Module 9 Assignment 2: Financial Time Series

Introduction

The purpose of this analysis is to accurately predict the future stock prices of the S&P 500 index using historical data. Predicting stock prices is critical for investors, financial institutions, and market analysts, as it informs investment decisions, risk management strategies, and broader economic analyses. In this study, we utilize Long Short-Term Memory (LSTM) networks, a type of Recurrent Neural Network (RNN), to model and forecast stock prices based on daily adjusted closing prices from the past five years.

Data Collection and Preprocessing

We collected five years of daily adjusted closing prices for the S&P 500 index from Yahoo Finance. The dataset includes the following columns: *Date*, *Open, High, Low, Close, Adj Close, and Volume*. For the purpose of this analysis, we focused on the Close prices.

Data Preprocessing Steps:

- Normalization: The Close prices were normalized using the MinMaxScaler to scale values between 0 and 1.
- Sequence Creation: A sequence length of 50 days was chosen to create input sequences for the LSTM models. The data was split into training (80%) and testing (20%) sets, ensuring that the training data contains the first 80% of the data and testing set consists of the most recent(last) data.

Model Development

We developed and evaluated three LSTM models with varying architectures to identify the best model for predicting future stock prices.

Model 1: Basic LSTM

- **Architecture**:
  - LSTM layer with 50 units and ReLU activation.
  - Dense layer with 25 units.
  - Output Dense layer with 1 unit.

- **Performance**:
    - **Training Loss**: 0.00028 (final epoch)
    - **Validation Loss**: 0.00028 (final epoch)
    - **Test Loss**: 0.00028

  Analysis: This model performed well with a low test loss, indicating a strong ability to capture the underlying patterns in the data.

Model 2: Stacked LSTM

- **Architecture**:
    - LSTM layer with 50 units, ReLU activation, and return sequences.
    - Additional LSTM layer with 50 units and ReLU activation.
    - Dense layers with 100 and 25 units.
    - Output Dense layer with 1 unit.
- **Performance**:
    - **Training Loss**: 0.00113 (final epoch)
    - **Validation Loss**: 0.00113 (final epoch)
    - **Test Loss**: 0.00113

  Analysis: The added complexity of stacking LSTM layers led to a higher test loss, suggesting potential overfitting, where the model might be learning noise rather than the underlying trend.

Model 3: LSTM with Dropout

- **Architecture**:
    - LSTM layer with 50 units, ReLU activation, and return sequences.
    - Additional LSTM layer with 50 units and ReLU activation.
    - Dense layers with 100 and 25 units.
    - Dropout layer with 20% dropout rate.
    - Output Dense layer with 1 unit.
- **Performance**:
    - **Training Loss**: 0.00063 (final epoch)
    - **Validation Loss**: 0.00063 (final epoch)

- **Test Loss**: 0.00063

Analysis: This model introduced dropout to mitigate overfitting, resulting in better generalization compared to Model 2. However, the test loss was still slightly higher than that of Model 1.

Conclusion

The results indicate that **Model 1** is the most effective for forecasting the S&P 500 index prices. Its simpler architecture yielded the lowest test loss, demonstrating that a straightforward LSTM model can efficiently capture the patterns in stock price data. While **Model 2** and **Model 3** provided valuable insights into the impact of additional complexity and regularization, their performance did not surpass that of the basic LSTM model.

When predicting financial time series data such as stock prices, a balance between model complexity and generalization is crucial. Overly complex models may lead to overfitting, while simpler models like Model 1 can achieve robust performance with lower computational costs. Future work may involve fine-tuning hyperparameters, exploring alternative architectures, or incorporating additional features to further enhance predictive accuracy.

Appendix

- Python Script to download last 5 years daily adjusted closing prices for the Standard & Poor's 500 index from finance.yahoo.com.
- Python Script which fulfils the Requirement (EDA, Model Building etc)

Script to download last 5 years of daily adjusted closing prices for the Standard & Poor's 500 index from finance.yahoo.com

```
import yfinance as yf
import datetime as dt

# Define the ticker symbol for the S&P 500 index
ticker = "^GSPC"

# Get the current date
end_date = dt.datetime.now()

# Calculate the start date as exactly 5 years before the current date
start_date = end_date - dt.timedelta(days=5*365)  # Approximate

# Download the data from Yahoo Finance for the defined date range
# yf.download handles the actual available data based on market days
sp500_data = yf.download(ticker, start=start_date.strftime('%Y-%m-
%d'), end=end_date.strftime('%Y-%m-%d'))
sp500_data.reset_index(inplace=True)

# Check the number of rows (trading days)
print(f"Number of trading days: {len(sp500_data)}")
print(f"Start Date: {(start_date.strftime('%Y-%m-%d'))} \t\t End Date:
{(end_date.strftime('%Y-%m-%d'))} ")

# Display the first and last few rows of the data
sp500_data.head(5)

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

Number of trading days: 1256
Start Date: 2019-08-15           End Date: 2024-08-13



        Date         Open         High          Low        Close
Adj Close  \
0 2019-08-15  2846.199951  2856.669922  2825.510010  2847.600098
2847.600098
1 2019-08-16  2864.739990  2893.629883  2864.739990  2888.679932
2888.679932
2 2019-08-19  2913.479980  2931.000000  2913.479980  2923.649902
2923.649902
3 2019-08-20  2919.010010  2923.629883  2899.600098  2900.510010
2900.510010
4 2019-08-21  2922.040039  2928.729980  2917.909912  2924.429932
2924.429932

       Volume
```

```
0   4041720000
1   3524080000
2   3221050000
3   3067710000
4   3016540000

sp500_data.to_csv('Standard & Poor’s 500 index.csv')
```

Module 9 Assignment 2: Financial Time Series - (Optional) Additional Points

Financial time series is an obvious area for the use of RNN, as the sequence is more important than the individual observations. By building models to forecast indices, you will learn how to employ them in time series modeling.

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MSDS-422

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Management/Research Question

In layman's terms, what is the management/research question of interest, and why would anyone care?

Requirements

1. Conduct your analysis using the specified 80 / 20 split.
2. Conduct EDA.
3. Build at least three RNN models based on hyperparameter tuning.
4. Evaluate goodness of fit metrics.
5. Discuss your model's performance.

