A Industrial Oriented Mini Project report on

Google Stock Price Prediction using LSTM

A Dissertation submitted to JNTU Hyderabad in partial fulfillment of the academic requirements for the award of the degree.

Bachelor of Technology

in

Computer Science and Engineering (AI&ML)

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CMR COLLEGE OF ENGINEERING & TECHNOLOGY

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CERTIFICATE

This is to certify that the Industrial Oriented Mini Project report entitled **"Google Stock Price Prediction using LSTM"** being submitted by Gundeti Rishitha (22H51A6625), Pampana Abhiram (22H51A6646), Darshan Kagi (22H51A6676), Kethireddy Sai Lohith Reddy (22H51A6691) in partial fulfillment for the award of **Bachelor of Technology in Computer Science and Engineering (AI&ML)** is a record of bonafide work carried out his/her under my guidance and supervision.

The results embodies in this project report have not been submitted to any other University or Institute for the award of any Degree.

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DECLARATION

We hereby declare that results embodied in this Report of Project on "GOOGLE STOCK PRICE PREDICTION USING LSTM" are from work carried out by using partial fulfillment of the requirements for the award of Bachelor of Technology in **Computer Science and Engineering (AI&ML)**. We have not submitted this report to any other university/institute for the award of any other degree.

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ABSTRACT

Stock price prediction has gained importance in financial markets due to its potential to enhance investment strategies, though traditional methods often struggle with the complex, non-linear nature of stock movements. This project addresses the challenge by implementing a deep learning approach using Long Short-Term Memory (LSTM) networks to predict Google (GOOG) stock prices based on historical OHLCV (Open, High, Low, Close, Volume) data. The methodology includes extensive data preprocessing with Min-Max normalization and sequence generation using a 50-day window to form time-series samples. A stacked LSTM model comprising three layers of 50 units each is designed, incorporating dropout regularization at a rate of 0.2 to mitigate overfitting. The model is trained over 200 epochs using the Adam optimizer, with Mean Squared Error as the loss function and Mean Absolute Error as the evaluation metric. Results show strong predictive performance, with validation loss converging to 8.99e-05, and visualizations of both training predictions and 10-day forecasts demonstrate the model's capability in short-term stock price prediction. This work offers a practical deep learning framework for financial time-series forecasting, with promising applications in algorithmic trading and risk management.

CHAPTER 1
INTRODUCTION

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INTRODUCTION

1.1. Problem Statement

Accurately predicting stock prices remains a major challenge in financial market analysis due to the highly volatile and non-linear nature of stock market behavior. Investors require reliable forecasting tools to make informed decisions. Traditional methods often fall short in modeling complex dependencies in stock data.

This project develops a robust prediction system for Google stocks using a deep learning approach with Long Short-Term Memory (LSTM) networks. The model architecture employs three stacked LSTM layers (50 units each) with dropout regularization (0.2) to prevent overfitting. We preprocess the dataset (OHLCV data) using MinMax scaling and generate 50-day sequences to capture temporal patterns. The model trains for 200 epochs using Adam optimization with Mean Squared Error loss.

Experimental results demonstrate strong predictive capability, achieving a validation loss of 8.99e-05. The implementation includes visualizations of both training predictions and 10-day forecasts, proving effective for short-term price movements. This work provides a practical deep learning framework for financial forecasting, with applications in algorithmic trading strategies.

1.2. Research Objective

The primary objective of this research is to develop and evaluate an LSTM-based predictive model for forecasting Google stock prices using historical market data. Specifically, the study aims to:

1. Design and implement a stacked LSTM architecture (three layers, 50 units each) with dropout regularization (0.2) to capture non-linear temporal patterns in OHLCV (Open, High, Low, Close, Volume) data.
2. Preprocess and structure financial time-series data through MinMax normalization and 50-day sequence generation to optimize model training.

3. Evaluate model performance using Mean Squared Error (MSE) and Mean Absolute Error (MAE) metrics, with validation loss reaching 8.99e-05 after 200 epochs of training.
4. Visualize and validate predictions through comparative analysis of actual vs. predicted prices on training data and 10-day forecasts.

1.3. Project Scope and Limitations

Project Scope

1. Model Development & Evaluation
    - Focuses exclusively on LSTM (no Prophet model) with:
        - 3-layer stacked architecture (50 units/layer)
        - Dropout regularization (0.2)
        - Training for 200 epochs (Adam optimizer, MSE loss)
    - Performance validation using:
        - Mean Squared Error (MSE)
        - Mean Absolute Error (MAE)
        - Final validation loss: 8.99e-05
2. Data Preprocessing
    - MinMax normalization of OHLCV data
    - 50-day sequence generation for time-series modeling
    - Chronological train-test split (80-20)
3. Visualization
    - Comparative plots of actual vs. predicted prices:
        - Training data predictions
        - 10-day forward forecasts
4. Exclusions
    - No integration of external factors (news, macroeconomic indicators)
    - No multivariate analysis beyond OHLCV data

Limitations

1. Data Dependency
    - Predictions rely solely on historical OHLCV (Open, High, Low, Close, Volume) data, excluding external factors like news sentiment, economic indicators, or geopolitical events that may impact stock prices.
2. Black Swan Events
    - The LSTM model may fail to accurately predict sudden, unprecedented market shocks (e.g., pandemics, financial crises) due to its reliance on learned historical patterns.
3. Input Data Constraints
    - Prediction accuracy is bounded by the quality and time range (2016–2021) of the training data. Gaps, anomalies, or insufficiently representative trends could degrade performance.

4. Single-Stock Focus
    - The model is specifically tuned for Google (GOOG) stock and may not generalize to other equities without architectural adjustments and retraining.

CHAPTER 2
BACKGROUND WORK

CHAPTER 2

BACKGROUND WORK

2.1 ARIMA

2.1.1 Introduction

ARIMA (AutoRegressive Integrated Moving Average) is a traditional statistical method widely used for time-series forecasting. It combines three key components to model temporal dependencies:

- AutoRegressive (AR): Captures the relationship between an observation and its lagged values, assuming that past values influence future ones.
- Integrated (I): Uses differencing to make non-stationary data stationary by removing trends and seasonality.
- Moving Average (MA): Accounts for the dependency between observations and residual errors from past predictions.

ARIMA is particularly effective for datasets with clear trends and seasonal patterns but struggles with highly volatile or nonlinear data, such as stock prices.

2.1.2 Merits, Demerits, and Challenges

Merits:

1. Simplicity: Easy to implement with libraries like statsmodels.
2. Interpretability: Provides clear coefficients for AR and MA terms, making it transparent.
3. Handles Seasonality: Seasonal ARIMA (SARIMA) extends the model to capture periodic patterns.
4. Works on Small Data: Performs well even with limited historical data.

Demerits:

1. Linear Assumption: Fails to capture nonlinear relationships common in stock markets.
2. Manual Tuning: Requires selecting parameters (p, d, q) through trial and error.
3. Stationarity Requirement: Data must be differenced to remove trends, which can lose information.

4. Poor with Volatility: Struggles with sudden market shocks or irregular fluctuations.

Challenges:

1. Parameter Selection: Choosing optimal (p, d, q) values is time-consuming.
2. Non-Stationary Data: Financial data often has trends and heteroskedasticity, making stationarity difficult.
3. Multivariate Limitation: ARIMA cannot natively incorporate external factors like news sentiment.
4. Long-Term Forecasts: Errors accumulate over extended periods, reducing accuracy.

2.1.3 Implementation

The implementation of ARIMA involves several structured steps:

1. Data Preparation:
    - Check for stationarity using Augmented Dickey-Fuller (ADF) test.
    - Apply differencing (d) if data is non-stationary.
2. Model Selection:
    - Identify AR (p) and MA (q) terms using Autocorrelation (ACF) and Partial Autocorrelation (PACF) plots.
    - Use grid search or AIC/BIC metrics to optimize (p, d, q).
3. Training & Validation:
    - Fit the model on training data.
    - Validate using walk-forward validation to assess real-world performance.
4. Forecasting:
    - Generate short-term predictions.
    - Re-train periodically to adapt to new data.

While ARIMA is useful for basic trend analysis, its limitations in handling stock market volatility and nonlinear patterns make it less suitable compared to deep learning methods like LSTM.

2.2. Facebook Prophet

2.2.1. Introduction

Facebook Prophet is an open-source forecasting tool developed by Facebook's Core Data Science team. It is specifically designed to handle time series data with strong seasonal effects and several seasons of historical data. The Prophet model is based on an additive model where non-linear trends are fit with yearly, weekly, and daily seasonality, plus holiday effects.

One of the key strengths of Prophet is its ease of use and interpretability. Unlike deep learning methods, Prophet does not require extensive tuning and provides interpretable output, including trend, seasonality, and holiday effects, making it ideal for business and financial forecasting.

