Uber's Financial Time Series Analysis

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MSDS 422 – Practical Machine Learning

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MANAGEMENT/RESARCH QUESTION

This research is important to the outside world as stock price predictions will help people like investors, businesses, and financial analysts make better decisions on market trends and investments. By using models like LSTM and GRU, we can understand which procedure will drive towards a positive answer for capturing patterns. Understanding these models will help improve forecasting accuracy, and this is very helpful for anyone who is in the financial-related fields.

I. OVERVIEW AND METHODOLGY

Module 09 focuses on the prediction of stock prices with the help of deep learning models. The data that will be used is from Yahoo Finance's historical stock price data of Uber, a ride-sharing company. The models that are being used in this research are RNNs (Recurrent Neural Networks), LSTMs (Long Short-Term Memory), and GRUs (Gated Recurrent Units). To improve the three models, hyperparameters will be used. Some hyperparameters consist of dropout rates, learning rates, and batch sizes. Afterwards, to measure their performance, Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Squared Error (MSE), and R^2 Score will be calculated. Alongside, there will be an evaluation of models using loss curves, residual analysis, and, last but not least, actual vs. predicted price comparisons. This module will teach us to understand which is the best model for predicting stock prices as well as understanding how well deep learning can be used for financial forecasting.

The following dataset focuses on the historical stock prices for the company Uber, which was collected from the library Yahoo Finance. The following data focuses on a 5-year period which includes the following columns: Close price (the final stock price at the end of each trading day), High price (the highest price Uber's stock reached on that specific day), Low price (the lowest price for that specific day), Open price (the stock price at the beginning of the trading day), and Volume (the total number of shares traded within that day). After retrieving the dataset, there were 1,257 rows and 5 columns (which were mentioned earlier).

II. <u>DETAILED STEPS AND CODE EXPLANATION</u>

In this research, the first important part was handling the data. The stock prices were converted to sequences so that models would be able to learn patterns in a better way. Then, a window size of 60 days was used to help the model analyze patterns while looking at Uber's stock prices over 60 days. With the dataset properly organized, it was divided into training and testing sets so the models could start learning and making predictions.

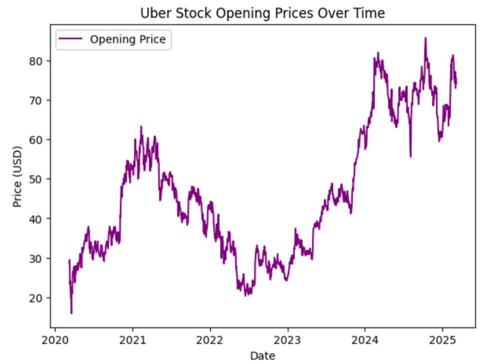
To develop the models, TensorFlow and Keras were used to train three different models, as specified in the assignment. The chosen models were LSTM (Long Short-Term Memory), a second LSTM with different hyperparameters, and GRU (Gated Recurrent Unit). Each model consisted of multiple layers, including either LSTM or GRU layers (which are required for time series), dense layers, and dropout layers. Dense layers are used to make predictions, and dropout layers are for overfitting prevention. The models were trained on the Adam optimizer and Mean Squared Error (MSE) as the loss function, which is a tool to measure prediction errors.

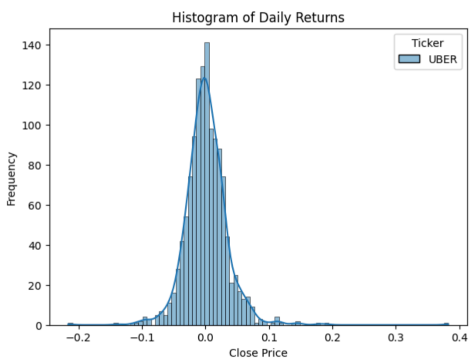
During the training process, the built-in function EarlyStopping was used to stop training if and only if the model stopped improving. The reason for this is that it prevents wasting time or causing unnecessary overfitting. Each model was trained on the training dataset, and the progress was tracked over epochs. After all the training, modeling, and evaluation steps were completed, the models were tested on unseen data, which refers to the split test data. Furthermore, performance metrics were used. The performance metrics include Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Squared Error (MSE), and R square Score. Additionally, loss curves, actual vs. predicted price plots, and residual analysis were also used.

III. VISUAL AND TABULAR INFORMATION

Summary statistics:

Price	Close	High	Low	Open	Volume
Ticker	UBER	UBER	UBER	UBER	UBER
count	1257.000000	1257.000000	1257.000000	1257.000000	1.257000e+03
mean	46.461901	47.316349	45.602602	46.474021	2.469845e+07
std	16.590126	16.740251	16.454736	16.628206	1.695152e+07
min	14.820000	17.799999	13.710000	15.960000	5.200400e+06
25%	32.360001	32.930000	31.510000	32.330002	1.579690e+07
50%	43.950001	44.830002	43.250000	44.000000	2.063350e+07
75%	59.930000	60.919998	58.689999	60.000000	2.828500e+07
max	86.339996	87.000000	84.180000	85.639999	3.642318e+08





To understand Uber's stock price data at a deeper perspective, the structure and several statistical properties were explored. The exploratory data analysis section showed that the dataset contains 1,257 rows and 5 columns, with no missing values. The summary statistics revealed that the minimum closing price was $14.820000 dollars and a maximum of $86.339996 dollars, which showed a lot of fluctuations over time. Few visualizations were demonstrated in order to observe stock price trends and patterns.

The daily returns histogram indicated that the most price changes are small, but there were some spikes within the years. Uber's closing and opening prices were also studied to see how price movements evolved over time. It showed how in the years 2023-2024, the stock price was very low, which can possibly mean a period of decline or market uncertainty.

IV. **CONCLUSION**

To conclude, overall, it was noticeable that the third model, or the model that used GRU, performed the best, which achieved the lowest errors compared to the three models. The GRU model had a Mean Absolute Error (MAE) which consisted of 0.0196, Root Mean Square Error (RMSE) of 0.0241, and lastly, Mean Square Error (MSE) of 0.0006, which shows this predicted Uber's stock prices the most accurately.The first LSTM model had an MAE of 0.1052, RMSE of 0.1172, and MSE of 0.0137, and the second LSTM model had performed better than Model 1 and had the following results: MAE of 0.0261, RMSE of 0.0318, and MSE of 0.001.

The R-squared measures how well a model is able to explain the stock price trends, and GRU showed the best score at 0.9582, which states that it is a strong model to be able to capture the trends. Model 02 showed an R-squared score of 0.9274, and the first model was extremely low at 0.0149. The reason it was low was that it was having a hard time predicting stock prices. Afterwards, model evaluation was required, and it was noticeable that the GRU model closely followed the stock prices. The two LSTM models were not showing a reliable outlook as they were showing more ups and downs.

The residual analysis then further helped to check how many of the predictions were different from the real prices, and overall, GRU had the least number of errors - which represents that it is a strong model.

From this research, it can be understood that GRU models are much better than the LSTM models for predicting stock prices, as they are able to check past trends more efficiently compared to an LSTM. Hyperparameter tuning is important as if we adjust settings, there is a major difference in performance, and that is what happened between the first and second LSTM model. Overall, GRU or the third model was the best to predict stock prices for the ride-sharing company. Future research can be focused on financial indicators, better feature selection, and as well as a larger dataset.

V. **REFERENCES**

Northwestern University. *Module 9 Assignment 2: Financial Time Series*. Accessed March 9, 2025. https://canvas.northwestern.edu/courses/222806/assignments/1546801.

VI. **APPENDIX**

LINK TO PANAPTO

https://northwestern.hosted.panopto.com/Panopto/Pages/Viewer.aspx?id=e95606ce-cbc9-4dcc-9b04-b29c00600d4d&start=8.208376

Module09_Financial Time Series

March 10, 2025

1 Module 09 Assignment 2: Financial Time Series

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MSDS 422 Practical Machine Learning

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1.0.1 PART 01 Introduction

Module 09 focuses on the prediction of stock prices with the help of deep learning models. The data that will be used is from Yahoo Finance's historical stock price data of Uber, a ride-sharing company. The models that are being used in this research are RNNs (Recurrent Neural Networks), LSTMs (Long Short-Term Memory), and GRUs (Gated Recurrent Units). To improve the three models, hyperparameters will be used. Some hyperparameters consist of dropout rates, learning rates, and batch sizes. Afterwards, to measure their performance, Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Squared Error (MSE), and R^2 Score will be calculated. Alongside, there will be an evaluation of models using loss curves, residual analysis, and, last but not least, actual vs. predicted price comparisons. This module will teach us to understand which is the best model for predicting stock prices as well as understanding how well deep learning can be used for financial forecasting.

1.0.2 PART 02 Data load / Libraries load

Libraries load

[1]:
```
import numpy as np
```

[2]:
```
from sklearn.model_selection import TimeSeriesSplit
```

[3]:
```
from tensorflow.keras.optimizers import Adam
```

[4]:
```
from tensorflow.keras.layers import GRU
```

[5]:
```
import pandas as pd
```

[6]:
```
from sklearn.metrics import r2_score
```

[7]:
```
import matplotlib.pyplot as plt
```

[8]:
```
import yfinance as yf
```

[9]:
```
from sklearn.preprocessing import MinMaxScaler
```

[10]:
```
from tensorflow.keras.models import Sequential
```

[11]:
```
import seaborn as sns
```

[12]:
```
from tensorflow.keras.layers import LSTM, Dense, Dropout
```

[13]:
```
from tensorflow.keras.callbacks import EarlyStopping
```

[14]:
```
import numpy as np
```

[15]:
```
import yfinance as yf
```

[16]:
```
from sklearn.preprocessing import MinMaxScaler
```

Data load

[61]:
```
np.random.seed(42)
ticker = 'UBER'
data = yf.download(ticker, period='5y')
print("Data shape:", data.shape)
data.head()
```

```
[*********************100%***********************]  1 of 1 completed
```

```
Data shape: (1257, 5)
```

[61]:

Price	Close	High	Low	Open	Volume
Ticker	UBER	UBER	UBER	UBER	UBER
Date					
2020-03-09	28.170000	30.320000	28.150000	28.500000	37439200
2020-03-10	28.969999	29.860001	27.000000	29.469999	36308300
2020-03-11	26.240000	28.139999	25.610001	27.910000	43067800
2020-03-12	22.610001	24.690001	22.110001	23.260000	54042000
2020-03-13	22.600000	24.809999	21.129999	24.010000	53844400

1.0.3 PART 03 Data Presentation

The following dataset focuses on the historical stock prices for the company Uber, which was collected from the library Yahoo Finance. The following data focuses on a 5-year period which includes the following columns: Close price (the final stock price at the end of each trading day), High price (the highest price Uber's stock reached on that specific day), Low price (the lowest price for that specific day), Open price

(the stock price at the beginning of the trading day), and Volume (the total number of shares traded within that day). After retrieving the dataset, there were 1,257 rows and 5 columns (which were mentioned earlier).