Import Libraries

```
# Import necessary libraries for data analysis and visualization
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import tensorflow as tf
from sklearn.preprocessing import MinMaxScaler
from tensorflow import keras
from tensorflow.keras import layers
from statsmodels.tsa.seasonal import seasonal_decompose
from sklearn.model_selection import train_test_split
import plotly.express as px
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout
import warnings
from keras.optimizers import Adam
warnings.filterwarnings("ignore")
```

EDA

```python
# Read in data from a CSV file and store it in a pandas DataFrame
data = pd.read_csv("./input/Standard & Poor’s 500 index.csv")
if 'Unnamed: 0' in data.columns:
        data.drop(columns=['Unnamed: 0'], axis=1, inplace=True)

data.shape
```

```
(1256, 7)
```

```python
data.head()
```


```
{"summary":"{\n  \"name\": \"data\",\n  \"rows\": 1256,\n  \"fields\":
[\n    {\n      \"column\": \"Date\",\n      \"properties\": {\n
\"dtype\": \"object\",\n        \"num_unique_values\": 1256,\n
\"samples\": [\n          \"2021-05-07\",\n          \"2020-01-09\",\n
\"2019-10-28\"\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"Open\",\n      \"properties\": {\n        \"dtype\": \"number\",\n
\"std\": 686.0645099972618,\n        \"min\": 2290.7099609375,\n
\"max\": 5644.08984375,\n        \"num_unique_values\": 1252,\n
\"samples\": [\n          3825.090087890625,\n
5428.7001953125,\n          4505.2998046875\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"High\",\n      \"properties\": {\n
\"dtype\": \"number\",\n        \"std\": 685.6392722216281,\n
\"min\": 2300.72998046875,\n        \"max\": 5669.669921875,\n
\"num_unique_values\": 1250,\n        \"samples\": [\n
4269.68017578125,\n          4790.7998046875,\n
3917.35009765625\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"Low\",\n      \"properties\": {\n        \"dtype\": \"number\",\n
\"std\": 687.01763246291,\n        \"min\": 2191.860107421875,\n
\"max\": 5639.02001953125,\n        \"num_unique_values\": 1253,\n
\"samples\": [\n          3889.659912109375,\n
5390.9501953125,\n          4458.97021484375\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"Close\",\n      \"properties\": {\
n        \"dtype\": \"number\",\n        \"std\": 686.1892602990669,\n
\"min\": 2237.39990234375,\n        \"max\": 5667.2001953125,\n
\"num_unique_values\": 1255,\n        \"samples\": [\n
5303.27001953125,\n          3274.699951171875,\n
3039.419921875\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\": \"Adj
Close\",\n      \"properties\": {\n        \"dtype\": \"number\",\n
\"std\": 686.1892602990669,\n        \"min\": 2237.39990234375,\n
\"max\": 5667.2001953125,\n        \"num_unique_values\": 1255,\n
\"samples\": [\n          5303.27001953125,\n
3274.699951171875,\n          3039.419921875\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
```

```
n    },\n    {\n      \"column\": \"Volume\",\n      \"properties\":
{\n        \"dtype\": \"number\",\n        \"std\": 1051511198,\n
\"min\": 1296530000,\n        \"max\": 9976520000,\n
\"num_unique_values\": 1253,\n        \"samples\": [\n
4840070000,\n          4592120000,\n          4347170000\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    }\n  ]\n}","type":"dataframe","variable_name":"data"}
```


```
data.isnull().sum()
```

```
Date         0
Open         0
High         0
Low          0
Close        0
Adj Close    0
Volume       0
dtype: int64
```

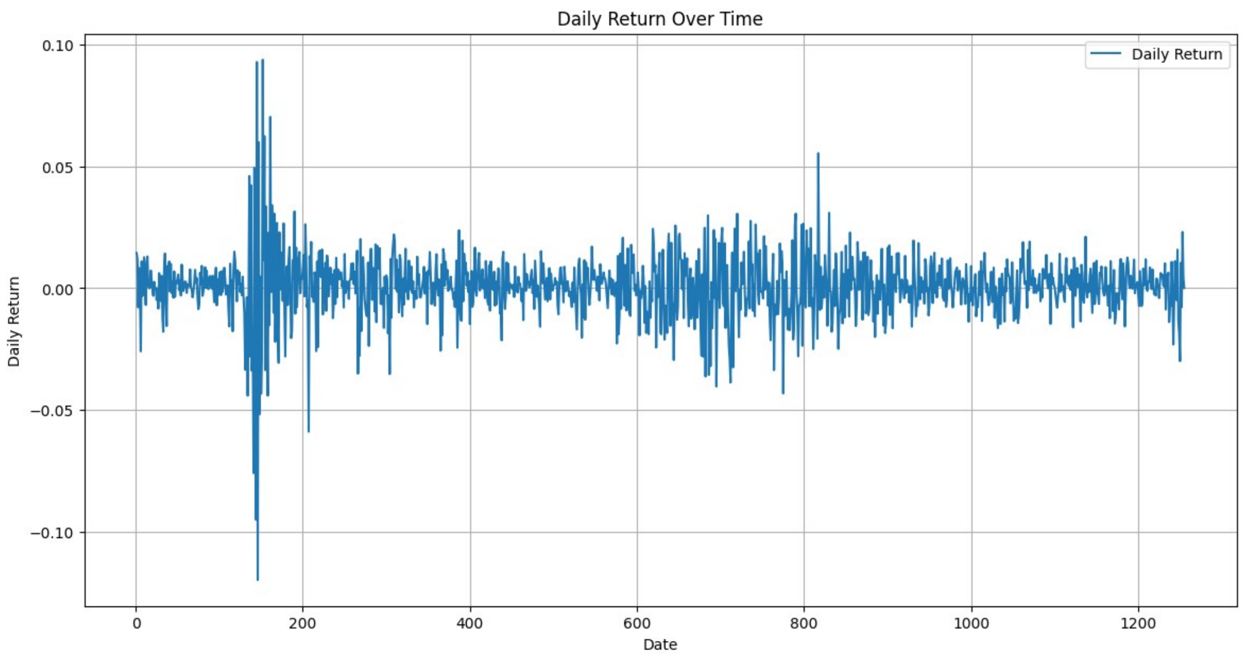
```
data['Date'] = pd.to_datetime(data['Date'])

# Set the figure size for the plot
plt.figure(figsize=(8, 6))

# Plot the 'Close' prices over time
plt.plot(data['Date'], data['Close'], label='Close', color='#053B50')

# Set the plot title
plt.title('Closing Prices Over Time')

# Label the x-axis as 'Date'
plt.xlabel('Date')

# Label the y-axis as 'Closing Price'
plt.ylabel('Closing Price')
plt.grid(True)
```

