shape[1], len(features))
X_test_corrected = X_test.reshape(X_test.shape[0], X_test.shape[1], len(features

# Predict on validation and test data using optimized LSTM model
y_val_pred_scaled_lstm = lstm_model.predict(X_val_corrected)
y_test_pred_scaled_lstm = lstm_model.predict(X_test_corrected)

# Inverse transform the predictions for validation
y_val_actual_lstm = scaler.inverse_transform(y_val.reshape(-1, y_val.shape[-1]))
y_val_pred_lstm = scaler.inverse_transform(y_val_pred_scaled_lstm.reshape(-1, y_
```

```
# Inverse transform the predictions for test
y_test_actual_lstm = scaler.inverse_transform(y_test.reshape(-1, y_test.shape[-1
y_test_pred_lstm = scaler.inverse_transform(y_test_pred_scaled_lstm.reshape(-1,
```

```
Epoch 1/20
```

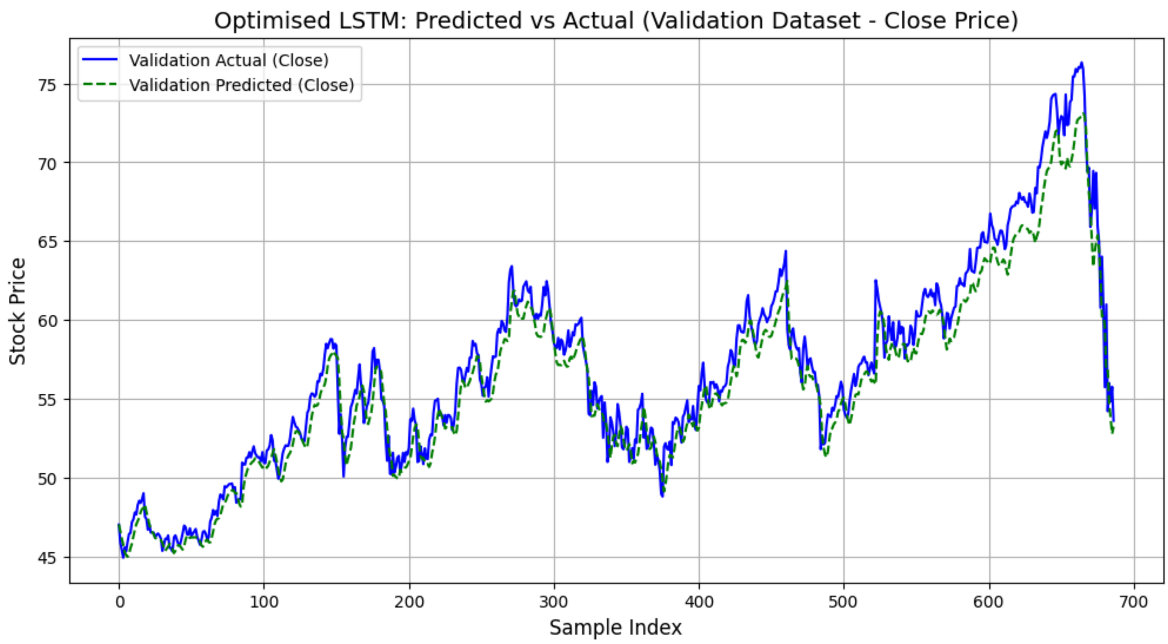
```
E:\Codes_data\try\envs\ai\lib\site-packages\keras\src\layers\rnn\rnn.py:200: User
Warning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using
Sequential models, prefer using an `Input(shape)` object as the first layer in th
e model instead.
  super().__init__(**kwargs)
```

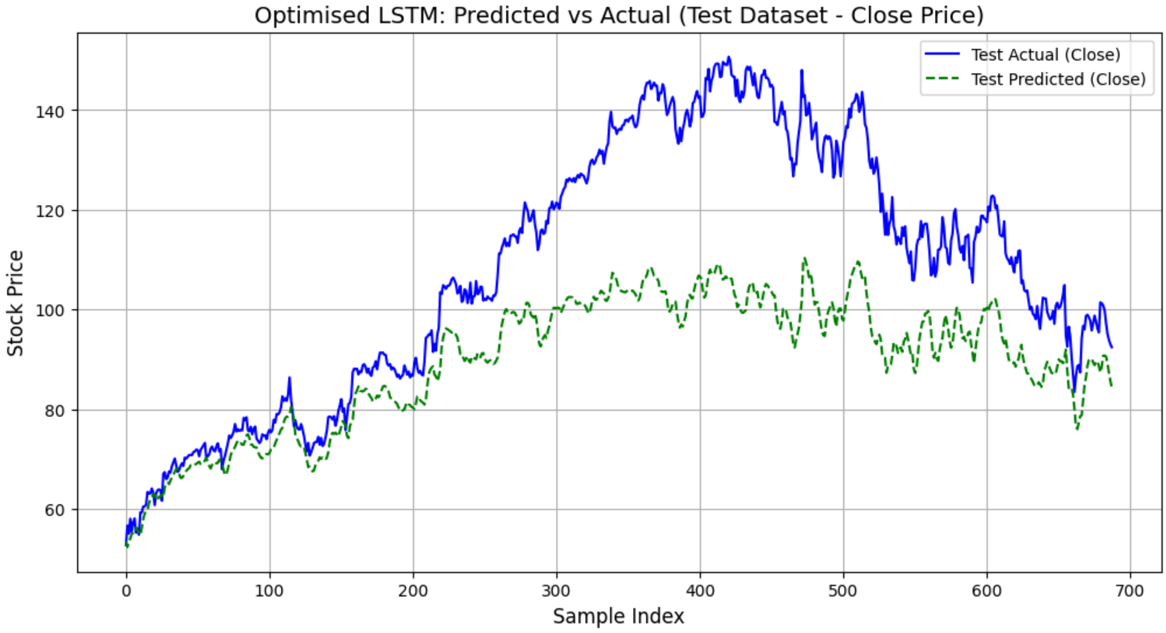
```
101/101 ━━━━━━━━━━━━━━━━━━━━ 2s 10ms/step - loss: 0.0375 - mae: 0.1134 - val_los
s: 0.0156 - val_mae: 0.0892
Epoch 2/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - loss: 0.0011 - mae: 0.0173 - val_loss:
0.0033 - val_mae: 0.0410
Epoch 3/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - loss: 8.5793e-04 - mae: 0.0154 - val_
loss: 0.0013 - val_mae: 0.0284
Epoch 4/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - loss: 7.9568e-04 - mae: 0.0146 - val_l
oss: 0.0036 - val_mae: 0.0471
Epoch 5/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - loss: 9.2309e-04 - mae: 0.0149 - val_
loss: 0.0013 - val_mae: 0.0262
Epoch 6/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - loss: 7.0272e-04 - mae: 0.0138 - val_l
oss: 0.0031 - val_mae: 0.0411
