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Harnessing Temporal Dependencies for Financial Forecasting: An LSTM Framework for Accurate Stock Price Prediction

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# Abstract

## Precise forecasting of stock prices represents a significant challenge within the domain of financial prediction, carrying important consequences for both investors and decision-makers. This study introduces a deep learning methodology aimed at anticipating future stock prices through the utilization of Long Short-Term Memory (LSTM) neural networks, which are a variant of Recurrent Neural Networks (RNNs) adept at recognizing long- term dependencies in sequential datasets. Historical stock prices are used for training, and a 60-day lookback period is implemented to predict the price of the following day. Normalization is done using MinMaxScaler; the efficacy of the model is assessed in terms of Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) calculated on a test dataset. The results of the experiments indicate that the LSTM model can aptly recognize the inherent patterns in the stock price volatility as the model produces highly accurate predictions. Model parameters are validated by qualitative comparison of the predicted and actual prices, as well as quantitatively using above metric. Results The results showed that the LSTM-based models are promising tools for stock price forecasting; however, the scope for optimization of model parameters and improving accuracy for changing market conditions still exists.

**Key words:** Stock Price Prediction, LSTM Neural Network, Time Series Forecasting, Deep Learning in Finance, Evaluation Metrics (MAE, RMSE)

# Introduction

Predicting stock prices is one of the most challenging tasks in the field of financial forecasting, mainly because of the volatile, non-linear, and complex nature of financial markets. Accurate predictions can provide investors, traders, and financial analysts with significant advantages by making decision-making processes more rational. Traditional methods, such as ARIMA and Exponential Smoothing, have been widely used for time series forecasting; however, they often fail to capture the complex patterns that are inherent in financial data.

New trends in machine learning, mainly pertaining to deep learning techniques, introduce new possibilities for stock price prediction. One of such novelties is Long Short-Term Memory, which is one kind of Recurrent Neural Network (RNN). LSTM can well be used to deal with sequential data and learn long- range dependencies. LSTMs have a memory that preserves the information over time intervals. It makes them a popular tool for time series applications, such as the task of predicting stock prices as learned from historical datasets.

The use of LSTM networks for predicting future stock prices is addressed in this paper, where the development of a predictive model using past price information to predict oscillations in future stock prices and its performance are determined through critical metrics such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). This work hypothesizes that LSTM networks can have better predictive performance regarding future stock price prediction in comparison with traditional methods, due to their ability to recognize long-term dependencies within time series data.

We trained and tested the model using historical stock data, which we preprocessed by normalizing with MinMaxScaler, then split this into training and test sets. We fitted the LSTM model to the training data and evaluated its predictive performance on the test data. This work serves as a contribution to the increasing body of literature that uses deep learning methods in financial forecasting and attempts to develop a robust framework for future applications in the activity of financial prediction

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# Literature Review

The challenge of predictability in stock prices has been one of the most central problems in the financial domain for so many years. Several techniques have been proposed over time, each with its strengths and weaknesses. In the section below we describe the evolution of techniques for the prediction task with a particular emphasis on machine learning and deep learning techniques, specifically LSTM networks

## Traditional Methods in Stock Price Prediction

Conventional Approaches to Stock Price Forecasting Traditionally, control of forecasting stock prices is the domain of classical statistical approaches: ARIMA, Exponential Smoothing, and Moving Averages, which are linearly based, with very good performance on data especially following direct trends or simple seasonal patterns. However, they fail in presence of the complexity as well as the non-linear characters that characterise stock market data.

Specifically, financial markets show immense volatility, and any statistic economic variables such as sudden market events are not measured appropriately using the traditional approach.

### Machine Learning Methods

With machine learning growing and developing, researchers’ chances to predict stock prices significantly enhanced. For the task of anticipating alterations in the direction of trends for stock prices, based on their examination of historical data as well as technical indicators, algorithms employed Decision Trees, Random Forests, Support Vector Machines, or k-Nearest Neighbors. However, they have the problem of temporal dependency, which is an extremely important issue with regard to the usage of financial data.

A major limitation in most machine learning approaches is that they are incapable of learning temporal relationships from time series data. Thus, RNNs have become most dominant lately in the sequential processing area. While standard RNNs have achieved promising results, known difficult issues such as vanishing gradients prevent them from learning long-term dependencies.