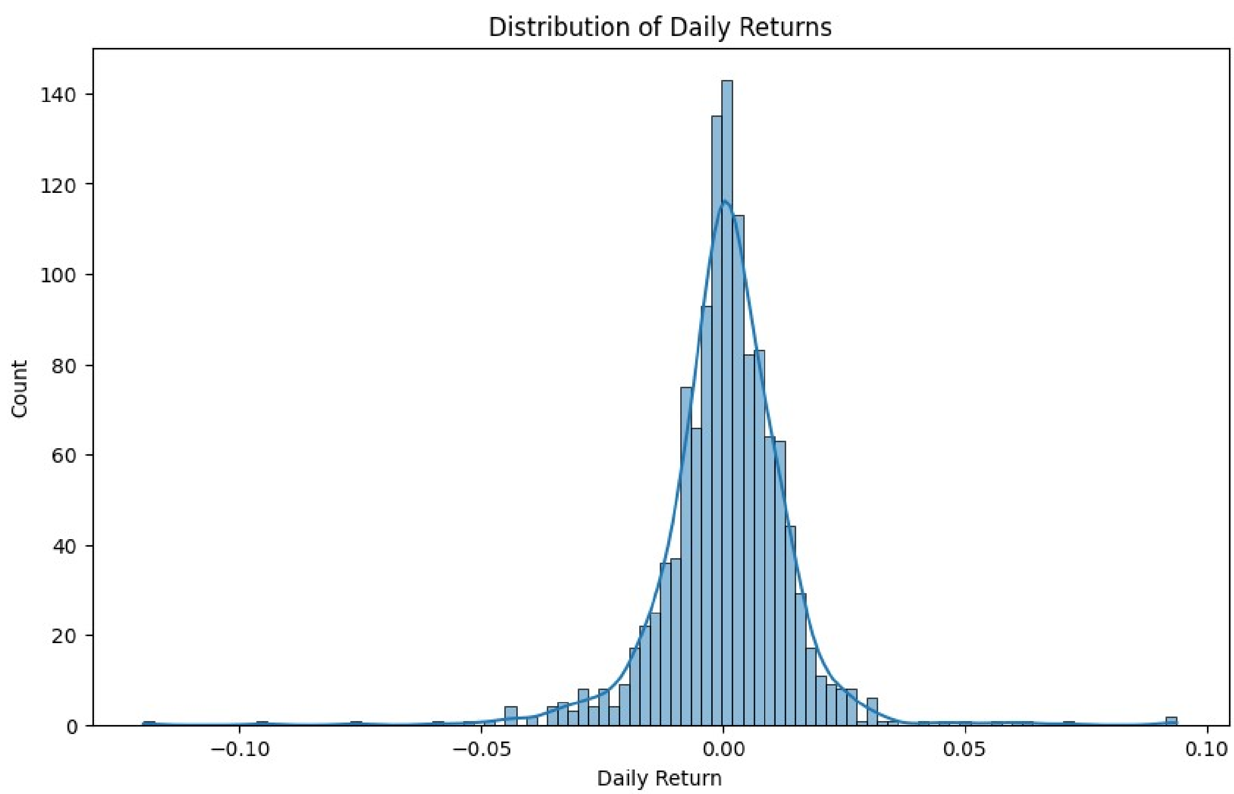

```
fig = px.line(data, x="Date", y="Volume", title="Trading Volume Over
Time")

# Customize the background color
fig.update_layout(plot_bgcolor='rgba(0, 0, 0, 0)')

# Customize the line color
fig.update_traces(line=dict(color="rgb(128, 0, 128)"))

# Set a wider figure size (adjust the width and height as needed)
fig.update_layout(width=800, height=400)

# Show the plot
fig.show()

# Create a scatter plot
plt.figure(figsize=(8, 6))
plt.scatter(data['Volume'], data['Adj Close'], marker='o',
color='#113946') # Set the figure size
plt.title('Scatter Plot of Volume vs. Adj Close') # Create a scatter
plot of 'Volume' vs. 'Adj Close'
```

```python
plt.xlabel('Volume') # Label for the x-axis
plt.ylabel('Adj Close') # Label for the y-axis
```

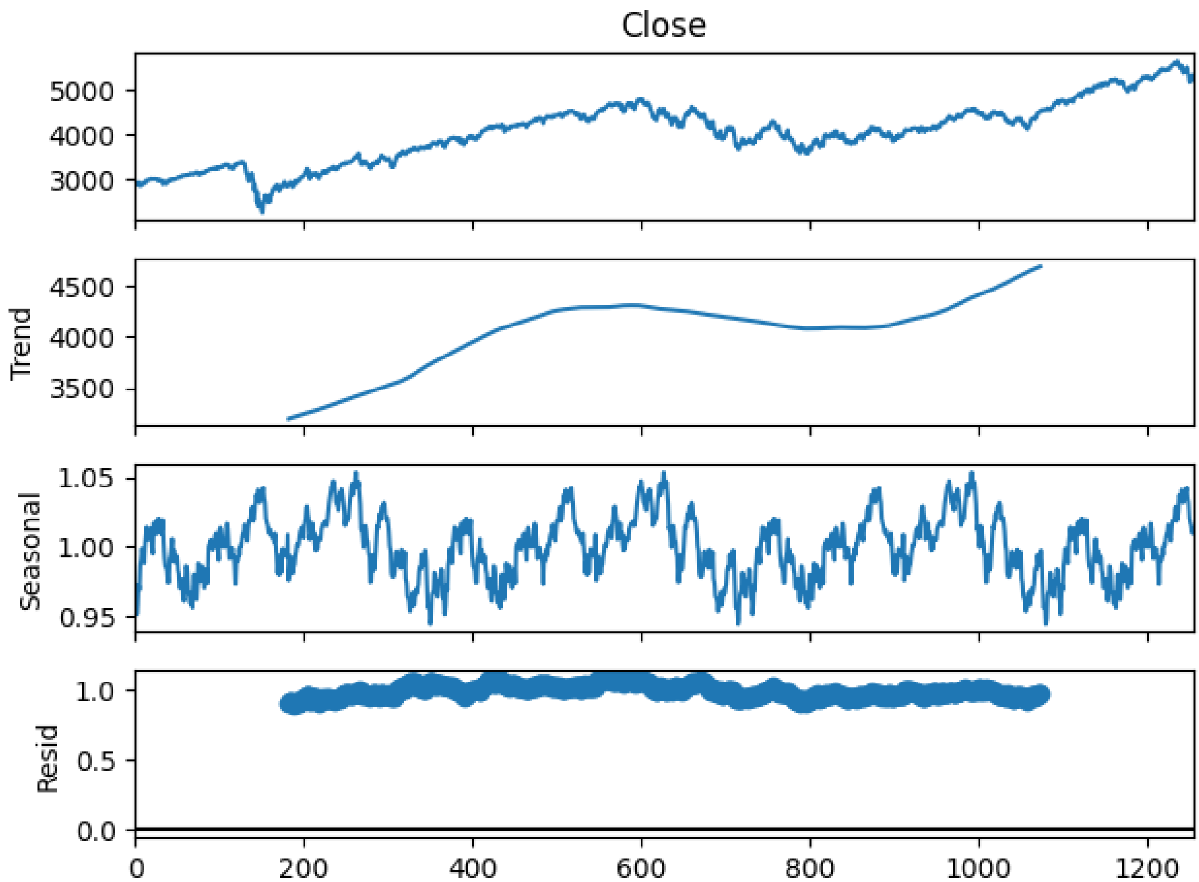
```
Text(0, 0.5, 'Adj Close')
```


```python
data["Daily Return"] = data["Close"].pct_change()
plt.figure(figsize=(14,7))
plt.plot(data["Daily Return"],label="Daily Return")
plt.title("Daily Return Over Time")
plt.xlabel("Date")
plt.ylabel("Daily Return")
plt.legend()
plt.grid(True)
plt.show()


plt.figure(figsize=(10,6))
sns.histplot(data['Daily Return'].dropna(), bins=100, kde=True)
plt.title('Distribution of Daily Returns')
plt.show()
```

