International Journal of Computing Sciences Research (ISSN print: 2546-0552; ISSN online: 2546-115X)
Vol. 8, pp. 3147-3156
doi: 10.25147/ijcsr.2017.001.1.209
https://stepacademic.net

Short Paper*

Stock Price Predictor: Implementing Stocks Predictive Model Using Deep Learning

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Date received: May 7, 2024
Date received in revised form: July 3, 2024
Date accepted: July 12, 2024

Recommended citation:

Abucay, G. A. B., Almonia K. C. C., Buray, R. D. S., & Gangoso, E. P. J. (2024). Stock price predictor: Implementing stocks predictive model using deep learning. *International Journal of Computing Sciences Research*, *8*, 3147-3156. https://doi.org/10.25147/ijcsr.2017.001.1.209

**Special Issue on International Research Conference on Computer Engineering and Technology Education (IRCCETE). Guest Associate Editors: Dr. Roben A. Juanatas (National University-Manila) and Dr. Nelson C. Rodelas (University of East).*

Abstract

Purpose – This paper proposes a novel deep neural network model, specifically long short-term memory (LSTM) networks, for predicting stock prices using historical data and financial indicators.

Method – LTSM can handle long sequences while capturing temporal dependencies, making it an excellent choice for NLP or time series. The model is trained and tested on the Ayala Corporation (AYALY) stock dataset from 2016 to 2019, using four financial indicators: earnings per share (EPS), EPS growth, price/earnings ratio, and price/earnings-to-growth ratio.

Results – The results show that the model achieves high accuracy and outperforms other Deep Neural Network variants as confirmed by assessing its performance using suitable metrics like mean squared error and mean absolute error. It effectively explored and selected relevant financial indicators, implemented data preprocessing techniques, and trained the model using historical data.

Conclusion – The project effectively explored and selected relevant financial indicators and trained LSTM models using historical data, and, thus, met its objectives to develop a deep neural network model for stock price prediction.

Recommendations – The authors recommend that future researchers continue to explore the integration of a diverse set of financial indicators, employ rigorous comparative analyses, and experiment with different time frames for future predictions to further enhance prediction accuracy.

Research Implications – This paper contributes to the ongoing development of machine-learning studies, especially in the Philippines, particularly for time-series forecasting. With more accurate predictions of stock prices, the study could enable investors to make informed investment decisions, trading strategies, and financial decision-making processes.

Keywords – Deep Neural Network, Long Short-Term Memory (LSTM) Networks, Machine Learning, Stock Price Prediction, Time Series Forecasting

INTRODUCTION

The prediction of stock market movements is a formidable challenge, owing to the multitude of influential factors, including interest rates, politics, and economic growth, which render stock prediction a volatile and exceedingly intricate undertaking (Avci, 2023). Given the significance of stock investment as a substantial financial market activity, a dearth of precise knowledge and comprehensive information inevitably leads to potential investment losses. The inherent uncertainties prevailing in market movements further compound the difficulty of accurately predicting the stock market (Mitchell, 2022). Accordingly, the stock price predictor seeks to empower users with reliable forecasts, enabling them to make informed decisions regarding buying, selling, or holding stocks. By analyzing historical data, and relevant indicators, the model aimed to uncover patterns and relationships that could assist in predicting future price movements. By developing an effective stock price predictor, the researchers aimed to address these challenges and provide users with valuable insights and forecasts that could mitigate risks and support well-informed investment decisions.

LITERATURE REVIEW

Studies on stock price prediction are vast and critical in the financial world with methods ranging from technical and fundamental analysis to advanced machine learning techniques (Ghorbani & Edwin, 2020). Traditional approaches like technical analysis rely on historical price trends, while fundamental analysis examines a company's financial health (Selvamuthu et al., 2019). However, these methods have limitations due to the dynamic nature of financial markets (Allwright, 2022).