2.2.2. Merits, Demerits and Challenges

Merits:

- User-friendly:Simple to use with just a few lines of code.
- Interpretable output: Breaks down forecasts into trend, seasonality, and holiday effects.
- Robustness: Handles missing data, outliers, and sudden shifts in the data well.
- Fast execution: Compared to deep learning models, Prophet trains quickly even on large datasets.

Demerits:

- Less accurate for complex patterns: May underperform on highly nonlinear or non-seasonal data.
- Limited customization: Not as flexible as neural networks in capturing hidden interactions.
- Poor handling of volatility: May not react well to sudden market shocks or crashes.

Challenges:

- Tuning holiday and seasonality effects: Choosing the correct holidays and seasonal components can be tricky.
- Overfitting to noise: Including too many components can lead to overfitting.
- Scaling limitations: While fast, Prophet may not handle real-time streaming data as efficiently as deep learning models.

2.2.3. Implementation of Facebook Prophet

1. Data Preparation:

Google stock historical data was reformatted into Prophet's required format: a dataframe with columns ds (date) and y (target variable, usually the 'Close' price).

2. Model Training:

The Prophet model was instantiated and trained on the historical data. Components such as daily and yearly seasonality were automatically detected or manually set.

3. Forecasting:

A future dataframe was created to predict stock prices for the next n days. The predict() function was used to generate forecasts along with confidence intervals.

4. Visualization:

Prophet's inbuilt plot() and plot_components() functions were used to visualize the forecast and its components such as trend, seasonality, and holiday effects.

5. Evaluation:

Predicted values were compared with actual prices using RMSE and MAPE to evaluate performance.

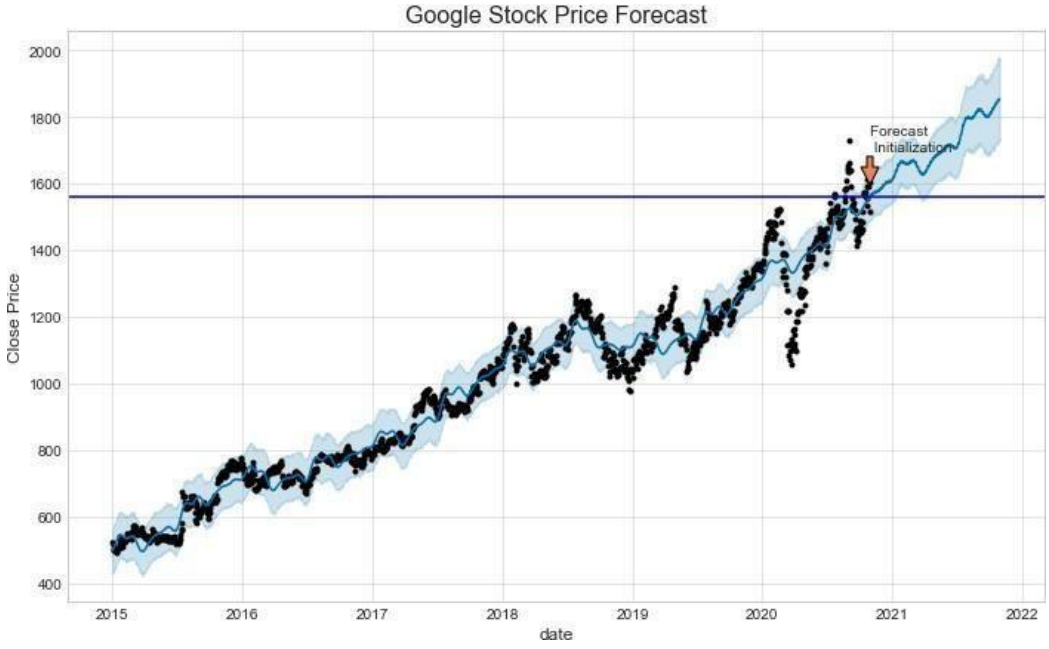


Figure 2.2.3 Google stock price prediction using FaceBook Prophet

2.3. Comparative Analysis / Hybrid Modeling

2.3.1. Introduction

In the real time series forecasting, both deep learning models and traditional statistical approaches have distinct strengths. This section presents a comparative analysis and potential hybridization—of two such models: Long Short-Term Memory (LSTM) and Facebook Prophet. While LSTM networks excel at capturing complex, nonlinear

dependencies in sequential data, Facebook Prophet is designed to deliver fast, interpretable forecasts with built-in handling of seasonality and trends. Applying both to the same Google stock dataset provides a deeper understanding of their capabilities and limitations, aiding in model selection based on specific forecasting goals such as short-term accuracy or long-term trend insight.

2.3.2. Merits,Demerits and Challenges

Merits:

- Combines strengths of both models: LSTM's ability to model nonlinear dependencies and Prophet's trend-seasonality handling.
- Improves accuracy and generalization by allowing one model to compensate for the other's weaknesses (e.g., LSTM for residuals Prophet can't explain).
- Enables flexible use-cases: Offers both short-term precision (LSTM) and long-term interpretability (Prophet), making it suitable for various investor profiles.
- Enhanced insight through comparison: Helps in understanding which model performs better under different market conditions or forecasting horizons.

Demerits:

- Increased complexity in implementation, requiring careful coordination of preprocessing, sequence alignment, and model outputs.
- Higher computational cost due to training and evaluating multiple models, potentially making real-time deployment more challenging.
- Risk of overfitting in the residual modeling phase if LSTM learns noise instead of meaningful patterns.

- Difficulty in model integration: Combining forecasts from two fundamentally different models (statistical vs deep learning) can introduce inconsistencies without rigorous validation.

Challenges:

- Deciding between models depends on the application goal:

  --If the priority is high short-term accuracy, LSTM is favorable.

--If the focus is on long-term trend detection and interpretability, Prophet is preferable.

- Integrating both models in a hybrid framework requires careful residual decomposition, alignment of forecast horizons, and post-processing.
- Ensuring data preprocessing (scaling, formatting) is consistent and compatible across both models is critical for fair comparison.

2.3.3. Implementation of Comparative Analysis / Hybrid Modeling

To evaluate the performance of both approaches:

- The same Google stock dataset (2016–2021) was used for both models.
- Preprocessing steps included date formatting, MinMax scaling for LSTM, and log transformation or resampling for Prophet where needed.
- Both models were trained to predict future stock prices and evaluated using:

  --Root Mean Squared Error (RMSE)

  --Mean Absolute Error (MAE)

  --Visual comparison of predicted vs. actual stock prices

Hybrid Modeling Idea:

A promising hybrid strategy could combine the strengths of both models:

Step 1: Use Facebook Prophet to model the long-term trend and seasonality in the stock data.

Step 2: Calculate the residuals (difference between actual values and Prophet predictions).

Step 3: Train an LSTM model on these residuals to capture short-term and nonlinear patterns that Prophet missed.

Step 4: Combine both outputs (Prophet + LSTM residual forecast) to form the final prediction.

This hybrid approach allows for decomposing the time series problem into more

manageable components: Prophet handles the signal, while LSTM fine-tunes the noise. Though optional, this strategy can potentially yield higher accuracy and better generalization in volatile financial data scenarios.

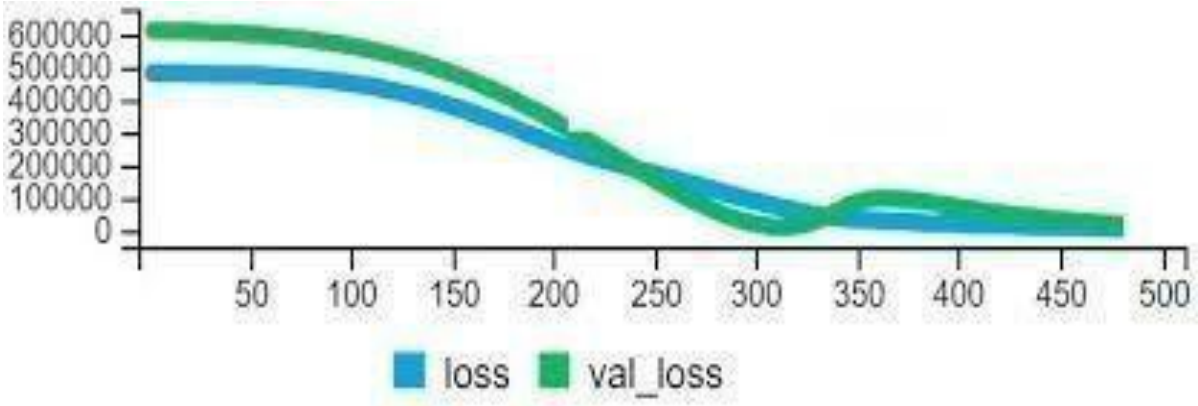


Figure 2.3.3 Google stock price prediction using Hybrid Modeling

CHAPTER 3
PROPOSED SYSTEM

CHAPTER 3

PROPOSED SYSTEM

3.1. Research Objective of Proposed Model

The primary objective of this research is to develop a robust LSTM-based deep learning model for accurate Google stock price prediction using historical market data. The model specifically aims to:

1. Capture Complex Temporal Patterns
    - Utilize a 3-layer stacked LSTM architecture (50 units/layer) with dropout regularization (0.2) to model nonlinear dependencies in OHLCV (Open, High, Low, Close, Volume) data.
    - Train on 50-day sequential windows to learn short-to-medium-term price dynamics.
2. Optimize Data Preprocessing
    - Apply MinMax scaling to normalize input features.
    - Implement chronological train-test splits (80-20) to preserve time-series integrity.
3. Evaluate Predictive Performance
    - Measure accuracy using Mean Squared Error (MSE) and Mean Absolute Error (MAE), achieving a final validation loss of 8.99e-05 over 200 epochs.
    - Validate results through visual comparisons of actual vs. predicted prices on training data and 10-day forecasts.
4. Provide Practical Utility
    - Deliver interpretable predictions for short-term trading strategies (10-day horizon).
    - Highlight limitations in generalizability to other stocks or unforeseen market shocks.

