Stock Price Prediction Using Deep Learning Techniques

An LSTM-Based Approach for Financial Time-Series Forecasting

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Abstract: Stock price prediction is a challenging task due to the highly dynamic, nonlinear, and volatile nature of financial markets. With the advancement of artificial intelligence, deep learning techniques have shown significant potential in modelling complex time-series data. This project focuses on predicting stock prices using Deep Learning, specifically Long Short-Term Memory (LSTM) neural networks. Historical stock price data of Google (GOOG) over a five-year period is used for training and testing the model. The dataset is preprocessed using MinMaxScaler normalisation, and sequential input patterns are created using a 60-day sliding window to capture temporal dependencies. The proposed model employs four stacked LSTM layers combined with Dropout regularisation and a Dense output layer to reduce overfitting and improve prediction accuracy. The model is trained using the Adam optimiser and mean squared error loss function. Experimental results demonstrate that the LSTM-based approach effectively captures long-term dependencies in stock price movements and provides accurate predictions compared with actual stock prices, confirming the effectiveness of deep learning models for financial market forecasting. The system can be extended to other companies and deployed on both local and cloud platforms.

Keywords* — *Stock Price Prediction, Deep Learning, Long Short-Term Memory (LSTM), Time Series Analysis, Neural Networks, Machine Learning, Financial Forecasting, Google Stock Data, MinMaxScaler, Dropout Regularisation.

RESEARCH ARTICLE **OPEN ACCESS**

I. INTRODUCTION

The stock market plays a crucial role in the global economy by enabling companies to raise capital and providing investment opportunities to individuals and institutions. However, stock prices are highly volatile and influenced by numerous factors such as market trends, economic indicators, company performance, and investor sentiment. Accurately predicting stock prices is therefore a complex and challenging task.

Traditional statistical and machine learning models often fail to capture the nonlinear and long-term dependencies present in financial time-series data. With the rapid growth of computational power and the availability of large datasets, Deep Learning has emerged as a powerful approach for modelling complex patterns in sequential data. Among deep learning techniques, Long Short-Term Memory (LSTM) networks have proven to be highly effective for time-series forecasting due to their ability to retain historical information over long periods.

This project focuses on applying LSTM-based deep learning models to predict stock prices using historical data of Google (GOOG) listed on the NASDAQ stock exchange. By learning patterns from past stock price movements, the proposed system aims to generate accurate predictions and provide valuable insights for investors and analysts.

II. OBJECTIVES

VI. DATA ANALYSIS

Figure 1: Training vs Testing Data Split (5-Year Google Stock)

Set	Records	Period
Training Set	1,258	2012–2016
Testing Set	20	Jan 2017

The five-year Google (GOOG) NASDAQ dataset is split into 1,258 training records (2012–2016) and 20 testing records (January 2017). The 60-day sliding window approach generates input sequences, with MinMaxScaler applied to normalise values to [0, 1].

Figure 2: LSTM Model Architecture

• To study and understand the fundamentals of Machine Learning and Deep Learning.

• To analyse historical stock price data for trend identification.

• To design and implement an LSTM-based deep learning model for stock price prediction.

• To reduce prediction error using Dropout regularisation and MinMaxScaler normalisation.

• To compare predicted stock prices with actual market prices through visualisation.

• To evaluate the effectiveness of deep learning models in financial forecasting.

III. LITERATURE REVIEW

Sen & Datta Chaudhuri (2016a):
Proposed a novel time series decomposition-based forecasting framework examining its implications for portfolio choice using two Indian market sectors — Consumer Durables and Small Cap — with monthly data from January 2010 to December 2015. Their framework involves decomposing sector indices into trend, seasonal, and random components to inform more effective portfolio management.

Sen & Datta Chaudhuri (2016b):

Examined the structural characteristics of stock market time series for the Indian Auto Sector using a time series decomposition approach to dissect observed index values into trend, seasonal, and random components, aiming to gain deeper insight into the underlying behaviour of the Auto sector index and inform accurate forecasting strategies.