1.0.4 PART 04 EDA of DATASET

[59]:
```
prices = data['Close'].values.reshape(-1, 1)
```

[62]:
```
data.head()
# column_names of the data
data.columns
```

[62]:
```
MultiIndex([( 'Close', 'UBER'),
            (  'High', 'UBER'),
            (   'Low', 'UBER'),
            (  'Open', 'UBER'),
            ('Volume', 'UBER')],
           names=['Price', 'Ticker'])
```

Summary Statistics

[63]:
```
print("\nSummary statistics:")
print(data.describe())
```

```
Summary statistics:
Price         Close         High          Low         Open        Volume
Ticker         UBER         UBER         UBER         UBER          UBER
count   1257.000000  1257.000000  1257.000000  1257.000000  1.257000e+03
mean      46.461901    47.316349    45.602602    46.474021  2.469845e+07
std       16.590126    16.740251    16.454736    16.628206  1.695152e+07
min       14.820000    17.799999    13.710000    15.960000  5.200400e+06
25%       32.360001    32.930000    31.510000    32.330002  1.579690e+07
50%       43.950001    44.830002    43.250000    44.000000  2.063350e+07
75%       59.930000    60.919998    58.689999    60.000000  2.828500e+07
max       86.339996    87.000000    84.180000    85.639999  3.642318e+08
```

Missing Values per Column

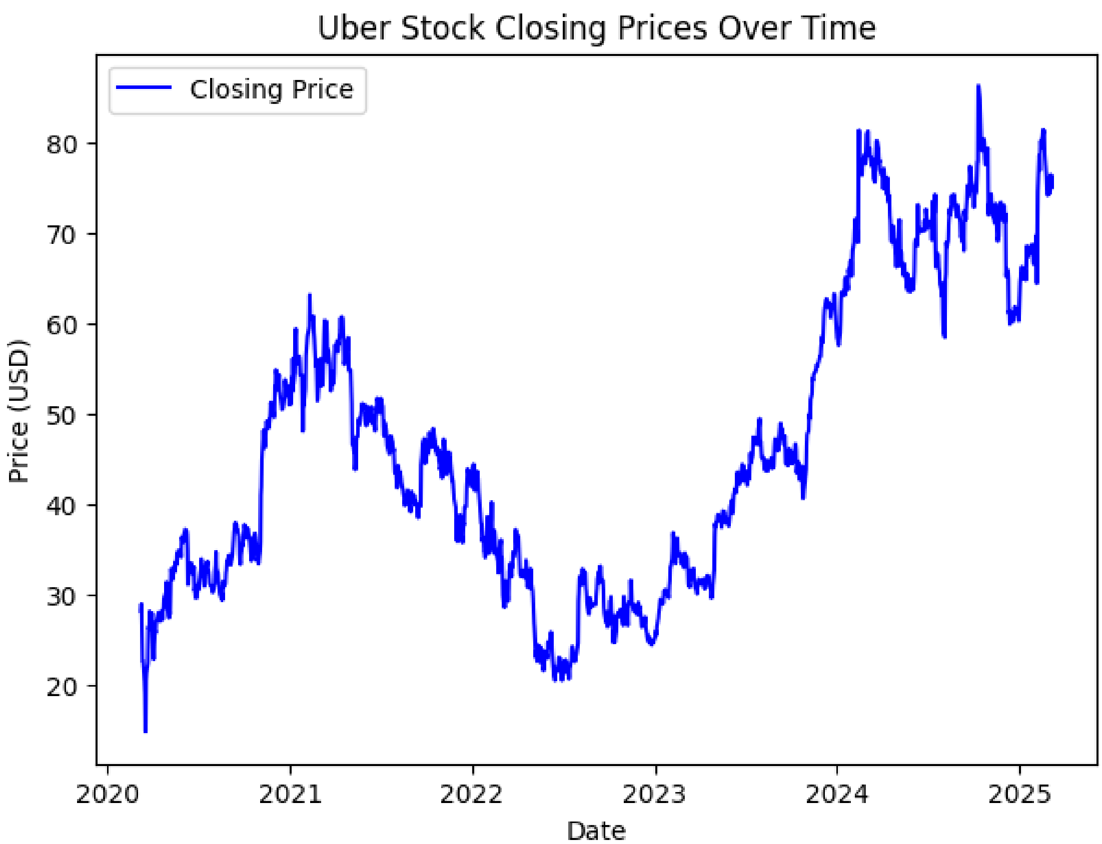
[64]:
```
print("\nMissing values per column:")
print(data.isnull().sum())
```

```
Missing values per column:
Price   Ticker
Close   UBER      0
High    UBER      0
Low     UBER      0
Open    UBER      0
```

```
Volume  UBER      0
dtype: int64
```

Uber's closing prices over time

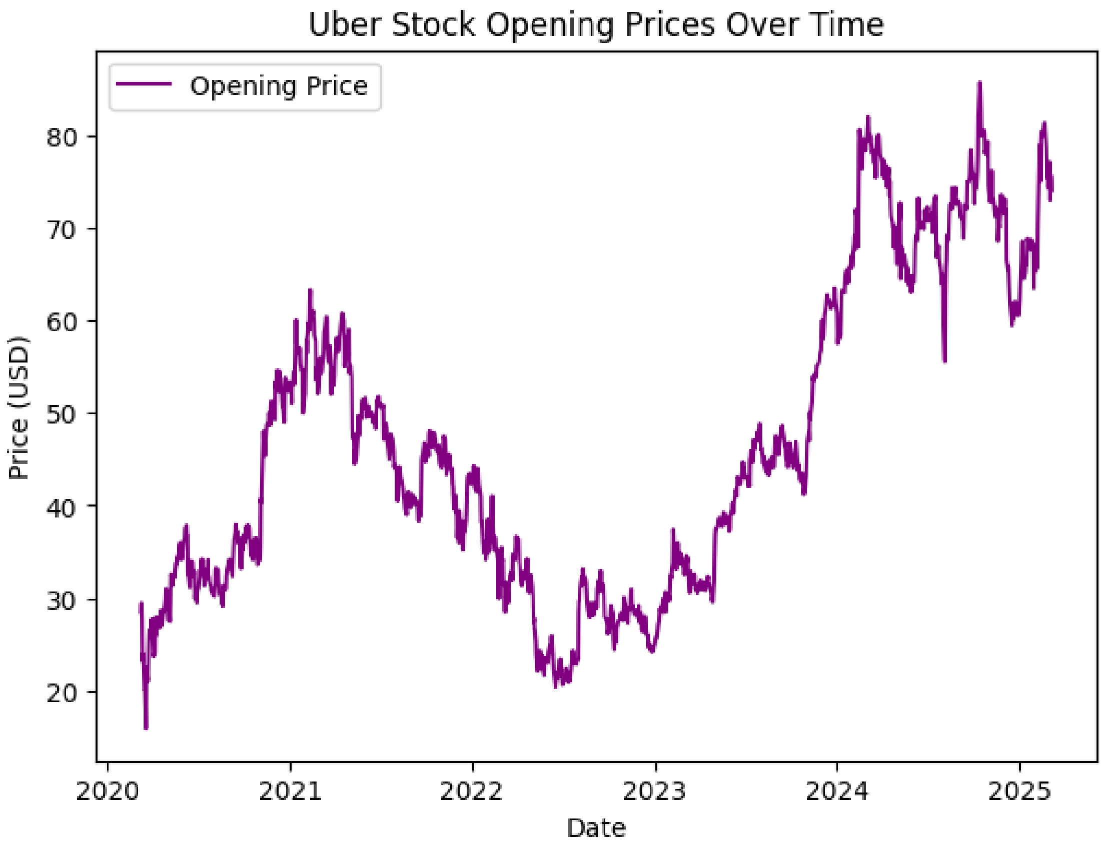
[65]:
```python
# Plot Uber's closing prices over time
plt.figure(figsize=(7, 5))
plt.plot(data['Close'], label="Closing Price", color='blue')
plt.title('Uber Stock Closing Prices Over Time')
plt.xlabel('Date')
plt.ylabel('Price (USD)')
plt.legend()
plt.show()
```



Opening Prices over time

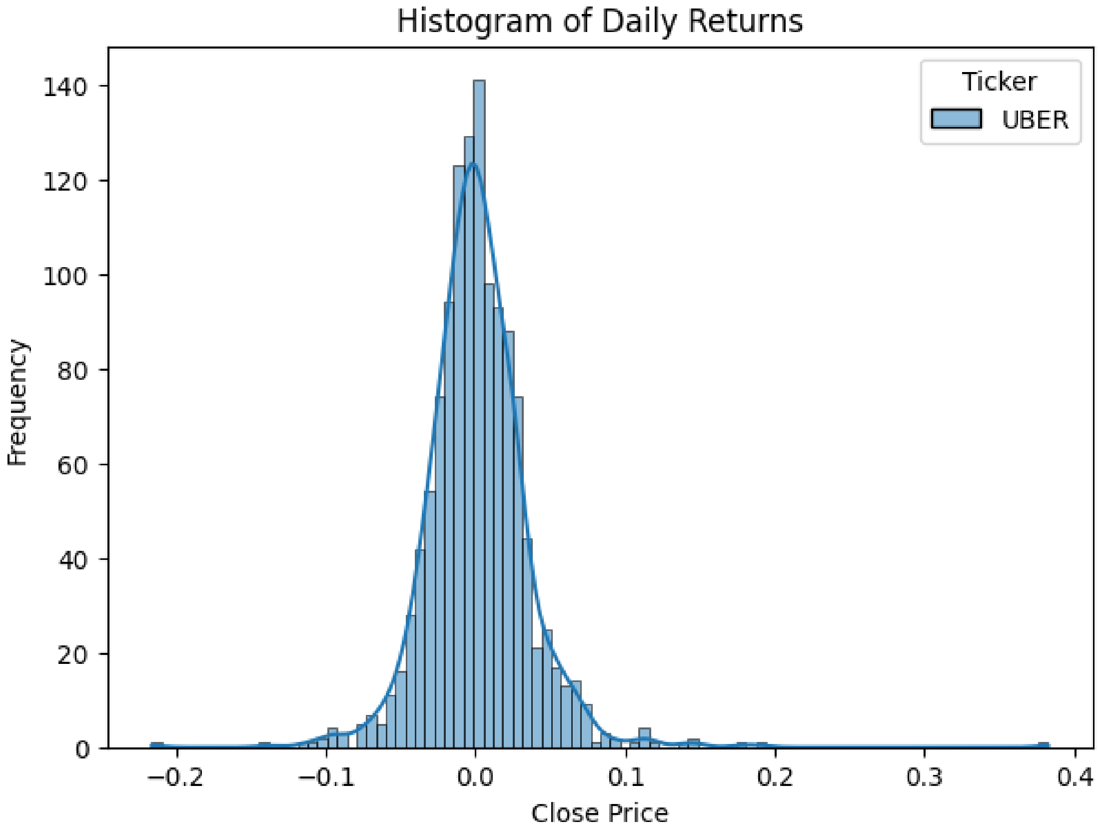
[70]:
```python
plt.figure(figsize=(7, 5))
plt.plot(data['Open'], label="Opening Price", color='Purple')
plt.title('Uber Stock Opening Prices Over Time')
plt.xlabel('Date')
plt.ylabel('Price (USD)')
```

```
plt.legend()
plt.show()
```



Histogram of Daily Returns

```
[71]: plt.figure(figsize=(7, 5))
sns.histplot(data['Close'].pct_change().dropna(), kde=True, color='blue')
plt.title('Histogram of Daily Returns')
plt.xlabel('Close Price')
plt.ylabel('Frequency')
plt.show()
```



1.0.5 PART 05 Overview of findings and next steps

To understand Uber's stock price data at a deeper perspective, the structure and several statistical properties were explored. The exploratory data analysis section showed that the dataset contains 1,257 rows and 5 columns, with no missing values. The summary statistics revealed that the minimum closing price was $14.820000 dollars and a maximum of $86.339996 dollars, which showed a lot of fluctuations over time. Few visualizations were demonstrated in order to observe stock price trends and patterns. The daily returns histogram indicated that the most price changes are small, but there were some spikes within the years. Uber's closing and opening prices were also studied to see how price movements evolved over time. It showed how in the years 2023-2024, the stock price was very low, which can possibly mean a period of decline or market uncertainty.The next steps in the research include preprocessing data by normalizing the data by using MinMaxScaler, and then splitting the model by training and testing datasets. Afterwards, training three models: LSTM, a second LSTM model, and lastly GRU. Each of these models will be evaluated to further understand if they were appropriate models. The evaluation will consist of MAE (Mean Absolute Error), RMSE (Root Mean Squared Error), MSE (Mean Squared Error), and R^2 Score to compare their performance.

1.0.6 PART 06 Cleansing and Preprocessing

it is done previously or will be done in next steps

1.0.7 PART 07 FEATURE ENGINEERING

[72]:
```
scaler = MinMaxScaler(feature_range=(0, 1))
scaled_prices = scaler.fit_transform(prices)
```

[73]:
```
# Define a function to create input sequences and corresponding targets from␣
↪the time series data.
def create_sequences(data, window_size):
    """
    This function converts a time series into sequences of a fixed window size.
    Each sequence (X) consists of 'window_size' consecutive data points,
    and the target (y) is the data point immediately following that sequence.

    Parameters:
      - data: The scaled time series data (a 2D NumPy array).
      - window_size: The number of time steps to include in each input sequence.

    Returns:
      - X: NumPy array of input sequences.
      - y: NumPy array of targets corresponding to each sequence.
    """
    # Initialize empty lists to store sequences and targets.
    X = []  # List to hold input sequences
    y = []  # List to hold corresponding targets

    # Loop through the data, stopping at a point that allows a full sequence of␣
↪the given window size
    for i in range(len(data) - window_size):
        # For each iteration, slice the data array to create a sequence of␣
↪'window_size' data points.
        # data[i:i+window_size, 0] extracts a sequence starting at index 'i'␣
↪and spanning 'window_size' steps.
        X.append(data[i:i+window_size, 0])

        # The target value (y) is the data point immediately after the current␣
↪sequence.
        y.append(data[i+window_size, 0])

    # Convert the lists of sequences and targets into NumPy arrays for␣
↪efficient processing.
    return np.array(X), np.array(y)

# Set the window size to 60, meaning each input sequence will contain 60␣
↪consecutive time steps.
```

```
# For example, the model will use the data from the past 60 days to predict the␣
↪next day's value.
window_size = 60

# Call the function to create sequences and targets from the scaled price data.
# 'scaled_prices' is our preprocessed dataset (with values scaled between 0 and␣
↪1).
X, y = create_sequences(scaled_prices, window_size)
```

1.0.8 PART 08 Overview presentation of the cleaned dataset

Before training the models, it was required to make sure the dataset was cleaned and prepared for the modeling part of the research. MinMaxScaler was used to scale Uber stock prices and adjust it to have it between 0 and 1, so that the models train more efficiently. Next, feature engineering was completed in order to have an organized dataset for modeling. The feature engineering consisted of converting the stock prices into sequences as the model will recognize trends faster and will be able to make predictions. Then, A window size of 60 days was used to help the model analyze patterns while looking at Uber's stock prices over 60 days. With the dataset now structured, it will be split into training and testing sets so the models can begin learning and making predictions.