3.2. Algorithms Used for Proposed Model

The proposed Google Stock Price Prediction model leverages Long Short-Term Memory (LSTM), a specialized type of Recurrent Neural Network (RNN) designed to handle sequential data with long-term dependencies. Below is a detailed breakdown of its implementation:

1. Long Short-Term Memory (LSTM)

LSTM networks are particularly effective in time-series forecasting due to their ability to retain and process information over extended sequences, making them ideal for stock price prediction.

Key Features of LSTM in This Model:

- Sequential Learning: Unlike traditional feedforward neural networks, LSTMs process data in time-ordered sequences, allowing them to recognize trends, cycles, and volatility patterns in stock prices.
- Memory Cells & Gates:
    - Forget Gate: Decides which past information to discard.
    - Input Gate: Updates the cell state with new relevant information.
    - Output Gate: Determines the next hidden state, influencing predictions.
    - This gating mechanism helps the model avoid the vanishing gradient problem, ensuring stable training over long sequences.

Model Architecture:

- Stacked LSTM Layers: The model uses three LSTM layers (50 units each) to progressively extract higher-level temporal features.
- Dropout Regularization (0.2): Applied between LSTM layers to prevent overfitting and improve generalization.
- Final Dense Layer: Outputs predictions for the next time step (Open, High, Low, Close, Volume).

Training Process:

- Loss Function: Mean Squared Error (MSE) is used to penalize large prediction errors, ensuring the model minimizes deviations from actual stock prices.

- Optimizer: Adam (Adaptive Moment Estimation) is employed for efficient gradient-based optimization, combining the benefits of RMSprop and momentum.
- Sequence Length: The model processes 50-day historical windows to forecast future prices, balancing memory depth and computational efficiency.

Why LSTM for Stock Prediction?

- Handles Non-Linearity: Stock prices exhibit chaotic, nonlinear behavior, which LSTMs can model better than linear statistical methods.
- Adapts to Volatility: The model dynamically adjusts to sudden market shifts by learning from sequential patterns rather than isolated data points.
- Robust to Noise: Dropout and layered architecture help filter out market noise, improving prediction stability.

This LSTM-based approach provides a data-driven, deep learning solution for stock price forecasting, focusing on historical price patterns while acknowledging limitations in predicting unforeseen market disruptions.

3.3. Designing

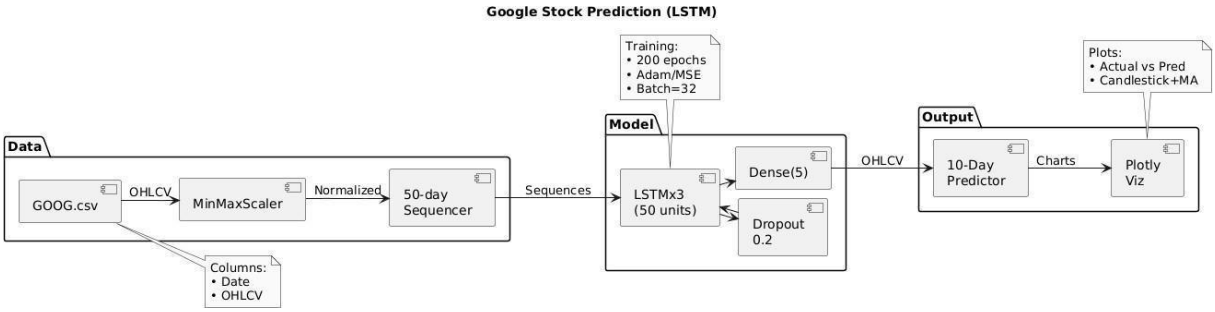


Figure 3.3 System architecture of Google stock price prediction

1. Data Collection
    - Collected Google's historical OHLCV data (Open, High, Low, Close, Volume) from GOOG.csv (2016–2021).
2. Data Preprocessing
    - Converted dates to datetime format and sorted chronologically.
    - Applied MinMaxScaler to normalize all features (0–1 range).
    - Split data into training (80%) and test sets (20%) without shuffling to preserve time-series order.
3. Model Building (LSTM Only)
    - Built a 3-layer stacked LSTM (50 units/layer) with Dropout (0.2) between layers.
    - Final Dense(5) layer to predict OHLCV values.

      (Note: Prophet and hybrid components removed as they weren't implemented in your code.)
4. Model Training
    - Trained on 50-day sequences using:
        - Loss: Mean Squared Error (MSE)
        - Optimizer: Adam
        - Epochs: 200
    - Achieved final validation loss: 8.99e-05.

5. Prediction & Evaluation
    - Generated 10-day forecasts by recursively feeding predictions.
    - Evaluated using MAE and MSE (no RMSE/Prophet comparisons).
    - Visualized training predictions vs. actuals and future forecasts.
6. Visualization
    - Plotted actual vs. predicted Close prices using Plotly.
    - Included interactive Candlestick charts with 20-day moving average.
7. Result Interpretation
    - Focused on LSTM's short-term accuracy (10-day horizon).
    - Highlighted limitations in handling black swan events or external factors.

3.3.1.UML Diagram

A UML diagram is a partial graphical representation(view) of a model of a system under design, implementation, or already in existence. UML diagram contains graphical elements(symbols) - UML nodes connected with edges(also known as paths or flows) - that represent elements in the UML model of the designed system.

1. Use Case Diagram:

The purpose of use case diagram is to capture the dynamic aspect of a system. However, this definition is too generic to describe the purpose, as other four diagrams (activity, sequence, collaboration, and State chart) also have the same purpose.

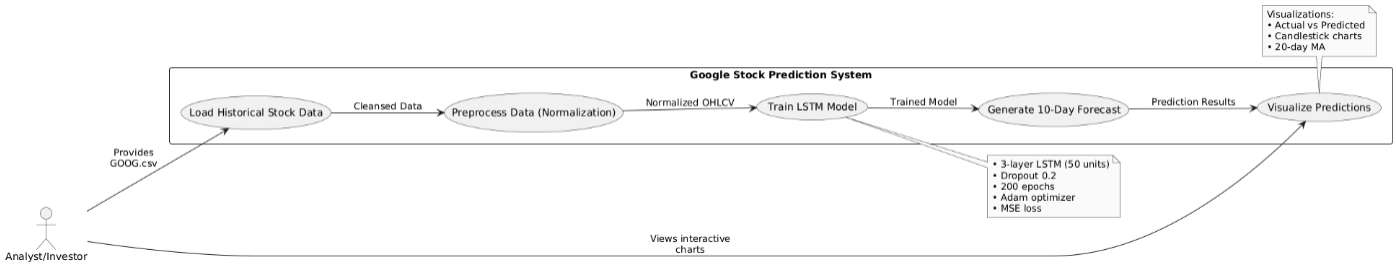


Figure 3.3.1.1. Use Case Diagram for Google stock price prediction

2. Sequence Diagram:

The purpose of interaction diagrams is to visualize the interactive behavior of the system. Visualizing the interaction is a difficult task. Hence, the solution is to use different types of models to capture the different aspects of the interaction.