Epoch 7/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - loss: 7.0936e-04 - mae: 0.0131 - val_l
oss: 0.0018 - val_mae: 0.0344
Epoch 8/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - loss: 7.5910e-04 - mae: 0.0137 - val_l
oss: 0.0016 - val_mae: 0.0293
Epoch 9/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 2s 15ms/step - loss: 7.7874e-04 - mae: 0.0130 - val_
loss: 0.0017 - val_mae: 0.0307
Epoch 10/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 0.0011 - mae: 0.0140 - val_los
s: 0.0013 - val_mae: 0.0284
Epoch 11/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - loss: 6.4467e-04 - mae: 0.0122 - val_l
oss: 8.3821e-04 - val_mae: 0.0214
Epoch 12/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - loss: 7.7479e-04 - mae: 0.0138 - val_l
oss: 8.4073e-04 - val_mae: 0.0219
Epoch 13/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - loss: 7.2410e-04 - mae: 0.0125 - val_l
oss: 7.0345e-04 - val_mae: 0.0190
Epoch 14/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 8.1236e-04 - mae: 0.0128 - val_
loss: 0.0014 - val_mae: 0.0282
Epoch 15/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 12ms/step - loss: 7.5714e-04 - mae: 0.0121 - val_
loss: 9.3978e-04 - val_mae: 0.0245
Epoch 16/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 12ms/step - loss: 6.8539e-04 - mae: 0.0121 - val_
loss: 0.0026 - val_mae: 0.0412
Epoch 17/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - loss: 6.9129e-04 - mae: 0.0120 - val_l
oss: 5.7092e-04 - val_mae: 0.0172
Epoch 18/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - loss: 7.1786e-04 - mae: 0.0114 - val_l
oss: 6.1358e-04 - val_mae: 0.0176
Epoch 19/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - loss: 6.2427e-04 - mae: 0.0108 - val_l
oss: 6.7274e-04 - val_mae: 0.0202
Epoch 20/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - loss: 6.3939e-04 - mae: 0.0114 - val_l
oss: 9.4295e-04 - val_mae: 0.0235
```

