LSTM Stock Prediction Project Plots | ECE 539 | Aidan Pierre-Louis

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

In [2]:
```
np.random.seed(42) # random seed for reproducability
tf.random.set_seed(42)

# dow jones companies to test model on
dowjones_comps = [
    "AAPL", "MSFT", "AMZN", "GOOGL",  # Big Tech # "FB"
    "JNJ", "PFE", "MRK", "UNH", "ABT",      # Healthcare
    "PG", "KO", "PEP", "WMT", "HD",         # Consumer
    "GS", "JPM", "V", "AXP", "CRM",         # Financials
    "DIS", "NFLX", "CMCSA", "T", "INTC",    # Media & Telecom
    "NKE", "MCD", "SBUX", "CAT", "MMM",     # Industrials
    "BA", "HON", "UNP", "DOW",       # Industrials #"UTX"
    "IBM", "CSCO", "AAP", "TRV", "CVX",     # Other
    "XOM", "VZ", "MS", "RTX", "WBA"         # Other
]
```

In [3]:
```
# Create lagged features for LSTM
def create_lagged_features(series, n_lags):
    df = pd.DataFrame(series)
    for i in range(1, n_lags + 1):
        df[f'lag_{i}'] = series.shift(i)
    #df.dropna(inplace=True)  # Drop rows with NaN values which are the result of shifting, use create_sequences()
    df.fillna(0.0, inplace=True) # replace rows with NaN values from shifting to prevent loss of indices, deprecates
    return df

# Prepare stock data with lagged features
def prepare_stock_data(stock_symbol, n_lags, start='2020-01-01', end='2023-01-01'):
```

```
    data = yf.download(stock_symbol, start=start, end=end)
    series = data['Close'].dropna()
    df = create_lagged_features(series, n_lags)
    scaler = MinMaxScaler(feature_range=(-1, 1))
    #scaler = MinMaxScaler(feature_range=(0, 1))
    scaled_data = scaler.fit_transform(df)
    return scaled_data, scaler, series

# Prepare data, Hyperparam lag features
n_lags = 10
comp_idx = 20 # change the index here for selecting dow jones company to train data on
scaled_data, scaler, series = prepare_stock_data(dowjones_comps[comp_idx], n_lags)
```

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

In [4]:
```
# Create sequences, deprecated function after altering create_lagged_features to maintain index count
def create_sequences(data, sequence_length):
    X, y = [], []
    for i in range(sequence_length, len(data)):
        X.append(data[i-sequence_length:i, :-1])
        y.append(data[i, -1])
    return np.array(X), np.array(y)

# new function to create sequences
def create_sequences_new(data):
    X, y = data[:, :-1], data[:, -1]
    # print(f'shape of x {len(X)}')
    return np.array(X), np.array(y)

def create_sequences_(data, sequence_length):
    X, y = [], []
    for i in range(len(data)):
        X.append(data[i-sequence_length:i, :-1])
        y.append(data[i, -1])
    return np.array(X), np.array(y)

sequence_length = n_lags
# X, y = create_sequences(scaled_data, sequence_length)
X, y = create_sequences_new(scaled_data)
```

In [5]:
```
# Split into training and testing sets
#split_percent = 0.9
```

```python
#split = int(split_percent * len(X))

#X_train, y_train = X[:split], y[:split]
#X_test, y_test = X[split:], y[split:]

# 70/15/15 split
train_size = int(0.7 * len(X))
val_size = int(0.15 * len(X))
test_size = len(X) - train_size - val_size

X_train, y_train = X[:train_size], y[:train_size]
X_val, y_val = X[train_size:train_size+val_size], y[train_size:train_size+val_size]
X_test, y_test = X[train_size+val_size:], y[train_size+val_size:]
```

In [6]:

```python
# Reshape data for LSTM
#X_train = X_train.reshape((X_train.shape[0], X_train.shape[1], X_train.shape[2])) # deprecated with create_sequences
#X_test = X_test.reshape((X_test.shape[0], X_test.shape[1], X_test.shape[2])) # deprecated with create_sequences
X_train = X_train.reshape((X_train.shape[0], X_train.shape[1]))
X_val = X_val.reshape((X_val.shape[0], X_val.shape[1]))
X_test = X_test.reshape((X_test.shape[0], X_test.shape[1]))

X_train = np.expand_dims(X_train, axis=-1)  # Add a new axis for features
X_val = np.expand_dims(X_val, axis=-1)  # Add a new axis for features
X_test = np.expand_dims(X_test, axis=-1)  # Add a new axis for features

# TODO redundancy, create method to do all this reshaping
first_values = X_train[:, 0]
X_train[:, :, 0] = first_values

first_values = X_val[:, 0]
X_val[:, :, 0] = first_values

first_values = X_test[:, 0]
X_test[:, :, 0] = first_values
```

