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Amazon Stock Price Prediction Using Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU)

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Abstract

Stocks have become one of the largest and most intricate financial markets globally due to their high popularity, making them very challenging to predict as they can process millions of transactions rapidly. The objective of this study is to enhance the field by creating a dependable and accurate model for predicting the stock price of Amazon. This will be achieved via the use of advanced algorithms such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU). This research utilised historical data on Amazon's stock price from the past five years, which was acquired from Yahoo Finance. The data was partitioned using a hold-out validation technique, allocating 80% for training and 20% for testing. The model underwent training using different optimizers (Adam, SGD, RMSprop), batch sizes (8, 16, 32), and learning rates (0.001, 0.0001). The evaluation criteria comprised of mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). The results suggest that the GRU model, when trained with the RMSprop optimizer using a batch size of 16 and a learning rate of 0.0001, as well as with the SGD optimizer using a batch size of either 16 or 32 and a learning rate of either 0.001 or 0.0001, produced the lowest error metrics, indicating superior performance. This study enables more precise forecasts of stock prices and more efficient investment techniques.

Keyword: Amazon, Deep Learning, Gated Recurrent Unit, Long Short-Term Memory, Prediction

1. INTRODUCTION

Due to the rapid fluctuations in stock prices over short periods, many investors remain wary of taking investment risks. Although various techniques have been developed to forecast future stock prices, they still face challenges, including issues related to long-term dependency [1]. Likewise with Amazon's stock price fluctuations, the downward trend began to be seen after 2022. Previously, Amazon shares had experienced a sharp surge to reach the range of $160 per share in 2020. However, it is estimated that Amazon's share price will stabilize in the range of $100-$125 per share in the future, with a moderate potential increase in the second half of this year [2]. Predicting stock prices is crucial in the investment world. Understanding a stock's performance provides numerous benefits, such as determining the best times to buy or sell. Despite numerous attempts to forecast stock prices using conventional investing methods, many fail. Accurately predicting stock prices remains a significant challenge [2].

The stock market holds a significant position in the national economy, attracting increasing attention from investors seeking methods to boost their returns and mitigate specific risks [3].Consequently, investors require a thorough understanding of stock market trends and precise tools for making trading decisions to maximize profits while minimizing risks. To address such complex data issues, deep learning is employed. The field of data science has been expanding due technological advancements and increased computing power [4].

Given their popularity, stocks have become one of the largest and most intricate financial markets globally, making prediction challenging due to their capacity to process millions of transactions within a short timeframe [5]. Amazon's share price has shown significant growth in the past decade, driven by dominance in the e-commerce industry and Amazon Web Services (AWS) [27]. The e-commerce company also has more than 200 large warehouses around the world. There are thousands of people working at each of these locations, which Amazon calls “associates” with a total floor space of hundreds of thousands of square feet [6]. Given the extensive reach of Amazon's platform, it undoubtedly holds appeal for investors, emphasizing the importance of accurately forecasting the e-commerce giant's stock price.

Previous studies have utilized Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) algorithms for predicting time series data, such as in research focused on stock price prediction. This research compared these algorithms with linear regression using publicly available datasets [7] Researchers used Root Mean Square Error (RMSE), Mean Squared Error (MSE), and Mean Absolute Error (MAE) as metrics to evaluate prediction performance using the KEJU stock price dataset, which spans from November 15, 2019, to June 8, 2021, and is sourced from the Indonesia Stock Exchange (IDX). Following the training and testing phases, the analysis indicated that the GRU algorithm demonstrated superior stock price prediction capabilities. This was evidenced by the GRU achieving the lowest values for RMSE (0.034), MSE (0.001), and MAE (0.024) among the models tested. Additionally, in a separate study focusing on predicting extreme climate changes, it was found that Recurrent Neural Network (RNN) outperformed Artificial Neural Network (ANN) and LSTM in forecasting temperature in Indonesia. RNN achieved a smaller Mean Absolute Percentage Error (MAPE) value (1.852%), along with an RMSE of 1.870 and an MSE of 3.497, highlighting its efficacy in this context.[8].