```
Optimized LSTM Results:
   Units  Batch Size  Test Loss  Test MAE
0     50          32   0.124292  0.258601
22/22 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step
22/22 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step
```

In [17]:

```
# Plot validation dataset results for optimized LSTM
plt.figure(figsize=(12, 6))
plt.plot(y_val_actual_lstm[:, 0, 3], label='Validation Actual (Close)', color='b
plt.plot(y_val_pred_lstm[:, 0, 3], label='Validation Predicted (Close)', color='
plt.title('Optimised LSTM: Predicted vs Actual (Validation Dataset - Close Price
plt.xlabel('Sample Index', fontsize=12)
plt.ylabel('Stock Price', fontsize=12)
plt.legend()
plt.grid(True)
plt.show()

# Plot test dataset results for optimized LSTM
plt.figure(figsize=(12, 6))
plt.plot(y_test_actual_lstm[:, 0, 3], label='Test Actual (Close)', color='blue',
plt.plot(y_test_pred_lstm[:, 0, 3], label='Test Predicted (Close)', color='green
plt.title('Optimised LSTM: Predicted vs Actual (Test Dataset - Close Price)', fo
plt.xlabel('Sample Index', fontsize=12)
plt.ylabel('Stock Price', fontsize=12)
plt.legend()
plt.grid(True)
plt.show()
```





Baseline GRU

In [18]:

```
# Build GRU baseline model
baseline_gru = Sequential([
    GRU(10, activation='relu', input_shape=(N, len(features))),
    Dense(M * len(features))
])

# Compile the model
baseline_gru.compile(optimizer=Adam(learning_rate=0.001), loss='mse', metrics=['

# Train the GRU baseline model
baseline_gru_history = baseline_gru.fit(X_train, y_train.reshape(y_train.shape[0
                                        validation_data=(X_val, y_val.reshape(y_
                                        epochs=20, batch_size=32, verbose=1)

# Evaluate on test data
baseline_gru_test_loss, baseline_gru_test_mae = baseline_gru.evaluate(X_test, y_
print(f"Baseline GRU Test Loss: {baseline_gru_test_loss}, Test MAE: {baseline_gr

# Predict on validation and test data
y_val_pred_baseline_gru = baseline_gru.predict(X_val)
y_test_pred_baseline_gru = baseline_gru.predict(X_test)