In [7]:

```python
#X_test.shape, X_test[:10, :, :]
```

In [8]:

```python
# Hyperparam, dropout prob
p = 0.2
hidden_units = 50
```

```python
# Build the LSTM model
model = Sequential([
    LSTM(hidden_units, return_sequences=True, input_shape=(X_train.shape[1], X_train.shape[2])),
    Dropout(p),
    LSTM(hidden_units, return_sequences=False),
    Dropout(p),
    Dense(25),
    Dense(1)
])
```

```
C:\Users\p_pie\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.12_qbz5n2kfra8p0\LocalCache\local-packages\Python312\site-packages\keras\src\layers\rnn\rnn.py:204: 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)
```

In [9]:

```python
# Hyperparameters
learning_rate = 0.001
batch_size = 16
epochs = 100

optimizer = Adam(learning_rate=learning_rate)
# Compile the model
model.compile(optimizer=optimizer, loss='mean_squared_error', metrics=['accuracy'])
# Train the model
history = model.fit(X_train, y_train, batch_size=batch_size, epochs=epochs, validation_data=(X_val, y_val), verbose=
```

```
Epoch 1/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 2s 12ms/step - accuracy: 0.0011 - loss: 0.0990 - val_accuracy: 0.0000e+00 - val_loss: 0.01
97
Epoch 2/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0271 - val_accuracy: 0.0000e+00 - val_loss: 0.048
2
Epoch 3/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0266 - val_accuracy: 0.0000e+00 - val_loss: 0.112
3
Epoch 4/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0280 - val_accuracy: 0.0000e+00 - val_loss: 0.129
8
Epoch 5/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0271 - val_accuracy: 0.0000e+00 - val_loss: 0.262
3
Epoch 6/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0276 - val_accuracy: 0.0000e+00 - val_loss: 0.293
2
Epoch 7/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0287 - val_accuracy: 0.0000e+00 - val_loss: 0.400
0
Epoch 8/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0299 - val_accuracy: 0.0000e+00 - val_loss: 0.261
5
Epoch 9/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0271 - val_accuracy: 0.0000e+00 - val_loss: 0.277
6
Epoch 10/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0288 - val_accuracy: 0.0000e+00 - val_loss: 0.486
5
Epoch 11/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0281 - val_accuracy: 0.0000e+00 - val_loss: 0.489
2
Epoch 12/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0277 - val_accuracy: 0.0000e+00 - val_loss: 0.425
1
Epoch 13/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0280 - val_accuracy: 0.0000e+00 - val_loss: 0.461
2
Epoch 14/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0289 - val_accuracy: 0.0000e+00 - val_loss: 0.380
7
```

```
Epoch 15/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0282 - val_accuracy: 0.0000e+00 - val_loss: 0.360
7
Epoch 16/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0279 - val_accuracy: 0.0000e+00 - val_loss: 0.460
0
Epoch 17/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0275 - val_accuracy: 0.0000e+00 - val_loss: 0.663
7
Epoch 18/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0278 - val_accuracy: 0.0000e+00 - val_loss: 0.463
3
Epoch 19/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0266 - val_accuracy: 0.0000e+00 - val_loss: 0.593
5
Epoch 20/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0275 - val_accuracy: 0.0000e+00 - val_loss: 0.708
4
Epoch 21/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0269 - val_accuracy: 0.0000e+00 - val_loss: 0.599
7
Epoch 22/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0279 - val_accuracy: 0.0000e+00 - val_loss: 0.684
7
Epoch 23/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0282 - val_accuracy: 0.0000e+00 - val_loss: 0.726
0
Epoch 24/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0274 - val_accuracy: 0.0000e+00 - val_loss: 0.965
8
Epoch 25/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0296 - val_accuracy: 0.0000e+00 - val_loss: 0.644
1
Epoch 26/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0269 - val_accuracy: 0.0000e+00 - val_loss: 0.657
6
Epoch 27/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0269 - val_accuracy: 0.0000e+00 - val_loss: 0.497
4
Epoch 28/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0271 - val_accuracy: 0.0000e+00 - val_loss: 0.670
