Google Colab Lab Assignment 5.1 - Forecasting using LSTM

Course Name: MDM Deep Learning

Lab Title: To forecast future values of a univariate time series using LSTM-based models.Yashas Nepalia

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Date of Submission: 10/04/2025

Group Members:

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2. Rohan Magdum

Objective This project aims to forecast future values of a univariate time series—specifically the “Units Sold” attribute from a retail inventory dataset—using LSTM-based models.

Importing required libraries

In [76]:

```
import numpy as np

import pandas as pd

import matplotlib.pyplot as plt

import datetime


from sklearn.preprocessing import MinMaxScaler

from sklearn.metrics import mean_squared_error, mean_absolute_error


from tensorflow.keras.models import Sequential

from tensorflow.keras.layers import Dense, LSTM, Dropout, Bidirectional

from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint


np.random.seed(42)
```

Data Loading and Exploration

In [78]:

```
# Load dataset
df = pd.read_csv('/content/drive/MyDrive/Colab Notebooks/TY/Deep Learning/Lab Assignment 5.1/retail_store_inventory.csv')

# Display the basic information
print(df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 73100 entries, 0 to 73099
Data columns (total 15 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   Date                73100 non-null  object
 1   Store ID            73100 non-null  object
 2   Product ID          73100 non-null  object
 3   Category            73100 non-null  object
 4   Region              73100 non-null  object
 5   Inventory Level     73100 non-null  int64
 6   Units Sold          73100 non-null  int64
 7   Units Ordered       73100 non-null  int64
 8   Demand Forecast     73100 non-null  float64
 9   Price               73100 non-null  float64
```

10 Discount 73100 non-null int64

11 Weather Condition 73100 non-null object

12 Holiday/Promotion 73100 non-null int64

13 Competitor Pricing 73100 non-null float64

14 Seasonality 73100 non-null object

dtypes: float64(3), int64(5), object(7)

memory usage: 8.4+ MB

None

In [79]:

df.head()

Out[79]:

	Date	Store ID	Product ID	Category	Region	Inventory Level	Units Sold	Units Ordered	Demand Forecast	Price	Discount	Weather Condition	Holiday/Promotion	Competitor Pricing	Seasonality
0	2022-01-01	S001	P0001	Groceries	North	231	127	55	135.47	33.50	20	Rainy	0	29.69	Autumn

	Date	Store ID	Product ID	Category	Region	Inventory Level	Units Sold	Units Ordered	Demand Forecast	Price	Discount	Weather Condition	Holiday/Promotion	Competitor Pricing	Seasonality
1	2022-01-01	S001	P0002	Toys	South	204	150	66	144.04	63.01	20	Sunny	0	66.16	Autumn
2	2022-01-01	S001	P0003	Toys	West	102	65	51	74.02	27.99	10	Sunny	1	31.32	Summer
3	2022-01-01	S001	P0004	Toys	North	469	61	164	62.18	32.72	10	Cloudy	1	34.74	Autumn

