Enhancing Stock Market Prediction Through LSTM Modeling and Analysis

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Abstract—The pursuit of profitable stock investments has driven the exploration of advanced techniques in data mining, machine learning, and mathematical models. Neural networks, particularly Long Short-Term Memory (LSTM) models, have emerged as highly successful tools due to their autonomous learning capabilities, stability, and capacity to represent intricate concepts. This research focuses on leveraging the LSTM model to predict future prices of GOOGL stocks based on historical price data. The study incorporates six essential indicators (Open, Close, High, Low, Adj Close, Volume) as inputs, employing min-max normalization and time steps for data preprocessing. Through a comparative analysis of models trained on different stock history datasets, the LSTM model surpasses the predictive performance of Xu and Cohen's model by 35.18% and K. Ullah and M. Qasim's model by 5.86%. These findings underscore the efficacy of the LSTM model in accurately forecasting Google stock prices, highlighting its potential for informed decision-making in stock investment strategies.

Keywords—Neural network, Stock price prediction, Long short term memory;

1. INTRODUCTION

The stock market is a fundamental component of the capital market, serving as a crucial source of information for macroeconomic development, investment institutions, and individual investors. Investing in stocks not only offers the potential for significant returns but also provides investors with liquidity and flexibility, allowing them to convert their investments into cash whenever required. As a result, the stock market has become an attractive avenue for individuals seeking to grow their wealth. Traditionally, stock investors relied on intelligent trading systems that predicted stock prices based on various factors and market conditions [1]. However, the financial stock market is characterized by its volatility, non-linearity, and susceptibility to rapid fluctuations. Numerous factors, such as corporate news, earnings reports, investor sentiment, social media rumors, and election results, influence stock prices [2]. Consequently, accurately predicting stock prices is essential for minimizing investment risks and maximizing returns. Machine learning algorithms offer significant advantages in processing and predicting vast amounts of complex financial data. These algorithms have the ability to capture intricate patterns and relationships, making them well-suited for stock price prediction tasks. Furthermore, they excel at handling large volumes of data and can adapt to changing market conditions.

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The usage of the LSTM deep neural network for stock price prediction is the main topic of this study. To improve the precision of stock price projections, this process requires analyzing a number of variables, including network structure and time series length. Through experimental analysis and iterative adjustments of the prediction model's hyperparameters, this research aims to provide valuable insights into stock market forecasting and assist investors in making informed investment decisions. By harnessing the power of machine learning and neural networks, this study contributes to the advancement of stock market prediction techniques and aids in the understanding of the dynamic nature of financial markets.

2. RELATED WORK

The prediction of stock prices involves utilizing diverse scientific approaches to anticipate future values of stocks. This is achieved by analyzing the patterns, historical data, and current state of the stock market's progress. Furthermore, it is crucial to take into account a substantial amount of stock market information and precise statistical surveys. Numerous researchers have dedicated their efforts to exploring and implementing different forecasting methods over time. Therefore, it is essential to engage with and comprehend relevant studies, in order to summarize and categorize these forecasting methods for future research purposes.

2.1. Fundamental Analysis

Fundamental analysis involves a comprehensive examination of various factors that influence the value of a company, including its balance sheet, income statement, as well as industry and economic conditions. This analytical approach aims to make long-term price predictions. A research conducted by Liu et al. (2015) investigated the impact of social media metrics on stock return fluctuations [3]. The study specifically focused on the influence of official Twitter accounts on the volatility of company stocks, based on samples collected from the NASDAQ and the New York Stock Exchange (NYSE). The results indicate that social media indicators demonstrate superior accuracy compared to industry categories when utilized for predicting stock movements.

2.2. Hybrid Analytical Model

Machine learning techniques serve as valuable tools for confirming the identification of underlying patterns within stock time series data. These techniques offer utility in the evaluation and projection of business performance and similar metrics. Namdari and Li (2018) [4] conducted a study centered around the implementation of a multilayer perceptron that combines fundamental and technical analysis of the stock market. The objective of their research was twofold: to enhance prediction accuracy and validate the efficacy of the hybrid model. To assess the data fitting accuracy of the hybrid model, the mean squared error (MSE) was compared against independent models using both training and test data sets. Furthermore, the accuracy of outcomes derived from basic and technical analyses was juxtaposed with the simulation results generated by the hybrid model. Collectively, these comparisons substantiated the superior performance of the hybrid model in relation to the alternative approaches.

2.3. Long short-term memory

The LSTM neural network, featuring a control gate structure, is unique and efficient for capturing long-term dependencies in time series data, including stock history data. Patel et al. (2021) put forward a deep learning model based on Long Short-Term Memory (LSTM) for the purpose of stock price prediction. The model employed a combination of regression models for textual information and LSTM for numerical information [5]. Their study showed that distributed representation based on textual information outperformed numerical data and bag-of-words methods, and LSTM had a superior impact on time series data compared to other models. Huang et al. (2018) used an advanced Bayesian-LSTM (B-LSTM) model for stock forecasting in their study, which demonstrated superior prediction accuracy compared to the conventional LSTM model with a notable improvement of over 25% [6]. The B-LSTM model dynamically estimated the number of units based on economic cycles, utilizing a Bayesian algorithm.