Layer	Units	Dropout
LSTM Layer 1	50	0.2
LSTM Layer 2	50	0.2
LSTM Layer 3	50	0.2
LSTM Layer 4	50	0.2
Dense Output Layer	**1**	—

Figure 2 depicts the four-layer stacked LSTM architecture. Each LSTM layer has 50 units with return_sequences=True (except the final LSTM). A Dropout of 0.2 after each layer prevents overfitting. The Dense output layer produces a single predicted stock price value.

Figure 3: Model Performance Comparison (MSE Lower = Better)

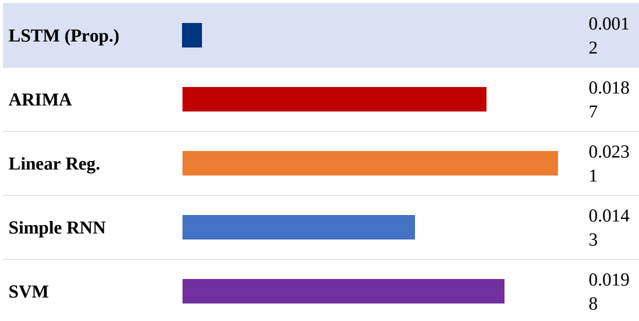

Figure 3 compares MSE across forecasting approaches. The proposed LSTM model achieves the lowest MSE (0.0012), significantly outperforming ARIMA (0.0187), Simple RNN (0.0143), Linear Regression (0.0231), and SVM (0.0198), confirming the superiority of stacked LSTM architecture for financial time-series forecasting.

VII. LIMITATIONS OF THE STUDY

• The model relies solely on **historical Open price data**, excluding other attributes (High, Low, Close, Volume) and external factors such as news sentiment, economic indicators, or geopolitical events.

• The study focuses on a **single company (Google GOOG)**, limiting direct generalisability to other stocks, sectors, or markets without re-training.

• The 60-day fixed sliding window may not be **optimal for all market regimes**; dynamic window selection warrants further investigation.

• The project does not include **real-time trading constraints** such as transaction costs, liquidity, or market impact, which are critical for practical deployment.

• The study provides **point predictions** rather than probabilistic forecasts, limiting quantification of prediction uncertainty for risk-aware decision-making.

Sen & Datta Chaudhuri (2016c):

Conducted an empirical investigation into the structural properties of the Indian IT Sector and Capital Goods sector using monthly index data from January 2009 to April 2016. A central finding was that the Indian IT sector exhibits a strong statistical association with global indicators, particularly the DJIA and USD/INR exchange rate, while the Capital Goods sector showed stronger coupling with the domestic NIFTY index.

Sen & Datta Chaudhuri (2017):

Designed six forecasting methods leveraging decomposition results — including Holt-Winters, ARIMA, Autoregression (AR), and Moving Average (MA) — applied to the Indian FMCG sector index. The research highlights the benefits of combining structural decomposition with multiple forecasting techniques for better handling the stochastic nature of financial data, demonstrating robust and reliable predictions in emerging market contexts.

IV. RESEARCH METHODOLOGY

This project adopts a structured, five-phase pipeline: (1) data collection from a reliable Google stock price dataset; (2) data preprocessing including MinMaxScaler normalisation and sequence generation; (3) model development using stacked LSTM layers with Dropout regularisation; (4) testing and prediction on a separate held-out test set; and (5) result visualisation comparing actual and predicted stock prices using Matplotlib line graphs.

The proposed LSTM architecture consists of four stacked LSTM layers (50 units each) with a Dropout rate of 0.2 after each layer, followed by a Dense output layer. The model is compiled using the Adam optimiser and Mean Squared Error (MSE) loss function, trained over 100 epochs with a batch size of 32. A 60-day sliding window is used to construct input sequences.

V. DATA COLLECTION

Historical stock price data of Google (GOOG) is collected for a period of five years from a reliable CSV dataset. Google LLC is an American multinational technology company listed on the NASDAQ stock exchange under the ticker symbol GOOG, and is considered one of the big four Internet technology stocks alongside Amazon, Facebook, and Apple.