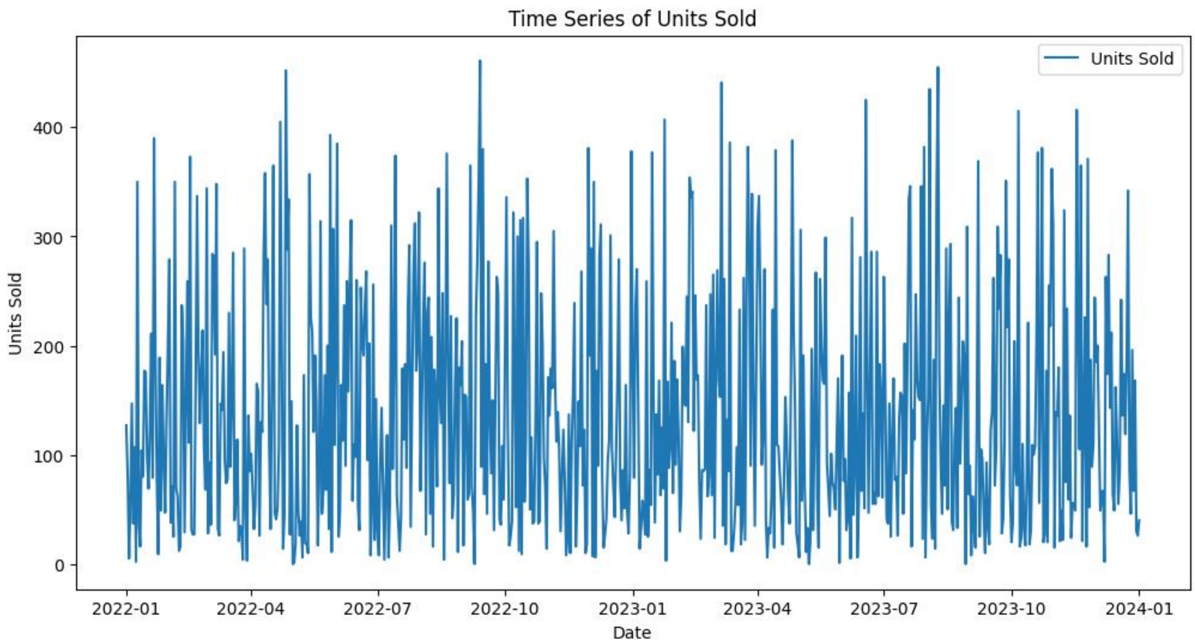
	Date	Store ID	Product ID	Category	Region	Inventory Level	Units Sold	Units Ordered	Demand Forecast	Price	Discount	Weather Condition	Holiday/Promotion	Competitor Pricing	Seasonality
4	2022-01-01	S001	P0005	Electronics	East	166	14	135	9.26	73.64	0	Sunny	0	68.95	Summer

In [80]:

```
# Filter for a single store and product
store_id = "S001"
product_id = "P0001"
df_filtered = df[(df['Store ID'] == store_id) & (df['Product ID'] == product_id)].copy()

# Ensure the Date column is in datetime format, sort by date, and drop missing values
df_filtered['Date'] = pd.to_datetime(df_filtered['Date'])
df_filtered.sort_values(by='Date', inplace=True)
df_filtered.dropna(inplace=True)
```

In [81]:

```
# Use the filtered data for a specific product
time_series = df_filtered[['Date', 'Units Sold']].copy()
time_series.set_index('Date', inplace=True)

# Visualize the time series
plt.figure(figsize=(12,6))
plt.plot(time_series.index, time_series['Units Sold'], label='Units Sold')
plt.xlabel('Date')
plt.ylabel('Units Sold')
plt.title('Time Series of Units Sold')
plt.legend()
plt.show()
```