7
```

```
Epoch 29/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0269 - val_accuracy: 0.0000e+00 - val_loss: 0.875
6
Epoch 30/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0291 - val_accuracy: 0.0000e+00 - val_loss: 0.782
6
Epoch 31/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0280 - val_accuracy: 0.0000e+00 - val_loss: 0.794
1
Epoch 32/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0289 - val_accuracy: 0.0000e+00 - val_loss: 0.604
5
Epoch 33/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0275 - val_accuracy: 0.0000e+00 - val_loss: 0.814
4
Epoch 34/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0271 - val_accuracy: 0.0000e+00 - val_loss: 0.725
6
Epoch 35/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0275 - val_accuracy: 0.0000e+00 - val_loss: 0.880
2
Epoch 36/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0287 - val_accuracy: 0.0000e+00 - val_loss: 0.574
8
Epoch 37/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0255 - val_accuracy: 0.0000e+00 - val_loss: 0.689
1
Epoch 38/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0284 - val_accuracy: 0.0000e+00 - val_loss: 0.950
6
Epoch 39/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0287 - val_accuracy: 0.0000e+00 - val_loss: 0.735
4
Epoch 40/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0278 - val_accuracy: 0.0000e+00 - val_loss: 0.727
9
Epoch 41/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0269 - val_accuracy: 0.0000e+00 - val_loss: 0.830
0
Epoch 42/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0294 - val_accuracy: 0.0000e+00 - val_loss: 1.102
8
```

```
Epoch 43/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0289 - val_accuracy: 0.0000e+00 - val_loss: 1.031
2
Epoch 44/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0280 - val_accuracy: 0.0000e+00 - val_loss: 0.896
1
Epoch 45/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0279 - val_accuracy: 0.0000e+00 - val_loss: 0.973
2
Epoch 46/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0268 - val_accuracy: 0.0000e+00 - val_loss: 0.824
3
Epoch 47/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0265 - val_accuracy: 0.0000e+00 - val_loss: 0.900
1
Epoch 48/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0267 - val_accuracy: 0.0000e+00 - val_loss: 1.133
2
Epoch 49/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0286 - val_accuracy: 0.0000e+00 - val_loss: 1.001
1
Epoch 50/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0273 - val_accuracy: 0.0000e+00 - val_loss: 1.269
2
Epoch 51/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0276 - val_accuracy: 0.0000e+00 - val_loss: 0.947
6
Epoch 52/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0287 - val_accuracy: 0.0000e+00 - val_loss: 1.002
6
Epoch 53/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0269 - val_accuracy: 0.0000e+00 - val_loss: 1.119
7
Epoch 54/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0265 - val_accuracy: 0.0000e+00 - val_loss: 0.966
1
Epoch 55/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0270 - val_accuracy: 0.0000e+00 - val_loss: 1.054
5
Epoch 56/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0280 - val_accuracy: 0.0000e+00 - val_loss: 1.472
8
```

```
Epoch 57/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0296 - val_accuracy: 0.0000e+00 - val_loss: 0.746
4
Epoch 58/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0271 - val_accuracy: 0.0000e+00 - val_loss: 1.149
4
Epoch 59/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.0011 - loss: 0.0273 - val_accuracy: 0.0000e+00 - val_loss: 1.092
0
Epoch 60/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0258 - val_accuracy: 0.0000e+00 - val_loss: 1.316
0
Epoch 61/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0266 - val_accuracy: 0.0000e+00 - val_loss: 0.940
2
Epoch 62/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0279 - val_accuracy: 0.0000e+00 - val_loss: 0.976
3
Epoch 63/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0273 - val_accuracy: 0.0000e+00 - val_loss: 1.205
2
Epoch 64/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0277 - val_accuracy: 0.0000e+00 - val_loss: 0.782