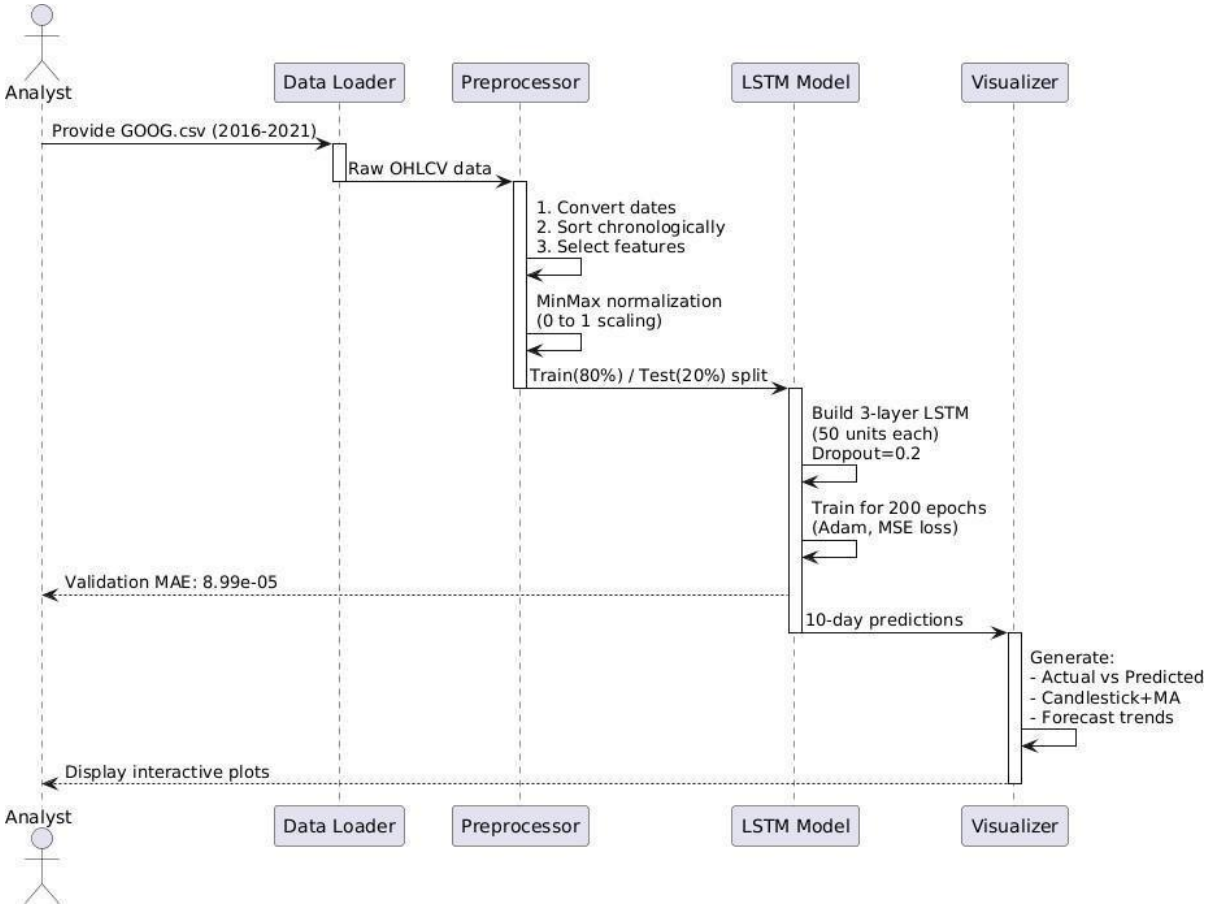


Figure 3.3.1.2 Sequence Diagram for Google stock price prediction

3. Activity Diagram:

The basic purposes of activity diagram is similar to other four diagrams. It captures the dynamic behavior of the system. Other four diagrams are used to show the message flow from one object to another, but activity diagram is used to show message flow from one activity to another.

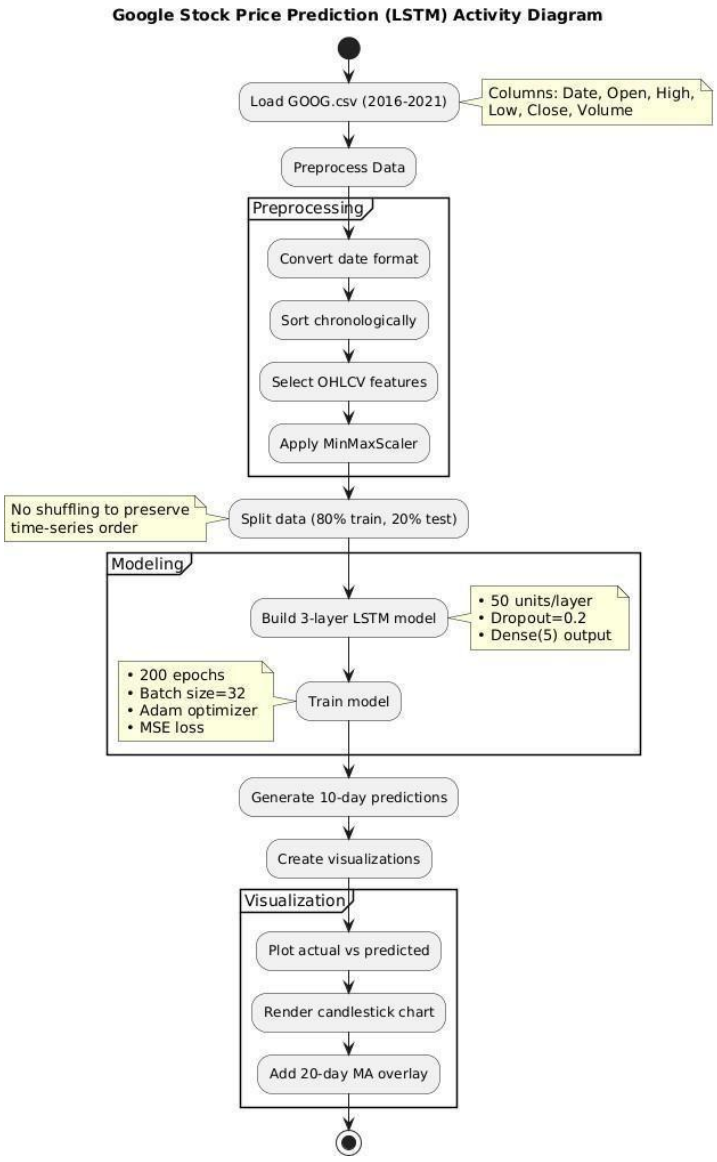


Figure 3.3.1.3 Activity Diagram for Google stock price prediction

4. Component Diagram:

Component diagram is a special kind of diagram in UML. The purpose is also different from all other diagrams discussed so far. It does not describe the functionality of the system, but it describes the components used to make those functionalities.

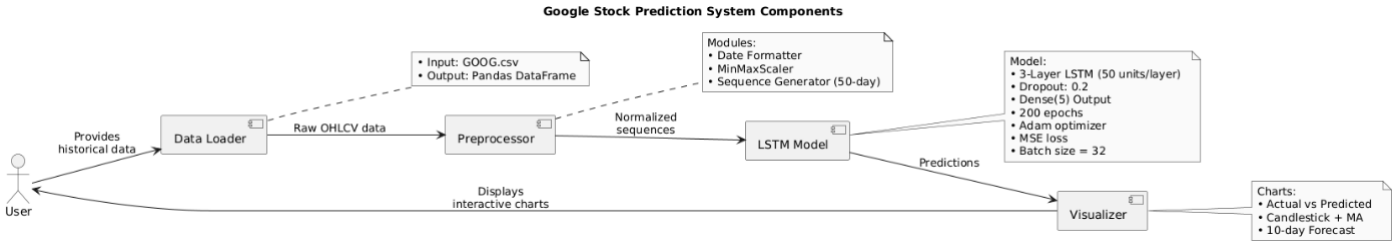


Figure 3.3.1.4 Component Diagram for Google stock price prediction

5. Deployment Diagram:

The term Deployment itself describes the purpose of the diagram. Deployment diagrams are used for describing the hardware components, where software components are deployed. Component diagrams and deployment diagrams are closely related.