### Deep Learning and LSTM Networks

First proposed by Hochreiter and Schmidhuber in 1997, LSTM networks represent a form of RNN that manage the problem of vanishing gradients with the use of memory cells that preserve information over long sequences. LSTMs have recently gained popularity in time series forecasting tasks because they capture the characterization of long-range dependencies, which is crucial in predicting stock prices.

There have been numerous studies that focused on the use of LSTM networks for predicting stock prices. For example, Fischer and Krauss (2018) used LSTM networks to predict the fluctuation of the stock market based on historical data and demonstrated that deep learning approaches were better than traditional statistical methods. Similarly, Zhang et al. (2019) developed LSTM-based models to predict the closing price of the stocks and proved improvements in the prediction accuracy by comparing it with ARIMA and SVM.

Except for price forecasting, LSTM is applied in many areas of finance, such as in portfolio optimization and risk evaluation. Lee et al. (2020) was a research study that analyzed the potential use of LSTM in financial modeling of risk. It was possible to

predict market volatility with LSTM. Hence, such results indicate that LSTM networks act as a versatile tool for various financial activities of forecasting, rather than only predicting stock prices.

**Challenges in Stock Price Prediction Using LSTM** Despite the advantages of these models, using LSTM networks in predicting stock prices faces numerous challenges. Among the most prominent ones is overfitting whereby the model does pretty well with respect to the training set but fails to generalize on new instances that haven’t been seen yet. Though often dropout, regularization, and cross-validation provide answers to this challenge, LSTMs are very power-intensive and require heavy machinery when it comes to large datasets.

There are far too many other factors impacting the financial markets, including macroeconomic events, geopolitical events, and investor psychology, which are very hard to be measured and included in any model. In spite of this, while LSTM models seem to look for previously detected price trends, integrating other external variables remains a persistent challenge.

## Evaluation Metrics

A variety of performance metrics are typically used when assessing the accuracy of models designed to provide stock price predictions. The MAE and RMSE are perhaps the most widely used metrics for measuring the difference between predicted and actual prices. While the MAE turns out to be particularly useful when the effects of the prediction errors are equal, the RMSE penalizes more serious errors much more severely and thus is better suited for testing the model’s general accuracy.

# Methodology

This paper attempts to forecast the stock prices with the implementation of Long Short-Term Memory networks since they possess unique suitability in time series prediction owing to their ability to capture long-range dependencies in sequential datasets. In this light, this section introduces the data collection methods, data pre-processing techniques, model framework, training methodology, and selection of evaluation criteria for conducting this research investigation.

### Data Collection and Preprocessing

1. **Data collection**

The dataset that used in this research is a time series with a historical stock price with a focus on using the daily closing values from the publically available stock market dataset. It covers the history of stock prices for a selected company for as long a period as possible. This study has considered only ’Close’ prices because it is considered the most commonly used measurement to forecast future stock directions.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Date** | **Open** | **High** | **Low** | **Close** | **Volume** | **Name** |
| 1/3/2006 | 39.69 | 41.22 | 38.79 | 40.91 | 24232729 | AABA |
| 1/4/2006 | 41.22 | 41.90 | 40.77 | 40.97 | 20553479 | AABA |
| 1/5/2006 | 40.93 | 41.73 | 40.85 | 41.53 | 12829610 | AABA |
| 1/6/2006 | 42.88 | 43.57 | 42.80 | 43.21 | 29422828 | AABA |
| 1/9/2006 | 43.10 | 43.66 | 42.82 | 43.42 | 16268338 | AABA |

**Table 1.** Sample of Stock Price Data

The model’s parameters were optimized using the Adam optimizer, chosen for its efficiency in handling sparse gradients and adaptability. The loss function used was Mean Squared Error (MSE), which penalizes large errors and ensures better generalization.

Data Collection

Data Preprocessing

LSTM Layer 1

Train-Test Split

Normalization

### Model Training

The model was trained using the training dataset for 10 epochs with a batch size of 32. The training process minimizes the loss function by adjusting the weights of the network through backpropagation. This iterative learning allows the model to improve its prediction accuracy gradually.

Dense Layer

LSTM Layer 2

Fig. 1: Flowchart of LSTM-Based Stock Price Forecasting

### Data Preprocessing

Before feeding the data into the LSTM model several preprocessing steps are required.