1.0.9 PART 09 Final EDA and comparisons

not required

1.0.10 PART 10 Data preprocessing specific to the model

will be shown in splitting section

1.0.11 PART 11 Splitting

[74]:
```
# Calculate the index to split the dataset into training and testing portions.
# We use 80% of the data for training and the remaining 20% for testing.
split = int(0.8 * len(X))

# Use array slicing to separate the input sequences and their corresponding␣
↪targets:
# - X_train and y_train will contain the first 80% of the data.
# - X_test and y_test will contain the remaining 20%.
X_train, X_test = X[:split], X[split:]
y_train, y_test = y[:split], y[split:]

# Neural network models such as LSTM require input data to be in a specific␣
↪3-dimensional format:
# [samples, time steps, features]
# Currently, our data (X_train and X_test) is in a 2D shape (samples, time␣
↪steps).
```

```python
# We reshape it to add a third dimension representing the single feature per time step.
X_train = np.reshape(X_train, (X_train.shape[0], X_train.shape[1], 1))
X_test  = np.reshape(X_test, (X_test.shape[0], X_test.shape[1], 1))

# Print the shapes of the training and testing sets to confirm the dimensions.
print("Training set shape:", X_train.shape)
print("Test set shape:", X_test.shape)
```

```
Training set shape: (957, 60, 1)
Test set shape: (240, 60, 1)
```

1.0.12 PART 12 Overview of the steps to be completed and the rationale

So far, the dataset has been cleaned up, preprocessed, and split into training and testing. The next steps will focus on model training, cross-validation, hyperparameter tuning, and, last but not least, model evaluation. The three models that will be used in the research are LSTM, a second LSTM with different settings, and finally, GRU. Each of the models will be trained with the dataset that was preprocessed above and with hyperparameter tuning. The hyperparameter tuning will include dropout rates, batch sizes, learning rates, and the number of layers. Once the models are trained, evaluations will be done in order to understand and assess their performance. The performance metrics include Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Squared Error (MSE), and R^2 Score. Furthermore, loss curves, actual vs. predicted price plots, and residual analysis will also be used. Lastly, after all the training, modeling, and evaluation steps are completed, the models will be tested on unseen data, which refers to the split test data.

1.0.13 PART 13 Model training cross-validation.

[75]:
```python
# Define a function that creates a new instance of the RNN model
def create_model(window_size):
    model = Sequential([
        LSTM(50, return_sequences=True, input_shape=(window_size, 1)),
        Dropout(0.2),
        LSTM(50, return_sequences=False),
        Dropout(0.2),
        Dense(25, activation='relu'),
        Dense(1)
    ])
    model.compile(optimizer='adam', loss='mean_squared_error')
    return model

# Set up TimeSeriesSplit for cross-validation (e.g., 5 splits)
tscv = TimeSeriesSplit(n_splits=5)

# List to store validation loss for each fold
val_losses = []
```

```
# Loop through each split of the training data
for fold, (train_index, val_index) in enumerate(tscv.split(X_train)):
    print(f"Training fold {fold+1}")

    # Split the data into current fold's training and validation sets
    X_train_cv, X_val_cv = X_train[train_index], X_train[val_index]
    y_train_cv, y_val_cv = y_train[train_index], y_train[val_index]

    # Create a new model instance for each fold
    model_cv = create_model(window_size)

    # Setup EarlyStopping to monitor validation loss for the current fold
    early_stop = EarlyStopping(monitor='val_loss', patience=5,␣
 ↪restore_best_weights=True)

    # Train the model on the current fold's training data
    history_cv = model_cv.fit(
        X_train_cv, y_train_cv,
        epochs=50,
        batch_size=32,
        validation_data=(X_val_cv, y_val_cv),
        callbacks=[early_stop],
        verbose=0  # Set verbose to 0 to reduce output clutter; change to 1 for␣
 ↪more details
    )

    # Evaluate the model on the current fold's validation data
    fold_val_loss = model_cv.evaluate(X_val_cv, y_val_cv, verbose=0)
    print(f"Fold {fold+1} Validation Loss: {fold_val_loss}")
    val_losses.append(fold_val_loss)

# Calculate the average validation loss across all folds
average_val_loss = np.mean(val_losses)
print("Cross-validation validation losses:", val_losses)
print("Average validation loss:", average_val_loss)
```

```
Training fold 1
```

```
/opt/homebrew/Caskroom/miniforge/base/envs/tf-mac/lib/python3.9/site-
packages/keras/src/layers/rnn/rnn.py:200: UserWarning: 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 the model instead.
  super().__init__(**kwargs)
```

```
Fold 1 Validation Loss: 0.0007296802941709757
Training fold 2
Fold 2 Validation Loss: 0.0008995721582323313
```

```
Training fold 3
Fold 3 Validation Loss: 0.0012095586862415075
Training fold 4
Fold 4 Validation Loss: 0.0005094103398732841
Training fold 5
Fold 5 Validation Loss: 0.0008105927845463157
Cross-validation validation losses: [0.0007296802941709757,
0.0008995721582323313, 0.0012095586862415075, 0.0005094103398732841,
0.0008105927845463157]
Average validation loss: 0.0008317628526128829
```

1.0.14 PART 14 Model Hypertuning

Model 01

[76]:
```
def build_lstm_model1(window_size): # Model 1
    model = Sequential([ # LSTM model with 2 layers
        LSTM(64, return_sequences=True, input_shape=(window_size, 1)), # 64␣
 ↪units
        Dropout(0.3),  # Dropout layer to prevent overfitting
        LSTM(64, return_sequences=False), # 64 units
        Dropout(0.3), # Dropout layer to prevent overfitting
        Dense(50, activation='relu'), # 50 units
        Dense(1) # Output layer
    ])

    model.compile(optimizer=Adam(learning_rate=0.001),␣
 ↪loss='mean_squared_error') # Adam optimizer with learning rate of 0.001
    return model

# Train Model 1
model1 = build_lstm_model1(window_size) # Build Model 1
early_stop = EarlyStopping(monitor='val_loss', patience=5,␣
 ↪restore_best_weights=True) # Early stopping to prevent overfitting

history1 = model1.fit( # Fit Model
    X_train, y_train,# Training data
    epochs=50, # 50 epochs
    batch_size=32, # Batch size of 32
    validation_split=0.1, # 10% validation split
    callbacks=[early_stop], # Early stopping
    verbose=1 # Verbose mode
)

# Evaluate performance
val_loss1 = model1.evaluate(X_test, y_test) # Evaluate Model 1 on test data
print(f"Model 1 Validation Loss: {val_loss1}")  # Print validation loss
```

```
Epoch 1/50
27/27            2s 31ms/step -
loss: 0.0871 - val_loss: 0.0035
Epoch 2/50
27/27            1s 21ms/step -
loss: 0.0053 - val_loss: 0.0024
Epoch 3/50
27/27            1s 21ms/step -
loss: 0.0045 - val_loss: 0.0038
Epoch 4/50
27/27            1s 21ms/step -
loss: 0.0037 - val_loss: 7.8587e-04
Epoch 5/50
27/27            1s 22ms/step -
loss: 0.0031 - val_loss: 0.0018
Epoch 6/50
27/27            1s 21ms/step -
loss: 0.0031 - val_loss: 0.0029
Epoch 7/50
27/27            1s 21ms/step -
loss: 0.0026 - val_loss: 0.0013
Epoch 8/50
27/27            1s 22ms/step -
loss: 0.0033 - val_loss: 9.5119e-04
Epoch 9/50
27/27            1s 22ms/step -
loss: 0.0207 - val_loss: 7.7453e-04
Epoch 10/50
27/27            1s 20ms/step -
loss: 0.0206 - val_loss: 0.0199
Epoch 11/50
27/27            1s 22ms/step -
loss: 0.0119 - val_loss: 0.0051
Epoch 12/50
27/27            1s 23ms/step -
loss: 0.0113 - val_loss: 0.0019
Epoch 13/50
27/27            1s 21ms/step -
loss: 0.0066 - val_loss: 0.0011
Epoch 14/50
27/27            1s 20ms/step -
loss: 0.0061 - val_loss: 0.0190
8/8            0s 10ms/step - loss:
0.0086
Model 1 Validation Loss: 0.013729481026530266
```

Model 02

```
[77]: def build_lstm_model2(window_size): # Model 2
    model = Sequential([ # LSTM model with 2 layers
        LSTM(128, return_sequences=True, input_shape=(window_size, 1)),     #␣
 ↪128 units
        Dropout(0.2),    # Dropout layer to prevent overfitting
        LSTM(128, return_sequences=False),  # 128 units
        Dropout(0.2),    # Dropout layer to prevent overfitting
        Dense(50, activation='relu'),       # 50 units
        Dense(1)    # Output layer
    ])

    model.compile(optimizer=Adam(learning_rate=0.0005),␣
 ↪loss='mean_absolute_error') # Adam optimizer with learning rate of 0.0005
    return model

# Train Model 2
model2 = build_lstm_model2(window_size) # Build Model 2

history2 = model2.fit(  # Fit Model 2
    X_train, y_train,   # Training data
    epochs=50,      # 50 epochs
    batch_size=64,  # Increased batch size
    validation_split=0.1,       # 10% validation split
    callbacks=[early_stop],    # Early stopping
    verbose=1   # Verbose mode
)

# Evaluate performance
val_loss2 = model2.evaluate(X_test, y_test) # Evaluate Model 2 on test data
print(f"Model 2 Validation Loss: {val_loss2}")  # Print validation loss
```

```
Epoch 1/50
14/14               3s 48ms/step -
loss: 0.2898 - val_loss: 0.1520
Epoch 2/50
14/14               0s 23ms/step -
loss: 0.0636 - val_loss: 0.0923
Epoch 3/50
14/14               0s 25ms/step -
loss: 0.0461 - val_loss: 0.0541
Epoch 4/50
14/14               0s 24ms/step -
loss: 0.0376 - val_loss: 0.0249
Epoch 5/50
14/14               0s 24ms/step -
loss: 0.0351 - val_loss: 0.0415
Epoch 6/50
14/14               0s 26ms/step -
```

```
loss: 0.0334 - val_loss: 0.0234
Epoch 7/50
14/14              0s 24ms/step -
loss: 0.0322 - val_loss: 0.0220
Epoch 8/50
14/14              0s 24ms/step -
loss: 0.0305 - val_loss: 0.0213
Epoch 9/50
14/14              0s 29ms/step -
loss: 0.0304 - val_loss: 0.0222
Epoch 10/50
14/14              0s 24ms/step -
loss: 0.0312 - val_loss: 0.0205
Epoch 11/50
14/14              1s 37ms/step -
loss: 0.0297 - val_loss: 0.0225
Epoch 12/50
14/14              0s 26ms/step -
loss: 0.0290 - val_loss: 0.0278
Epoch 13/50
14/14              0s 23ms/step -
loss: 0.0292 - val_loss: 0.0241
Epoch 14/50
14/14              0s 25ms/step -
loss: 0.0304 - val_loss: 0.0191
Epoch 15/50
14/14              0s 25ms/step -
loss: 0.0281 - val_loss: 0.0278
Epoch 16/50
14/14              0s 24ms/step -
loss: 0.0292 - val_loss: 0.0255
Epoch 17/50
14/14              0s 24ms/step -
loss: 0.0279 - val_loss: 0.0181
Epoch 18/50
14/14              0s 25ms/step -
loss: 0.0268 - val_loss: 0.0266
Epoch 19/50
14/14              0s 24ms/step -
loss: 0.0290 - val_loss: 0.0275
Epoch 20/50
14/14              0s 24ms/step -
loss: 0.0302 - val_loss: 0.0487
Epoch 21/50
14/14              0s 24ms/step -
loss: 0.0286 - val_loss: 0.0309
Epoch 22/50
14/14              0s 25ms/step -
```

```
loss: 0.0289 - val_loss: 0.0275
8/8              0s 12ms/step - loss:
0.0239
Model 2 Validation Loss: 0.026142248883843422
```