Various previous studies have underlined the potential of the LSTM algorithm in predicting stock prices, including Amazon (AMZN) stock. The study by Varadharajan et al. discussed the LSTM-RNN model for predicting the closing price of Amazon stock, showing quite high accuracy with an RMSE of 2.51 and MAPE of 1.84% [28]. This study also evaluated the effect of hyperparameters in improving model performance. Zhou1 emphasized the performance comparison of two-layer and three-layer LSTMs, where the three-layer model showed superiority in the accuracy of predicting Amazon stock price trends based on Kaggle data [29]. These two studies prove that the layer structure in LSTM plays an important role in improving prediction accuracy.

Tan and Li et al. add evidence to the relevance of LSTMs in stock prediction [30][31]. Tan used long data (2002-2023) and highlighted the advantages of LSTM over linear regression, especially during periods of turmoil such as the COVID-19 pandemic [30]. Li et al. extended the use of LSTM by predicting the stocks of several large technology companies, including Amazon, using a two-layer structure optimized with Adam and MSE [31]. This study shows that the LSTM model can capture complex patterns in technology stock data, including Amazon, with good prediction accuracy.

This research differs from previous studies by integrating the GRU algorithm as the main comparison to LSTM, as well as optimizing the model using various methods such as Adaptive Moment Estimation (Adam), Stochastic Gradient Descent (SGD), and Root Mean Square Propagation (RMSprop). This research also utilizes historical data of Amazon stocks for the past five years from Yahoo Finance, focusing on evaluating various combinations of hyperparameters such as batch size and learning rate. Thus, this research makes a new contribution in creating a more precise and efficient prediction model for Amazon stock, which has not been exhaustively covered in previous studies.

This study seeks to contribute to the existing literature by developing a robust and precise model for predicting Amazon stock prices. The suggested method takes advantage of LSTM and GRU's strengths to successfully record data's long-term dependencies as well as its short-term variations. The motivation behind this research stems from the increasing complexity of stock market dynamics and the challenges posed by rapid price fluctuations, which complicate accurate prediction efforts. Unlike previous studies, this research innovatively combines LSTM and GRU algorithms specifically tailored for Amazon stocks while employing comprehensive evaluation metrics such as RMSE, MSE, and MAE. The anticipated outcomes aim to offer valuable insights for companies and investors involved with Amazon, facilitating more effective decision-making through enhanced stock price predictions.

2. MATERIAL AND METHOD

This research follows a structured approach, beginning with the collection of historical Amazon stock price data spanning the last five years, sourced from Yahoo Finance. The collected data undergoes initial preprocessing stages, including the creation of sequential data points for target value prediction. The data is partitioned using the hold-out validation approach, with 80% designated for training and 20% for testing, to guarantee a comprehensive evaluation. This is followed by training the prediction models using the LSTM and GRU algorithms. To make the model better, optimisation methods like Adam, SGD, and RMSprop are used during training. To find the best model settings, we run a battery of experiments testing different batch sizes (8, 16, and 32 samples) and learning rates (0.001 and 0.0001). For the purpose of determining the best performing model, all trained models are subjected to extensive testing and evaluation using metrics like Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). The selected model is then implemented to forecast future periods of Amazon stock prices. Figure 1 depicts the consecutive phases of this study process.

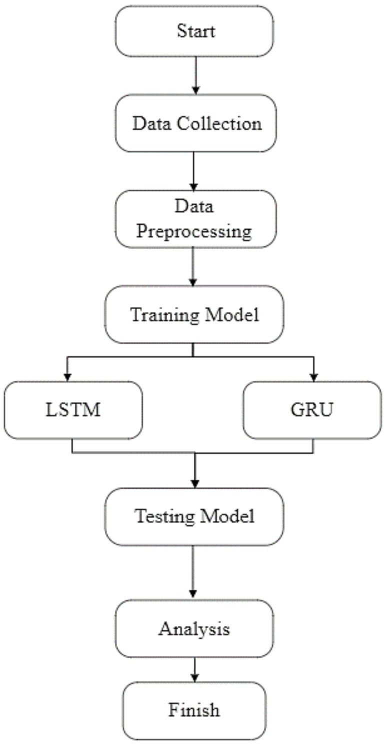

Figure 1. Research Methodology

2.1. Stocks

Investors need an effective investment strategy that minimizes portfolio risk while maximizing returns [9]. Stocks are among the most favored financial market assets, chosen by many investors for their ability to yield attractive returns [10]. Stocks represent ownership or participation in a company or limited liability entity held by individuals or organizations.