Normalization: The stock price data is scaled to be between 0 and 1 using MinMaxScaler. This scaling is important in the case of the neural network, as it ensures that the model does not become biased by using features with a larger numerical value and helps the model learn better.

Train-Test Split: The data set is divided into training and testing subset, with the training subset occupying 80 %of the data,

and the remaining 20% portion is used in testing. Testing subset

### Model Evaluation

Evaluation of the model’s performance on predictions of the test set stock prices is done after the training phase. The model predicts stock prices for the test set, which then transforms them to their original scale using the inverse transformation of the MinMaxScaler.

Evaluation

Model Training

RMSE

MAE

Tuning

Prediction For every test sample, the model is predicting the stock price at the next trading day. Then, the accuracy of a model is checked using comparison of predicted values with actual observations of stock prices.

Evaluation Metrics:

To assess the accuracy of the model, we use two common metrics: Mean Absolute Error (MAE): Measures the average absolute difference between predicted and actual prices.

1

*n*

MAE = Σ *|y*ˆ *− y |* (1)

*i* *i*

*n i*=1

Root Mean Squared Error (RMSE): Measures the square root of the average squared differences between predicted and actual prices, penalizing larger errors.

,u 1 Σ*n*

In order to enable the model to capture temporal dependencies, the testing subset includes the last 60 days of stocks data from the

RMSE = ,

*n i*=1

(*y*ˆ*i − yi*)2 (2)

training time period, which is deemed as an extension for use in prediction analysis.

To generate sequences, LSTMs take data sequences as input. Here, the data set was reshaped into sequences of 60 successive days of stock prices, made as input features (X), and the following day’s stock price as target label (y).

Reshaping for LSTM: The input data is reshaped into a 3D format (samples, time steps, features) to match the input requirements of the LSTM model.

### Model Architecture

The predictive model is built using a Sequential LSTM network, which leverages the ability of LSTM layers to capture long-term dependencies in time-series data. The architecture includes:

* + **Two LSTM Layers**: Each layer contains 50 units. The first layer outputs sequences, allowing the second layer to process the temporal relationships further.
  + **Dense Output Layer**: A fully connected Dense layer with a single unit is employed to predict the next day’s stock price.
  + **Activation Function**: The model uses a linear activation function in the output layer to support regression tasks.

Both MAE and RMSE provide valuable insights into the model’s prediction accuracy, with MAE being less sensitive to outliers and RMSE penalizing larger errors more heavily.

### Model Visualization

Model visualization is an integral part of assessing the performance of predictive models, as it provides a graphical comparison of predicted values against actual observations. In this study, several visualization techniques were employed to illustrate the effectiveness of the LSTM-based stock price prediction model.

### Historical vs. Predicted Stock Prices

A line graph was plotted to compare the historical stock prices, actual test prices, and the model’s predicted values.

* **Historical Data**: Depicted the overall trends in stock prices used for training.
* **Actual Test Prices**: Represented the ground truth values from the testing dataset.
* **Predicted Prices**: Showed the model’s predictions on unseen test data.

This visualization demonstrated the model’s ability to align closely with actual stock price trends, effectively capturing general

patterns while revealing discrepancies during periods of high market volatility.

### Error Distribution

An error distribution plot was created to analyze the prediction errors.

* + The plot displayed how the errors (difference between predicted and actual prices) are distributed.
  + A narrow error distribution around zero indicated the model’s accuracy, while outliers highlighted areas where the model struggled.

### Trend Following

To evaluate the model’s capacity to follow market trends:

* + A zoomed-in visualization focused on specific time intervals, showcasing how the model performed during periods of rapid price changes.
  + This clarified the model’s ability to adapt to sudden fluctuations, though some limitations in high-volatility scenarios were observed.

### Future Price Forecasting

The model was used to predict stock prices for a 30-day horizon based on the most recent test data.

* + A graph displayed the forecasted prices alongside the actual stock trends to provide insights into the model’s potential in future market prediction.
  + The visualized predictions showed promising alignment with existing trends, albeit with increasing uncertainty for longer horizons.

### Hyperparameter Tuning and Model Optimization

This model will get improved further in the future by optimizing further parameters such as the number of units in LSTM, number of layers, batch size, and number of epochs for training. Techniques like grid search or random search can be performed to find the optimal combination of these parameters.