Model 03

[78]:
```python
def build_gru_model(window_size): # Model 3
    model = Sequential([ # GRU model with 2 layers
        GRU(64, return_sequences=True, input_shape=(window_size, 1)),   # 64␣
↪units
        Dropout(0.2),  # Dropout layer to prevent overfit
        GRU(64, return_sequences=False),    # 64 units
        Dropout(0.2), # Dropout layer to prevent overfit
        Dense(50, activation='relu'),  # 50 units
        Dense(1)    # Output layer
    ])

    model.compile(optimizer=Adam(learning_rate=0.001),␣
↪loss='mean_squared_error') # Adam optimizer with learning rate of 0.001
    return model

model3 = build_gru_model(window_size) # Build Model 3

early_stop = EarlyStopping(monitor='val_loss', patience=5,␣
↪restore_best_weights=True) # Early stopping

history3 = model3.fit(  # Fit Model 3
    X_train, y_train,   # Training data
    epochs=50,     # 50 epochs
    batch_size=32, # Batch size of 32
    validation_split=0.1,  # 10% validation split
    callbacks=[early_stop], # Early stopping
    verbose=1  # Verbose mode
)

val_loss3 = model3.evaluate(X_test, y_test) # Evaluate Model 3 on test data
print(f"Model 3 (GRU) Validation Loss: {val_loss3}")    # Print validation loss
```

```
Epoch 1/50
27/27              2s 30ms/step -
loss: 0.0922 - val_loss: 0.0135
Epoch 2/50
27/27              1s 21ms/step -
loss: 0.0044 - val_loss: 0.0042
Epoch 3/50
27/27              1s 21ms/step -
loss: 0.0032 - val_loss: 0.0015
```

```
Epoch 4/50
27/27              1s 22ms/step -
loss: 0.0024 - val_loss: 3.8833e-04
Epoch 5/50
27/27              1s 23ms/step -
loss: 0.0023 - val_loss: 7.4032e-04
Epoch 6/50
27/27              1s 21ms/step -
loss: 0.0021 - val_loss: 3.1687e-04
Epoch 7/50
27/27              1s 21ms/step -
loss: 0.0019 - val_loss: 3.2254e-04
Epoch 8/50
27/27              1s 21ms/step -
loss: 0.0018 - val_loss: 3.4349e-04
Epoch 9/50
27/27              1s 21ms/step -
loss: 0.0018 - val_loss: 4.3406e-04
Epoch 10/50
27/27              1s 21ms/step -
loss: 0.0015 - val_loss: 3.0153e-04
Epoch 11/50
27/27              1s 20ms/step -
loss: 0.0015 - val_loss: 3.0780e-04
Epoch 12/50
27/27              1s 21ms/step -
loss: 0.0014 - val_loss: 4.3086e-04
Epoch 13/50
27/27              1s 21ms/step -
loss: 0.0012 - val_loss: 2.9956e-04
Epoch 14/50
27/27              1s 21ms/step -
loss: 0.0013 - val_loss: 3.0755e-04
Epoch 15/50
27/27              1s 22ms/step -
loss: 0.0011 - val_loss: 2.9137e-04
Epoch 16/50
27/27              1s 21ms/step -
loss: 0.0012 - val_loss: 6.7288e-04
Epoch 17/50
27/27              1s 21ms/step -
loss: 0.0012 - val_loss: 2.9831e-04
Epoch 18/50
27/27              1s 20ms/step -
loss: 0.0010 - val_loss: 2.8146e-04
Epoch 19/50
27/27              1s 20ms/step -
loss: 9.1737e-04 - val_loss: 3.6584e-04
```

```
Epoch 20/50
27/27              1s 20ms/step -
loss: 9.7879e-04 - val_loss: 5.2188e-04
Epoch 21/50
27/27              1s 24ms/step -
loss: 0.0010 - val_loss: 3.0452e-04
Epoch 22/50
27/27              1s 21ms/step -
loss: 9.8181e-04 - val_loss: 4.9175e-04
Epoch 23/50
27/27              1s 21ms/step -
loss: 9.6620e-04 - val_loss: 3.1468e-04
8/8              0s 11ms/step - loss:
5.3740e-04
Model 3 (GRU) Validation Loss: 0.000582014792598784
```

[79]:
```
print(f"Model 1 Validation Loss (Standard LSTM): {val_loss1}")
print(f"Model 2 Validation Loss (Alternative LSTM): {val_loss2}")
print(f"Model 3 Validation Loss (GRU): {val_loss3}")
```

```
Model 1 Validation Loss (Standard LSTM): 0.013729481026530266
Model 2 Validation Loss (Alternative LSTM): 0.026142248883843422
Model 3 Validation Loss (GRU): 0.000582014792598784
```

1.0.15 PART 15 Model Testing

[80]:
```
loss_model1 = model1.evaluate(X_test, y_test, verbose=1) # testing on model 1
loss_model2 = model2.evaluate(X_test, y_test, verbose=1)  # testing on model 2
loss_model3 = model3.evaluate(X_test, y_test, verbose=1)  # testing on model 3

print(f"Model 1 (LSTM) Test Loss: {loss_model1}") # testing on model 1
print(f"Model 2 (LSTM with different settings) Test Loss: {loss_model2}") #
  ↪testing on model 2
print(f"Model 3 (GRU) Test Loss: {loss_model3}") # testing on model 3
```

```
8/8              0s 7ms/step - loss:
0.0086
8/8              0s 7ms/step - loss:
0.0239
8/8              0s 7ms/step - loss:
5.3740e-04
Model 1 (LSTM) Test Loss: 0.013729481026530266
Model 2 (LSTM with different settings) Test Loss: 0.026142248883843422
Model 3 (GRU) Test Loss: 0.000582014792598784
```

[81]:
```
pred_model1 = model1.predict(X_test)
pred_model2 = model2.predict(X_test)
pred_model3 = model3.predict(X_test)
```

```
WARNING:tensorflow:5 out of the last 17 calls to <function
TensorFlowTrainer.make_predict_function.<locals>.one_step_on_data_distributed at
0x344a91790> triggered tf.function retracing. Tracing is expensive and the
excessive number of tracings could be due to (1) creating @tf.function
repeatedly in a loop, (2) passing tensors with different shapes, (3) passing
Python objects instead of tensors. For (1), please define your @tf.function
outside of the loop. For (2), @tf.function has reduce_retracing=True option that
can avoid unnecessary retracing. For (3), please refer to
https://www.tensorflow.org/guide/function#controlling_retracing and
https://www.tensorflow.org/api_docs/python/tf/function for  more details.
8/8              0s 27ms/step
8/8              0s 26ms/step
8/8              0s 22ms/step
```

1.0.16 PART 16 Model evaluation

[82]:
```python
from sklearn.metrics import mean_absolute_error, mean_squared_error
import numpy as np

# Compute MAE and RMSE for each model
mae_model1 = mean_absolute_error(y_test, pred_model1)
rmse_model1 = np.sqrt(mean_squared_error(y_test, pred_model1))
mse_model1 = mean_squared_error(y_test, pred_model1)

mae_model2 = mean_absolute_error(y_test, pred_model2)
rmse_model2 = np.sqrt(mean_squared_error(y_test, pred_model2))
mse_model2 = mean_squared_error(y_test, pred_model2)

mae_model3 = mean_absolute_error(y_test, pred_model3)
rmse_model3 = np.sqrt(mean_squared_error(y_test, pred_model3))
mse_model3 = mean_squared_error(y_test, pred_model3)

print(f"Model 1 (LSTM) - MAE: {mae_model1:.4f}, RMSE: {rmse_model1:.4f}, MSE: 
 ↪{mse_model1:.4f}")
print(f"Model 2 (LSTM with different settings) - MAE: {mae_model2:.4f}, RMSE: 
 ↪{rmse_model2:.4f}, MSE: {mse_model2:.4f}")
print(f"Model 3 (GRU) - MAE: {mae_model3:.4f}, RMSE: {rmse_model3:.4f}, MSE: 
 ↪{mse_model3:.4f}")
```

```
Model 1 (LSTM) - MAE: 0.1052, RMSE: 0.1172, MSE: 0.0137
Model 2 (LSTM with different settings) - MAE: 0.0261, RMSE: 0.0318, MSE: 0.0010
Model 3 (GRU) - MAE: 0.0196, RMSE: 0.0241, MSE: 0.0006
```

[83]:
```python
y_test_unscaled = scaler.inverse_transform(y_test.reshape(-1, 1))

pred_model1_unscaled = scaler.inverse_transform(pred_model1.reshape(-1, 1))
pred_model2_unscaled = scaler.inverse_transform(pred_model2.reshape(-1, 1))
pred_model3_unscaled = scaler.inverse_transform(pred_model3.reshape(-1, 1))
```

[84]:
```python
import pandas as pd
# Create a DataFrame for model comparison
model_results = pd.DataFrame({
    'Model': ['LSTM Model 1', 'LSTM Model 2', 'GRU Model 3'],
    'MAE': [mae_model1, mae_model2, mae_model3],
    'RMSE': [rmse_model1, rmse_model2, rmse_model3],
    'MSE': [mse_model1, mse_model2, mse_model3]
})


print("Model Comparison:")
model_results
```

```
Model Comparison:
```

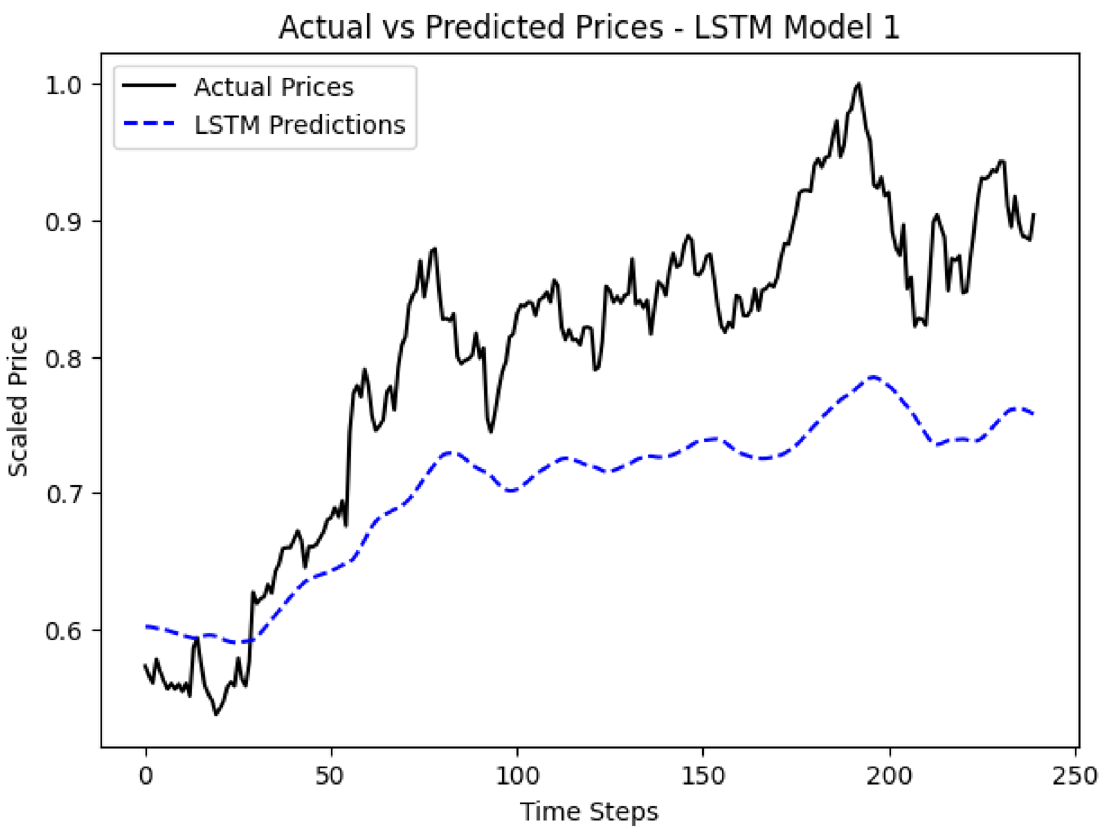
[84]:

	Model	MAE	RMSE	MSE
0	LSTM Model 1	0.105207	0.117173	0.013729
1	LSTM Model 2	0.026142	0.031819	0.001012
2	GRU Model 3	0.019611	0.024125	0.000582

Actual vs Predicted

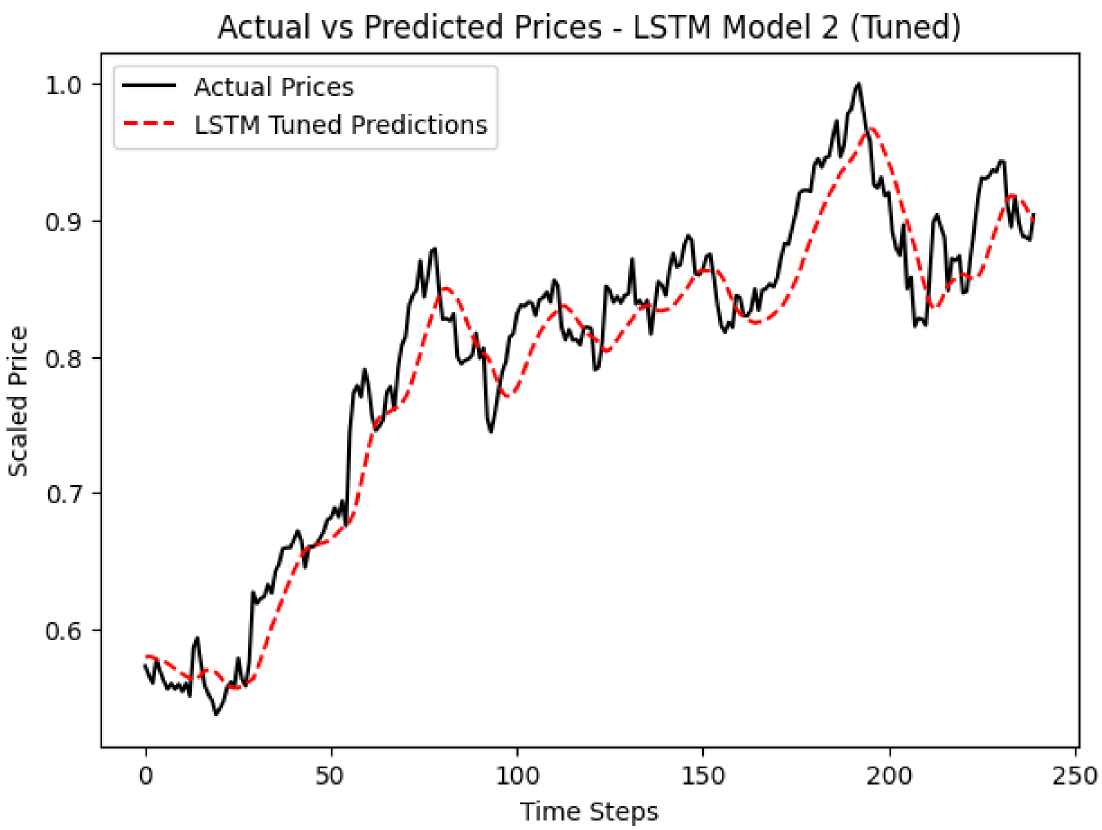
Model 01 - LTSM

[85]:
```python
import matplotlib.pyplot as plt

plt.figure(figsize=(7, 5))
plt.plot(y_test, label='Actual Prices', color='black')
plt.plot(pred_model1, label='LSTM Predictions', color='blue',␣
 ↪linestyle='dashed')
plt.title('Actual vs Predicted Prices - LSTM Model 1')
plt.xlabel('Time Steps')
plt.ylabel('Scaled Price')
plt.legend()
plt.show()
```



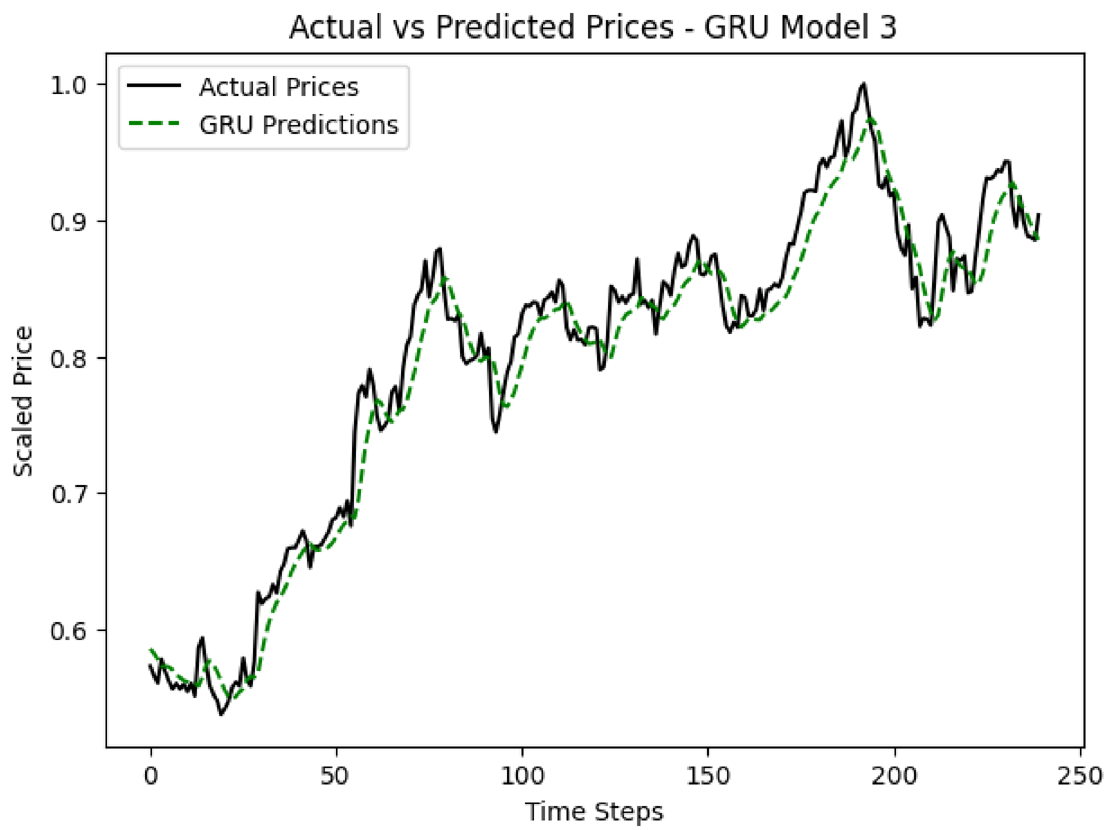
Model 02 - LTSM TUNED

[86]:
```
plt.figure(figsize=(7, 5))
plt.plot(y_test, label='Actual Prices', color='black')
plt.plot(pred_model2, label='LSTM Tuned Predictions', color='red',␣
 ↪linestyle='dashed')
plt.title('Actual vs Predicted Prices - LSTM Model 2 (Tuned)')
plt.xlabel('Time Steps')
plt.ylabel('Scaled Price')
plt.legend()
plt.show()
```



Model 03- GRU

[87]:
```
plt.figure(figsize=(7, 5))
plt.plot(y_test, label='Actual Prices', color='black')
plt.plot(pred_model3, label='GRU Predictions', color='green',␣
  ↪linestyle='dashed')
plt.title('Actual vs Predicted Prices - GRU Model 3')
plt.xlabel('Time Steps')
plt.ylabel('Scaled Price')
plt.legend()
plt.show()
```

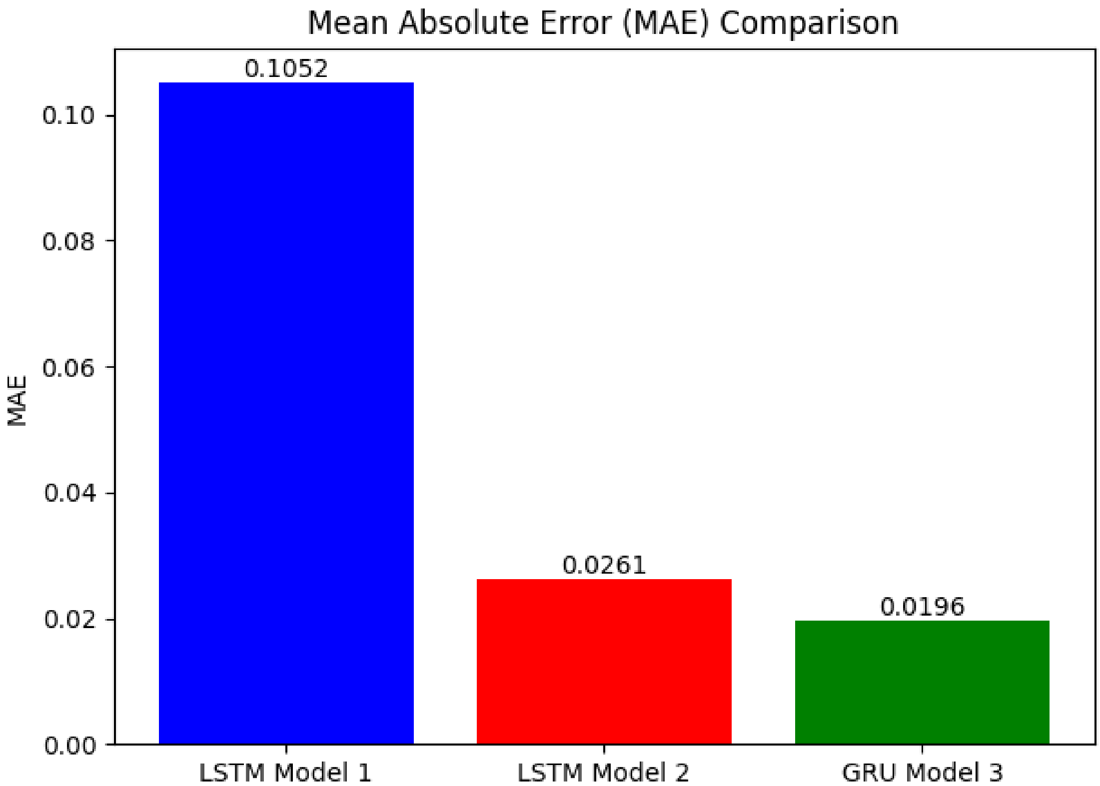


PEROFRMANCE METRICS

[88]:
```
models = ["LSTM Model 1", "LSTM Model 2", "GRU Model 3"]
mae_values = [mae_model1, mae_model2, mae_model3]
rmse_values = [rmse_model1, rmse_model2, rmse_model3]
mse_values = [mse_model1, mse_model2, mse_model3]
```

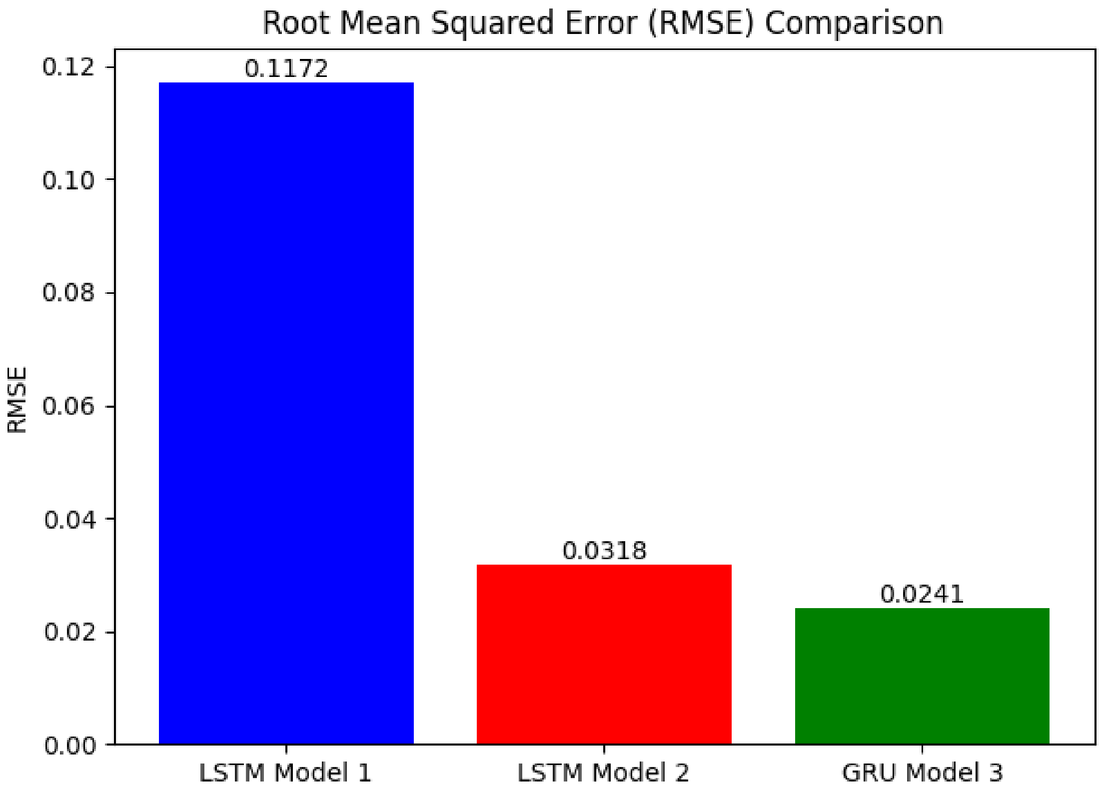
MAE

[89]:
```
plt.figure(figsize=(7, 5))
bars = plt.bar(models, mae_values, color=['blue', 'red', 'green'])
plt.title('Mean Absolute Error (MAE) Comparison')
plt.ylabel('MAE')

for bar in bars:
    yval = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2, yval, f"{yval:.4f}", ha='center',␣
 ↪va='bottom')

plt.show()
```