2
Epoch 65/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0282 - val_accuracy: 0.0000e+00 - val_loss: 1.327
7
Epoch 66/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0294 - val_accuracy: 0.0000e+00 - val_loss: 1.126
3
Epoch 67/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0279 - val_accuracy: 0.0000e+00 - val_loss: 1.318
6
Epoch 68/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0280 - val_accuracy: 0.0000e+00 - val_loss: 1.202
0
Epoch 69/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0285 - val_accuracy: 0.0000e+00 - val_loss: 1.156
3
Epoch 70/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0287 - val_accuracy: 0.0000e+00 - val_loss: 1.534
3
```

```
Epoch 71/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0276 - val_accuracy: 0.0000e+00 - val_loss: 1.298
4
Epoch 72/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0262 - val_accuracy: 0.0000e+00 - val_loss: 1.525
8
Epoch 73/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0277 - val_accuracy: 0.0000e+00 - val_loss: 1.479
1
Epoch 74/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0279 - val_accuracy: 0.0000e+00 - val_loss: 1.464
1
Epoch 75/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0272 - val_accuracy: 0.0000e+00 - val_loss: 1.269
7
Epoch 76/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.0011 - loss: 0.0254 - val_accuracy: 0.0000e+00 - val_loss: 1.308
9
Epoch 77/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0265 - val_accuracy: 0.0000e+00 - val_loss: 1.289
8
Epoch 78/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0280 - val_accuracy: 0.0000e+00 - val_loss: 1.218
6
Epoch 79/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0280 - val_accuracy: 0.0000e+00 - val_loss: 1.472
3
Epoch 80/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0278 - val_accuracy: 0.0000e+00 - val_loss: 1.382
3
Epoch 81/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0276 - val_accuracy: 0.0000e+00 - val_loss: 1.528
5
Epoch 82/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0262 - val_accuracy: 0.0000e+00 - val_loss: 1.289
9
Epoch 83/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0271 - val_accuracy: 0.0000e+00 - val_loss: 1.433
1
Epoch 84/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0259 - val_accuracy: 0.0000e+00 - val_loss: 1.239
3
```

```
Epoch 85/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0269 - val_accuracy: 0.0000e+00 - val_loss: 1.064
5
Epoch 86/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0267 - val_accuracy: 0.0000e+00 - val_loss: 0.800
9
Epoch 87/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0258 - val_accuracy: 0.0000e+00 - val_loss: 0.957
7
Epoch 88/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0265 - val_accuracy: 0.0000e+00 - val_loss: 1.277
9
Epoch 89/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0270 - val_accuracy: 0.0000e+00 - val_loss: 1.104
5
Epoch 90/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.0011 - loss: 0.0270 - val_accuracy: 0.0000e+00 - val_loss: 1.112
1
Epoch 91/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0287 - val_accuracy: 0.0000e+00 - val_loss: 0.911
0
Epoch 92/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0262 - val_accuracy: 0.0000e+00 - val_loss: 1.139
8
Epoch 93/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0274 - val_accuracy: 0.0000e+00 - val_loss: 1.161
3
Epoch 94/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0265 - val_accuracy: 0.0000e+00 - val_loss: 0.971
5
Epoch 95/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0280 - val_accuracy: 0.0000e+00 - val_loss: 0.937
3
Epoch 96/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0274 - val_accuracy: 0.0000e+00 - val_loss: 0.831
7
Epoch 97/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0278 - val_accuracy: 0.0000e+00 - val_loss: 0.844
3
Epoch 98/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0267 - val_accuracy: 0.0000e+00 - val_loss: 0.935
8
```

```
Epoch 99/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0275 - val_accuracy: 0.0000e+00 - val_loss: 1.050
0
Epoch 100/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.0011 - loss: 0.0278 - val_accuracy: 0.0000e+00 - val_loss: 0.770
6
```