Recent advancements in machine learning, particularly deep learning, have introduced new methodologies that promise greater accuracy (Yang et al., 2020). Deep Neural Networks (DNNs), including recurrent and convolutional structures, are now at the forefront, leveraging temporal data for predictions. Lara-Benítez et al. (2021) noted recurrent neural networks, especially Long Short-Term Memory (LSTM) networks, for their ability to capture long-term dependencies while ignoring irrelevant data, making them suitable for stock price prediction, which is considered a type of time-series forecasting.

Comparative studies have shown that LSTMs can outperform traditional models, but they also have their own set of challenges, such as handling sudden market fluctuations. The literature suggests that while no single model is universally superior, LSTMs show promise in the predictive modeling of stock prices, provided they are coupled with comprehensive feature engineering and robust evaluation metrics (Ji et al., 2021; Kamalov et al., 2020, Shen & Shafiq, 2020; Shchutskaya, 2021; Staffini, 2022,).

METHODOLOGY

Figure 1 outlines the sequential steps involved in building a deep neural network model for financial analysis. This study utilized the Efficient Market Hypothesis (EMH), which asserts that financial markets operate efficiently, and stock prices incorporate all existing information (Downey, 2023). This concept would provide insight into market behavior and the difficulties associated with forecasting stock prices. The efficient market hypothesis (EMH) asserts that stocks are traded at their accurate valuations on stock exchanges, rendering it impractical for investors to purchase undervalued stocks or sell stocks at inflated prices (CommerceMates, 2022).

Figure 1. Process Flow Diagram

Designing the Deep Neural Network

The theoretical framework emphasized the use of deep neural networks as a powerful machine learning approach for capturing intricate patterns in financial data. The research explored various DNN architectures, such as feedforward networks, recurrent neural networks (RNNs), or long short-term memory networks (LSTMs), to identify the most suitable model for stock price prediction. For price prediction, a time window of the preceding 30 days was utilized. The input comprises prices from the past 30 days, while the output predicts the price for the next 7 days.

Financial Indicators and Feature Selection

Relevant financial indicators which were price-to-earnings ratio (P/E), price-to-earnings growth (PEG), earnings per share (EPS), and earnings per share growth (EPSG) were explored to identify those that contribute significantly to reliable stock price predictions. The feature selection process was also guided by financial theories and empirical evidence.

Data Preprocessing Techniques

This research utilized data preprocessing techniques such as data cleaning and normalization, specifically the utilization of the MinMax scaler, to ensure high-quality input data for the deep neural network model. These techniques would improve the model's ability to learn meaningful patterns and reduce noise.

Model Training and Optimization

Five LSTM models were used. The LSTM Models are LSTM-1 and LSTM-FI. Techniques like backpropagation and stochastic gradient descent were employed to optimize the model's weights and biases for improved prediction accuracy.

The LSTM-1 architecture consists of four layers. The initial layer, designated as the input layer, accommodates a set of 30 input parameters, providing the network with a comprehensive dataset for training and prediction. Following this, two subsequent LSTM layers are employed, each consisting of 30 and 50 units, respectively. These LSTM layers are pivotal in capturing temporal dependencies within the financial time series data, enabling the model to discern intricate patterns and trends. To improve the model's robustness and reduce overfitting, a dropout layer with a rate of 0.2 was inserted strategically after the LSTM layers, facilitating regularization during training. The final layer is a dense layer with 7 units, representing the output layer that generates the predicted stock prices.

For LSTM-FI architecture, the initial layer serves as the input layer for the LSTM network. This accommodates a total of 31 parameters, including 30 parameters representing historical stock prices, capturing the temporal dynamics of the market, and an additional parameter corresponding to a specific financial indicator. Subsequently, two LSTM layers follow with the first layer comprising 30 parameters and 50 units, and the second layer comprising 50 units. Lastly, the final layer is a dense layer with 7 units, representing the output layer responsible for generating the predicted stock prices for the next 7 days.

The model hyperparameters are set as follows: The dropout rate is set at 0.02 with the Adam optimizer algorithm. The learning rate, which determines the iteration’s step size moving towards a minimum of a loss function, is set at 0.001. Lastly, the model is trained for 1000 epochs to sufficiently learn from the data.