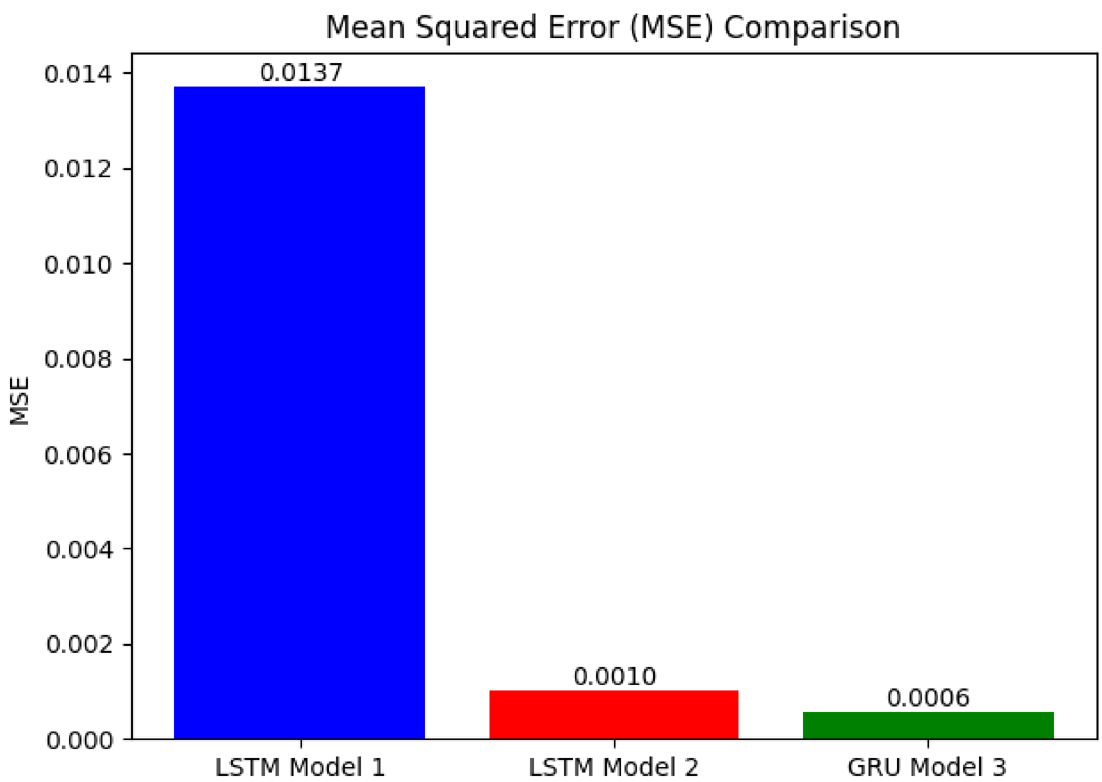
RMSE

[90]:
```
plt.figure(figsize=(7, 5))
bars = plt.bar(models, rmse_values, color=['blue', 'red', 'green'])
plt.title('Root Mean Squared Error (RMSE) Comparison')
plt.ylabel('RMSE')
for bar in bars:
    yval = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2, yval, f"{yval:.4f}", ha='center',␣
 ↪va='bottom')

plt.show()
```



MSE

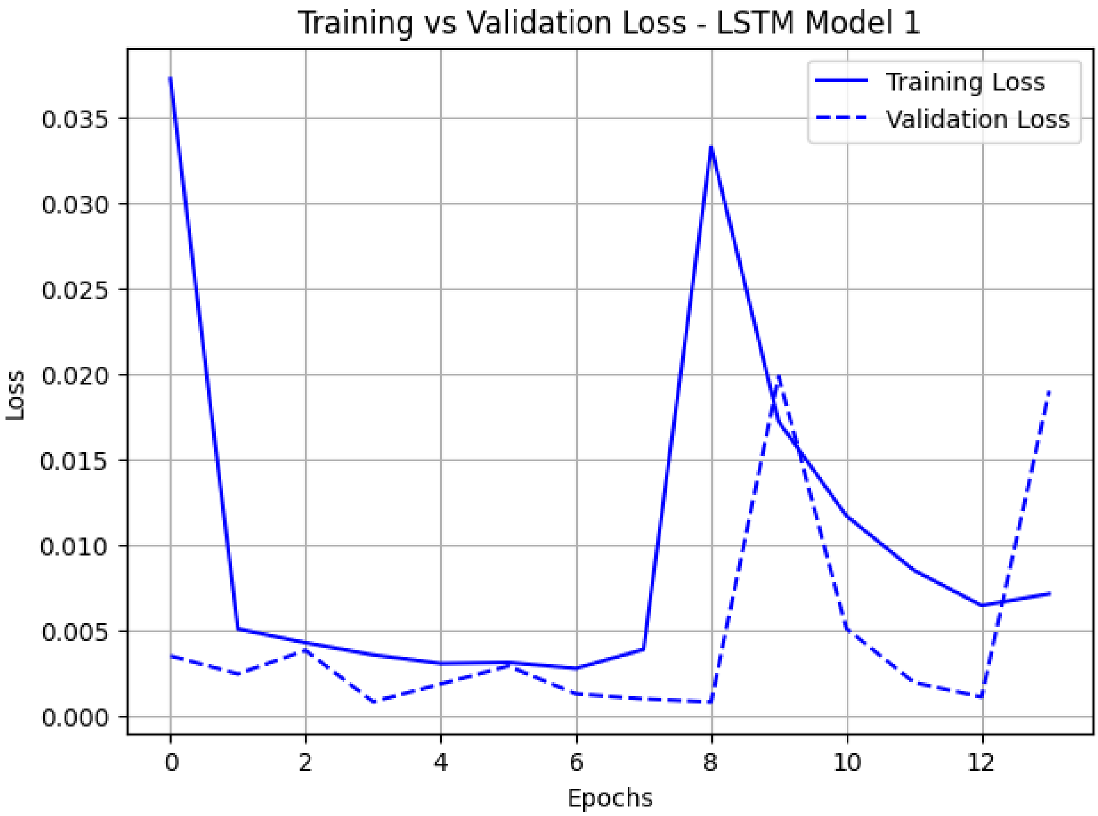
[91]:
```
plt.figure(figsize=(7, 5))
bars= plt.bar(models, mse_values, color=['blue', 'red', 'green'])
plt.title('Mean Squared Error (MSE) Comparison')
plt.ylabel('MSE')
for bar in bars:
    yval = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2, yval, f"{yval:.4f}", ha='center',
 ↪va='bottom')
plt.show()
```



Loss Curves

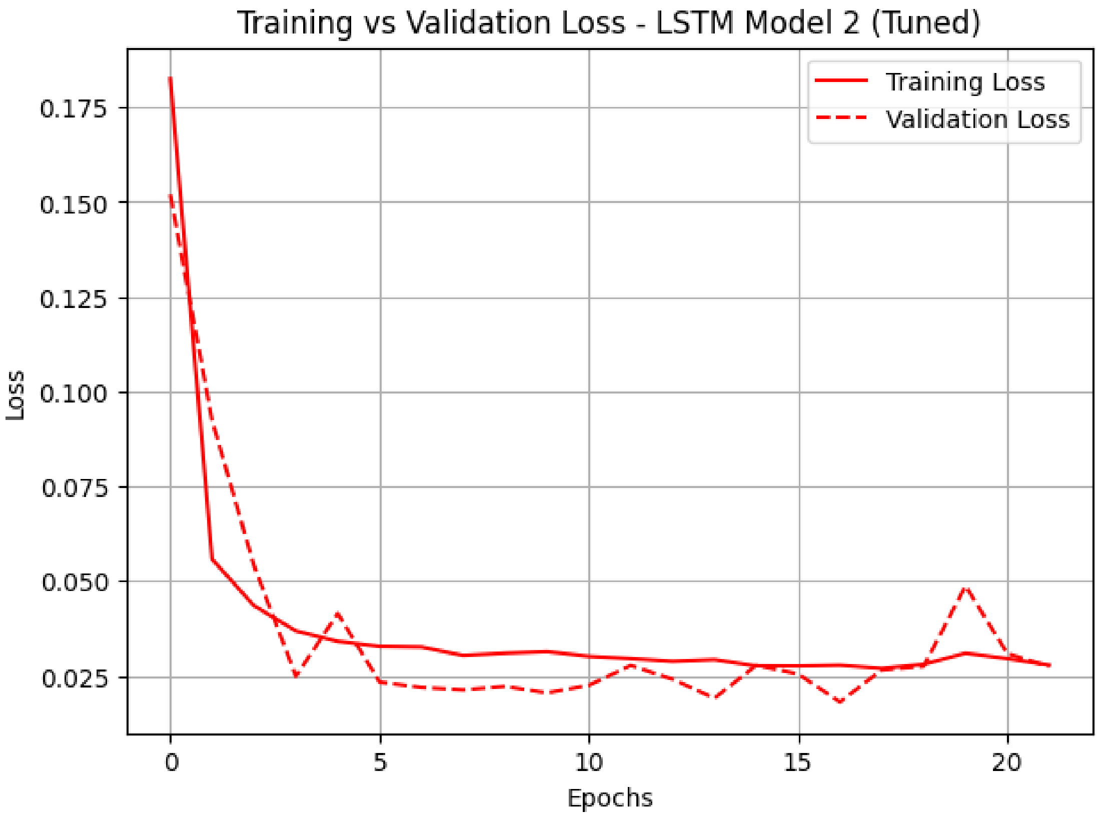
Model 01

[92]:
```
plt.figure(figsize=(7, 5))
plt.plot(history1.history['loss'], label='Training Loss', color='blue')
plt.plot(history1.history['val_loss'], label='Validation Loss', color='blue',␣
  ↪linestyle='dashed')
plt.title('Training vs Validation Loss - LSTM Model 1')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.grid()
plt.show()
```