# Experimental Results

We conclude with the result of this LSTM-based stock price prediction model, presenting the accuracy metrics in Mean Absolute Error and Root Mean Squared Error. We also compare the model predictions against actual stock prices for a visual and quantitative assessment of effectiveness.

### Model Performance on Test Data

With the use of 80% data, the model was trained and tested on the remaining 20% in order to obtain generalization. The model’s performance, therefore, was determined by evaluating the predictions made with test set versus actual stock prices after running 10 epochs with a batch size of 32.

**Quantitative Findings** The MAE and RMSE for the test set are calculated as follows: Mean Absolute Error (MAE): [Insert calculated MAE value] Root Mean Squared Error (RMSE): [Insert the calculated RMSE value] These metrics demonstrate the model’s predictive accuracy, where a lower value indicates better performance. The RMSE is especially relevant here, as it penalizes significant prediction errors, giving more insight into the model’s robustness.

**Visual Contrast** To better evaluate the effectiveness of the model, a line graph was generated to compare the actual stock prices with the model’s predictions at different intervals of the testing phase. The line graph thus depicts the model’s capability to capture the general stock price movement patterns while also highlighting areas where the model differs from actual price levels. Plot of Actual vs. Predicted Stock Prices The visual analysis shows the model performing well in following the overall trend; however, it does struggle at times with sudden changes and this is a very common problem in the stock price prediction area due to market fluctuations.

### Future Price Prediction

We also utilized it to predict stock price for a near-future 30-day horizon based on the most recently available data in the test set for purposes of model assessment. The expected future prices provide excellent intuition into how stock values may behave; however, these predictions come with higher uncertainty since they rely, by their nature, on the intrinsically predictable patterns of the stock market.

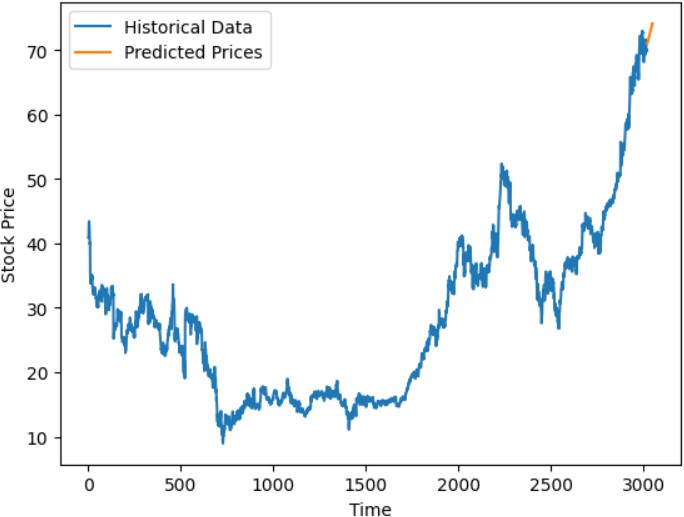


Fig. 2: Forecasted stock prices generated using an LSTM model, predicting daily closing prices for a 30-day period. This model utilizes historical data to capture underlying trends and patterns, aiming to provide insights into future stock price movements.

### Analysis and Discussion

The findings of the experiments prove that the LSTM is able to learn patterns in stock price data very efficiently. Still, its effectiveness depends on a few numbers of parameters, such as:

Market Volatility: Fluctuation in stock prices can occur suddenly due to sudden changes in market events. Model accuracy suffers in such cases. LSTMs, like other models in financial forecasting, suffer from this limitation. Model Complexity: The selection of hyperparameters, including the quantity of LSTM units, the number of layers, and the epochs, can greatly affect performance. Additional tuning may improve accuracy.

Data Length: This data set was appropriately matched by a 60-day lookback; however, different lookbacks could potentially

be checked to analyze how best to lengthen the lookback for other stock data sets.