# Inverse transform the predictions
y_val_actual_baseline_gru = scaler.inverse_transform(y_val.reshape(-1, y_val.sha
y_val_pred_baseline_gru = scaler.inverse_transform(y_val_pred_baseline_gru.resha
y_test_actual_baseline_gru = scaler.inverse_transform(y_test.reshape(-1, y_test.
y_test_pred_baseline_gru = scaler.inverse_transform(y_test_pred_baseline_gru.res
```

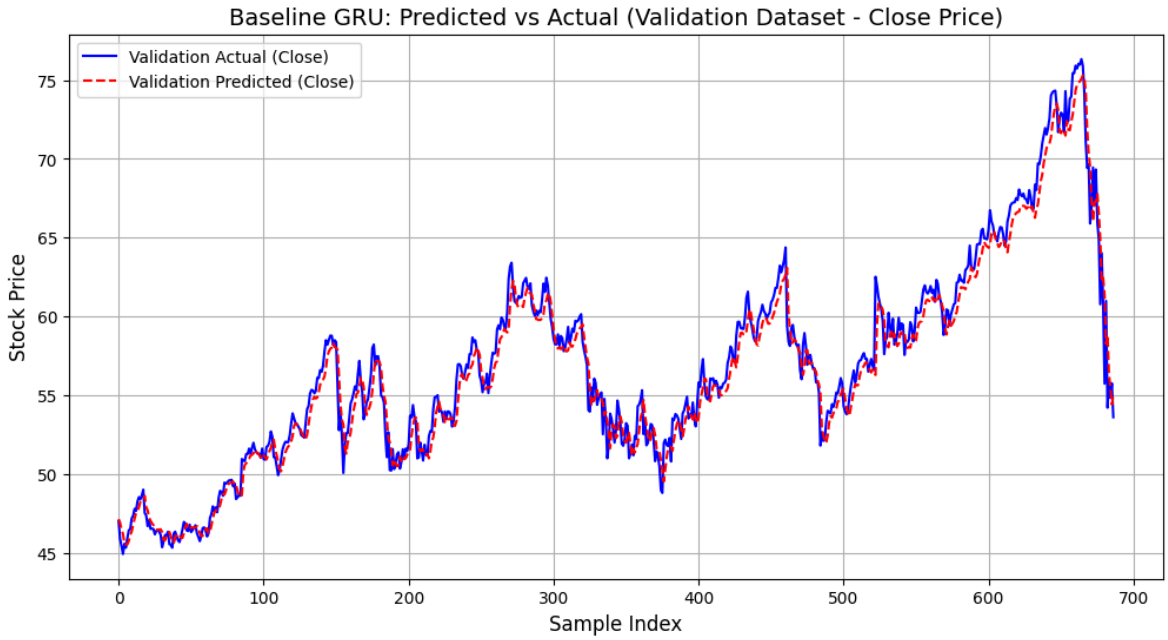
```
Epoch 1/20
E:\Codes_data\try\envs\ai\lib\site-packages\keras\src\layers\rnn\rnn.py:200: User
Warning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using
Sequential models, prefer using an `Input(shape)` object as the first layer in th
e model instead.
  super().__init__(**kwargs)
```

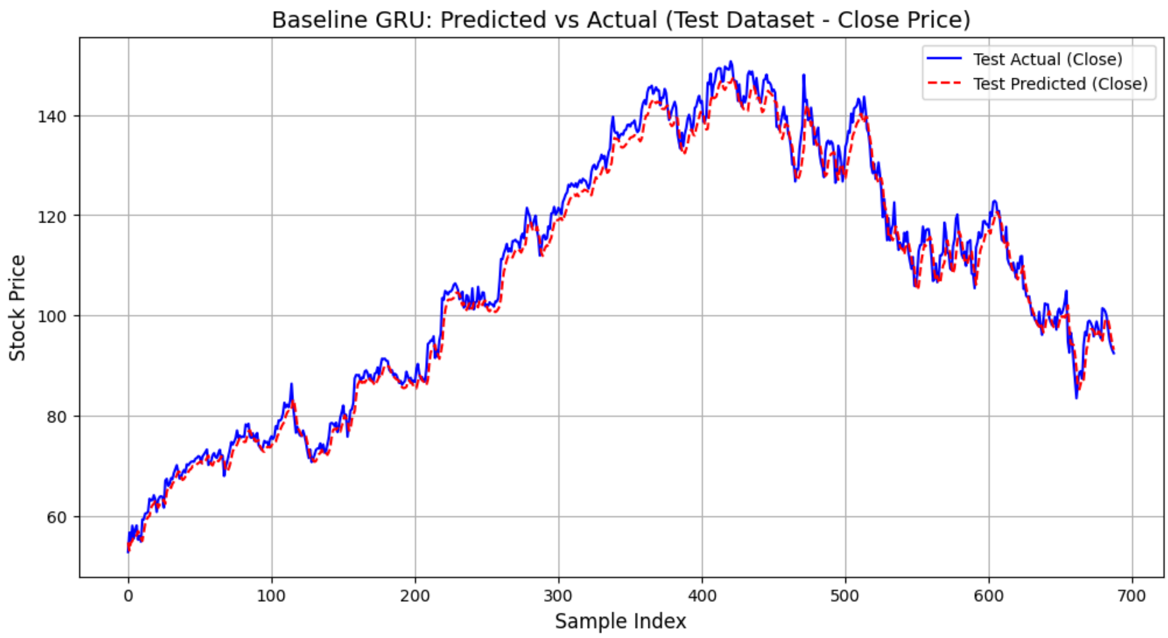
```
101/101 ━━━━━━━━━━━━━━━━━━━━ 3s 10ms/step - loss: 0.1327 - mae: 0.2736 - val_loss: 0.3800 - val_mae: 0.5631
Epoch 2/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - loss: 0.0193 - mae: 0.0915 - val_loss: 0.0405 - val_mae: 0.1778
Epoch 3/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - loss: 0.0027 - mae: 0.0351 - val_loss: 0.0052 - val_mae: 0.0513
Epoch 4/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - loss: 0.0010 - mae: 0.0198 - val_loss: 0.0035 - val_mae: 0.0389
Epoch 5/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - loss: 0.0010 - mae: 0.0182 - val_loss: 0.0033 - val_mae: 0.0386
Epoch 6/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - loss: 9.9803e-04 - mae: 0.0175 - val_loss: 0.0036 - val_mae: 0.0402
Epoch 7/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - loss: 8.9335e-04 - mae: 0.0165 - val_loss: 0.0032 - val_mae: 0.0377
Epoch 8/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - loss: 9.2576e-04 - mae: 0.0160 - val_loss: 0.0035 - val_mae: 0.0395