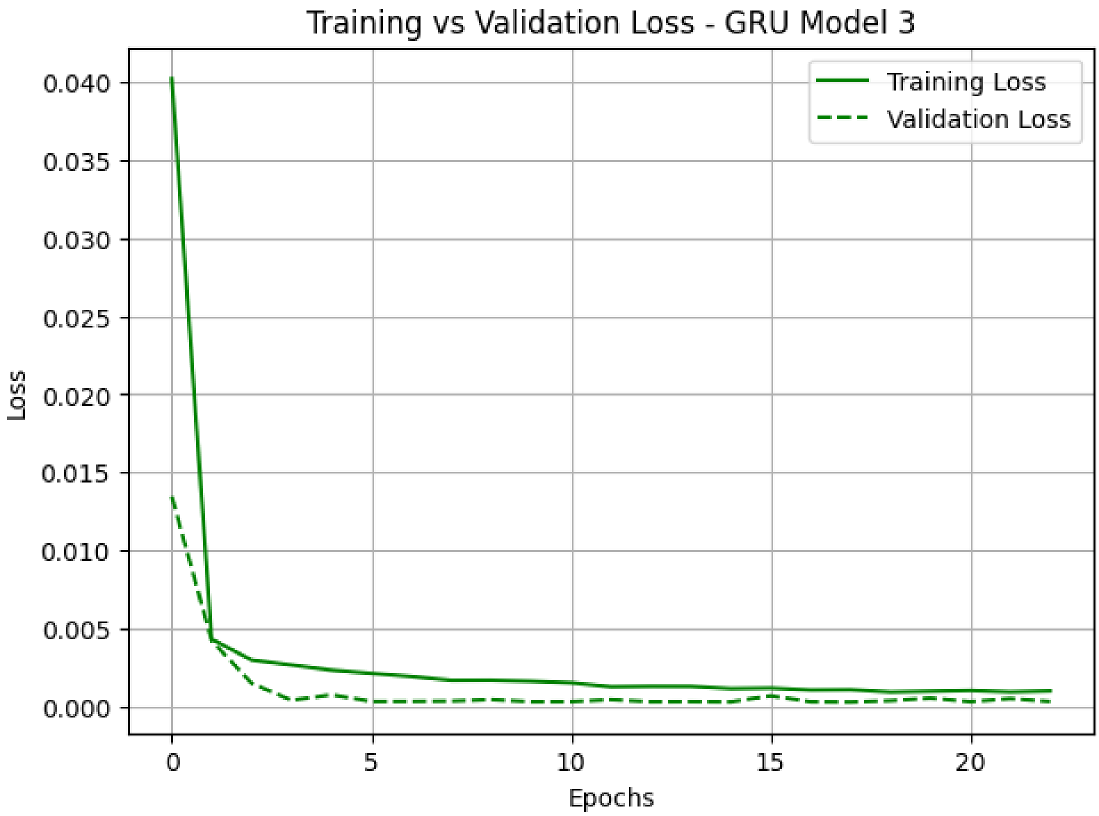
Model 02

[93]:
```
plt.figure(figsize=(7, 5))
plt.plot(history2.history['loss'], label='Training Loss', color='red')
plt.plot(history2.history['val_loss'], label='Validation Loss', color='red',␣
  ↪linestyle='dashed')
plt.title('Training vs Validation Loss - LSTM Model 2 (Tuned)')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.grid()
plt.show()
```



Model 03

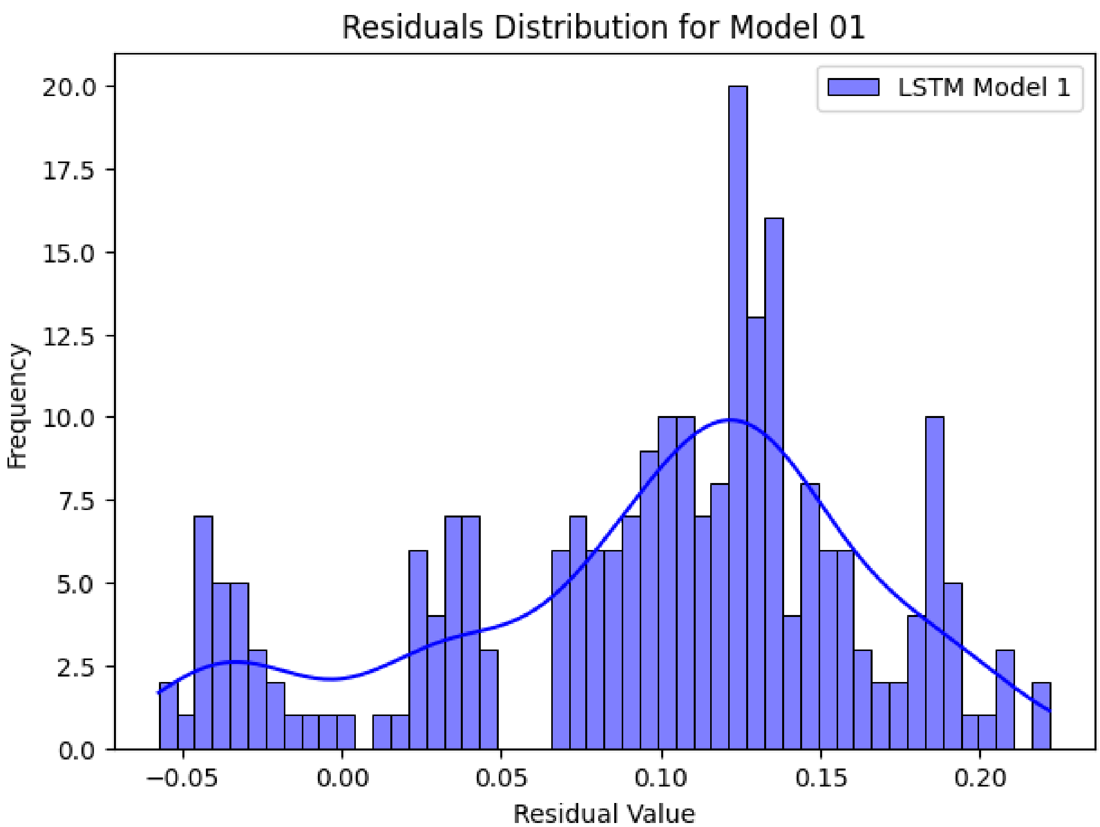
[94]:
```
plt.figure(figsize=(7, 5))
plt.plot(history3.history['loss'], label='Training Loss', color='green')
plt.plot(history3.history['val_loss'], label='Validation Loss', color='green',␣
↪linestyle='dashed')
plt.title('Training vs Validation Loss - GRU Model 3')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.grid()
plt.show()
```



Residual Analysis

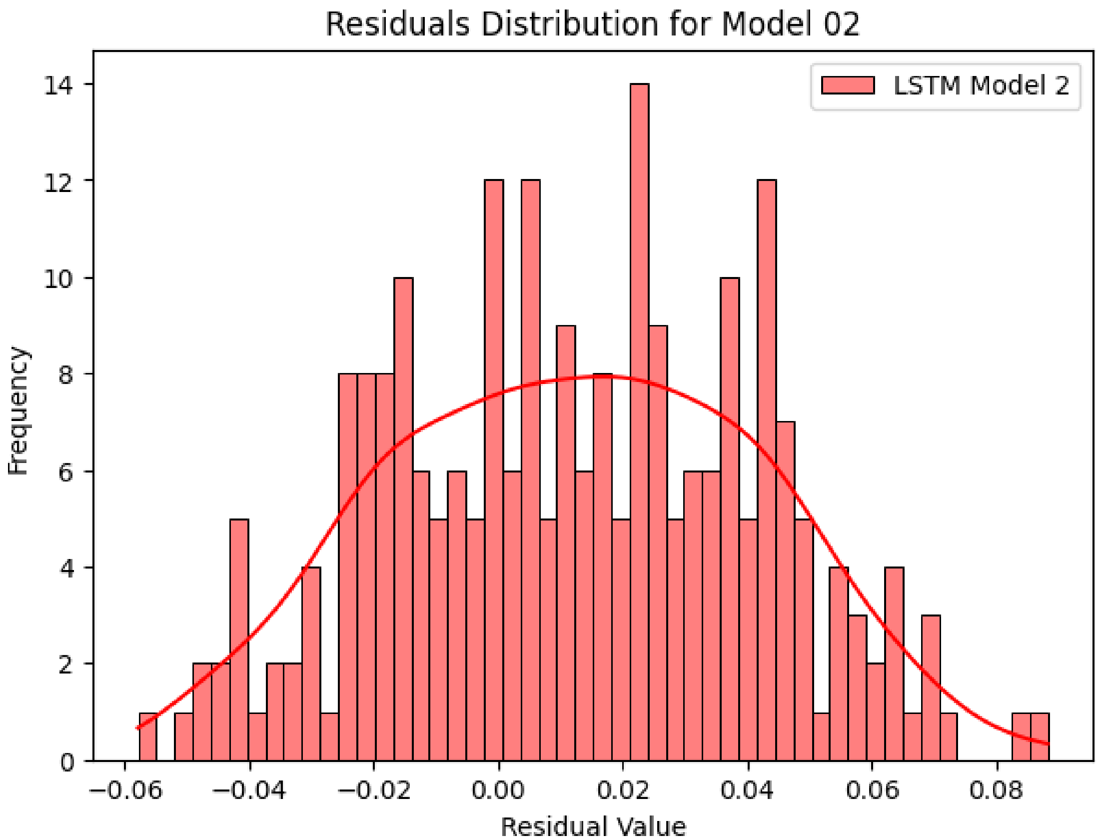
[95]:
```
residuals_model1 = y_test - pred_model1.flatten()
residuals_model2 = y_test - pred_model2.flatten()
residuals_model3 = y_test - pred_model3.flatten()
```

[96]:
```
plt.figure(figsize=(7, 5))
sns.histplot(residuals_model1, bins=50, color="blue", label="LSTM Model 1",␣
 ↪kde=True)
plt.title('Residuals Distribution for Model 01')
plt.xlabel('Residual Value')
plt.ylabel('Frequency')
plt.legend()
plt.show()
```



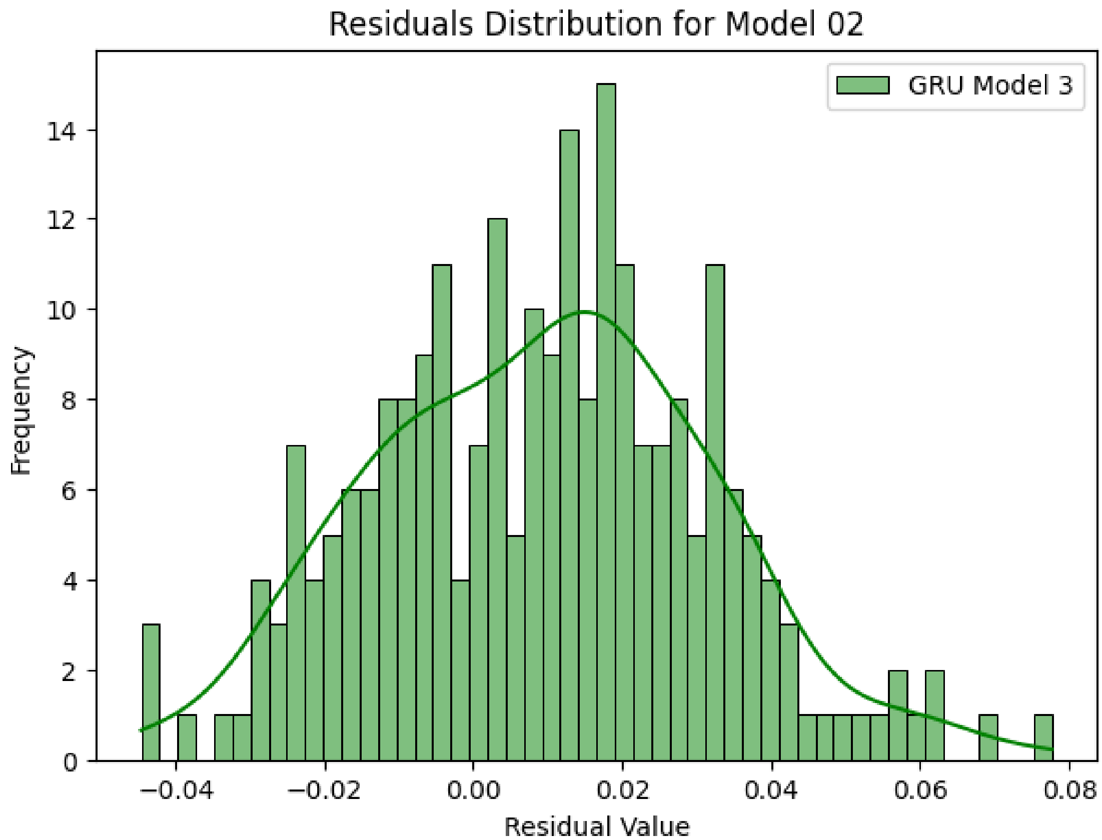
Model 02

[97]:
```
plt.figure(figsize=(7, 5))
sns.histplot(residuals_model2, bins=50, color="red", label="LSTM Model 2",␣
 ↪kde=True)
plt.title('Residuals Distribution for Model 02')
plt.xlabel('Residual Value')
plt.ylabel('Frequency')
plt.legend()
plt.show()
```



Model 03

[98]:
```
plt.figure(figsize=(7, 5))
sns.histplot(residuals_model3, bins=50, color="green", label="GRU Model 3",␣
    ↪kde=True)
plt.title('Residuals Distribution for Model 02')
plt.xlabel('Residual Value')
plt.ylabel('Frequency')
plt.legend()
plt.show()
```



R_squared

[99]:
```
r2_model1 = r2_score(y_test, pred_model1)
r2_model2 = r2_score(y_test, pred_model2)
r2_model3 = r2_score(y_test, pred_model3)
```

[100]:
```
print(f"Model 1 (LSTM) R_squared Score: {r2_model1:.4f}")
print(f"Model 2 (LSTM Tuned) R_squared Score: {r2_model2:.4f}")
print(f"Model 3 (GRU) R_squared Score: {r2_model3:.4f}")
```