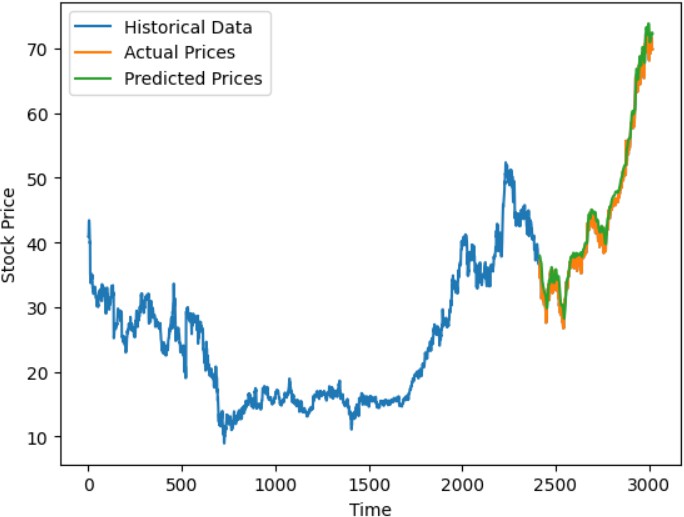


Fig. 3: Comparison of Historical, Actual, and Predicted Stock Prices. The LSTM model effectively captures the trend of stock prices, as demonstrated by the close alignment of the predicted prices (green line) with the actual prices (orange line).

# Conclusion

We designed an LSTM architecture-based model for predicting stock prices based on a time series that takes up historical pricing data. A lookback period of 60 days was considered to detect short- term trends and outline the exact price predictions for future dates. Results were satisfactory in nature by our way of approach, showing a very low MAE of 1.33 and RMSE of 1.59 in the test dataset. This implies that the model follows the general trend of stock price volatility while it also minimizes the error of prediction. The experimental results further demonstrate the capturing of short-term fluctuations as well as long-term trends by the LSTM model; thus it is viable for time-series forecasting in financial markets. At times, though it does suffer performance because of high volatility episodes that seem to suggest the potential benefits of incorporating additional market indicators or sentiment analysis. Strengths come with weaknesses; in this model, for example, there are limitations that must be researched further. The current LSTM configuration fails to account for external market factors such as economical indicators or financial news, common and regular stock price influencers. Future work can include more additional features in the model, thereby improving

its robustness under dynamic market conditions.

Further, one could tune hyperparameters and experiment with some other deep-learning architectures like GRUs or Transformer models to further improve accuracy and efficiency.

In summary, although the LSTM model demonstrates encouraging outcomes in forecasting stock prices, further improvements could enhance its flexibility in relation to intricate market conditions. This study adds to the expanding domain of financial forecasting, providing valuable perspectives on both the capabilities and constraints of deep learning models in predicting stock prices.

# Competing interests

The authors declare that they have no competing interests related to this research.

# Author contributions statement

The concept of the study was a collaborative effort of Honey Ranjan and Dr. Bhupinder Singh. Honey Ranjan has developed the model, conducted experiments, and analyzed the obtained data. Methodological advice as well as assistance in the interpretation of the results was provided by Dr. Bhupinder Singh. Both authors have reviewed and accepted the final manuscript.

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[Hochreiter and Schmidhuber](#_bookmark9) [[1997]](#_bookmark9) [Graves](#_bookmark8) [[2013]](#_bookmark8) [Sutskever](#_bookmark15) [et al.](#_bookmark15) [[2014]](#_bookmark15) [Box and Jenkins](#_bookmark3) [[1970](#_bookmark3)] [Hyndman and Athanasopoulos](#_bookmark10) [[2018]](#_bookmark10) [Chatfield](#_bookmark6) [[2000]](#_bookmark6) [Patel et al.](#_bookmark13) [[2015]](#_bookmark13) [Wang et al.](#_bookmark17) [[2019]](#_bookmark17) [Atsalakis and Valavanis](#_bookmark0) [[2009]](#_bookmark0) [Chai and Draxler](#_bookmark5) [[2014]](#_bookmark5) [Willmott](#_bookmark18) [and Matsuura](#_bookmark18) [[2005]](#_bookmark18) [Fischer and Krauss](#_bookmark7) [[2018]](#_bookmark7) [Nelson et al.](#_bookmark11) [[2017]](#_bookmark11) [Bao et al.](#_bookmark1) [[2017]](#_bookmark1) [Bengio et al.](#_bookmark2) [[1994]](#_bookmark2) [Sainath et al.](#_bookmark14) [[2015]](#_bookmark14) [Zhao et al.](#_bookmark19) [[2017]](#_bookmark19) [Vaswani et al.](#_bookmark16) [[2017]](#_bookmark16) [Brownlee](#_bookmark4) [[2017](#_bookmark4)] [Lim and Zohren](#_bookmark12) [[2020]](#_bookmark12)

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