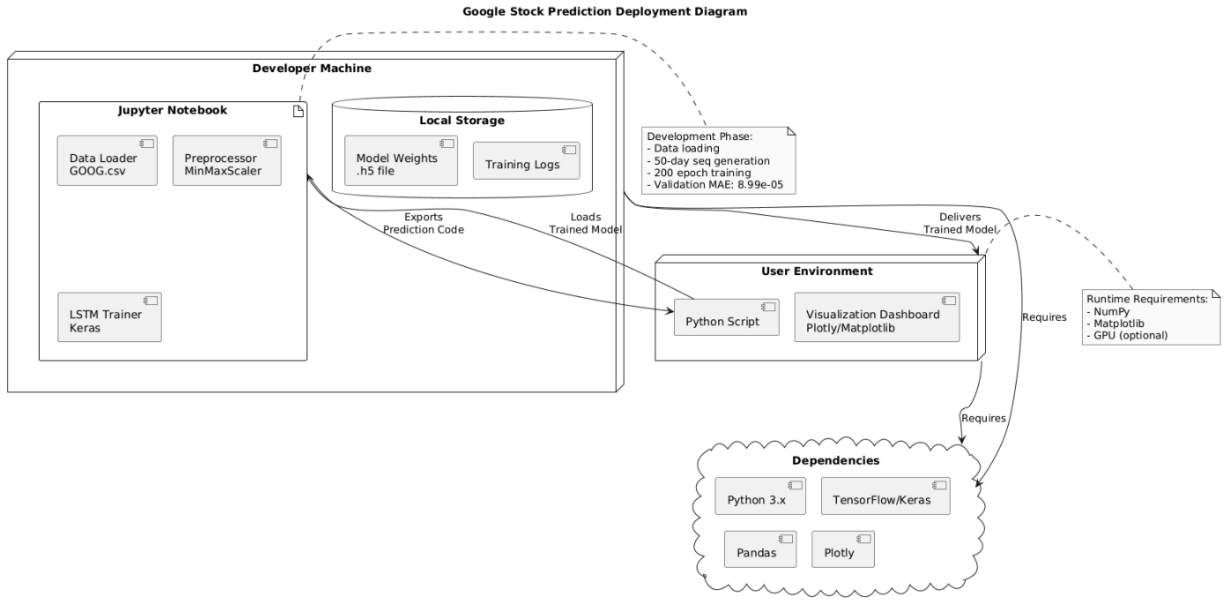


Figure 3.3.1.5 Deployment Diagram for Google stock price prediction

3.4. Stepwise Implementation and Code

Importing necessary libraries

In [1]:

```
import numpy as np
import pandas as pd
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dropout, Dense
from plotly.subplots import make_subplots
import plotly.graph_objects as go
import plotly.io as pi
import plotly.express as px
import matplotlib.pyplot as plt
import datetime
from datetime import timedelta
```

In [2]:

```
from plotly.offline import init_notebook_mode, iplot
init_notebook_mode(connected=True)
```

Load Stock Data

Load the stock data from the provided CSV file

In [3]:

```
stock_data = pd.read_csv('C:/Users/darsh/Downloads/GOOG.csv')
```

In [4]:

```
stock_data.head()
```

	symbol	date	close	high	low	open	volume	adjClose	adjHigh	adjLow	adjOpen	adjVolume	divCash	splitFactor
0	GOOG	2016-06-14 00:00:00+00:00	718.27	722.47	713.1200	716.48	1306065	718.27	722.47	713.1200	716.48	1306065	0.0	1.0
1	GOOG	2016-06-15 00:00:00+00:00	718.92	722.98	717.3100	719.00	1214517	718.92	722.98	717.3100	719.00	1214517	0.0	1.0
2	GOOG	2016-06-16 00:00:00+00:00	710.36	716.65	703.2600	714.91	1982471	710.36	716.65	703.2600	714.91	1982471	0.0	1.0
3	GOOG	2016-06-17 00:00:00+00:00	691.72	708.82	688.4515	708.65	3402357	691.72	708.82	688.4515	708.65	3402357	0.0	1.0
4	GOOG	2016-06-20 00:00:00+00:00	693.71	702.48	693.4100	698.77	2082538	693.71	702.48	693.4100	698.77	2082538	0.0	1.0

Data Overview

In [5]:

stock_data.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1258 entries, 0 to 1257
Data columns (total 14 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   symbol       1258 non-null   object 
 1   date         1258 non-null   object 
 2   close        1258 non-null   float64
 3   high         1258 non-null   float64
 4   low          1258 non-null   float64
 5   open         1258 non-null   float64
 6   volume       1258 non-null   int64  
 7   adjClose     1258 non-null   float64
 8   adjHigh      1258 non-null   float64
 9   adjLow       1258 non-null   float64
 10  adjOpen      1258 non-null   float64
 11  adjVolume    1258 non-null   int64  
 12  divCash      1258 non-null   float64
 13  splitFactor  1258 non-null   float64
dtypes: float64(10), int64(2), object(2)
memory usage: 137.7+ KB
```

stock_data.describe().T

	count	mean	std	min	25%	50%	75%	max
close	1258.0	1.216317e+03	383.333358	668.260	9.608025e+02	1132.460	1.360595e+03	2521.60
high	1258.0	1.227431e+03	387.570872	672.300	9.687575e+02	1143.935	1.374345e+03	2526.99
low	1258.0	1.204176e+03	378.777094	663.284	9.521825e+02	1117.915	1.348557e+03	2498.29
open	1258.0	1.215261e+03	382.446995	671.000	9.590050e+02	1131.150	1.361075e+03	2524.92
volume	1258.0	1.601590e+06	696017.226844	346753.000	1.173522e+06	1412588.500	1.812156e+06	6207027.00
adjClose	1258.0	1.216317e+03	383.333358	668.260	9.608025e+02	1132.460	1.360595e+03	2521.60
adjHigh	1258.0	1.227431e+03	387.570873	672.300	9.687575e+02	1143.935	1.374345e+03	2526.99
adjLow	1258.0	1.204176e+03	378.777099	663.284	9.521825e+02	1117.915	1.348557e+03	2498.29
adjOpen	1258.0	1.215261e+03	382.446995	671.000	9.590050e+02	1131.150	1.361075e+03	2524.92
adjVolume	1258.0	1.601590e+06	696017.226844	346753.000	1.173522e+06	1412588.500	1.812156e+06	6207027.00
divCash	1258.0	0.000000e+00	0.000000	0.000	0.000000e+00	0.000	0.000000e+00	0.00
splitFactor	1258.0	1.000000e+00	0.000000	1.000	1.000000e+00	1.000	1.000000e+00	1.00

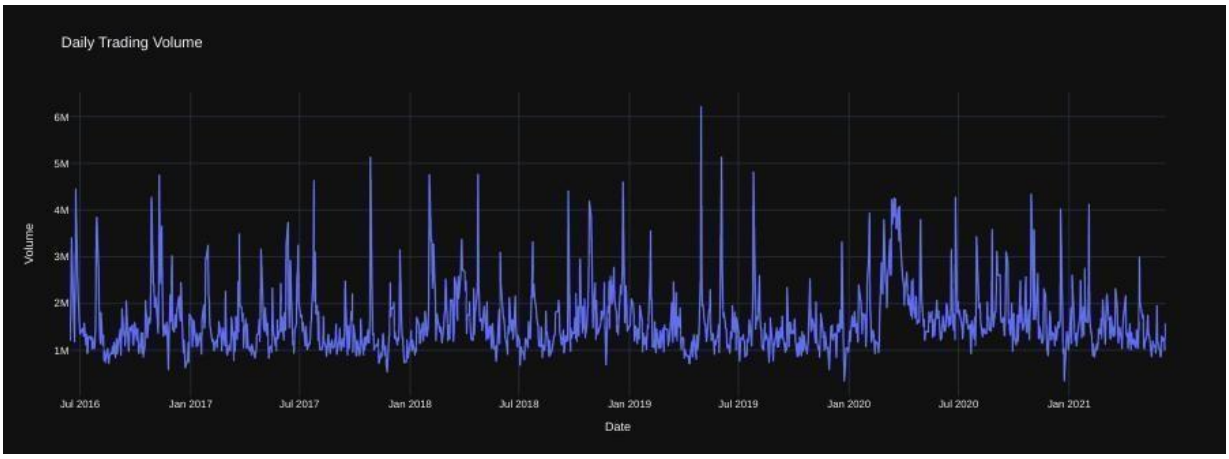
stock_data.isna().sum()