In [10]:

```python
# Make predictions
predictions = model.predict(X_test)
predictions = scaler.inverse_transform(np.concatenate((np.zeros((predictions.shape[0], n_lags)), predictions), axis=1
```

```
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step
```

In [11]:

```python
# Forecast next forecast_length days using the days from the test set, Hyperparam forecast length
forecast_length = 30
input_seq = X_test[-1]

# function deprecated with create_sequences
def forecast_predictions(forecast_length=30, input_seq=[]):
    predictions = []
    for _ in range(forecast_length):
        print(f'Forecast step {_+1}:')
        pred = model.predict(input_seq.reshape(1, sequence_length, X_test.shape[2]))
        new_row = np.append(input_seq[1:, -1], pred)  # Append the new prediction
        input_seq = np.vstack((input_seq[1:], new_row))  # Update the input sequence with the new prediction
        pred_inverse_scaled = scaler.inverse_transform(np.concatenate((np.zeros((1, n_lags)), pred), axis=1))[:, -1]
        predictions.append(pred_inverse_scaled[0])
    return predictions



# forecasted_values = forecast_predictions(forecast_length, input_seq)

def forecast_predictions_new(model, data, sequence_length, forecast_length, scaler):
    predictions = []
    last_sequence = data[-n_lags:]  # Take the last n_lags closing prices as the initial input
    for _ in range(forecast_length):
        print(f'Forecast step {_+1}:')
        # Reshape last_sequence to match the model input shape (1, sequence_length, 1)
        last_sequence = last_sequence.reshape((1, sequence_length, 1))
        # Predict the next value
        next_value = model.predict(last_sequence)[0, 0]
```

```
        # Append the prediction
        predictions.append(next_value)
        # Update the sequence, rolling it forward
        next_value = np.array([[next_value]])  # Reshape next_value to be 3D: (1, 1, 1)
        last_sequence = np.append(last_sequence[:, 1:, :], next_value.reshape(1, 1, 1), axis=1)
    # Inverse scale the predictions after the loop
    predictions = np.array(predictions).reshape(-1, 1)
    future_predictions = scaler.inverse_transform(np.concatenate((np.zeros((len(predictions), sequence_length)), pred
    return future_predictions

# Use the model to forecast the next n_future days
forecasted_values = forecast_predictions_new(model, input_seq, sequence_length, forecast_length, scaler)