Epoch 9/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - loss: 8.2174e-04 - mae: 0.0152 - val_loss: 0.0024 - val_mae: 0.0325
Epoch 10/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - loss: 8.0826e-04 - mae: 0.0149 - val_loss: 0.0025 - val_mae: 0.0342
Epoch 11/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - loss: 0.0011 - mae: 0.0144 - val_loss: 0.0026 - val_mae: 0.0350
Epoch 12/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - loss: 8.2144e-04 - mae: 0.0135 - val_loss: 0.0026 - val_mae: 0.0349
Epoch 13/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - loss: 7.4288e-04 - mae: 0.0130 - val_loss: 0.0021 - val_mae: 0.0307
Epoch 14/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - loss: 6.7239e-04 - mae: 0.0124 - val_loss: 0.0028 - val_mae: 0.0361
Epoch 15/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - loss: 8.1676e-04 - mae: 0.0125 - val_loss: 0.0020 - val_mae: 0.0304
Epoch 16/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - loss: 7.5826e-04 - mae: 0.0122 - val_loss: 0.0021 - val_mae: 0.0318
Epoch 17/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - loss: 6.7853e-04 - mae: 0.0117 - val_loss: 0.0020 - val_mae: 0.0316
Epoch 18/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - loss: 7.1416e-04 - mae: 0.0115 - val_loss: 0.0020 - val_mae: 0.0314
Epoch 19/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - loss: 6.8312e-04 - mae: 0.0111 - val_loss: 0.0017 - val_mae: 0.0291
Epoch 20/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - loss: 6.8170e-04 - mae: 0.0109 - val_loss: 0.0013 - val_mae: 0.0252
22/22 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0171 - mae: 0.0831
```