2.2. Data Collection

Data is collected from Yahoo Finance, specifically focusing on Amazon's historical stock price data spanning six months for this study. Yahoo Finance is known as a trusted source of financial data. Although no previous research has used this dataset in Amazon stock prediction studies, the validity of this data is supported by Yahoo Finance's track record as a major reference in financial analysis, such as in Moghar and Hamiche's (2020) paper entitled "Stock market prediction using LSTM recurrent neural network", the researchers used a dataset derived from Yahoo Finance to test the LSTM model in predicting stock prices. This dataset includes historical stock prices taken from various companies listed on the stock market [32].

2.3. Preprocessing Data

Data normalisation using the sklearn library's min-max scaling approach is part of the data preprocessing in this study[11].The approach involves transforming real or original values into scaled values within specified intervals. In this study, to optimize prediction accuracy, the dataset is normalized using two experiments: [0,1] and [1,1]. Here is the normalisation as equation 1.

$$x' = \frac{\mathrm{x-xmin}}{\mathrm{xmax-xmin}} \tag{1}$$

Where, x′ represents the normalization result, x is the original data value to be normalized, xmin is the minimum data value, and xmax is the maximum data value. With this approach, the normalized data becomes more homogeneous and suitable for training prediction models.

2.4. Data Sharing

In order to train prediction models, one needs training data, which includes both historical records of past events and factual information. The accuracy of these models' predictions can be assessed using testing data[12]. Given that the dataset is a time series, a sequential strategy is employed to partition the data into training and test sets. This method guarantees that the data will remain in the same sequence and will not be randomly shuffled. Using an 80:20 ratio, the data is divided into two sets. The model is trained using the first 80% of the dataset, and its predictions are evaluated using the remaining 20%.

2.5. Long Short-Term Memory (LSTM)

LSTM is a type of Recurrent Neural Network (RNN) that incorporates a unique architecture to address issues such as vanishing and exploding gradients commonly encountered in traditional RNNs [13]. LSTM is known for its capability to retain and utilize long-term memory within sequential data [25]. The vanishing gradient problem can cause traditional RNNs to struggle to capture long-term dependencies effectively[14]. Nevertheless, issues like vanishing and exploding gradients can lead to reduced accuracy in RNN models, especially over longer time spans, thereby impacting the final predictions [15].

The three gates that make up the LSTM architecture are the input gate, the forget gate, and the output gate. There is a specific purpose for each gate in regulating the flow of data. By taking into account both the current input and the previous state, the input gate controls the adjustments made to the internal state. The forget gate establishes the level of disregard for the previous internal state. A system's overall response to changes in its internal state can be controlled by the output gate [16]. Here is the equation 2 – 6 for the LSTM algorithm.

$$it = \sigma(Wi\ .[ht{-}1,\ xt\ ] + bi) \tag{2}$$

$$ft = \sigma(Wf.[ht{-}1,\ xt\ ] + bf) \tag{3}$$

$$Ct = tanh(Wc\ .[ht{-}1,\ xt\ ] + bc) \tag{4}$$

$$Ct = ft * Ct{-}1 + it * Ct \tag{5}$$

$$ht = Ot + \tanh(\ Ct) \tag{6}$$

An equation describing the LSTM algorithm has multiple variables. The input gate is represented by ib, the forget gate by Zb, the candidate state by cb, the cell state by cb, the hidden state by hb, weights are denoted by W and U, the bias term is denoted by b, and the input value is indicated by at.

2.6. Gated Recurrent Unit (GRU)

GRU is employed for forecasting time-series outcomes using recent historical data [17].GRU represents an advancement over LSTM, featuring a streamlined and optimized structure that preserves the performance of LSTM networks. GRU is functionally equivalent to LSTM, except in its hidden state, it combines the input and forget gates into a single component called the update gate [18].