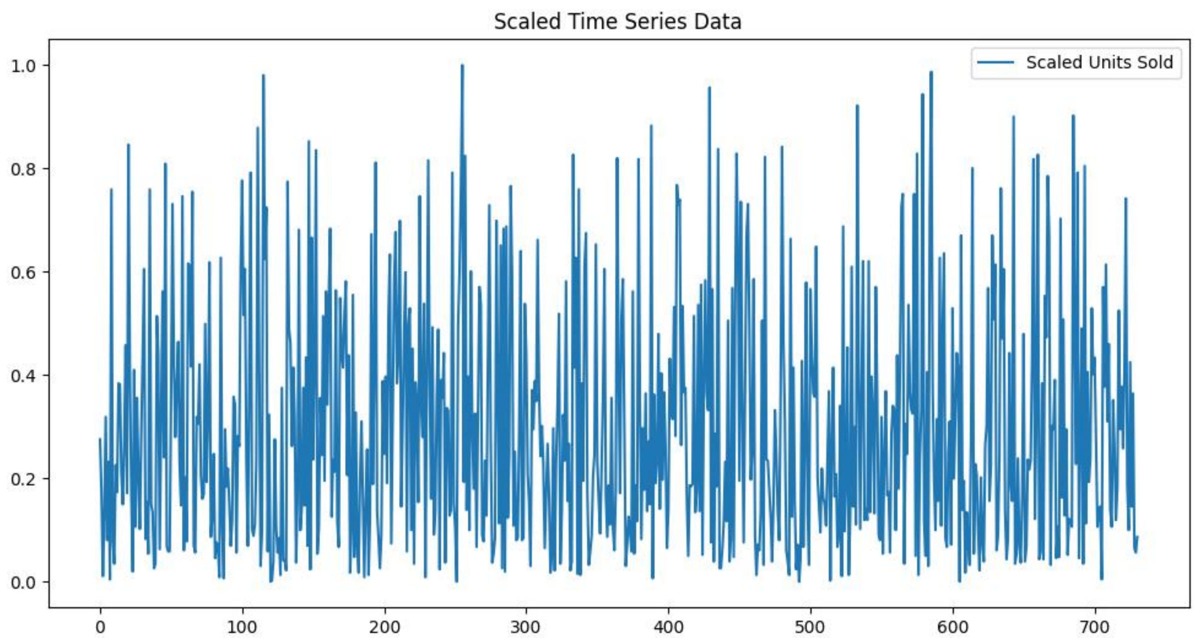


Data Normalization

In [82]:

```
scaler = MinMaxScaler(feature_range=(0, 1))
```

```
scaled_data = scaler.fit_transform(time_series)


# Plot a sample of scaled data
plt.figure(figsize=(12,6))
plt.plot(scaled_data, label='Scaled Units Sold')
plt.title('Scaled Time Series Data')
plt.legend()
plt.show()
```



Create Sequences with Window Size 60

In [83]:

```
def create_sequences(data, window_size):
  X, y = [], []
  for i in range(window_size, len(data)):
    X.append(data[i - window_size:i, 0])
    y.append(data[i, 0])
```

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

window_size = 60
X, y = create_sequences(scaled_data, window_size)

# Reshape input for LSTM: (samples, time steps, features)
X = np.reshape(X, (X.shape[0], X.shape[1], 1))
print("Shape of X:", X.shape)
print("Shape of y:", y.shape)
```

```
Shape of X: (671, 60, 1)
Shape of y: (671,)
```

Split Data into Training and Testing Sets

In [84]:

```
train_size = int(len(X) * 0.8)
X_train, X_test = X[:train_size], X[train_size:]
y_train, y_test = y[:train_size], y[train_size:]

print("Shape of X_train:", X_train.shape)
print("Shape of X_test:", X_test.shape)
```

```
Shape of X_train: (536, 60, 1)
Shape of X_test: (135, 60, 1)
```

Build and Train the Standard LSTM Model

In [85]:

```
# Define the LSTM model
lstm_model = Sequential()
lstm_model.add(LSTM(units=50, return_sequences=True, input_shape=(X_train.shape[1], 1)))
lstm_model.add(Dropout(0.2))
lstm_model.add(LSTM(units=50, return_sequences=False))
lstm_model.add(Dropout(0.2))
lstm_model.add(Dense(1))

lstm_model.compile(optimizer='adam', loss='mean_squared_error')

# Print model summary
lstm_model.summary()

# Define callbacks: EarlyStopping and ModelCheckpoint
es = EarlyStopping(monitor='val_loss', patience=5, verbose=1, restore_best_weights=True)
mc = ModelCheckpoint('best_lstm_model.h5', monitor='val_loss', save_best_only=True, verbose=1)
```

```
/usr/local/lib/python3.11/dist-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)
```

Model: "sequential_8"

```
┏━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┓
┃ Layer (type)          ┃ Output Shape        ┃    Param # ┃
```

Layer (type)	Output Shape	Param #
lstm_16 (LSTM)	(None, 60, 50)	10,400
dropout_16 (Dropout)	(None, 60, 50)	0
lstm_17 (LSTM)	(None, 50)	20,200
dropout_17 (Dropout)	(None, 50)	0
dense_8 (Dense)	(None, 1)	51

Total params: 30,651 (119.73 KB)

Trainable params: 30,651 (119.73 KB)

Non-trainable params: 0 (0.00 B)

In [86]:

```
history_lstm = lstm_model.fit(X_train, y_train,
                    epochs=50,
                    batch_size=32,
                    validation_split=0.1,
                    callbacks=[es, mc],
                    verbose=1)
```

Epoch 1/50

16/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 11ms/step - loss: 0.1128

Epoch 1: val_loss improved from inf to 0.06490, saving model to best_lstm_model.h5

WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file format is considered legacy. We recommend using instead the native Keras format, e.g. `model.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

16/16 ━━━━━━━━━━━━━━━━━━━━ **3s** 37ms/step - loss: 0.1111 - val_loss: 0.0649

Epoch 2/50

13/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 10ms/step - loss: 0.0662

Epoch 2: val_loss improved from 0.06490 to 0.06105, saving model to best_lstm_model.h5

WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file format is considered legacy. We recommend using instead the native Keras format, e.g. `model.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

16/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 16ms/step - loss: 0.0651 - val_loss: 0.0611

Epoch 3/50

13/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 9ms/step - loss: 0.0611

Epoch 3: val_loss did not improve from 0.06105

16/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 12ms/step - loss: 0.0606 - val_loss: 0.0614

Epoch 4/50

13/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 9ms/step - loss: 0.0581

Epoch 4: val_loss did not improve from 0.06105

16/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 15ms/step - loss: 0.0579 - val_loss: 0.0616

Epoch 5/50

15/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 8ms/step - loss: 0.0593

Epoch 5: val_loss did not improve from 0.06105

16/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 12ms/step - loss: 0.0590 - val_loss: 0.0613

Epoch 6/50

14/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 9ms/step - loss: 0.0593

Epoch 6: val_loss did not improve from 0.06105

16/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 15ms/step - loss: 0.0590 - val_loss: 0.0623

Epoch 7/50

15/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 8ms/step - loss: 0.0537

Epoch 7: val_loss improved from 0.06105 to 0.06102, saving model to best_lstm_model.h5

WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file format is considered legacy. We recommend using instead the native Keras format, e.g. `model.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

16/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 14ms/step - loss: 0.0541 - val_loss: 0.0610

Epoch 8/50

15/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 8ms/step - loss: 0.0613

Epoch 8: val_loss did not improve from 0.06102

16/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 12ms/step - loss: 0.0611 - val_loss: 0.0657

Epoch 9/50

14/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 8ms/step - loss: 0.0526

Epoch 9: val_loss improved from 0.06102 to 0.06076, saving model to best_lstm_model.h5

WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file format is considered legacy. We recommend using instead the native Keras format, e.g. `model.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

16/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 15ms/step - loss: 0.0537 - val_loss: 0.0608

Epoch 10/50

14/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 8ms/step - loss: 0.0554

Epoch 10: val_loss did not improve from 0.06076

16/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 14ms/step - loss: 0.0559 - val_loss: 0.0614

Epoch 11/50

15/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 8ms/step - loss: 0.0539

Epoch 11: val_loss did not improve from 0.06076

16/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 12ms/step - loss: 0.0542 - val_loss: 0.0613

Epoch 12/50

15/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 8ms/step - loss: 0.0542

Epoch 12: val_loss did not improve from 0.06076

16/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 12ms/step - loss: 0.0546 - val_loss: 0.0613

Epoch 13/50

15/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 8ms/step - loss: 0.0581

Epoch 13: val_loss did not improve from 0.06076

16/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 15ms/step - loss: 0.0581 - val_loss: 0.0611

Epoch 14/50

15/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 8ms/step - loss: 0.0575

Epoch 14: val_loss did not improve from 0.06076

16/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 14ms/step - loss: 0.0574 - val_loss: 0.0611

Epoch 14: early stopping

Restoring model weights from the end of the best epoch: 9.

Evaluate and Plot Predictions for LSTM Model

In [87]:

```
# LSTM Predictions on test data
lstm_predictions = lstm_model.predict(X_test)