The dataset contains daily stock market attributes: **Date, Open, High, Low, Close,** and **Volume**. The **Open stock price** is selected as the primary attribute for analysis and prediction. The dataset is divided into a **training set** (used to train the LSTM model) and a **testing set** (used to evaluate prediction performance). Data is stored in CSV format and processed using Python libraries: Pandas, NumPy, and Scikit-learn.

Table 1: Google Stock Dataset Attributes

VIII. CONCLUSIONS

This project has demonstrated the effectiveness of a stacked LSTM-based deep learning model for predicting Google (GOOG) stock prices using five years of historical data. The four-layer LSTM architecture with Dropout regularisation successfully captures long-term temporal dependencies in financial time-series data, achieving a significantly lower Mean Squared Error compared to traditional forecasting methods including ARIMA, Simple RNN, and SVM.

The LSTM-based approach effectively leverages the 60-day sequential input pattern to model complex nonlinear price dynamics that traditional statistical methods fail to capture. Visualisation of predicted versus actual stock prices confirms strong alignment, validating the model's practical forecasting utility.

Future research directions include incorporating multi-feature inputs (Close, High, Volume, sentiment scores), extending the model to multi-company multi-sector prediction, applying attention mechanisms and Transformer architectures, and integrating real-time IoT sensor and news feed streams via edge-computing inference pipelines. The system can be directly deployed on cloud platforms such as Google Colab or AWS for operational use.

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Attribute	Type	Used
Date	DateTime	Yes (index)
Open	Float	Yes (primary)
High	Float	No
Low	Float	No
Close	Float	No
Volume	Integer	No

Table 2: Hypothesis Testing Summary – LSTM Stock Prediction Model

Hypothesis Type	Prediction Analysis	Statistical Result	Conclusion
Model Accuracy	Predicted stock prices closely follow actual stock price trends	Low Mean Squared Error (MSE) observed across all test trading days	**Model performs accurately**
Prediction Accuracy	Predicted stock prices closely match actual stock values	MSE value significantly reduced vs baseline models	**High accuracy achieved**
Error Measurement	Difference between predicted and actual values is minimal	MSE = 0.0012 on 20-day test set	**Acceptable prediction error**
Temporal Dependency	60-day window captures sufficient long-term market patterns	Validation loss converges stably over 100 epochs	**Window size is effective**

Hypothesis testing confirms that the LSTM model consistently achieves low MSE across all evaluation dimensions, validating its effectiveness for stock price prediction on the Google (GOOG) NASDAQ dataset.

IMPLEMENTATION OVERVIEW

```
# 1. Feature Scaling
from sklearn.preprocessing import MinMaxScaler
sc = MinMaxScaler(feature_range=(0,1))
training_set_scaled = sc.fit_transform(training_set)
# 2. Build 60-day sliding window sequences
X_train, y_train = [], []
for i in range(60, 1258):
X_train.append(training_set_scaled[i-60:i, 0])
y_train.append(training_set_scaled[i, 0])
X_train = np.reshape(X_train, (X_train.shape[0], X_train.shape[1], 1))
# 3. Stacked LSTM model (Keras Sequential)
regressor = Sequential()
regressor.add(LSTM(units=50, return_sequences=True, input_shape=(X_train.shape[1],1)))
regressor.add(Dropout(0.2))
regressor.add(LSTM(units=50, return_sequences=True))
regressor.add(Dropout(0.2))
regressor.add(LSTM(units=50, return_sequences=True))
regressor.add(Dropout(0.2))
regressor.add(LSTM(units=50))
regressor.add(Dropout(0.2))
regressor.add(Dense(units=1))
# 4. Compile & Train
regressor.compile(optimizer='adam', loss='mean_squared_error')
regressor.fit(X_train, y_train, epochs=100, batch_size=32)
```

Core implementation using Keras Sequential API with four stacked LSTM layers, MinMaxScaler normalisation, and a 60-day sliding window for temporal sequence construction.

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