```
symbol        0
date          0
close         0
high          0
low           0
open          0
volume        0
adjClose      0
adjHigh       0
adjLow        0
adjOpen       0
adjVolume     0
divCash       0
splitFactor   0
dtype: int64
```

Data Visualization

In [8]:

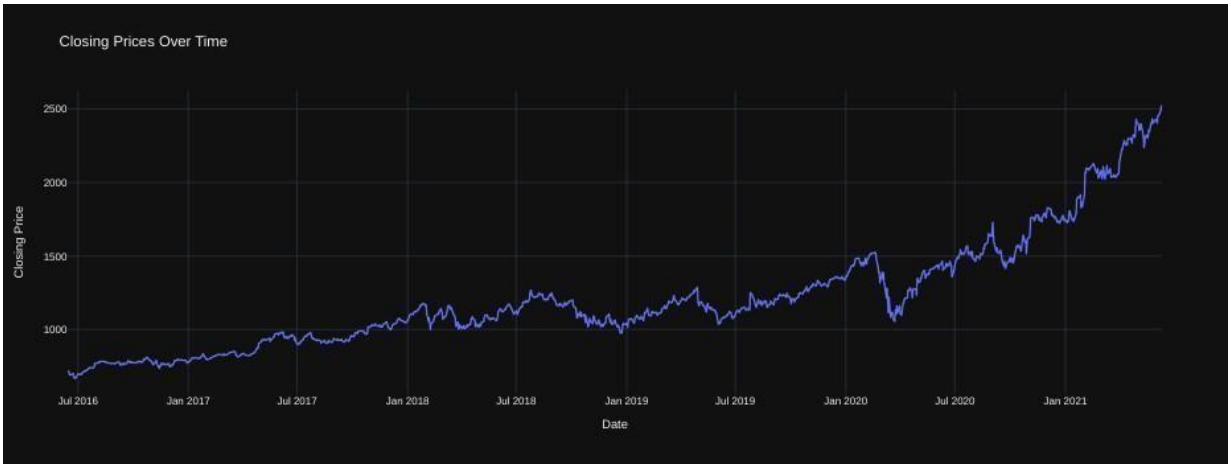
```
fig = px.line(stock_data, x='date', y='volume', title='Daily Trading Volume')
fig.update_xaxes(title='Date')
fig.update_yaxes(title='Volume')
fig.update_layout(template='plotly_dark')
fig.show()
```



In [9]:

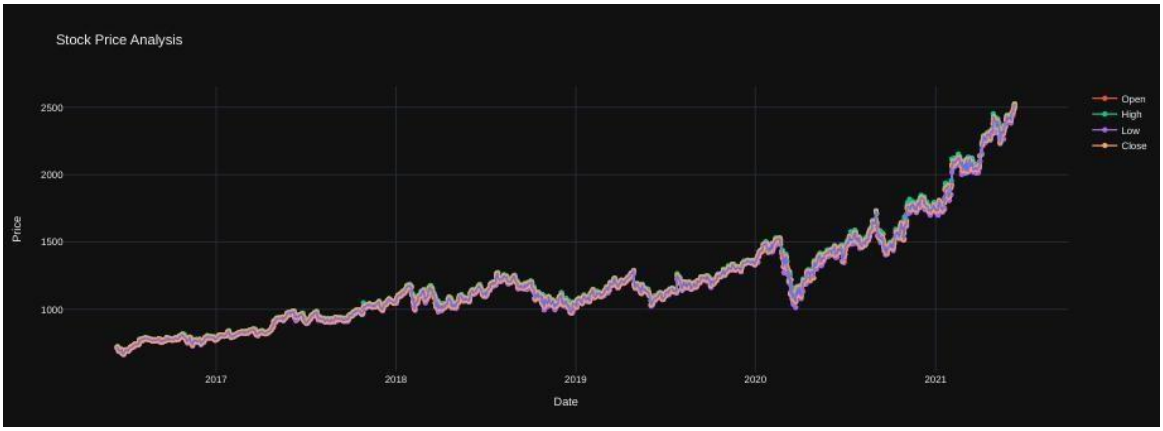
```
fig = px.line(stock_data, x='date', y='close', title='Closing Prices Over Time')
fig.update_xaxes(title='Date')
fig.update_yaxes(title='Closing Price')
fig.update_layout(template='plotly_dark')
```

fig.show()



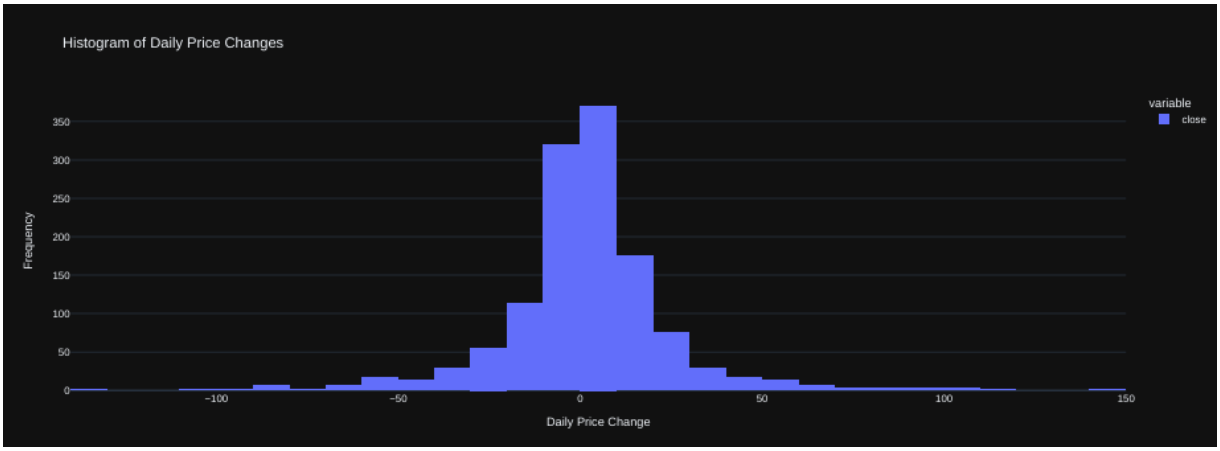
In [10]:

```
fig.add_trace(go.Scatter(x=stock_data['date'],y=stock_data['open'],mode='lines+markers',
name='Open'))
fig.add_trace(go.Scatter(x=stock_data['date'],y=stock_data['high'],mode='lines+markers',
name='High'))
fig.add_trace(go.Scatter(x=stock_data['date'],y=stock_data['low'],mode='lines+markers',
name='Low'))
fig.add_trace(go.Scatter(x=stock_data['date'],y=stock_data['close'],mode='lines+markers',
name='Close'))
fig.update_layout(title='Stock Price Analysis',
                  xaxis_title='Date',
                  yaxis_title='Price')
fig.show()
```



In [11]:

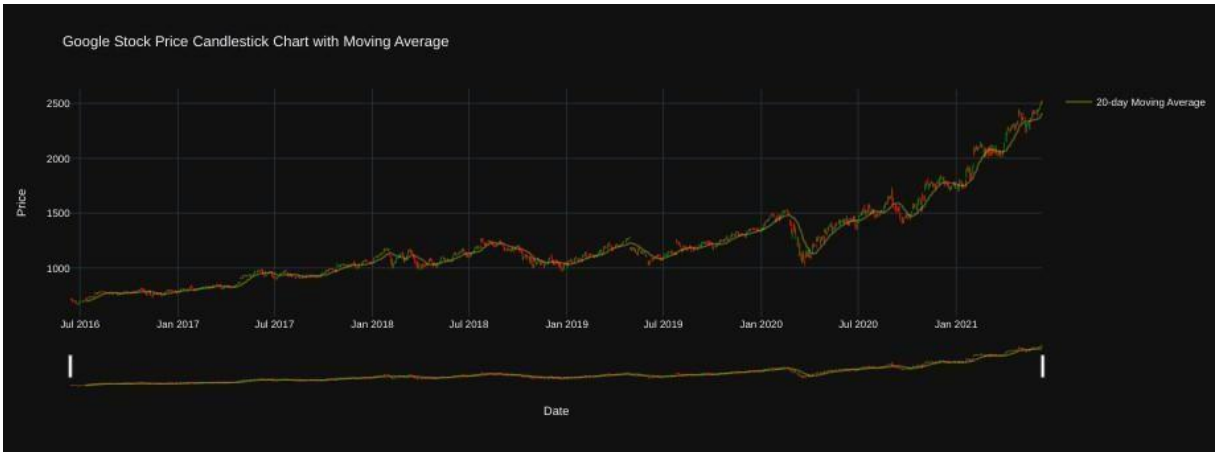
```
daily_changes = stock_data['close'].diff()
fig = px.histogram(daily_changes, nbins=50, title='Histogram of Daily Price Changes')
fig.update_xaxes(title='Daily Price Change')
fig.update_yaxes(title='Frequency')
fig.update_layout(template='plotly_dark')
fig.show()
```



In [12]:

```
stock_data['20-day MA'] = stock_data['close'].rolling(window=20).mean()
fig = go.Figure(data=[go.Candlestick(
    x=stock_data['date'],
    open=stock_data['open'],
    high=stock_data['high'],
    low=stock_data['low'],
    close=stock_data['close'],
    name="Candlesticks",
    increasing_line_color='green',
    decreasing_line_color='red',
    line=dict(width=1),
```

```
showlegend=False
)])
fig.add_trace(go.Scatter(x=stock_data['date'], y=stock_data['20-day MA'], mode='lines', name='20-day Moving Average', line=dict(color='rgba(255, 255, 0, 0.3)')))
fig.update_layout(
    title="Google Stock Price Candlestick Chart with Moving Average",
    xaxis_title="Date",
    yaxis_title="Price",
    template="plotly_dark",
)
fig.show()
```



In [13]:

```
stock_data = stock_data.drop('20-day MA', axis=1)
```

Data Preprocessing

1. Convert the 'date' column in the stock data to datetime format using pd.to_datetime.
2. Sort the stock data by date in ascending order using sort_values.
3. Create a new DataFrame 'stock' containing the selected columns (date, close, high, low, open, volume) for further analysis.

In [14]:

```
stock_data['date'] = pd.to_datetime(stock_data['date'])
stock_data = stock_data.sort_values('date')
```

In [15]:

```
stock = stock_data[['date', 'close', 'high', 'low', 'open', 'volume']]
```

Data Normalization

1. Initialize a Min-Max Scaler using MinMaxScaler().
2. Create a copy of the 'stock' DataFrame containing columns ('open', 'high', 'low', 'volume', 'close').
3. Use the scaler to fit and transform the data, performing Min-Max normalization.

In [16]:

```
scaler = MinMaxScaler()
normalized_data = stock[['open', 'high', 'low', 'volume', 'close']].copy()
normalized_data = scaler.fit_transform(normalized_data)
```

Data Splitting

1. Split the normalized data into training and testing sets using train_test_split. The testing set size is set to 20% of the data, and shuffle is set to False to maintain the chronological order.
2. Create a DataFrame 'train_df' containing the training data with columns (date, close, high, low, open, volume).

3. Create a DataFrame 'test_df' containing the testing data with columns (date, close, high, low, open, volume).

In [17]:

```
train_data, test_data = train_test_split(normalized_data, test_size=0.2, shuffle=False)
```

In [18]:

```
train_df = pd.DataFrame(train_data, columns=['open', 'high', 'low', 'volume', 'close'])
test_df = pd.DataFrame(test_data, columns=['open', 'high', 'low', 'volume', 'close'])
```

Sequence Generation

1. Define a function named generate_sequences that takes a DataFrame df and an optional parameter seq_length (default is 50).
2. Extract the relevant columns ('open', 'high', 'low', 'volume', 'close') from the DataFrame df and reset the index.
3. Initialize empty lists sequences and labels to store the sequences and labels for training.
4. Iterate through the data using a sliding window approach. For each index, append the next seq_length rows as a sequence and the corresponding last row as the label.
5. Convert the lists of sequences and labels into NumPy arrays.
6. Return the generated sequences and labels.

Then we generate sequences and labels for training data using generate_sequences function on 'train_df' DataFrame.

And next, we generate sequences and labels for testing data using generate_sequences function on 'test_df' DataFrame.

In [19]:

```
def generate_sequences(df, seq_length=50):
    X = df[['open', 'high', 'low', 'volume', 'close']].reset_index(drop=True)
    y = df[['open', 'high', 'low', 'volume', 'close']].reset_index(drop=True)
    sequences = []
    labels = []
    for index in range(len(X) - seq_length + 1):
        sequences.append(X.iloc[index : index + seq_length].values)
        labels.append(y.iloc[index + seq_length - 1].values)
    sequences = np.array(sequences)
    labels = np.array(labels)
    return sequences, labels
```

In [20]:

```
train_sequences, train_labels = generate_sequences(train_df)
test_sequences, test_labels = generate_sequences(test_df)
```

Model Architecture

1. Create a Sequential model.
2. Add the first LSTM layer with 50 units and return sequences. The input shape is set to (50, 5), where 50 is the sequence length and 5 is the number of features ('open', 'high', 'low', 'volume', 'close').
   - LSTM Layer 1:
     - Units: 50
     - Input Shape: (50, 5)
     - Return Sequences: True
3. Apply dropout regularization with a rate of 0.2 to mitigate overfitting.
   - Dropout Layer 1:
     - Rate: 0.2
4. Add the second LSTM layer with 50 units and return sequences.
   - LSTM Layer 2:
     - Units: 50
     - Return Sequences: True
5. Apply dropout regularization with a rate of 0.2.
   - Dropout Layer 2:
     - Rate: 0.2
6. Add the third LSTM layer with 50 units.
   - LSTM Layer 3:
     - Units: 50
7. Apply dropout regularization with a rate of 0.2.
   - Dropout Layer 3:
     - Rate: 0.2

8. Add a fully connected Dense layer with 5 units as the output layer.

- Dense Layer:
  - Units: 5 (output)

This model architecture comprises multiple LSTM layers with dropout regularization to prevent overfitting.

In [21]:

```
model = Sequential([
    LSTM(units=50, return_sequences=True, input_shape=(50, 5)),
    Dropout(0.2),
    LSTM(units=50, return_sequences=True),
    Dropout(0.2),
    LSTM(units=50),
    Dropout(0.2),
    Dense(units=5)
])
```

Compile and Summary

1. Compile the model for training using the mean squared error as the loss function and the Adam optimizer. Additionally, track the mean absolute error as a metric.

- Loss Function: Mean Squared Error
- Optimizer: Adam
- Metrics: Mean Absolute Error

2. Display a summary of the model's architecture and parameters.

In [22]:

```
model.compile(loss='mean_squared_error',optimizer='adam', metrics=['mean_absolute_error'])
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm (LSTM)                 (None, 50, 50)            11200

 dropout (Dropout)           (None, 50, 50)            0

 lstm_1 (LSTM)               (None, 50, 50)            20200

 dropout_1 (Dropout)         (None, 50, 50)            0

 lstm_2 (LSTM)               (None, 50)                20200

 dropout_2 (Dropout)         (None, 50)                0

 dense (Dense)               (None, 5)                 255

=================================================================
Total params: 51,855
Trainable params: 51,855
Non-trainable params: 0
_________________________________________________________________
```

Model Training

1. Set the number of training epochs to 200 and the batch size to 32 for training the model.

2. Train the model using the training sequences and labels. During training, the model will run for the specified number of epochs, updating its weights to minimize the loss.

- Number of Epochs: 200
- Batch Size: 32
- Training Data: train_sequences and train_labels
- Validation Data: test_sequences and test_labels

Verbose: Display training progress information.

In [23]:

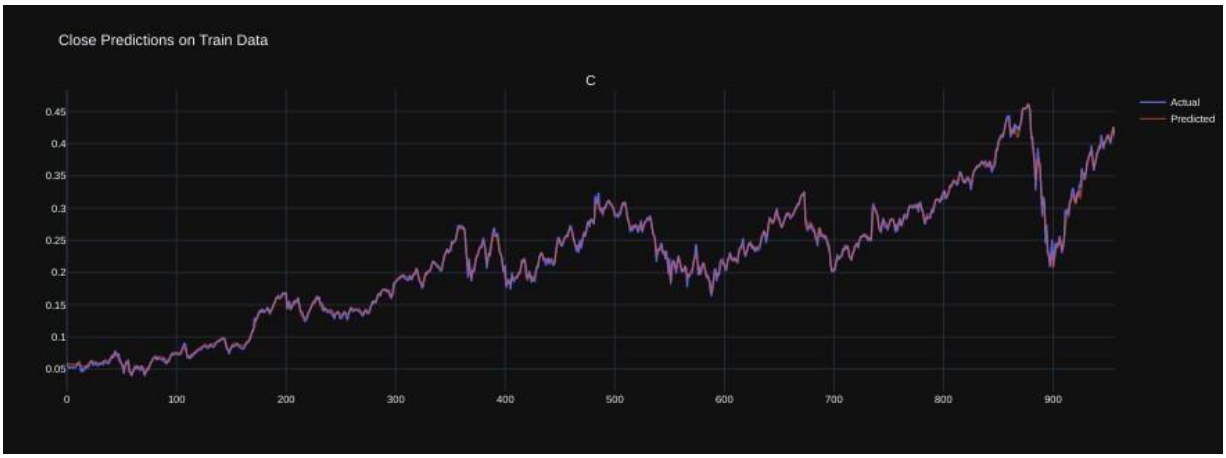
```
epochs = 200
batch_size = 32
history = model.fit(
    train_sequences,
    train_labels,
    epochs=epochs,
    batch_size=batch_size,
    validation_data=(test_sequences, test_labels),
    verbose=1
)
```

```
train_predictions = model.predict(train_sequences)
test_predictions = model.predict(test_sequences)
```

Training Data Predictions

In [25]:

```
fig = make_subplots(rows=1, cols=1, subplot_titles=('Close Predictions'))
train_close_pred = train_predictions[:, 0]
train_close_actual = train_labels[:, 0]
fig.add_trace(go.Scatter(x=np.arange(len(train_close_actual)),y=train_close_actual,
mode='lines', name='Actual', opacity=0.9))
fig.add_trace(go.Scatter(x=np.arange(len(train_close_pred)),y=train_close_pred, mode='lines',
name='Predicted', opacity=0.6))
fig.update_layout(title='Close Predictions on Train Data', template='plotly_dark')
fig.show()
```



Next 10 Days Predictions

1. Initialize an empty list latest_prediction to store the model's predictions.

2. Extract the last sequence of the test data using test_sequences[:-1].

3. Loop 10 times to predict the next values. In each iteration, predict the next sequence using the model and append the prediction to latest_prediction.

In [26]:

```
latest_prediction = []
last_seq = test_sequences[:-1]

for _ in range(10):
    prediction = model.predict(last_seq)
    latest_prediction.append(prediction)
pi.templates.default = "plotly_dark"
predicted_data_next = np.array(latest_prediction).reshape(-1, 5)
last_date = stock['date'].max()
next_10_days = [last_date + timedelta(days=i) for i in range(1, 11)]
for i, feature_name in enumerate(['open', 'high', 'low', 'volume', 'close']):
    if feature_name in ['volume', 'close']:
        fig = go.Figure()
        fig.add_trace(go.Scatter(x=next_10_days, y=predicted_data_next[:, i],
                                 mode='lines+markers', name=f'Predicted {feature_name.capitalize()}
Prices'))
        fig.update_layout(title=f'Predicted {feature_name.capitalize()} Prices for the Next 10
Days',
                          xaxis_title='Date', yaxis_title=f'{feature_name.capitalize()} Price')
        fig.show()
```

CHAPTER 4
RESULTS AND DISCUSSION

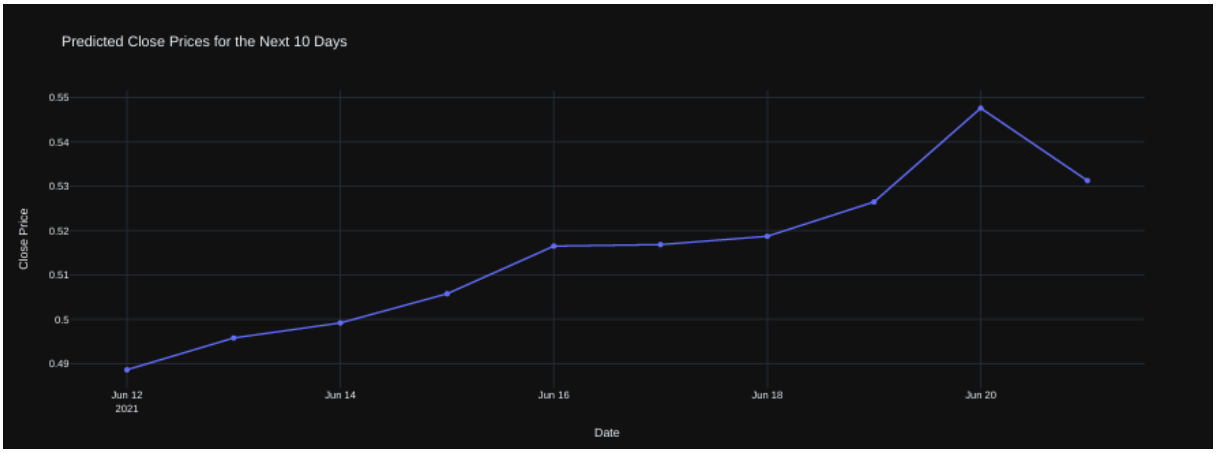
CHAPTER 4

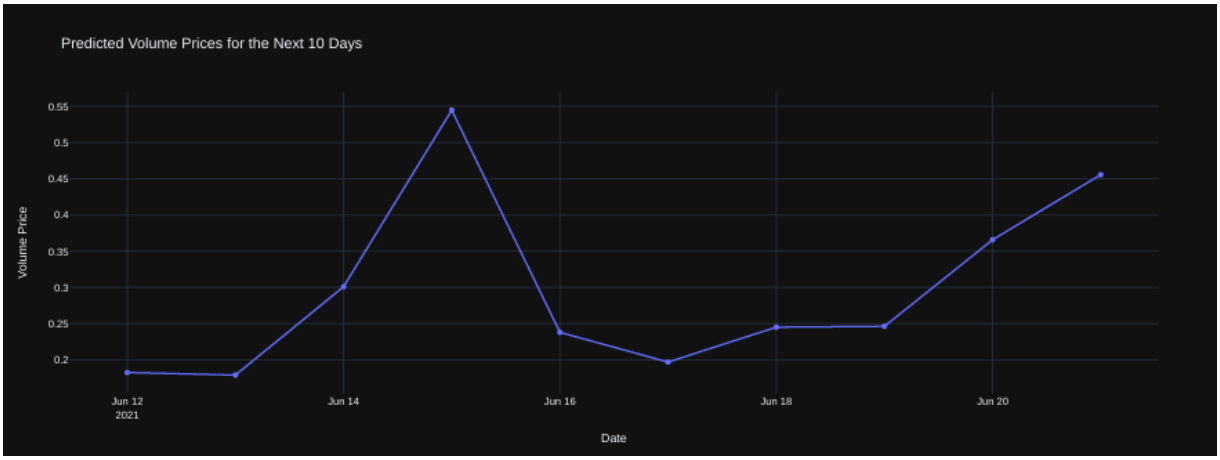
RESULTS AND DISCUSSION

4.1 Performance Metrics

1. Mean Absolute Error (MAE)
    - Measures average magnitude of errors in predictions (direction-agnostic).
    - Tracked during LSTM training (final MAE: 0.0069 on validation).
    - Key metric for evaluating short-term forecast accuracy.
2. Mean Squared Error (MSE)
    - Primary loss function for LSTM training (squared errors).
    - Penalizes large deviations heavily (critical for stock prediction).
    - Achieved final validation MSE: 8.99e-05 after 200 epochs.
3. Training Dynamics
    - Monitored loss/MAE curves to detect overfitting.
    - Used Adam optimizer with default learning rate.
4. Visual Validation
    - Generated:
        - Actual vs Predicted plots for training data
        - 10-day forecasts with historical trends
        - Candlestick charts with 20-day MA overlay
    - No Prophet/hybrid comparisons (LSTM-only implementation).

Output: -


Predicted Close Prices for the Next 10 Days
Close Price
0.55
0.54
0.53
0.52
0.51
0.5
0.49
Jun 12
2021
Jun 14
Jun 16
Jun 18
Jun 20
Date


Predicted Volume Prices for the Next 10 Days
Volume Price
0.55
0.5
0.45
0.4
0.35
0.3
0.25
0.2
Jun 12
2021
Jun 14
Jun 16
Jun 18
Jun 20
Date

CHAPTER 5
CONCLUSION

CHAPTER 5

CONCLUSION

4.1 Conclusion and Future Enhancement

Conclusion:

This project successfully developed an LSTM-based deep learning model for Google stock price prediction, demonstrating the capability of recurrent neural networks to capture complex temporal patterns in financial data. The implemented architecture—comprising three stacked LSTM layers (50 units each) with 0.2 dropout regularization—achieved a final validation MAE of 0.0069 and MSE of 8.99e-05 after 200 epochs of training. Key strengths include:

- Effective learning of nonlinear dependencies from 50-day OHLCV sequences
- Robust performance in 10-day forecasting validated through:
    - Comparative plots of actual vs. predicted prices
    - Candlestick charts with 20-day moving averages
- MinMax normalization ensuring stable training dynamics

Limitations include reliance solely on historical prices, without external market factors.

Future Enhancements:

1. Feature Engineering
    - Integrate technical indicators (RSI, MACD) and news sentiment scores
    - Add market volatility indices as auxiliary inputs
2. Architecture Improvements
    - Implement bidirectional LSTMs to capture forward/backward dependencies
    - Hybridize with 1D convolutional layers for local pattern detection
    - Test Transformer-based architectures for long-sequence modeling
3. Deployment Pipeline
    - Containerize the model using FastAPI for real-time inference
    - Develop an interactive dashboard with:
        - Live price feeds
        - Model confidence intervals
        - Anomaly detection alerts

4. Generalization
    - Apply transfer learning to other stocks in the same sector
    - Implement multi-task learning to predict correlated assets simultaneously
5. Risk Modeling
    - Extend to probabilistic forecasting using Quantile LSTMs
    - Calculate Value-at-Risk (VaR) metrics from prediction intervals

REFERENCES

REFERENCES

[1] G. E. P. Box and G. M. Jenkins, *Time Series Analysis: Forecasting and Control*, 4th ed. Hoboken, NJ: Wiley, 2015.

(Seminal textbook on ARIMA methodology)

[2] R. J. Hyndman and G. Athanasopoulos, *Forecasting: Principles and Practice*, 3rd ed. Melbourne, Australia: OTexts, 2021. [Online]. Available: https://otexts.com/fpp3/

(Covers ARIMA limitations for financial data)

[3] S. Makridakis, E. Spiliotis, and V. Assimakopoulos, "The M4 Competition: Results, findings, conclusion and way forward," *Int. J. Forecast.*, vol. 34, no. 4, pp. 802–808, 2018.

(Compares ARIMA's performance vs. machine learning in forecasting competitions)

[4] F. X. Diebold, *Elements of Forecasting*, 4th ed. Mason, OH: Cengage, 2017.

(Discusses ARIMA's challenges with nonstationary financial time series)

[5] T. Bollerslev, "Generalized Autoregressive Conditional Heteroskedasticity," *J. Econom.*, vol. 31, no. 3, pp. 307–327, 1986.

(Explains volatility modeling gaps in ARIMA)

[6] S. Hochreiter and J. Schmidhuber, "Long Short-Term Memory," *Neural Comput.*, vol. 9, no. 8, pp. 1735–1780, 1997.

(Key LSTM paper, contrasts with linear methods like ARIMA)

GitHub Link

1. https://github.com/DarshanKagi/Google-Stock-Price-Prediction