In their hidden state, GRU and LSTM cells perform similarly; however, GRU simplifies the process by combining the input and forget gates into one update gate. Also, unlike LSTM, GRU cells merge the cell and hidden states into one, cutting the number of gates more especially, the update and reset gates in half [19]. The equation for the GRU algorithm is as equation 7 - 10.

$$z\text{t} = \sigma(Xt\ U\ z + St{-}1Wz) \tag{7}$$

$$r\text{t} = \sigma(Xt\ U\ r + St{-}1Wr) \tag{8}$$

$$h\text{t} = tanh(Xt\ U\ h + (St{-}1o\ r)Wh\ ) \tag{9}$$

$$St = (1 - z)o\ h + z\ o\ St{-}1 \tag{10}$$

W and U stand for weights, b is the bias term, aZ is the input value, rtZ is the reset gate, zb is the forget gate, $\tilde{h}t$ is the candidate state, and sb is the hidden state in the GRU algorithm equation.

2.7. Optimizer

An optimisation method known as Stochastic Gradient Descent (SGD) uses gradient descent and adjusts parameters for each training example. Speeding up the optimisation process at the expense of increased variability, SGD uses approximations rather than finding the true gradient [20]. Next, we employed the RMSProp optimizer, an adaptive learning rate technique introduced by G. Hinton. Root Mean Square Propagation (RMSProp) adjusts the learning rate by scaling it exponentially in relation to the decaying average of squared gradients [21]. One optimisation method, Adaptive Moment Estimation (Adam), allows you to set the learning rate for each parameter separately. Adam maintains an exponentially decaying average of past gradients, just as Adadelta and RMSProp do [20] Adam and RMSProp are the two most renowned adaptive stochastic algorithms used for training deep neural networks. Numerous real-world examples have demonstrated that these methods can exhibit different behaviors, even in convex scenarios [22].

2.8. Analysis and Evaluation

Metrics like MSE, RMSE, MAE, and MAPE will be used to test and evaluate the trained model in order to determine the optimal model. We will use the model that has the lowest values for these metrics to predict Amazon stock prices for the next term. MSE quantifies the quality of an estimator, always yielding non-negative values, with values closer to zero indicating better performance.

RMSE consolidates the discrepancies between the model's predictions and the actual observed values into a single metric, reflecting the model's predictive accuracy [23]. If the test set has numerous outliers, the model's performance might be mediocre, however MAE is effective when outliers indicate tainted data. A simple measure for regression model performance is MAPE, which stands for mean absolute percentage error. For jobs where relative changes are more important than absolute ones, its intuitive representation of relative inaccuracy makes it a great choice [24].

$$\mathrm{MSE} = \frac{1}{\mathrm{T}}\sum_{\mathrm{t}=1}^{\mathrm{T}}\left(\mathrm{P_t} - \widehat{\mathrm{Z}}_{\mathrm{t}}\right)^2 \tag{11}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{T}}\sum_{\mathrm{t}=1}^{\mathrm{T}}\left(\mathrm{P_t} - \widehat{\mathrm{Z}}_{\mathrm{t}}\right)^2} \tag{12}$$

$$\mathrm{MAE} = \frac{1}{\mathrm{T}}\sum_{\mathrm{t}=1}^{\mathrm{T}}\left|\mathrm{P_t} - \widehat{\mathrm{Z}}_{\mathrm{t}}\right| \tag{13}$$

$$\mathrm{MAPE} = \frac{1}{\mathrm{T}}\sum_{\mathrm{t}=1}^{\mathrm{T}}\left|\frac{\mathrm{P_t} - \widehat{\mathrm{Z}}_{\mathrm{t}}}{\mathrm{Z_t}}\right| \tag{14}$$

3. RESULTS AND DISCUSSION

In order to find the best model for predicting stock prices using LSTM and GRU algorithms, several experiments are conducted. A variety of parameters, including learning rates (0.001 and 0.0001), batch sizes (8, 16, and 32), and optimizers (Adam, SGD, and RMSprop), are considered in the tests. Using a callback (checkpoint), each model goes through 100 training cycles to see how well it performs. You can see the outcomes of the LSTM and GRU models in Tables 1 and 2, respectively.

3.1. LSTM Algorithm Modeling Evaluation Results

Based on the experiments conducted, the LSTM model using the RMSprop optimizer (with a batch size of 16 and a learning rate of 0.001) demonstrated the best performance among all LSTM configurations. By producing MSE 6.62, RMSE 2.57, MAE 1.93, and MAPE 1.27%.