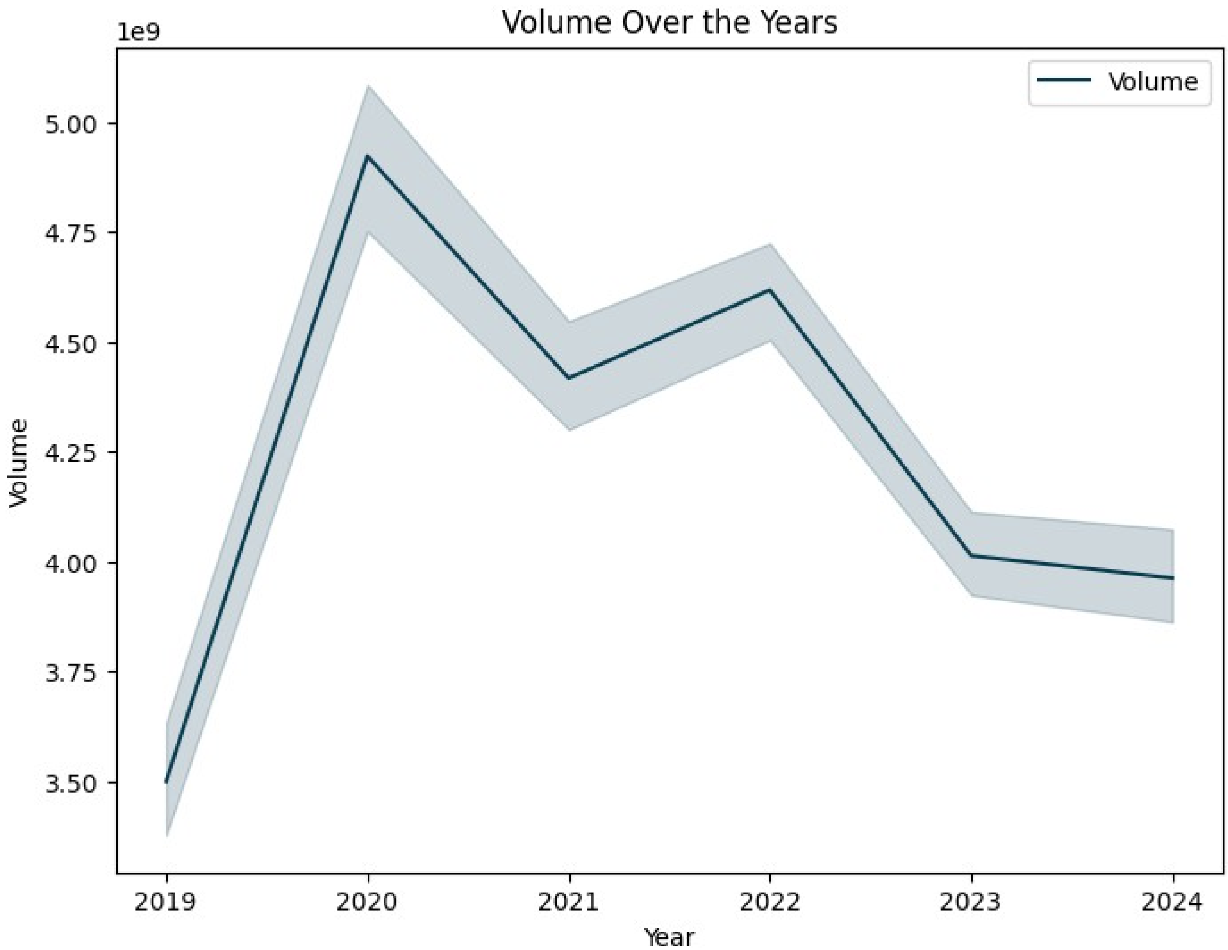





```
result =
seasonal_decompose(data["Close"],model="multiplicative",period=365)
result.plot()
plt.show()
```

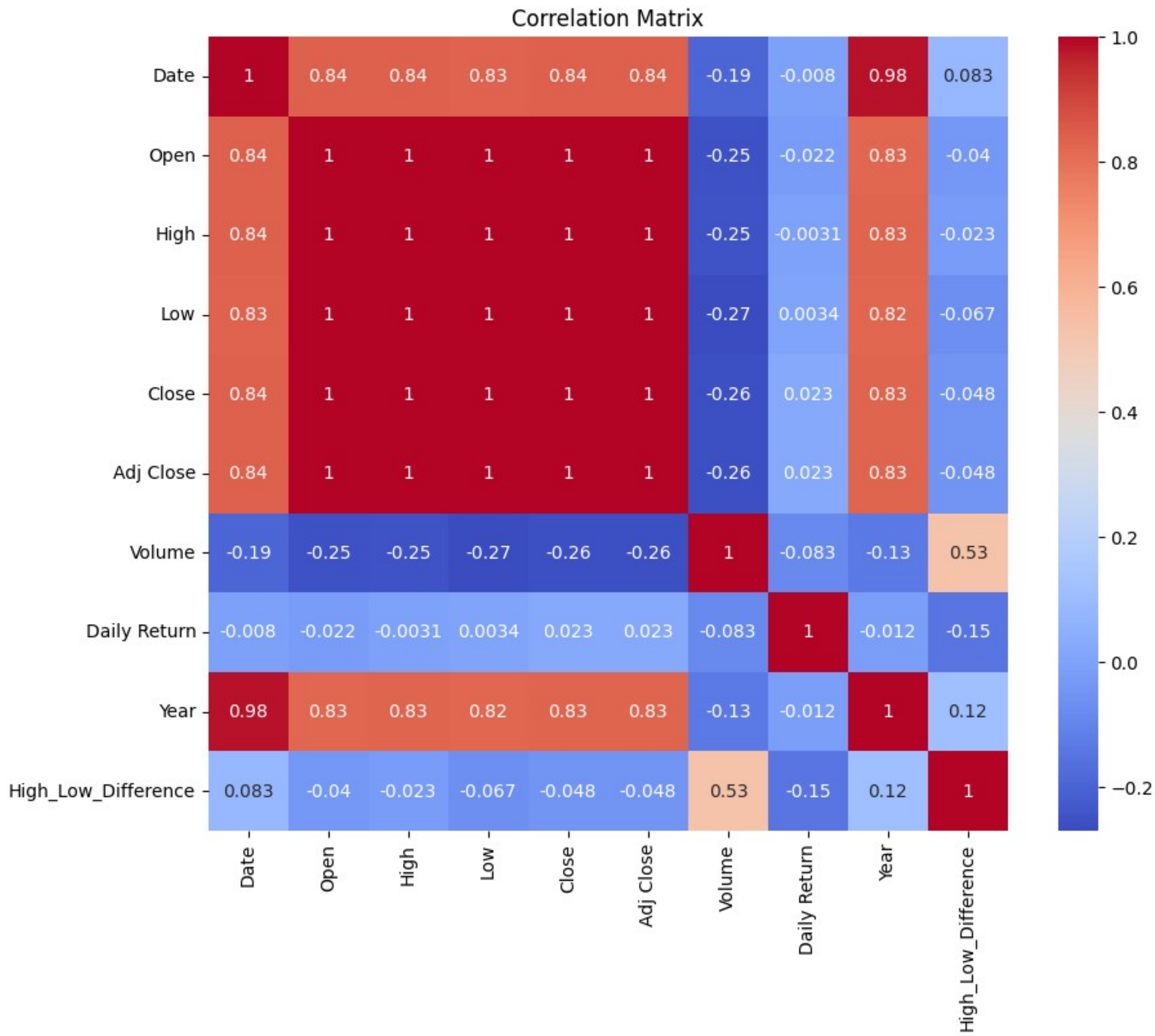



```
# Create the line plot using Seaborn
data['Year'] = data['Date'].dt.year
plt.figure(figsize=(8, 6)) # Set the figure size

# Create a line plot using Seaborn to visualize how the 'Volume' has
changed over the years
sns.lineplot(data=data, x='Year', y='Volume', color='#053B50',
label='Volume')

plt.title('Volume Over the Years')  # Set the title of the plot
plt.xlabel('Year') # Label for the x-axis
plt.ylabel('Volume') # Label for the y-axis

Text(0, 0.5, 'Volume')
```