Performance Metrics

To evaluate the effectiveness of the predictive model, the performance metrics mean absolute error (MAE) and mean squared error (MSE) were employed. These metrics assessed the model's ability to provide reliable stock price predictions and quantify its performance in comparison to other approaches.

RESULTS

Various financial indicators, including earnings per share (EPS), EPS growth, price/earnings ratio, and price/earnings-to-growth ratio were trained on AYALY 2016 to 2019 stock dataset. However, to identify which financial indicators perform best for predicting stock prices.

Afterward, the results of the model’s performance in terms of its accuracy and efficiency for predicting stock prices using the selected financial indicators were then analyzed. The objective was to identify the most reliable financial indicators based on its MSE and MAE, the evaluation criteria used. Tables 1, 2, and 3 below show the results from the different architectural models and different metrics in predicting stock prices in the AYALY stock dataset.

Table 1. Overall results of all the model's futures in Mean Absolute Error (MAE) and Mean Squared Error (MSE).

Metrics	LSTM-1	LSTM-FI (EPS)	LSTM-FI (EPSG)	LSTM-FI (P/E)	LSTM-FI (PEG)
MAE	0.048430	0.046365	0.057645	0.054848	0.065843
MSE	0.007673	0.005316	0.005653	0.007057	0.009995

Table 2. Results and Comparison of Mean Absolute Error (MAE)

Futures	**LSTM-1**	**LSTM-FI (EPS)**	**LSTM-FI (EPSG)**	**LSTM-FI (P/E)**	**LSTM-FI (PEG)**
Future 1	0.032825	0.033376	0.040282	0.041950	0.045329
Future 2	0.040448	0.037337	0.051027	0.043601	0.047323
Future 3	0.042935	0.041677	0.052459	0.051344	0.057541
Future 4	0.047351	0.047048	0.058922	0.055078	0.070743
Future 5	0.051874	0.051765	0.064887	0.058085	0.078517
Future 6	0.058869	0.055473	0.062226	0.064090	0.080303
Future 7	0.064713	0.057882	0.073715	0.069789	0.081146

Table 3. Results and Comparison of Mean Squared Error (MSE)

Futures	**LSTM-1**	**LSTM-FI (EPS)**	**LSTM-FI (EPSG)**	**LSTM-FI (P/E)**	**LSTM-FI (PEG)**
Future 1	0.003458	0.002617	0.002889	0.003613	0.005559
Future 2	0.005574	0.003481	0.004271	0.004141	0.006019
Future 3	0.007033	0.004342	0.004183	0.006747	0.007514
Future 4	0.007445	0.005214	0.005182	0.007370	0.010666
Future 5	0.008689	0.005956	0.006895	0.007796	0.012668
Future 6	0.010117	0.007119	0.006971	0.009378	0.013820
Future 7	0.011401	0.008486	0.009181	0.010357	0.013718

Figure 2 shows the prediction of the model from future 1 to future 7.

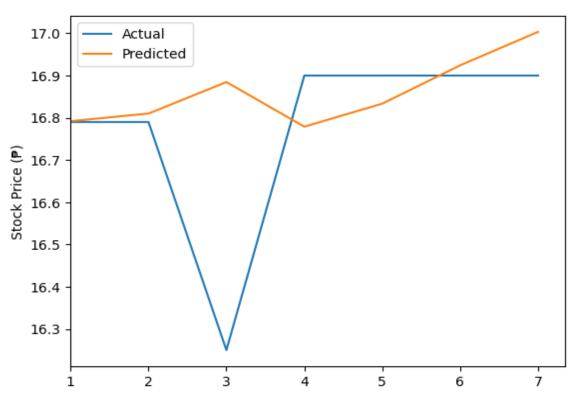

Figure 2. Model Predictions

DISCUSSION

Our findings demonstrate that incorporating financial indicators into LSTM models can improve stock price prediction accuracy on the AYALY dataset (2016-2019). Among the evaluated metrics, Mean Absolute Error (MAE) and Mean Squared Error (MSE) consistently highlighted two models, LSTM-FI (EPS) and LSTM-FI (EPSG), achieving superior performance. Interestingly, these models exhibited a complementary strength, with LSTM-FI (EPS) excelling in predicting Futures 1, 2, 5, and 7, while LSTM-FI (EPSG) performed better in Futures 3, 4, and 6. This complementary performance across different futures underscores the robustness of both models in capturing various market conditions.