```

```
Forecast step 1:
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 13ms/step
Forecast step 2:
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step
Forecast step 3:
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step
Forecast step 4:
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step
Forecast step 5:
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step
Forecast step 6:
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step
Forecast step 7:
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step
Forecast step 8:
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step
Forecast step 9:
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step
Forecast step 10:
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step
Forecast step 11:
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step
Forecast step 12:
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step
Forecast step 13:
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step
Forecast step 14:
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step
Forecast step 15:
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step
Forecast step 16:
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step
Forecast step 17:
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step
Forecast step 18:
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step
Forecast step 19:
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step
Forecast step 20:
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step
Forecast step 21:
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step
```

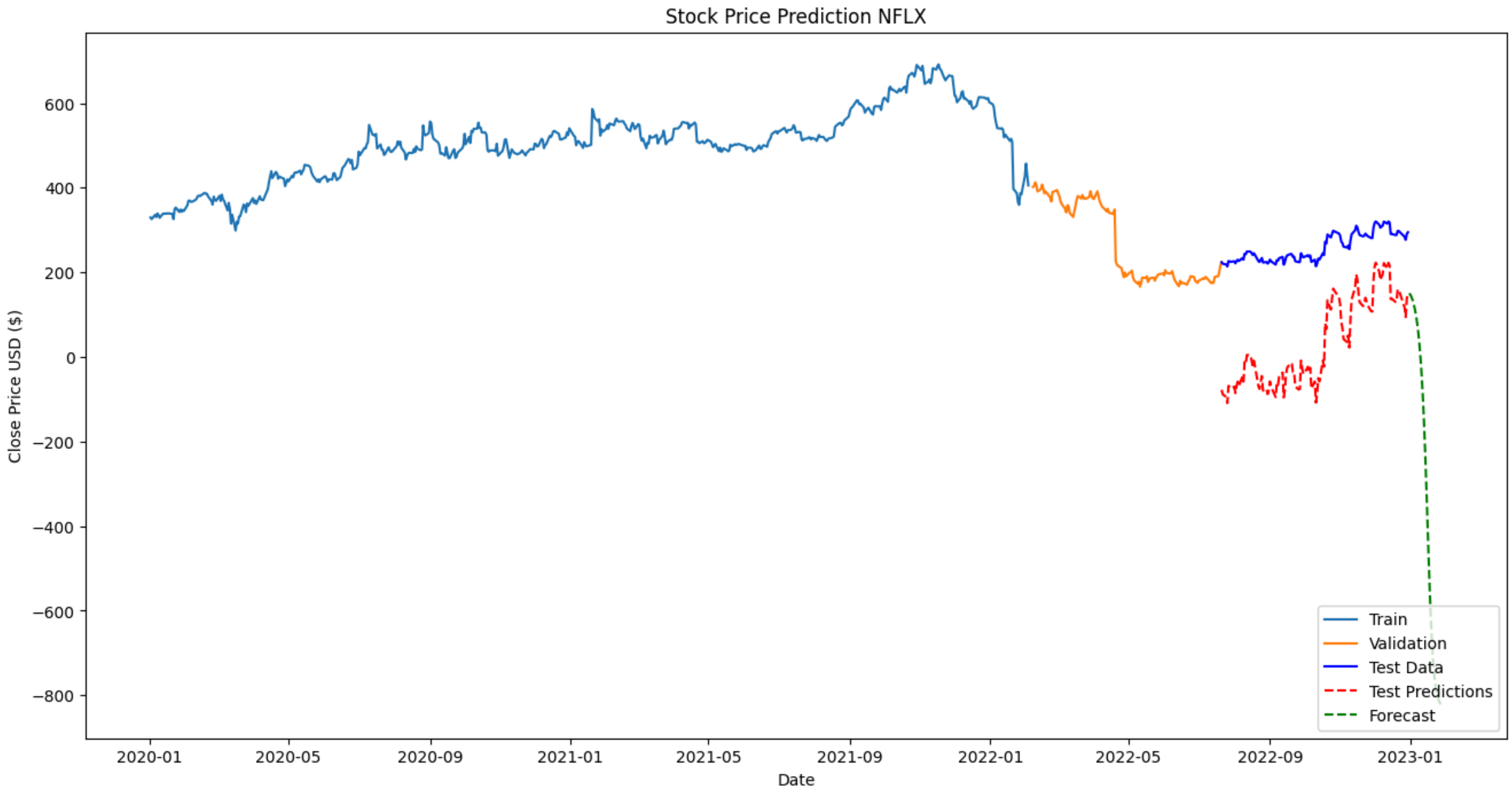
```
Forecast step 22:
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step
Forecast step 23:
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 15ms/step
Forecast step 24:
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step
Forecast step 25:
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step
Forecast step 26:
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step
Forecast step 27:
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step
Forecast step 28:
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step
Forecast step 29:
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step
Forecast step 30:
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step
```