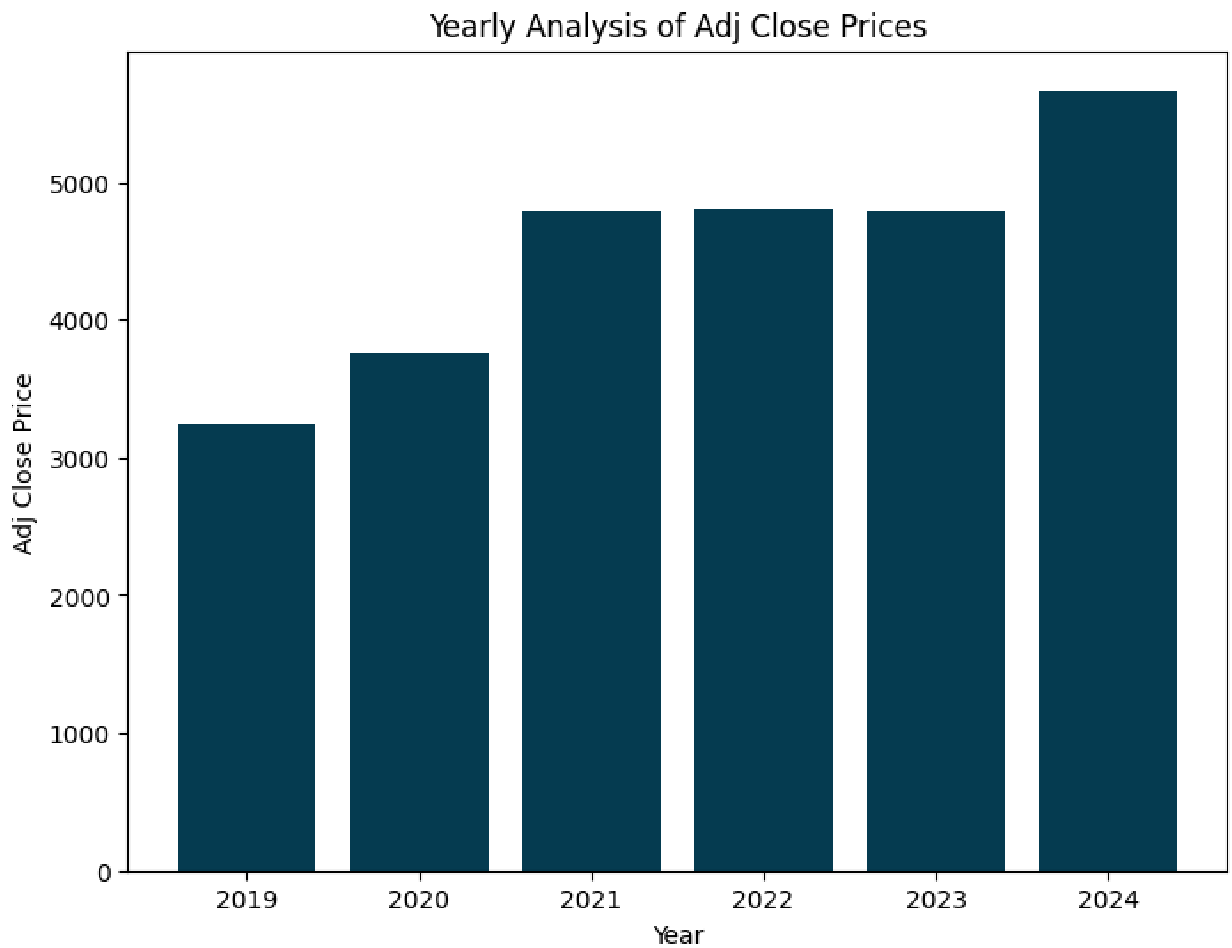

```
# Calculate the difference between 'High' and 'Low' prices
data['High_Low_Difference'] = data['High'] - data['Low']

# Create a bar plot to visualize the difference
plt.figure(figsize=(8, 6))  # Set the figure size
plt.bar(data['Year'], data['High_Low_Difference'], color='#053B50')
plt.title('Difference Between High and Low Prices')  # Set the title
of the plot
plt.xlabel('Date')  # Label for the x-axis
plt.ylabel('Price Difference')  # Label for the y-axis

Text(0, 0.5, 'Price Difference')
```


```
corr_matrix =data.corr()

plt.figure(figsize=(10,8))
sns.heatmap(corr_matrix,annot=True,cmap="coolwarm")
plt.title("Correlation Matrix")
plt.show()
```




```
# Create a bar plot to visualize the relationship between 'Year' and 'Adj Close' prices
plt.figure(figsize=(8, 6))
plt.bar(data['Year'], data['Adj Close'], color='#053B50')
plt.title('Yearly Analysis of Adj Close Prices')
plt.xlabel('Year')
plt.ylabel('Adj Close Price')
```

```
Text(0, 0.5, 'Adj Close Price')
```




```
data.columns
```

```
Index(['Date', 'Open', 'High', 'Low', 'Close', 'Adj Close', 'Volume',
       'Daily Return', 'Year', 'High_Low_Difference'],
      dtype='object')
```

```
#droping temp columns
data.drop(columns=['Daily Return', 'Year', 'High_Low_Difference'],
axis=1, inplace=True)
```

Model Building

We will build RNN models with the first 80% of the data and forecast the last 20%. We have make sure to put test data in the last portion of overall data.