```
Baseline GRU Test Loss: 0.027351034805178642, Test MAE: 0.11057111620903015
22/22 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step
22/22 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step
```

In [19]:

```
# Plot validation dataset results for baseline GRU
plt.figure(figsize=(12, 6))
plt.plot(y_val_actual_baseline_gru[:, 0, 3], label='Validation Actual (Close)',
plt.plot(y_val_pred_baseline_gru[:, 0, 3], label='Validation Predicted (Close)',
plt.title('Baseline GRU: Predicted vs Actual (Validation Dataset - Close Price)'
plt.xlabel('Sample Index', fontsize=12)
plt.ylabel('Stock Price', fontsize=12)
plt.legend()
plt.grid(True)
plt.show()

# Plot test dataset results for baseline GRU
plt.figure(figsize=(12, 6))
plt.plot(y_test_actual_baseline_gru[:, 0, 3], label='Test Actual (Close)', color
plt.plot(y_test_pred_baseline_gru[:, 0, 3], label='Test Predicted (Close)', colc
plt.title('Baseline GRU: Predicted vs Actual (Test Dataset - Close Price)', font
plt.xlabel('Sample Index', fontsize=12)
plt.ylabel('Stock Price', fontsize=12)
plt.legend()
plt.grid(True)
plt.show()
```





Optimised GRU Hyperparameters

In [20]:

```
# Function to build and evaluate GRU model with different hyperparameters
def build_and_evaluate_gru(units, batch_size):
    model = Sequential([
        GRU(units, activation='relu', input_shape=(N, len(features))),
        Dense(M * len(features))
    ])
    model.compile(optimizer=Adam(learning_rate=0.001), loss='mse', metrics=['mae
    history = model.fit(X_train, y_train.reshape(y_train.shape[0], -1),
                        validation_data=(X_val, y_val.reshape(y_val.shape[0], -1
                        epochs=20, batch_size=batch_size, verbose=1)
    test_loss, test_mae = model.evaluate(X_test, y_test.reshape(y_test.shape[0],
    return test_loss, test_mae, model, history

# Test different hyperparameter combinations for GRU
gru_results = []
for units in [50]:
    for batch_size in [32]:
        test_loss, test_mae, gru_model, gru_history = build_and_evaluate_gru(uni
        gru_results.append((units, batch_size, test_loss, test_mae))

# Display results
gru_results_df = pd.DataFrame(gru_results, columns=['Units', 'Batch Size', 'Test
print("\Optimised GRU Results:")
print(gru_results_df)

# Ensure input shapes are consistent for prediction
X_val_corrected = X_val.reshape(X_val.shape[0], X_val.shape[1], len(features))
X_test_corrected = X_test.reshape(X_test.shape[0], X_test.shape[1], len(features

# Predict on validation and test data using optimized GRU model
y_val_pred_scaled_gru = gru_model.predict(X_val_corrected)
y_test_pred_scaled_gru = gru_model.predict(X_test_corrected)

# Inverse transform the predictions for validation
y_val_actual_gru = scaler.inverse_transform(y_val.reshape(-1, y_val.shape[-1])).
y_val_pred_gru = scaler.inverse_transform(y_val_pred_scaled_gru.reshape(-1, y_va
```

```
# Inverse transform the predictions for test
y_test_actual_gru = scaler.inverse_transform(y_test.reshape(-1, y_test.shape[-1]
y_test_pred_gru = scaler.inverse_transform(y_test_pred_scaled_gru.reshape(-1, y_
```