In [12]:

```python
# Split the series into training, validation, and test parts
train = series[:train_size]
val = series[train_size:train_size+val_size]
test = series[train_size+val_size:]

# if slicing logic is wrong due to integer math
if len(val) != len(test):
    train = series[:train_size-1]
    val = series[train_size:train_size+val_size+1]
    test = series[train_size+val_size:]

# Convert to DataFrame
train = train.to_frame()
val = val.to_frame()
test = test.to_frame()

# Ensure `valid` is renamed to `val`
# Generate predictions for validation and forecast as needed
# Add predictions to the validation set
test['Predictions'] = np.nan
test['Predictions'].iloc[:len(predictions)] = predictions

# Create forecast dates (adjust if needed)
```

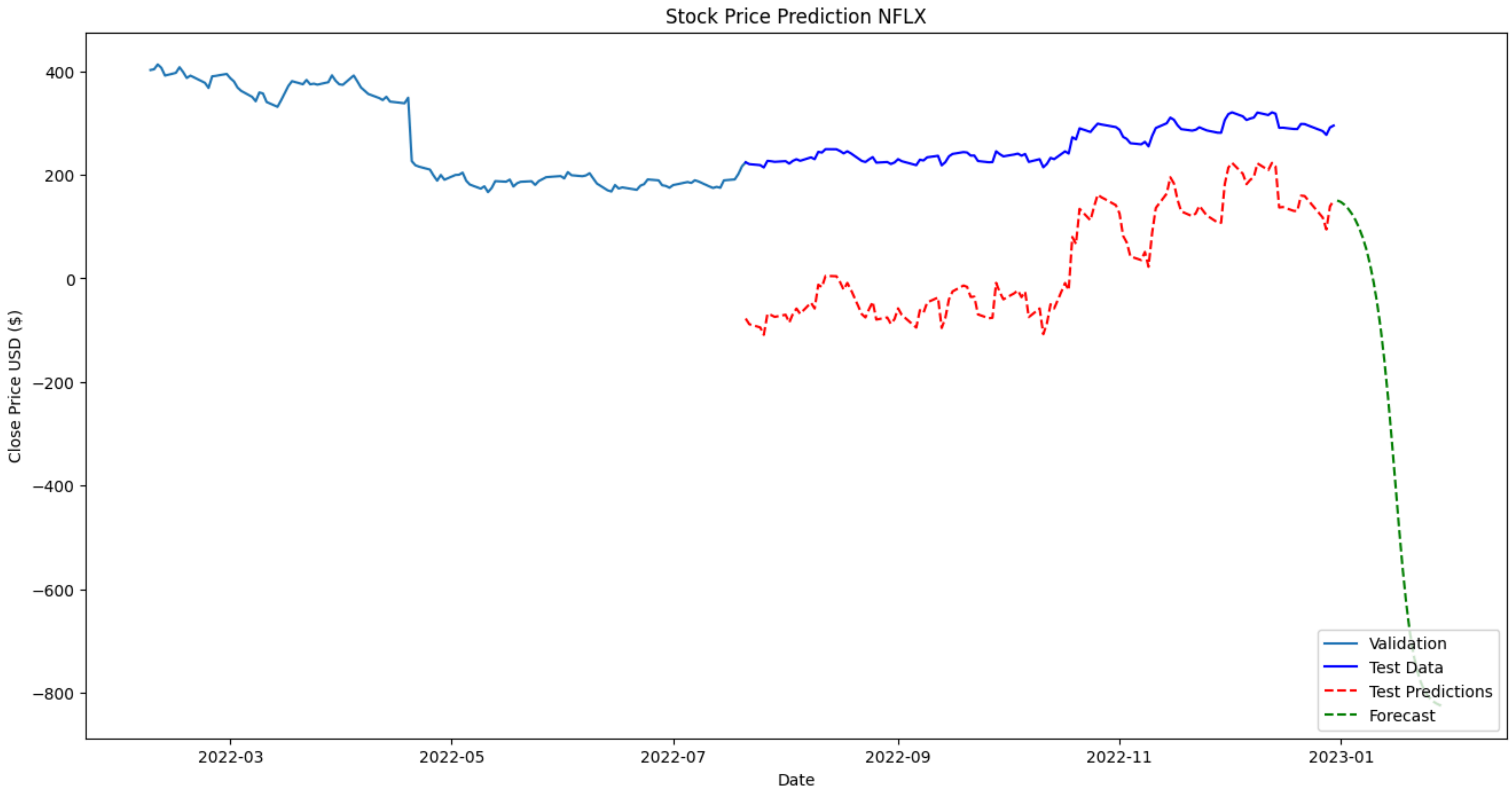
```
forecast_dates = pd.date_range(start=test.index[-1], periods=forecast_length + 1, inclusive='right')

# Create a DataFrame for forecasted values
forecast = pd.DataFrame(forecasted_values, index=forecast_dates, columns=['Predictions'])

# Plot the results
plt.figure(figsize=(16, 8))
plt.title(f'Stock Price Prediction {dowjones_comps[comp_idx]}')
plt.xlabel('Date')
plt.ylabel('Close Price USD ($)')
plt.plot(train, label='Train')
plt.plot(val, label='Validation')
plt.plot(test['Close'], label='Test Data', linestyle='-', color='b')
plt.plot(test['Predictions'], label='Test Predictions', linestyle='--', color='r')
plt.plot(forecast, label='Forecast', linestyle='--', color='g')
plt.legend(loc='lower right')
plt.show()
```

```
C:\Users\p_pie\AppData\Local\Temp\ipykernel_18844\610895317.py:21: FutureWarning: ChainedAssignmentError: behaviour w
ill change in pandas 3.0!
You are setting values through chained assignment. Currently this works in certain cases, but when using Copy-on-Writ
e (which will become the default behaviour in pandas 3.0) this will never work to update the original DataFrame or Se
ries, because the intermediate object on which we are setting values will behave as a copy.
A typical example is when you are setting values in a column of a DataFrame, like:

df["col"][row_indexer] = value

Use `df.loc[row_indexer, "col"] = values` instead, to perform the assignment in a single step and ensure this keeps u
pdating the original `df`.

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning
-a-view-versus-a-copy

  test['Predictions'].iloc[:len(predictions)] = predictions
```