Prep Data

```
close_data = data[["Close"]]

# Normalize the data
scaler = MinMaxScaler(feature_range=(0, 1))
```

```
scaled_data = scaler.fit_transform(close_data)

# Create sequences for LSTM
def create_sequences(data, sequence_length):
    sequences = []
    labels = []
    for i in range(len(data) - sequence_length):
        sequences.append(data[i:i + sequence_length])
        labels.append(data[i + sequence_length])
    return np.array(sequences), np.array(labels)

sequence_length = 50
X, y = create_sequences(scaled_data, sequence_length)

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

Model 1: LSTM (RNN) Model

```
model = Sequential()
model.add(LSTM(50, activation = "relu", input_shape=(sequence_length,
1)))
model.add(Dense(25))
model.add(Dense(1))
model.compile(optimizer = 'adam', loss = 'mse')
model.summary()
```

```
Model: "sequential_5"

┏━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┓
━━━━━━━━━━━━━━━━━┓
┃ Layer (type)                         ┃ Output Shape                ┃
Param # ┃
┡━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┩
━━━━━━━━━━━━━━━━━┩
│ lstm_7 (LSTM)                        │ (None, 50)                  │
10,400 │
├──────────────────────────────────────┼─────────────────────────────┤
─────────────────┤
│ dense_5 (Dense)                      │ (None, 25)                  │
1,275 │
├──────────────────────────────────────┼─────────────────────────────┤
─────────────────┤
│ dense_6 (Dense)                      │ (None, 1)                   │
26 │
└──────────────────────────────────────┴─────────────────────────────┘
─────────────────┘

 Total params: 11,701 (45.71 KB)
```

```
 Trainable params: 11,701 (45.71 KB)

 Non-trainable params: 0 (0.00 B)
```

```
history = model.fit(X_train, y_train, epochs=20, batch_size=10,
validation_data=(X_test, y_test))
```

```
Epoch 1/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 6s 19ms/step - loss: 0.0495 - val_loss:
7.1147e-04
Epoch 2/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 3s 7ms/step - loss: 6.3655e-04 - val_loss:
8.4546e-04
Epoch 3/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 5.3064e-04 - val_loss:
3.8671e-04
Epoch 4/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 4.3157e-04 - val_loss:
8.7470e-04
Epoch 5/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 4.9989e-04 - val_loss:
3.4521e-04
Epoch 6/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 4.7561e-04 - val_loss:
4.1317e-04
Epoch 7/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 3.6646e-04 - val_loss:
3.1755e-04
Epoch 8/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 3.2498e-04 - val_loss:
2.3484e-04
Epoch 9/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 3.4715e-04 - val_loss:
3.1747e-04
Epoch 10/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 3.3907e-04 - val_loss:
4.2302e-04
Epoch 11/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - loss: 3.0563e-04 - val_loss:
2.0658e-04
Epoch 12/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - loss: 3.0989e-04 - val_loss:
2.5929e-04
Epoch 13/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - loss: 3.4104e-04 - val_loss:
2.8211e-04
Epoch 14/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 3.4645e-04 - val_loss:
1.8888e-04
Epoch 15/20
```

```
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 3.1904e-04 - val_loss:
4.9089e-04
Epoch 16/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 2.9852e-04 - val_loss:
7.7725e-04
Epoch 17/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 3.0817e-04 - val_loss:
5.0110e-04
Epoch 18/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 2.9104e-04 - val_loss:
2.0937e-04
Epoch 19/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 2.8337e-04 - val_loss:
2.5973e-04
Epoch 20/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 3.1762e-04 - val_loss:
2.8071e-04
```

```
loss = model.evaluate(X_test, y_test)
print(f'Test Loss: {loss}')
```

```
8/8 ━━━━━━━━━━━━━━━━━━━━ 0s 26ms/step - loss: 2.7235e-04
Test Loss: 0.0002807149139698595
```

```
# Make predictions
y_pred = model.predict(X_test)
```

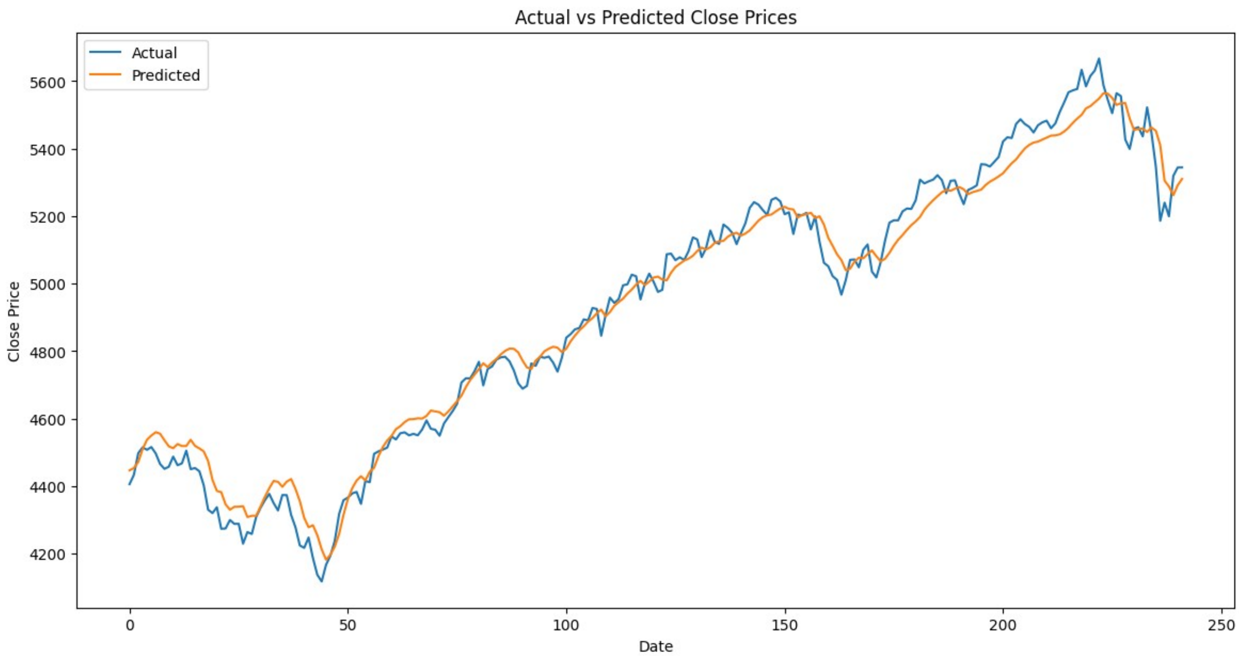
```
WARNING:tensorflow:5 out of the last 17 calls to <function
TensorFlowTrainer.make_predict_function.<locals>.one_step_on_data_dist
ributed at 0x7c9d88725b40> triggered tf.function retracing. Tracing is
expensive and the excessive number of tracings could be due to (1)
creating @tf.function repeatedly 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 ━━━━━━━━━━━━━━━━━━━━ 1s 52ms/step
```

```
y_pred = scaler.inverse_transform(y_pred)
y_test = scaler.inverse_transform(y_test)
```