```
Epoch 1/20
```

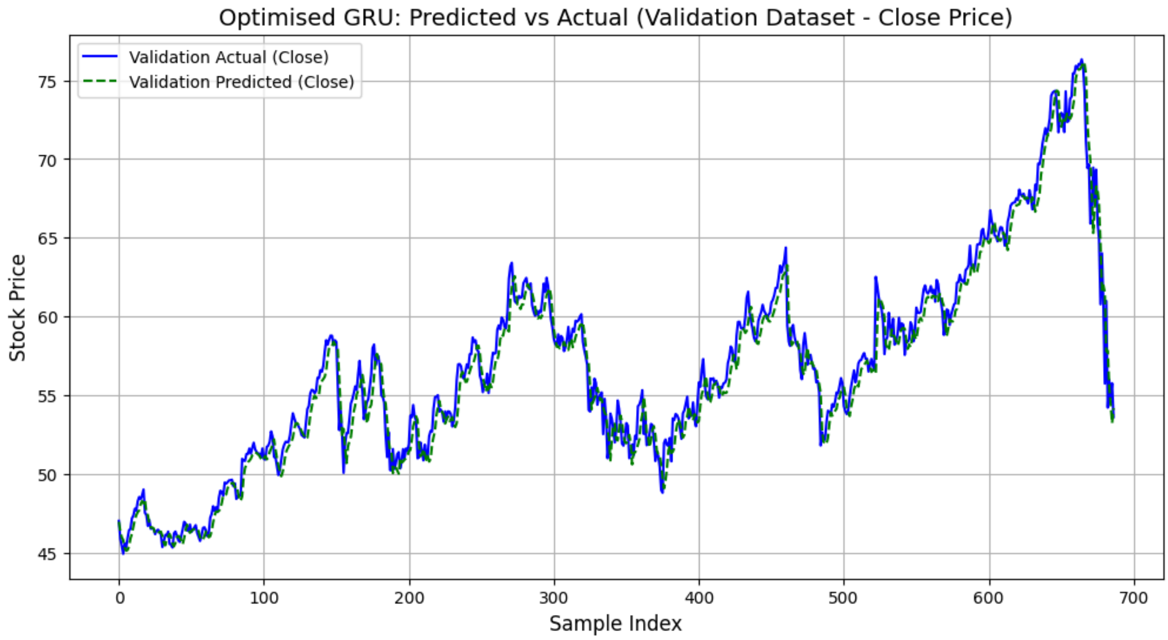
```
E:\Codes_data\try\envs\ai\lib\site-packages\keras\src\layers\rnn\rnn.py:200: User
Warning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using
Sequential models, prefer using an `Input(shape)` object as the first layer in th
e model instead.
  super().__init__(**kwargs)
```

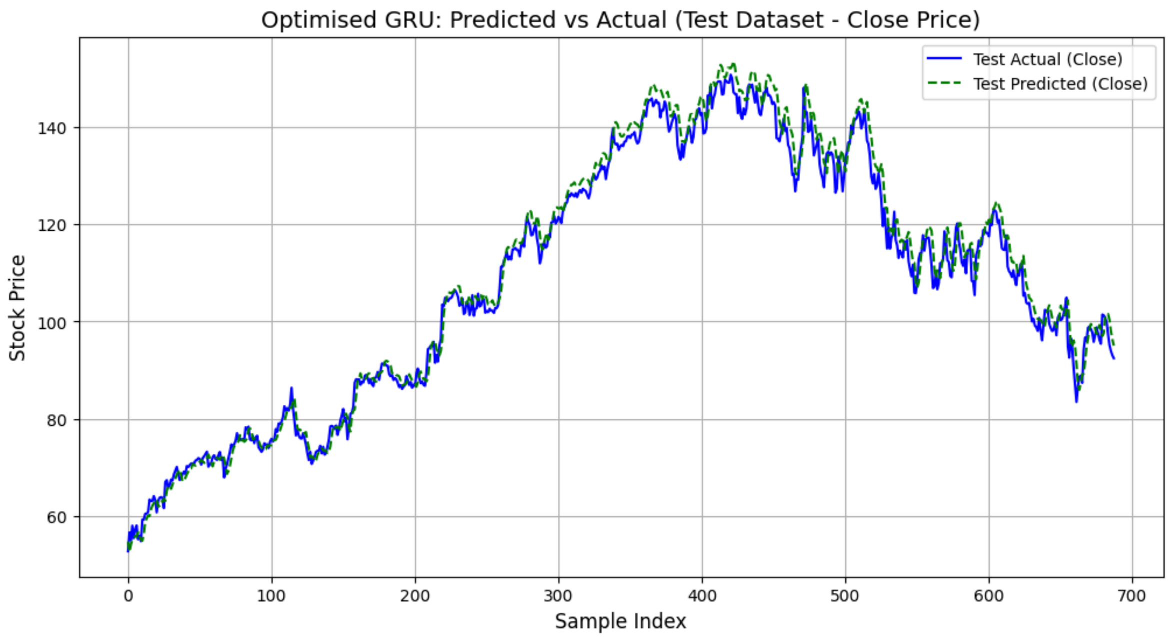
```
101/101 ━━━━━━━━━━━━━━━━━━━━ 2s 11ms/step - loss: 0.0535 - mae: 0.1565 - val_los
s: 0.0050 - val_mae: 0.0543
Epoch 2/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - loss: 9.4849e-04 - mae: 0.0152 - val_l
oss: 0.0024 - val_mae: 0.0310
Epoch 3/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - loss: 8.1039e-04 - mae: 0.0123 - val_l
oss: 0.0016 - val_mae: 0.0259
Epoch 4/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - loss: 5.9471e-04 - mae: 0.0109 - val_l
oss: 0.0020 - val_mae: 0.0308
Epoch 5/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - loss: 7.1676e-04 - mae: 0.0112 - val_l
oss: 0.0012 - val_mae: 0.0226
Epoch 6/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - loss: 6.8268e-04 - mae: 0.0107 - val_l
oss: 0.0012 - val_mae: 0.0248
Epoch 7/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 6.1866e-04 - mae: 0.0107 - val_
loss: 5.4517e-04 - val_mae: 0.0162
Epoch 8/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - loss: 7.0301e-04 - mae: 0.0108 - val_l
oss: 6.5114e-04 - val_mae: 0.0179
Epoch 9/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - loss: 6.3712e-04 - mae: 0.0101 - val_l
oss: 6.0381e-04 - val_mae: 0.0172
Epoch 10/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - loss: 5.9942e-04 - mae: 0.0100 - val_l
oss: 5.2412e-04 - val_mae: 0.0157
Epoch 11/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - loss: 6.3993e-04 - mae: 0.0103 - val_l
oss: 0.0010 - val_mae: 0.0248
Epoch 12/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - loss: 6.4190e-04 - mae: 0.0103 - val_l
oss: 5.2727e-04 - val_mae: 0.0167
Epoch 13/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - loss: 6.1962e-04 - mae: 0.0099 - val_l
oss: 5.0726e-04 - val_mae: 0.0153
Epoch 14/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - loss: 6.6464e-04 - mae: 0.0102 - val_l
oss: 6.7599e-04 - val_mae: 0.0196
Epoch 15/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - loss: 6.9220e-04 - mae: 0.0104 - val_l
oss: 4.7752e-04 - val_mae: 0.0160
Epoch 16/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - loss: 6.9018e-04 - mae: 0.0100 - val_l
oss: 4.7253e-04 - val_mae: 0.0152
Epoch 17/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - loss: 5.8048e-04 - mae: 0.0097 - val_l
oss: 4.7958e-04 - val_mae: 0.0156
Epoch 18/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - loss: 5.9993e-04 - mae: 0.0098 - val_l
oss: 5.5458e-04 - val_mae: 0.0164
Epoch 19/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - loss: 5.0256e-04 - mae: 0.0095 - val_l
oss: 7.2159e-04 - val_mae: 0.0218
Epoch 20/20
101/101 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - loss: 7.0906e-04 - mae: 0.0106 - val_l
oss: 4.9825e-04 - val_mae: 0.0167
\Optimised GRU Results:
```