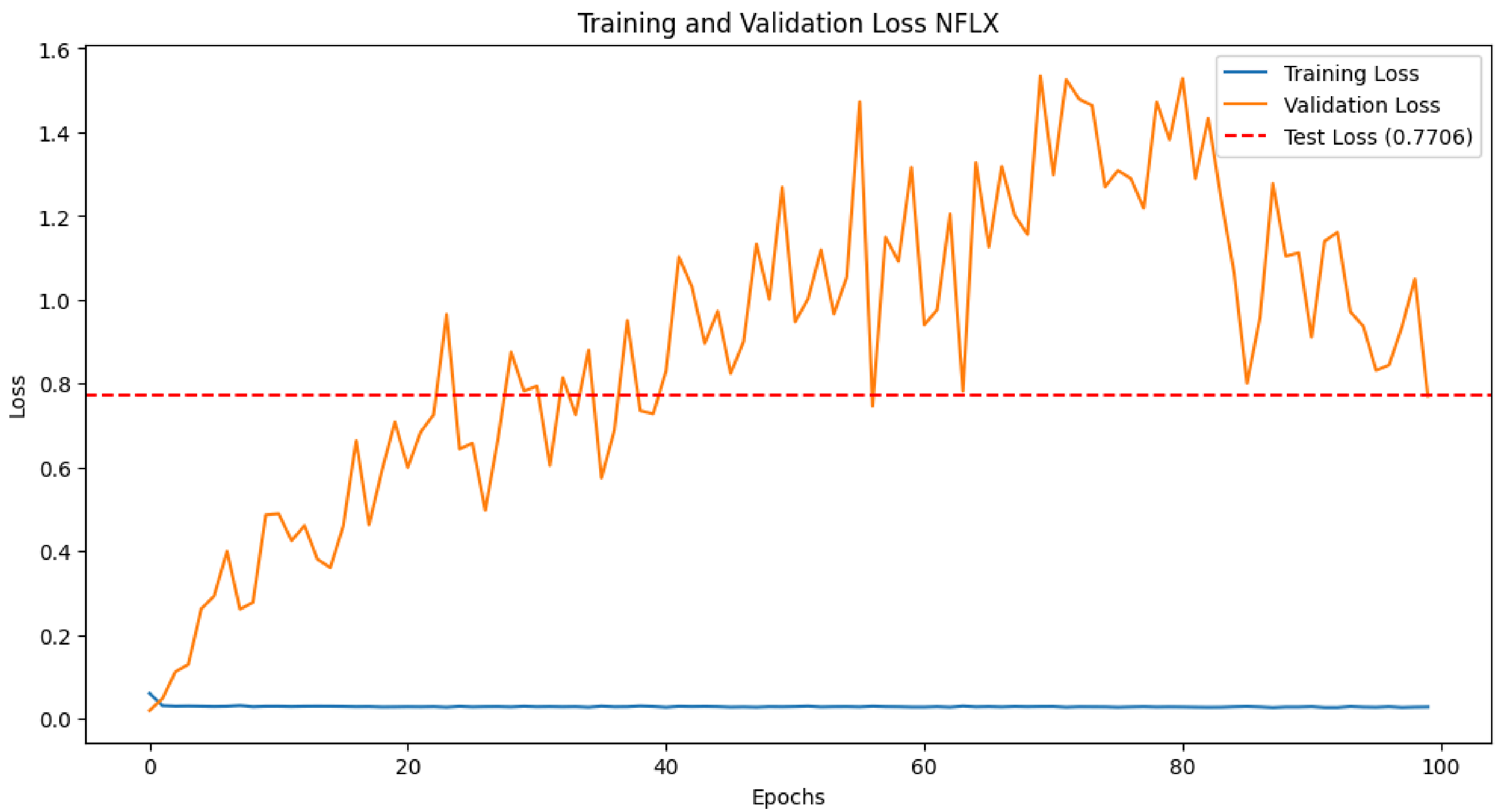
In [13]:

```
# Plot the results
plt.figure(figsize=(16, 8))
plt.title(f'Stock Price Prediction {dowjones_comps[comp_idx]}')
plt.xlabel('Date')
plt.ylabel('Close Price USD ($)')
plt.plot(val, label='Validation')
plt.plot(test['Close'], label='Test Data', linestyle='-', color='b')
plt.plot(test['Predictions'], label='Test Predictions', linestyle='--', color='r')
plt.plot(forecast, label='Forecast', linestyle='--', color='g')
plt.legend(loc='lower right')
plt.show()
```



In [14]:
```
# Extract loss and accuracy
loss = history.history['loss']
val_loss = history.history['val_loss']
accuracy = history.history.get('accuracy', [])  # If your model records accuracy
val_accuracy = history.history.get('val_accuracy', [])

# Compute test loss
results = model.evaluate(X_val, y_val, batch_size=batch_size, verbose=0)
test_loss = results[0]

# Plot Training and Validation Loss
plt.figure(figsize=(12, 6))
plt.plot(loss, label='Training Loss')
plt.plot(val_loss, label='Validation Loss')
```

```
plt.axhline(y=test_loss, color='r', linestyle='--', label=f'Test Loss ({test_loss:.4f})')
plt.title(f'Training and Validation Loss {dowjones_comps[comp_idx]}')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```



In [15]:

```
# Plot Training and Validation Accuracy (if applicable)
if accuracy and val_accuracy:
    plt.figure(figsize=(12, 6))
    plt.plot(accuracy, label='Training Accuracy')
    plt.plot(val_accuracy, label='Validation Accuracy')
    plt.title(f'Training and Validation Accuracy {dowjones_comps[comp_idx]}')
    plt.xlabel('Epochs')
```

```
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```