3. PROBLEM STATEMENTS

The stock market operates in a stochastic environment characterized by unpredictable fluctuations and the influence of various behavioral factors on investment decisions. These behavioral factors encompass risk aversion, cognitive biases, and limited expertise, which significantly impact stock price movements. As a result, accurately predicting stock prices becomes a complex task that requires addressing multiple challenges. Traditional forecasting methods, such as linear regression models and time series forecasting techniques, have shown limitations in capturing the non-linear relationships present in stock data. In contrast, neural networks, with their non-linear and parameter-free nature, have demonstrated significant potential for modeling complex financial data. They possess the ability to learn from historical patterns and make predictions based on the learned knowledge. Deep neural networks, specifically Long Short-Term Memory (LSTM) models, have gained prominence in stock price prediction research. LSTM models excel in processing time series data, capturing long-term dependencies, and mitigating the vanishing gradient problem commonly encountered in recurrent neural networks. These models are particularly suitable for stock price prediction due to their ability to capture complex patterns and handle the inherent volatility of stock markets.

4. RESEARCH OBJECTIVES

4.1. Implementing the LSTM model

The primary objective is to develop and deploy the LSTM model for stock forecasting. The LSTM model's ability to capture long-term dependencies and handle complex patterns makes it suitable for accurately predicting stock prices.

4.2. Fine-tuning the proposed approach hyperparameters

This objective aims to optimize and fine-tune the hyperparameters of the proposed approach to enhance the model's predictive capabilities [14]. By finding the optimal values for hyperparameters, the model can be better tailored to the specific characteristics of the stock data.

4.3. Applying min-max normalization technique

Normalization is an essential preprocessing step in stock price prediction. The objective is to employ the min-max normalization technique to normalize the input data, bringing it within a specific range. The normalization procedure employed in this study enhances the precision and robustness of the LSTM model through the mitigation of outlier effects and the establishment of uniform scales for all input features [15].

5. RESEARCH METHODOLOGY

5.1. Min-Max Normalization

Min-max normalization, commonly known as outlier normalization, is employed to linearly transform the source data in order to constrain it within the [0, 1] range. This normalization process involves mapping the minimum value of each feature to 0 and the maximum value to 1.

$$X_{std} = \frac{X - X \cdot \min(\text{ axis } = 0)}{X \cdot \max(\text{ axis } = 0) - X \cdot \min(\text{ axis } = 0)} \quad (1)$$

$$X_{\text{scaled}} = X_{std} \times (\max - \min) + \min \quad (2)$$

In the context of this study, the vectors $X.min(axis = 0)$and$X.max(axis = 0)$ represent the minimum and maximum values, respectively, for each column of the data. By default, max and min denote the upper and lower bounds of the target interval, with pre-established values of 1 and 0, respectively. The resulting transformed data is denoted as X_{std} (standardized result), while X_{scaled} represents the normalized result. The principal advantage of applying normalization lies in its ability to expedite the convergence speed and enhance the accuracy of iterative solutions. However, it is important to note that when new data is introduced, adjustments to the maximum and minimum values may be necessary, requiring a redefinition of these bounds.

5.2. LSTM Architecture

LSTM, a modified network structure of RNN, exhibits a chain-like architecture similar to RNN. However, it introduces distinct enhancements by incorporating controllable gate units, enabling the learning of long-term dependencies [7]. Consequently, the repeating module in LSTM differs from that of a standard neural network. It comprises four specialized neural network layers, known as $tanh$ layers, which interact in a specific manner, distinct from the single layer found in traditional architectures.

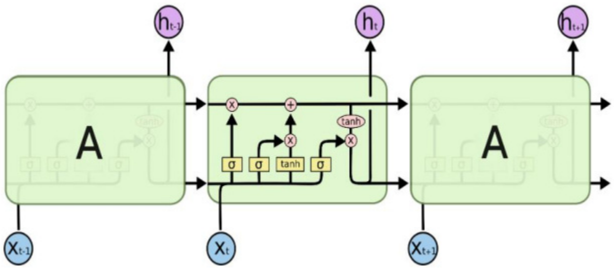

Fig 1. A standard LSTM's repeating module (Colah, 2015)

The LSTM model comprises four layers, each characterized by three parameters: units, return_sequences, and input_shape. The units parameter determines the dimensionality of the output space, representing the number of neurons. By specifying the return_sequences parameter as true, the LSTM layers are configured to be arranged in a sequential manner, where the input to the subsequent layer is a three-dimensional sequence [11-13]. The input_shape parameter defines the structure of the training dataset, denoting its shape.