The most significant finding is that incorporating Earnings per Share (EPS) as a financial indicator yielded the best overall results for both MAE and MSE. This suggests that EPS serves as a strong indicator of a company's profitability and potential future performance, aligning well with its intended purpose.

It is important to acknowledge the limitations observed in Figure 2. The noticeable discrepancies between predicted and actual prices, particularly around Future 3, highlight a potential shortcoming of the LSTM models. As mentioned earlier, these models may struggle with sudden and significant fluctuations in stock prices.

CONCLUSIONS AND RECOMMENDATIONS

The project achieved its objectives by developing a deep neural network model for stock price prediction. It effectively explored and selected relevant financial indicators, implemented data preprocessing techniques, and trained the model using historical data. The architecture of the model was designed for enhanced prediction accuracy. The model’s effectiveness was confirmed by assessing its performance using suitable metrics like mean squared error and mean absolute error. Thus, the project met its aim of providing valuable insights for informed investment decisions.

Based on the findings of this study, future research in the realm of stock predictive modeling should continue to explore the integration of a diverse set of financial indicators to enhance prediction accuracy. Moreover, to ensure robust model evaluation, researchers should employ rigorous comparative analyses, considering various models with distinct financial indicators.

Experimenting with different time frames for future predictions could also provide valuable insights into the temporal dynamics of financial markets and the predictive power of certain indicators over others. Additionally, other than the company’s financial indicators, efforts should be directed toward identifying and testing other input features. For example, NLP on news analyses might help predict sudden stock price dips. Testing these models across different businesses and corporations could further enhance their generalizability and reliability. Collaborative initiatives between data scientists, financial analysts, and industry professionals could facilitate the development of more comprehensive models that not only outperform their counterparts but also translate into actionable insights for traders and investors.

Ultimately, the success of these models lies not only in their theoretical soundness but also in their ability to make a tangible impact on decision-making processes in the dynamic and unpredictable landscape of the financial markets.

IMPLICATIONS

This paper is significant for both the field of finance and artificial intelligence. With only a few published papers observed locally, it would contribute to the ongoing development and refinement of machine-learning studies, especially in the Philippines, particularly those used for time-series forecasting.

On top of that, the utilization of deep learning models, such as Deep Neural Networks (DNNs) and Long Short-Term Memory Networks (LSTMs), could potentially lead to more accurate predictions of stock prices and could revolutionize trading strategies and financial decision-making processes. With a user-friendly platform to predict stock prices, the need for extensive knowledge of stock price prediction techniques is eliminated, enabling average investors to make informed investment decisions confidently.

ACKNOWLEDGEMENT

Our deep and sincere gratitude to the researchers' parents Mrs. Alilie Abucay, Mrs. Vivian Almonia, Mrs. Anna Delsa Buray, and Mr. and Mrs. Peter Lee Gangoso for their love and support through their continual prayers, care, and financial sacrifices, and to the university for providing the opportunity to make the study possible.

FUNDING

The study received partial funding from La Salle University – Ozamiz.

DECLARATIONS

Conflict of Interest

The authors declared that there is no interest in conflict associated with this research.

Informed Consent

Data used to train the model were scraped from public sources. No direct, private personal information was used in the conduct of this research

Ethics Approval

As there were no private and personal information was used in the research, ethics approval is not necessary.

Python Model Availability

The source code and pre-trained models presented in the study are available on GitHub (https://github.com/earlpeterg/stock_price_predictor). For further inquiries, please contact the authors.

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