```
   Units  Batch Size  Test Loss  Test MAE
0     50          32   0.022206   0.11088
22/22 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step
22/22 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step
```

In [21]:

```
# Plot validation dataset results for optimized GRU
plt.figure(figsize=(12, 6))
plt.plot(y_val_actual_gru[:, 0, 3], label='Validation Actual (Close)', color='bl
plt.plot(y_val_pred_gru[:, 0, 3], label='Validation Predicted (Close)', color='g
plt.title('Optimised GRU: Predicted vs Actual (Validation Dataset - Close Price)
plt.xlabel('Sample Index', fontsize=12)
plt.ylabel('Stock Price', fontsize=12)
plt.legend()
plt.grid(True)
plt.show()

# Plot test dataset results for optimized GRU
plt.figure(figsize=(12, 6))
plt.plot(y_test_actual_gru[:, 0, 3], label='Test Actual (Close)', color='blue',
plt.plot(y_test_pred_gru[:, 0, 3], label='Test Predicted (Close)', color='green'
plt.title('Optimised GRU: Predicted vs Actual (Test Dataset - Close Price)', fon
plt.xlabel('Sample Index', fontsize=12)
plt.ylabel('Stock Price', fontsize=12)
plt.legend()
plt.grid(True)
plt.show()
```





In [ ]:

Acknowledgment

In this assignment, some of the code and techniques were adapted from various sources, including internet resources, ChatGPT, and workshop materials. These sources provided a foundation for building and optimising the deep learning models used in the project. However, significant modifications were made to tailor the code to the specific requirements of this assignment, including adjustments to the model architectures, hyperparameter tuning, and data processing steps.