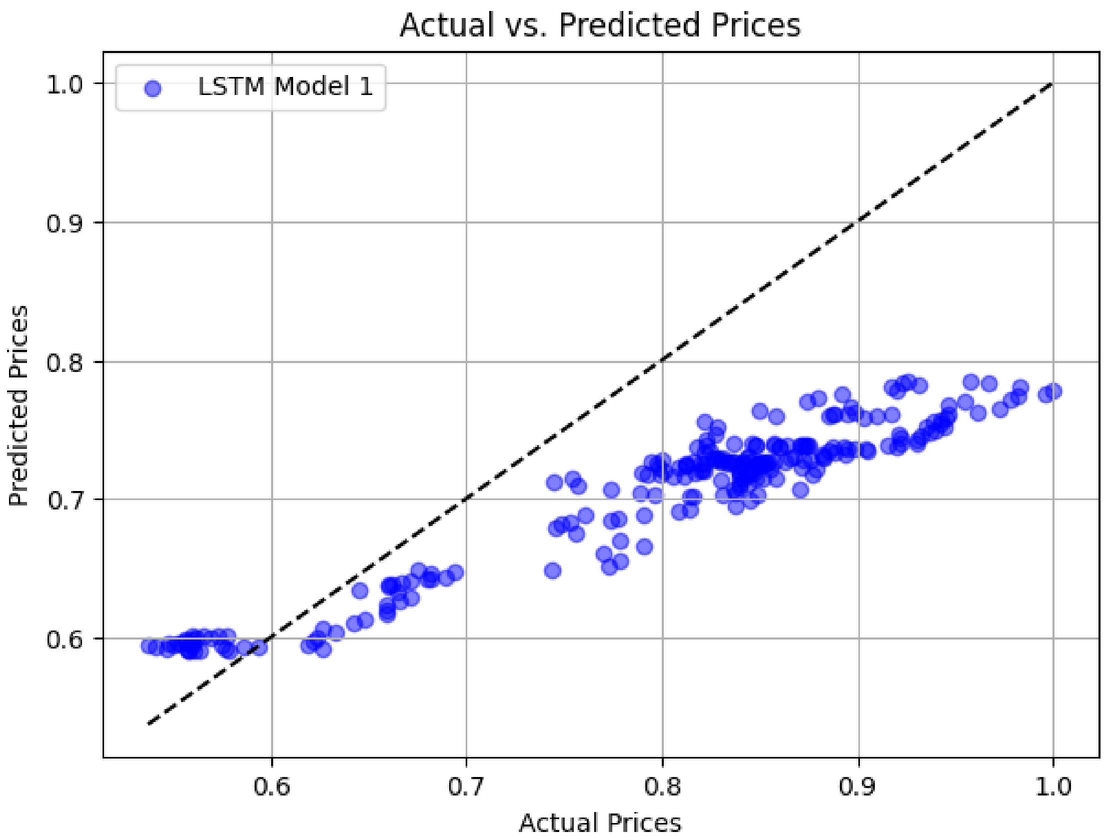
```
Model 1 (LSTM) R_squared Score: 0.0149
Model 2 (LSTM Tuned) R_squared Score: 0.9274
Model 3 (GRU) R_squared Score: 0.9582
```

Actual vs Predicted

Model 01

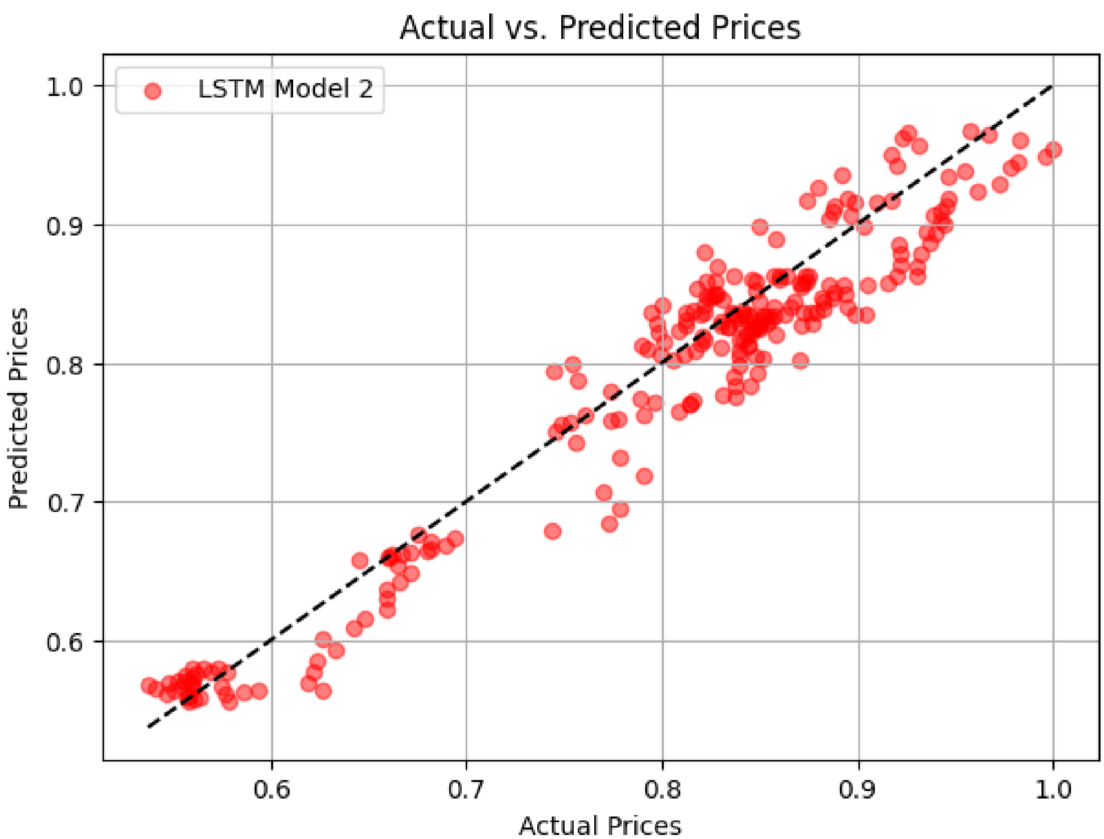
[101]:
```
plt.figure(figsize=(7, 5))
plt.scatter(y_test, pred_model1, color='blue', alpha=0.5, label="LSTM Model 1")
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)],␣
↪linestyle="--", color="black")
```

```
plt.title("Actual vs. Predicted Prices")
plt.xlabel("Actual Prices")
plt.ylabel("Predicted Prices")
plt.legend()
plt.grid()
plt.show()
```

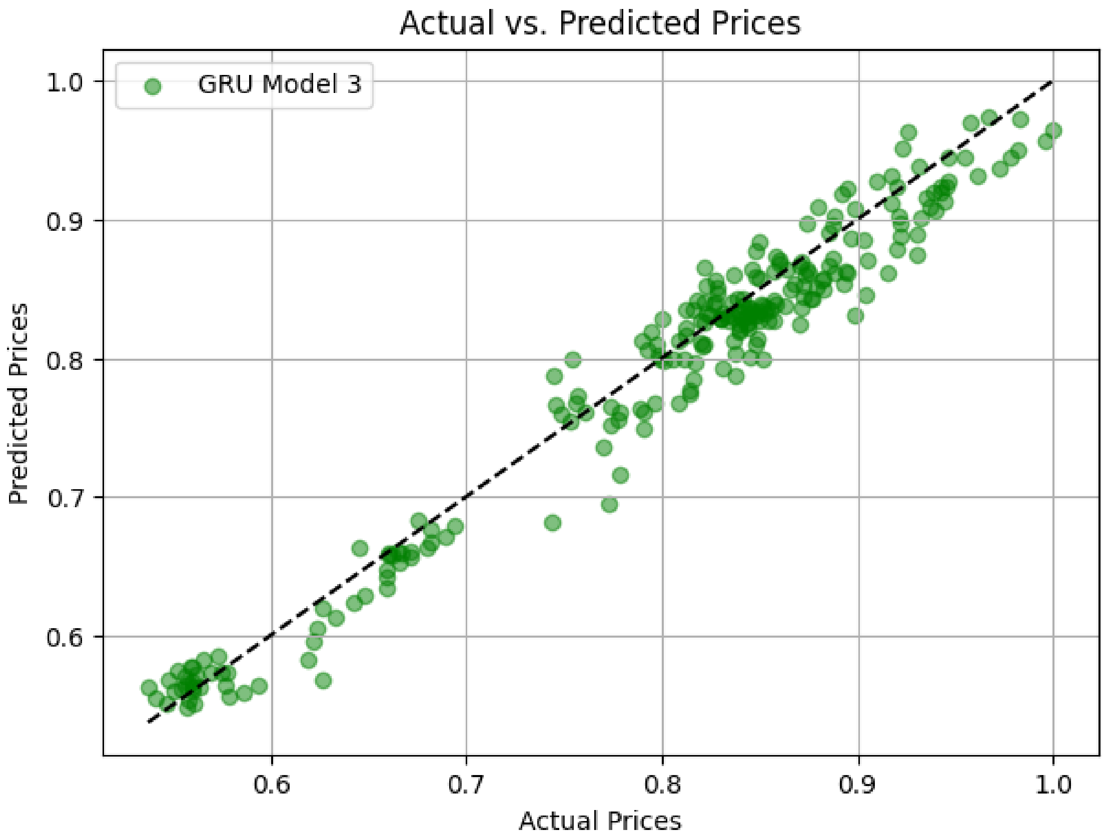


Model 02

[102]:
```
plt.figure(figsize=(7, 5))
plt.scatter(y_test, pred_model2, color='red', alpha=0.5, label="LSTM Model 2")
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)],␣
↪linestyle="--", color="black")
plt.title("Actual vs. Predicted Prices")
plt.xlabel("Actual Prices")
plt.ylabel("Predicted Prices")
plt.legend()
plt.grid()
plt.show()
```



[103]:
```
plt.figure(figsize=(7, 5))
plt.scatter(y_test, pred_model3, color='green', alpha=0.5, label="GRU Model 3")
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)],␣
 ↪linestyle="--", color="black")
plt.title("Actual vs. Predicted Prices")
plt.xlabel("Actual Prices")
plt.ylabel("Predicted Prices")
plt.legend()
plt.grid()
plt.show()
```



1.0.17 PART 17 Conclusion

To conclude, overall, it was noticeable that the third model, or the model that used GRU, performed the best, which achieved the lowest errors compared to the three models. The GRU model had a Mean Absolute Error (MAE) which consisted of 0.0196, Root Mean Square Error (RMSE) of 0.0241, and lastly, Mean Square Error (MSE) of 0.0006, which shows this predicted Uber's stock prices the most accurately.The first LSTM model had an MAE of 0.1052, RMSE of 0.1172, and MSE of 0.0137, and the second LSTM model had performed better than Model 1 and had the following results: MAE of 0.0261, RMSE of 0.0318, and MSE of 0.001. The R-squared measures how well a model is able to explain the stock price trends, and GRU showed the best score at 0.9582, which states that it is a strong model to be able to capture the trends. Model 02 showed an R-squared score of 0.9274, and the first model was extremely low at 0.0149. The reason it was low was that it was having a hard time predicting stock prices. Afterwards, model evaluation was required, and it was noticeable that the GRU model closely followed the stock prices. The two LSTM models were not showing a reliable outlook as they were showing more ups and downs. The residual analysis then further helped to check how many of the predictions were different from the real prices, and overall, GRU had the least amount of errors - which represents that it is a strong model. From this research, it can be understood that GRU models

are much better than the LSTM models for predicting stock prices, as they are able to check past trends more efficiently compared to an LSTM. Hyperparameter tuning is important as if we adjust settings, there is a major difference in performance, and that is what happened between the first and second LSTM model. Overall, GRU or the third model was the best to predict stock prices for the ride-sharing company. Future research can be focused on financial indicators, better feature selection, and as well as a larger dataset.

1.0.18 PART 18 Management Question

This research is important to the outside world as stock price predictions will help people like investors, businesses, and financial analysts make better decisions on market trends and investments. By using models like LSTM and GRU, we can understand which procedure will drive towards a positive answer for capturing patterns. Understanding these models will help improve forecasting accuracy, and this is very helpful for anyone who is in the financial-related fields.

1.0.19 PART 20 References

Northwestern University. *Module 9 Assignment 2: Financial Time Series.* https://canvas.northwestern.edu/courses/222806/assignments/1546801. Accessed March 9, 2025.