```
plt.figure(figsize=(14,7))
plt.plot(y_test, label='Actual')
plt.plot(y_pred, label='Predicted')
plt.title('Actual vs Predicted Close Prices')
plt.xlabel('Date')
plt.ylabel('Close Price')
```

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



Model 2: LSTM (RNN) Model

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

model2 = Sequential()
model2.add(LSTM(50, activation="relu", return_sequences=True,
input_shape=(sequence_length, 1)))
model2.add(LSTM(50, activation="relu"))
model2.add(Dense(100))
model2.add(Dense(25))
model2.add(Dense(1))
opt1=Adam(learning_rate=0.001,beta_1=0.9,beta_2=0.999)
model2.compile(optimizer=opt1, loss='mse')
model2.summary()

Model: "sequential_7"

┏━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┓
━━━━━━━━━━━━━━━━┓
┃ Layer (type)                         ┃ Output Shape                ┃
Param # ┃
┡━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇
━━━━━━━━━━━━━━━━┩
│ lstm_10 (LSTM)                       │ (None, 50, 50)              │
10,400 │
├──────────────────────────────────────┼─────────────────────────────┼
```

```
─────────────────┤
│ lstm_11 (LSTM)                      │ (None, 50)                 │
20,200 │
├─────────────────────────────────────┼────────────────────────────┼
─────────────────┤
│ dense_10 (Dense)                    │ (None, 100)                │
5,100 │
├─────────────────────────────────────┼────────────────────────────┼
─────────────────┤
│ dense_11 (Dense)                    │ (None, 25)                 │
2,525 │
├─────────────────────────────────────┼────────────────────────────┼
─────────────────┤
│ dense_12 (Dense)                    │ (None, 1)                  │
26 │
└─────────────────────────────────────┴────────────────────────────┴
─────────────────┘

 Total params: 38,251 (149.42 KB)

 Trainable params: 38,251 (149.42 KB)

 Non-trainable params: 0 (0.00 B)
```

```
history2 = model2.fit(X_train, y_train, epochs=20, batch_size=10,
validation_data=(X_test, y_test))
```

```
Epoch 1/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 9s 43ms/step - loss: 0.0417 - val_loss:
0.0028
Epoch 2/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 5s 11ms/step - loss: 0.0012 - val_loss:
0.0031
Epoch 3/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 0.0011 - val_loss:
0.0011
Epoch 4/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 8.7544e-04 - val_loss:
0.0014
Epoch 5/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - loss: 8.1023e-04 - val_loss:
0.0021
Epoch 6/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 12ms/step - loss: 8.3698e-04 - val_loss:
5.6460e-04
Epoch 7/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 12ms/step - loss: 8.8984e-04 - val_loss:
0.0022
Epoch 8/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 8.1796e-04 - val_loss:
```

```
9.5795e-04
Epoch 9/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 6.1927e-04 - val_loss:
3.9493e-04
Epoch 10/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 5.2122e-04 - val_loss:
4.0494e-04
Epoch 11/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 5.9364e-04 - val_loss:
3.4473e-04
Epoch 12/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 5.7336e-04 - val_loss:
3.3650e-04
Epoch 13/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 5.2186e-04 - val_loss:
5.5327e-04
Epoch 14/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 5.6838e-04 - val_loss:
3.1400e-04
Epoch 15/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 4.1163e-04 - val_loss:
0.0011
Epoch 16/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - loss: 6.6480e-04 - val_loss:
3.1656e-04
Epoch 17/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 12ms/step - loss: 5.5637e-04 - val_loss:
5.2034e-04
Epoch 18/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 12ms/step - loss: 4.0886e-04 - val_loss:
6.1071e-04
Epoch 19/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 3.9968e-04 - val_loss:
2.5854e-04
Epoch 20/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - loss: 4.2390e-04 - val_loss:
0.0011
```

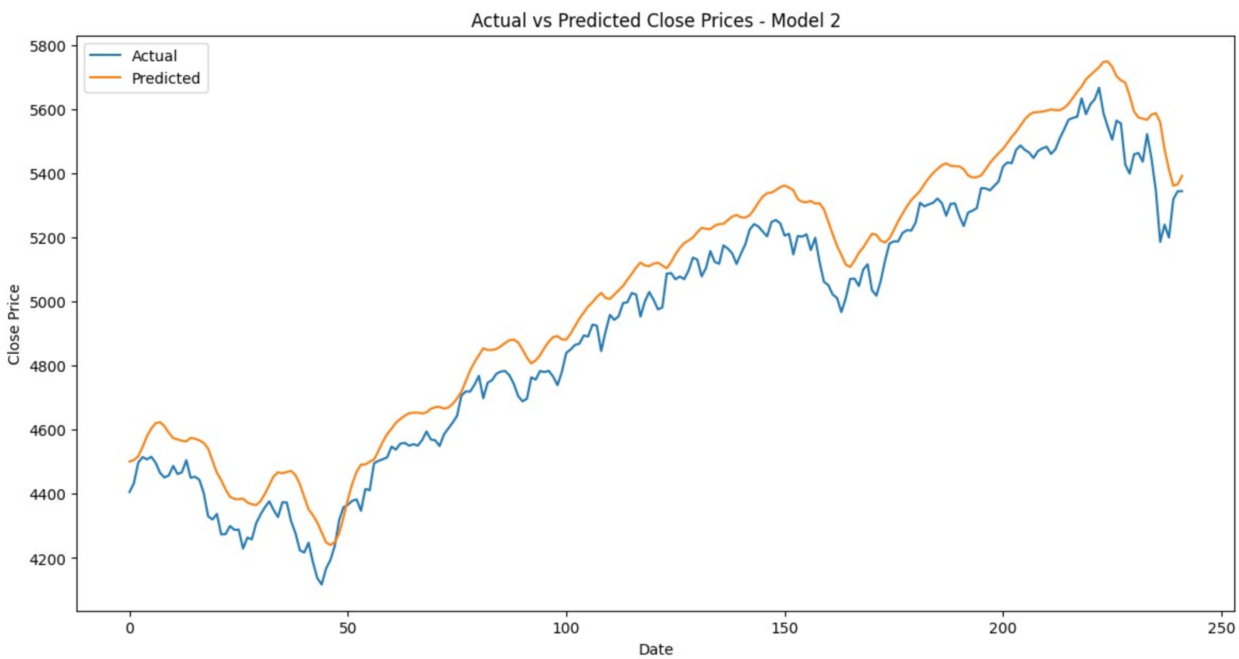
```python
loss2 = model2.evaluate(X_test, y_test)
print(f'Test Loss: {loss2}')
```

```
8/8 ━━━━━━━━━━━━━━━━━━━━ 0s 13ms/step - loss: 0.0010
Test Loss: 0.0011253617703914642
```

```python
# Make predictions
y_pred = model2.predict(X_test)
```

```
8/8 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step
```

```
y_pred = scaler.inverse_transform(y_pred)
y_test = scaler.inverse_transform(y_test)

# Plotting
plt.figure(figsize=(14,7))
plt.plot(y_test, label='Actual')
plt.plot(y_pred, label='Predicted')
plt.title('Actual vs Predicted Close Prices - Model 2')
plt.xlabel('Date')
plt.ylabel('Close Price')
plt.legend()
plt.show()
```



Model 3: LSTM (RNN) Model

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

# Model 3: LSTM with Dropout
model3 = Sequential()
model3.add(LSTM(50, activation="relu", return_sequences=True,
input_shape=(sequence_length, 1)))
model3.add(LSTM(50,return_sequences=False,activation='relu'))
model3.add(Dense(100))
model3.add(Dropout(0.2))
model3.add(Dense(25))
model3.add(Dense(1))
opt1=Adam(learning_rate=0.001,beta_1=0.9,beta_2=0.999)
```

```
model3.compile(optimizer=opt1, loss='mse')
model3.summary()
```

```
Model: "sequential_8"