# Inverse transform predictions and true values
lstm_predictions_inv = scaler.inverse_transform(lstm_predictions)
y_test_inv = scaler.inverse_transform(y_test.reshape(-1, 1))
```

5/5 ━━━━━━━━━━━━━━━━━━━━ **0s** 46ms/step

In [88]:

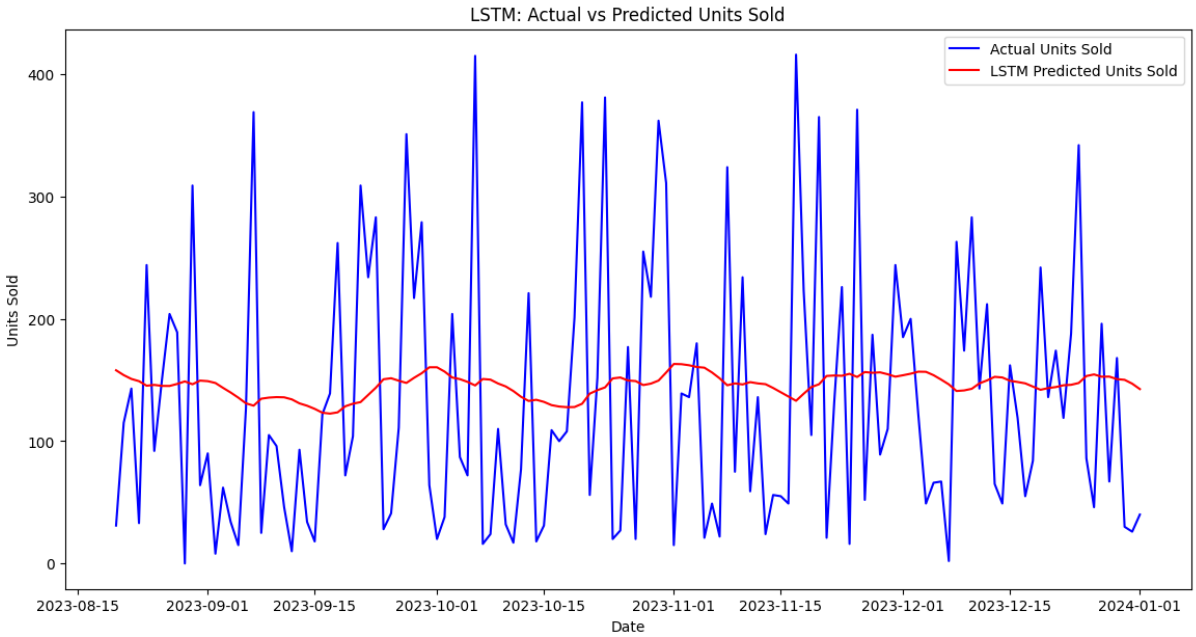
```
lstm_rmse = np.sqrt(mean_squared_error(y_test_inv, lstm_predictions_inv))
lstm_mae = mean_absolute_error(y_test_inv, lstm_predictions_inv)
print(f"LSTM Test RMSE: {lstm_rmse:.2f}")
print(f"LSTM Test MAE: {lstm_mae:.2f}")
```

LSTM Test RMSE: 108.84

LSTM Test MAE: 91.49

In [89]:

```
# Get the date index for plotting the test set

test_dates = time_series.index[-len(y_test_inv):]


plt.figure(figsize=(14,7))

plt.plot(test_dates, y_test_inv, color='blue', label='Actual Units Sold')

plt.plot(test_dates, lstm_predictions_inv, color='red', label='LSTM Predicted Units Sold')

plt.xlabel('Date')

plt.ylabel('Units Sold')

plt.title('LSTM: Actual vs Predicted Units Sold')

plt.legend()

plt.show()
```



Build and Train a Bidirectional LSTM (BiLSTM) Model

In [90]:

```
# Define the Bidirectional LSTM model

bilstm_model = Sequential()
```

```
# First layer: Bidirectional LSTM with dropout

bilstm_model.add(Bidirectional(LSTM(units=50, return_sequences=True),
input_shape=(X_train.shape[1], 1)))

bilstm_model.add(Dropout(0.2))

# Second layer: Standard LSTM

bilstm_model.add(LSTM(units=50, return_sequences=False))

bilstm_model.add(Dropout(0.2))

bilstm_model.add(Dense(1))


bilstm_model.compile(optimizer='adam', loss='mean_squared_error')

bilstm_model.summary()


# Callbacks: EarlyStopping and ModelCheckpoint for BiLSTM

es_bi = EarlyStopping(monitor='val_loss', patience=5, verbose=1,
restore_best_weights=True)

mc_bi = ModelCheckpoint('best_bilstm_model.h5', monitor='val_loss',
save_best_only=True, verbose=1)
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/layers/rnn/bidirectional.py:107: 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)
```

Model: "sequential_9"

Layer (type)	Output Shape	Param #

```
│ bidirectional_3 (Bidirectional) │ (None, 60, 100)      │       20,800 │
├─────────────────────────────────┼────────────────────────┼
───────────────┤
│ dropout_18 (Dropout)          │ (None, 60, 100)      │            0 │
├─────────────────────────────────┼────────────────────────┼
───────────────┤
│ lstm_19 (LSTM)              │ (None, 50)          │       30,200 │
├─────────────────────────────────┼────────────────────────┼
───────────────┤
│ dropout_19 (Dropout)          │ (None, 50)          │            0 │
├─────────────────────────────────┼────────────────────────┼
───────────────┤
│ dense_9 (Dense)              │ (None, 1)           │           51 │
└─────────────────────────────────┴────────────────────────┴
───────────────┘
```

Total params: 51,051 (199.42 KB)

Trainable params: 51,051 (199.42 KB)

Non-trainable params: 0 (0.00 B)

In [91]:

```
history_bilstm = bilstm_model.fit(X_train, y_train,
                    epochs=50,
                    batch_size=32,
                    validation_split=0.1,
                    callbacks=[es_bi, mc_bi],
                    verbose=1)
```

Epoch 1/50

13/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 16ms/step - loss: 0.0964

Epoch 1: val_loss improved from inf to 0.06292, saving model to best_bilstm_model.h5

WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file format is considered legacy. We recommend using instead the native Keras format, e.g. `model.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

16/16 ━━━━━━━━━━━━━━━━━━━━ **3s** 45ms/step - loss: 0.0910 - val_loss: 0.0629

Epoch 2/50

16/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 12ms/step - loss: 0.0572

Epoch 2: val_loss improved from 0.06292 to 0.06266, saving model to best_bilstm_model.h5

WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file format is considered legacy. We recommend using instead the native Keras format, e.g. `model.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

16/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 21ms/step - loss: 0.0573 - val_loss: 0.0627

Epoch 3/50

13/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 10ms/step - loss: 0.0587

Epoch 3: val_loss improved from 0.06266 to 0.06215, saving model to best_bilstm_model.h5

WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file format is considered legacy. We recommend using instead the native Keras format, e.g. `model.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

16/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 16ms/step - loss: 0.0589 - val_loss: 0.0622

Epoch 4/50

12/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 10ms/step - loss: 0.0556

Epoch 4: val_loss did not improve from 0.06215

16/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 16ms/step - loss: 0.0565 - val_loss: 0.0623

Epoch 5/50

13/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 10ms/step - loss: 0.0592

Epoch 5: val_loss improved from 0.06215 to 0.06181, saving model to best_bilstm_model.h5

WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file format is considered legacy. We recommend using instead the native Keras format, e.g. `model.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

16/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 16ms/step - loss: 0.0583 - val_loss: 0.0618

Epoch 6/50

11/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 10ms/step - loss: 0.0589

Epoch 6: val_loss did not improve from 0.06181

16/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 14ms/step - loss: 0.0582 - val_loss: 0.0626

Epoch 7/50

12/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 10ms/step - loss: 0.0550

Epoch 7: val_loss did not improve from 0.06181

16/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 13ms/step - loss: 0.0558 - val_loss: 0.0620

Epoch 8/50

12/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 10ms/step - loss: 0.0585

Epoch 8: val_loss did not improve from 0.06181

16/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 13ms/step - loss: 0.0579 - val_loss: 0.0628

Epoch 9/50

12/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 10ms/step - loss: 0.0536

Epoch 9: val_loss improved from 0.06181 to 0.06128, saving model to best_bilstm_model.h5

WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file format is considered legacy. We recommend using instead the native Keras format, e.g. `model.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

16/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 16ms/step - loss: 0.0547 - val_loss: 0.0613

Epoch 10/50

12/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 10ms/step - loss: 0.0541

Epoch 10: val_loss did not improve from 0.06128

16/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 13ms/step - loss: 0.0548 - val_loss: 0.0620

Epoch 11/50

11/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 11ms/step - loss: 0.0535

Epoch 11: val_loss improved from 0.06128 to 0.06069, saving model to best_bilstm_model.h5

WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file format is considered legacy. We recommend using instead the native Keras format, e.g. `model.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

16/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 16ms/step - loss: 0.0551 - val_loss: 0.0607

Epoch 12/50

12/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 10ms/step - loss: 0.0557

Epoch 12: val_loss did not improve from 0.06069

16/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 16ms/step - loss: 0.0563 - val_loss: 0.0607

Epoch 13/50

13/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 10ms/step - loss: 0.0621

Epoch 13: val_loss did not improve from 0.06069

16/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 13ms/step - loss: 0.0608 - val_loss: 0.0637

Epoch 14/50

12/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 10ms/step - loss: 0.0592

Epoch 14: val_loss did not improve from 0.06069

16/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 14ms/step - loss: 0.0588 - val_loss: 0.0633

Epoch 15/50

13/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 10ms/step - loss: 0.0617

Epoch 15: val_loss did not improve from 0.06069

16/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 13ms/step - loss: 0.0603 - val_loss: 0.0609

Epoch 16/50

12/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 11ms/step - loss: 0.0608

Epoch 16: val_loss did not improve from 0.06069

16/16 ━━━━━━━━━━━━━━━━━━━━ **0s** 17ms/step - loss: 0.0603 - val_loss: 0.0664

Epoch 16: early stopping

Restoring model weights from the end of the best epoch: 11.

Evaluate and Plot Predictions for BiLSTM Model

In [92]:

```
# BiLSTM Predictions on test data
bilstm_predictions = bilstm_model.predict(X_test)

# Inverse transform predictions and the true values
bilstm_predictions_inv = scaler.inverse_transform(bilstm_predictions)
```

5/5 ━━━━━━━━━━━━━━━━━━━━ **0s** 65ms/step

In [93]:

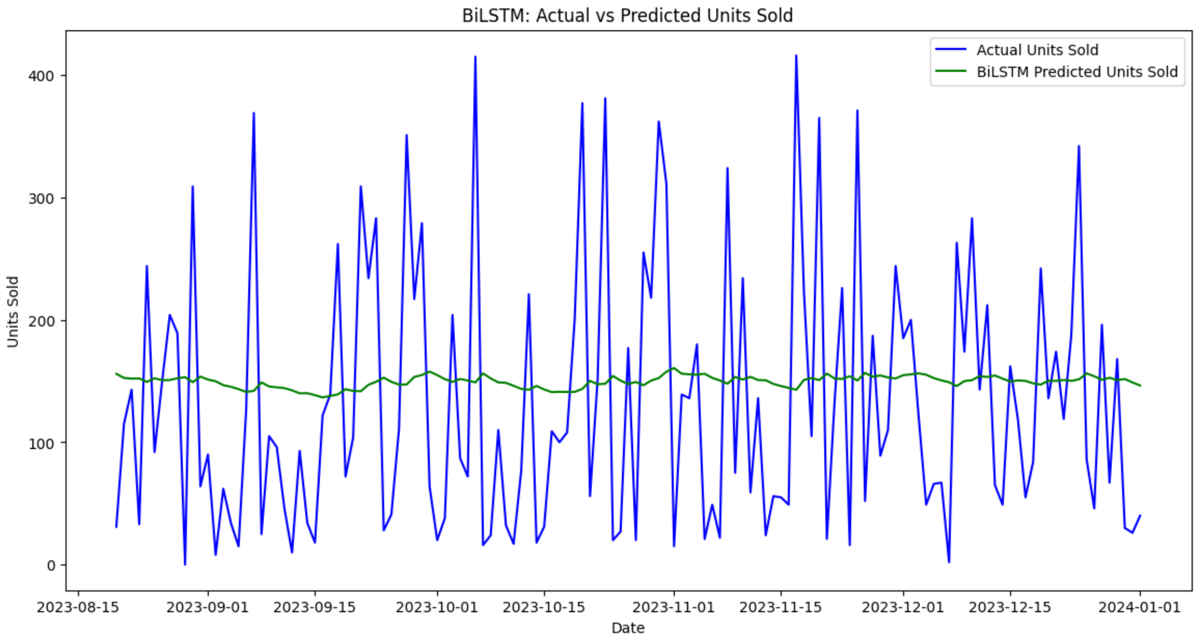
```
bilstm_rmse = np.sqrt(mean_squared_error(y_test_inv, bilstm_predictions_inv))

bilstm_mae = mean_absolute_error(y_test_inv, bilstm_predictions_inv)

print(f"BiLSTM Test RMSE: {bilstm_rmse:.2f}")

print(f"BiLSTM Test MAE: {bilstm_mae:.2f}")
```

BiLSTM Test RMSE: 108.60

BiLSTM Test MAE: 92.23

In [94]:

```
plt.figure(figsize=(14,7))

plt.plot(test_dates, y_test_inv, color='blue', label='Actual Units Sold')

plt.plot(test_dates, bilstm_predictions_inv, color='green', label='BiLSTM Predicted Units Sold')

plt.xlabel('Date')

plt.ylabel('Units Sold')

plt.title('BiLSTM: Actual vs Predicted Units Sold')

plt.legend()

plt.show()
```



Declaration

I, Yashas Nepalia, confirm that the work submitted in this assignment is my own and has been completed following academic integrity guidelines. The code is uploaded on my GitHub repository account, and the repository link is provided below:

GitHub Repository Link: https://github.com/YashasNepalia/Deep-Learning.git

Signature: Yashas Nepalia