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm (LSTM)                  (None, 3, 100)            42800
_________________________________________________________________
dropout (Dropout)            (None, 3, 100)            0
_________________________________________________________________
lstm_1 (LSTM)                (None, 3, 50)             30200
_________________________________________________________________
dropout_1 (Dropout)          (None, 3, 50)             0
_________________________________________________________________
lstm_2 (LSTM)                (None, 3, 100)            60400
_________________________________________________________________
dropout_2 (Dropout)          (None, 3, 100)            0
_________________________________________________________________
lstm_3 (LSTM)                (None, 30)                15720
_________________________________________________________________
dense (Dense)                (None, 1)                 31
=================================================================
Total params: 149,151
Trainable params: 149,151
Non-trainable params: 0
```

Fig 2. Model Summary

In this specific experiment, the model incorporates four layers with 100, 50, 100, and 30 units, respectively. To prevent overfitting, units and their associated connections in the neural network are randomly dropped during the training process. In the first three layers, dropout () is applied to discard 20%, 10%, and 50% of the units, respectively. The rendered model, depicted in Figure 2, demonstrates a total of approximately 150,000 trainable parameters.

6. ANALYSIS OF RESULTS

Three distinct datasets were used to train separate models, namely historical stock data of Google Inc and Apple Inc. The trained models will undergo evaluation and comparison. No changes were made to the training parameters of the implementation model. The training dataset comprises 1,133 data points, spanning from January 1, 2014, to July 1, 2018. The test dataset consists of 377 data points, covering the period from July 1, 2018, to December 31, 2019. Take Google Inc as an example.

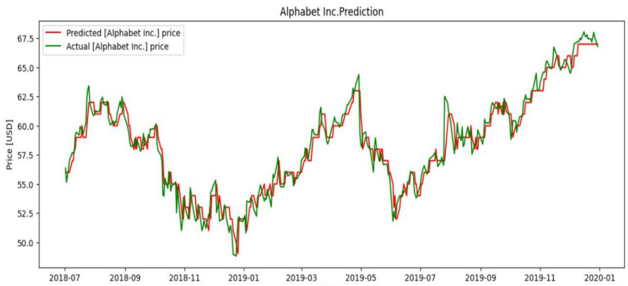

Fig 3. The Predicted Versus Actual Prices of Google’s Stock

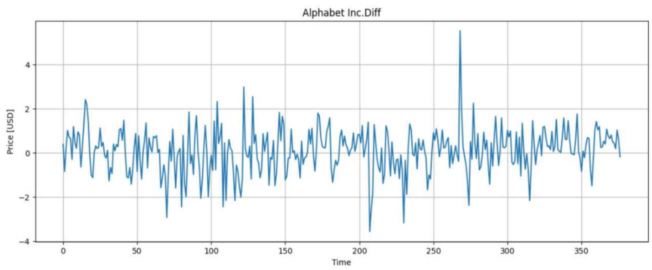

Fig 4. The Difference Between Actual and Predicted Prices of Google’s Stock

Figure 3 presents a graphical representation depicting a comparative analysis between the forecasted and observed prices of Google's stock. The veridical closing price trajectory of Google's stock is depicted by the green curve, whereas the red curve signifies the predicted closing prices generated by the model. Upon observation of Figure 3 and Figure 4, it is evident that the predicted closing price closely aligns with the actual closing price. This suggests that the model's prediction capability is relatively accurate. In Figure 3, it is noticeable that the red line slightly lags behind the green line. This lag issue is a common challenge encountered in LSTM models for stock prediction.

Table 1. Comparing the Accuracy of the Model before and after Modification

Evaluation Indicators	Original Model (keep two decimals)	Final Model (keep two decimals)
MSE	2.22	1.00
RMSE	1.49	1.00
R^2	0.87	0.94
Accuracy	80.30%	86.77%

Table 1 clearly demonstrates that all evaluation metrics of the final model outperform those of the original model. The final model exhibits significantly smaller values for mean squared error (MSE) and root mean squared error (RMSE). Furthermore, the R^2 coefficient is remarkably close to 1, and the accuracy reaches an impressive 86.77%.

Overall, the proposed model showcases an approximate 6% increase in accuracy compared to the original model.

7. CONCLUSION

Predicting stock prices is an immense challenge due to their dynamic and volatile nature, influenced by numerous complex factors. LSTM neural network models have demonstrated their effectiveness in stock market prediction, and optimization algorithms have been explored to enhance accuracy. However, accurately predicting short-term stock prices remains a challenge.

This paper utilized Google's stock price data from 2014 to 2019, employing six carefully selected indicators as input features. By designing the LSTM model with optimal hyperparameters, accurate predictions were achieved. The model's superior performance was confirmed through comparisons with different datasets, historical periods, and existing literature.

Future research in stock price prediction can leverage LSTM neural networks for text learning and sentiment analysis. Developing a comprehensive model that incorporates stock market sentiment analysis, national economic policies, and relevant indicators can enable informed economic judgments and improve stock price predictions. Further exploration includes investigating different deep learning models, discovering more reliable approaches for handling time series data, and employing advanced algorithms or their combinations.

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