┏━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳
━━━━━━━━━━━━━━━━━┓
┃ Layer (type)                          ┃ Output Shape                 ┃
Param # ┃
┡━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇
━━━━━━━━━━━━━━━━━┩
│ lstm_12 (LSTM)                        │ (None, 50, 50)               │
10,400 │
├───────────────────────────────────────┼──────────────────────────────┼
─────────────────┤
│ lstm_13 (LSTM)                        │ (None, 50)                   │
20,200 │
├───────────────────────────────────────┼──────────────────────────────┼
─────────────────┤
│ dense_13 (Dense)                      │ (None, 100)                  │
5,100 │
├───────────────────────────────────────┼──────────────────────────────┼
─────────────────┤
│ dropout_1 (Dropout)                   │ (None, 100)                  │
0 │
├───────────────────────────────────────┼──────────────────────────────┼
─────────────────┤
│ dense_14 (Dense)                      │ (None, 25)                   │
2,525 │
├───────────────────────────────────────┼──────────────────────────────┼
─────────────────┤
│ dense_15 (Dense)                      │ (None, 1)                    │
26 │
└───────────────────────────────────────┴──────────────────────────────┴
─────────────────┘

 Total params: 38,251 (149.42 KB)

 Trainable params: 38,251 (149.42 KB)

 Non-trainable params: 0 (0.00 B)
```

```
history3 = model3.fit(X_train, y_train, epochs=20, batch_size=10,
validation_data=(X_test, y_test))
```

```
Epoch 1/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 9s 39ms/step - loss: 0.0481 - val_loss:
0.0020
Epoch 2/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 6s 11ms/step - loss: 0.0022 - val_loss:
9.8544e-04
```

```
Epoch 3/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 0.0019 - val_loss:
8.6685e-04
Epoch 4/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 0.0014 - val_loss:
7.5509e-04
Epoch 5/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 0.0014 - val_loss:
6.8803e-04
Epoch 6/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 0.0013 - val_loss:
0.0025
Epoch 7/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 0.0013 - val_loss:
9.9781e-04
Epoch 8/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 12ms/step - loss: 0.0010 - val_loss:
5.6705e-04
Epoch 9/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 13ms/step - loss: 0.0011 - val_loss:
5.2072e-04
Epoch 10/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - loss: 0.0013 - val_loss:
9.6376e-04
Epoch 11/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 0.0010 - val_loss:
4.6171e-04
Epoch 12/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 8.2943e-04 - val_loss:
7.1183e-04
Epoch 13/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 9.6711e-04 - val_loss:
0.0010
Epoch 14/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 8.1339e-04 - val_loss:
5.5226e-04
Epoch 15/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 9.2371e-04 - val_loss:
0.0018
Epoch 16/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 6.1603e-04 - val_loss:
0.0012
Epoch 17/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 7.1251e-04 - val_loss:
0.0013
Epoch 18/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 6.6953e-04 - val_loss:
0.0011
Epoch 19/20
```

```
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 12ms/step - loss: 6.7198e-04 - val_loss:
0.0013
Epoch 20/20
97/97 ━━━━━━━━━━━━━━━━━━━━ 1s 12ms/step - loss: 5.7441e-04 - val_loss:
6.3385e-04
```

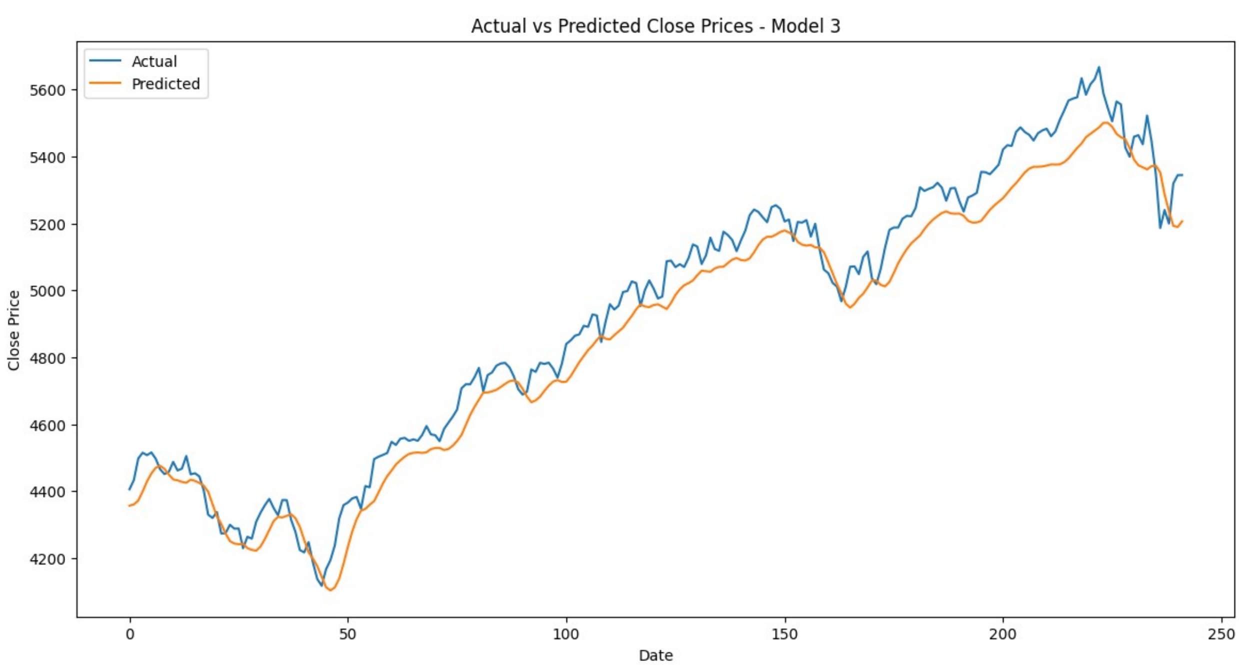
```
loss3 = model3.evaluate(X_test, y_test)
print(f'Test Loss: {loss3}')
```

```
8/8 ━━━━━━━━━━━━━━━━━━━━ 1s 48ms/step - loss: 4.9011e-04
Test Loss: 0.0006338502280414104
```

```
# Make predictions
y_pred = model3.predict(X_test)
```

```
8/8 ━━━━━━━━━━━━━━━━━━━━ 1s 79ms/step
```

```
y_pred = scaler.inverse_transform(y_pred)
y_test = scaler.inverse_transform(y_test)

# Plotting
plt.figure(figsize=(14,7))
plt.plot(y_test, label='Actual')
plt.plot(y_pred, label='Predicted')
plt.title('Actual vs Predicted Close Prices - Model 3')
plt.xlabel('Date')
plt.ylabel('Close Price')
plt.legend()
plt.show()
```



The management or research question of interest is:

How can we accurately predict the future stock prices of the S&P 500 index using historical data?

Why is this important?

1. **Investment Decision-Making**: Accurate stock price predictions can help investors make informed decisions about buying, selling, or holding assets. This can maximize returns and minimize risks.

2. **Risk Management**: For financial institutions and individual investors, understanding potential future price movements is crucial for managing risk. It helps in setting appropriate stop-loss levels, hedging strategies, and portfolio allocations.

3. **Market Analysis**: Businesses and analysts use stock price forecasts to gauge market trends and economic health. This can influence broader business strategies, such as expansion plans or cost-cutting measures.