Table 1. Evaluation Result of LSTM Algorithm Modeling

Optimizer	Batch Size	Learnig Rate	MSE	RMSE	MAE	MAPE
Adam	8	0.001	7.12	2.67	1.95	1.26%
Adam	8	0.0001	7.12	2.67	1.95	1.26%
Adam	16	0.001	7.03	2.65	2.03	1.35%
Adam	16	0.0001	7.03	2.65	2.03	1.35%
Adam	32	0.001	7.03	2.65	2.03	1.35%
Adam	32	0.0001	7.03	2.65	2.03	1.35%
SGD	8	0.001	7.31	2.7	2.02	1.29%
SGD	8	0.0001	7.12	2.67	1.95	1.26%
SGD	16	0.001	10.5	3.24	2.51	1.58%
SGD	16	0.0001	10.5	3.24	2.51	1.58%
SGD	32	0.001	10.5	3.24	2.51	1.58%
SGD	32	0.0001	10.5	3.24	2.51	1.58%
RMSprop	8	0.001	7.12	2.67	1.95	1.26%
RMSprop	8	0.0001	7.12	2.67	1.95	1.26%
RMSprop	16	0.001	6.62	2.57	1.93	1.27%
RMSprop	16	0.0001	26.33	5.13	4.2	2.69%
RMSprop	32	0.001	10.64	3.26	2.57	1.65%
RMSprop	32	0.0001	7.03	2.65	2.03	1.35%

3.2. GRU Algorithm Modeling Evaluation Results

In comparison to other GRU configurations, the one using the RMSprop optimizer with a batch size of 16 and a learning rate of 0.0001 performed exceptionally well. With MSE=6.06, RMSE=2.46, MAE=1.8, and MAPE=1.18%, it was successful. Moreover, this particular GRU configuration exhibited the most favourable error metrics compared to all other models and configurations, thus establishing itself as the best-performing model overall. Figure 2 depicts the forecast outcomes of the GRU model utilising the RMSprop optimizer on the test data.

Table 2. Evaluation Result of GRU Algorithm Modeling

Optimizer	Batch Size	Learnig Rate	MSE	RMSE	MAE	MAPE
Adam	8	0.001	9.56	3.09	2.39	1.50%
Adam	8	0.0001	6.92	2.63	1.92	1.23%
Adam	16	0.001	7.33	2.71	2.01	1.29%
Adam	16	0.0001	7.33	2.71	2.01	1.29%
Adam	32	0.001	7.33	2.71	2.01	1.29%
Adam	32	0.0001	7.33	2.71	2.01	1.29%
SGD	8	0.001	7.18	2.67	1.97	1.26%
SGD	8	0.0001	7.18	2.67	1.97	1.26%
SGD	16	0.001	6.14	2.48	1.8	1.18%
SGD	16	0.0001	6.14	2.48	1.8	1.18%
SGD	32	0.001	6.14	2.48	1.8	1.18%
SGD	32	0.0001	6.14	2.48	1.8	1.18%
RMSprop	8	0.001	7.18	2.67	1.97	1.26%
RMSprop	8	0.0001	7.18	2.67	1.97	1.26%
RMSprop	16	0.001	7.14	2.67	2.03	1.26%
RMSprop	16	0.0001	6.06	2.46	1.8	1.18%
RMSprop	32	0.001	6.22	2.49	1.82	1.20%
RMSprop	32	0.0001	6.14	2.48	1.8	1.18%

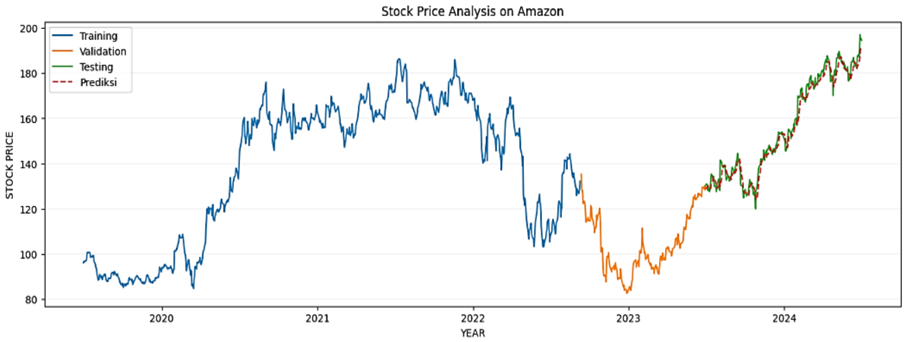

Figure 2. Stock Price Prediction on Test Data Using the GRU Model Utilizing the RMSprop Optimizer

The graph above shows the analysis of Amazon's stock price, by comparing the prediction (red) with the actual data (orange), we can evaluate the model's ability to predict the stock price. This graph helps assess the prediction model's performance, with a close alignment between the predicted and actual data indicating good model performance, while significant discrepancies suggest the need for further optimization. The visualization results of the GRU model's predictions with the RMSprop optimizer on the test data are shown in Figure 3.

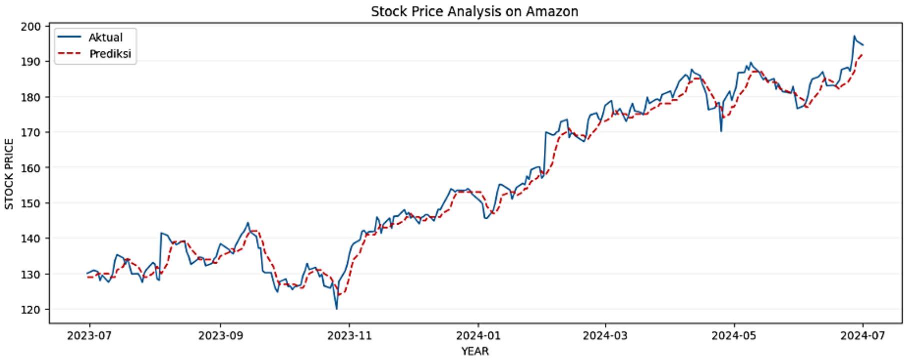

Figure 3. Stock Price Prediction on Test Data Using the GRU Model Utilizing the RMSprop Optimizer

In July 2024, the stock price predictions will be made using the GRU model, which was determined to be the best-performing model. The findings point to a decline in the stock price of Amazon that is anticipated. The prediction graphs from the GRU model are shown in Figures 4 and 5.

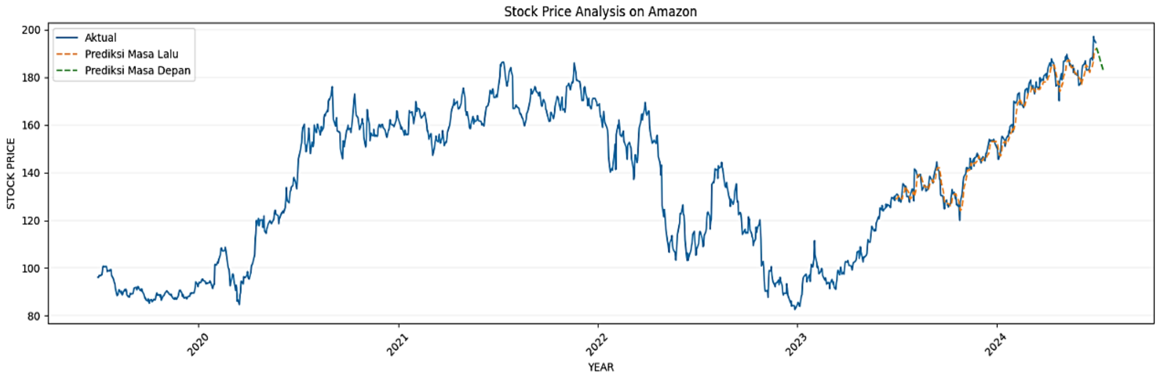

Figure 4. Stock Price Prediction for the Next 14 Days

This chart provides information on the predicted trend of the Amazon stock price over the next two weeks, showing a fairly steady decline in price. This can be important information for investors or market analysts to make decisions about Amazon stock. This downward trend can be considered an important indicator for short-term investment strategies.

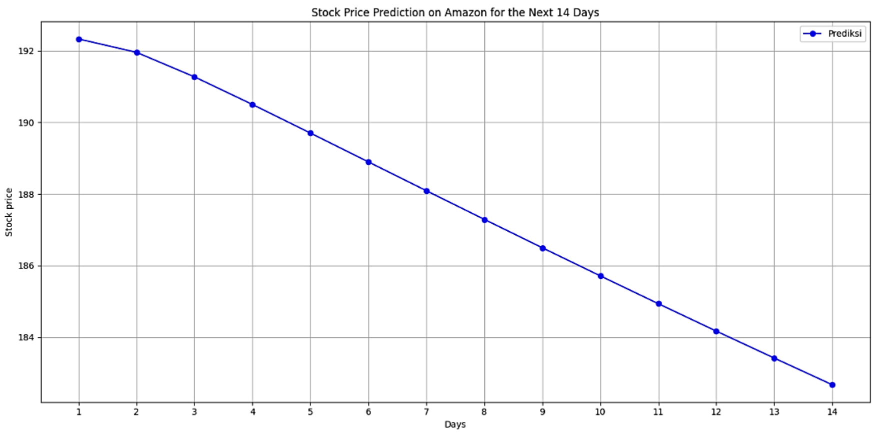

Figure 4. Stock Price Prediction for the Next 14 Days

3.3. Discusion

This research demonstrates that the GRU model configured with RMSprop, batch size 16, and a learning rate of 0.0001 outperforms LSTM in predicting Amazon stock prices. Previous research by Moghar and Hamiche (2020) supports this finding, emphasizing that although LSTM is effective in handling complex temporal dependencies, GRU provides faster training while maintaining accuracy. This advantage makes GRU more suitable for datasets with simpler temporal patterns or limited to shorter time spans [32].

On the other hand, LSTM with RMSprop achieves nearly equivalent performance, particularly on data with more complex temporal dependencies. This finding aligns with Tan (2023), who observed that adding layers to LSTM can enhance predictive accuracy in highly volatile market conditions, such as during the COVID-19 pandemic. These results suggest that LSTM remains valuable for capturing long-term dependencies and complex fluctuations in financial data, opening opportunities for model combinations that leverage the strengths of both LSTM and GRU [13].

Moreover, this study highlights that Naive model design focused only on historical price data may limit predictive capacity. Incorporating additional data such as trading volume, market sentiment, or macroeconomic indicators could strengthen predictive robustness. These external elements may enhance the adaptability of models when confronted with sudden shocks, policy changes, or global financial crises. Thus, this research provides a strong foundation for the exploration of hybrid or ensemble approaches that combine model architectures with external feature integration.

Furthermore, the experimental results indicate that GRU is not only efficient in training but also robust across multiple hyperparameter settings. For example, GRU trained with SGD at batch sizes of 16 and 32 and learning rates of 0.001 or 0.0001 achieved comparably low error metrics, underscoring the model's adaptability under different optimization strategies. This flexibility suggests that GRU is well-suited for practical stock forecasting applications, especially when balancing computational resources, training speed, and predictive performance.

Another key implication concerns the scalability of these models for longer temporal horizons and broader financial datasets. Since this study focused on five years of Amazon stock price data, extending the analysis to longer periods would provide insights into the models' ability to capture structural market cycles and sustained economic shifts. Testing hybrid configurations of LSTM and GRU on extended datasets may yield models that combine short-term responsiveness with long-term pattern recognition, making them more effective for real-world financial forecasting and investment decision-making.

4. CONCLUSION

This research successfully developed an Amazon stock price prediction model using the LSTM and GRU algorithms. The results showed that GRU with RMSprop configuration, batch size 16, and learning rate 0.0001 produced the best performance with MSE 6.06, RMSE 2.46, MAE 1.8, and MAPE 1.18%. These findings confirm the superiority of GRU in training efficiency and prediction accuracy on the dataset used.

Future research is recommended to integrate a hybrid model that combines the advantages of LSTM and GRU to overcome their respective limitations. In addition, the addition of external data such as market sentiment or macroeconomic indicators can be done to improve the accuracy of the model. The model also needs to be tested on datasets with longer temporal scales to evaluate its performance in detecting long-term patterns. This research makes a significant contribution in advancing stock price prediction methods and can serve as a basis for further innovation in this area.

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