International Journal Artificial Intelligent and Informatics
Vol. 2 No. 1, July 2024, pp. 41~46
ISSN: 2622-626X, DOI: https://doi.org/10.33292/ijarlit.v2i2.35

Stock Price Prediction of ReconAfrica (RECAF) Using Gated Recurrent Unit (GRU): Analysis and Implications for Investment Decisions

Tomás López Aníbal[1],Rabiu Okanlawon[2*]
[1] University of Otago, New Zealand
[2]University of Ghanaiversity of Pretoria, Ghana
Email: okanlawonr@gmail.com

Article Info

Article history:

Received: January 10, 2023
Revised: December 18, 2023
Accepted: January 30, 2024
Available Online: July 30, 2024

Keywords:

Stock Price Prediction
Gated Recurrent Unit (GRU)
ReconAfrica (RECAF)
Deep Learning
Financial Analytics
Investment Decision-Making

ABSTRACT

This study develops a stock price prediction model for ReconAfrica (RECAF) using Gated Recurrent Unit (GRU), an effective deep learning method for capturing temporal and non-linear patterns in stock price data. The model was trained and tested using five years of historical RECAF stock price data and evaluated with metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). The evaluation results show that the GRU model achieved an MAE of 0.0992, MSE of 0.0397, RMSE of 0.1993, and MAPE of 4.27, indicating a high predictive capability. These findings underscore the potential of the GRU model as a valuable tool for investors and market analysts in making more informed investment decisions. While the results are promising, the study also identifies opportunities for further development through the integration of external data and exploration of other deep learning architectures. Thus, this research contributes significantly to stock market analysis and improved investment strategies.

1. INTRODUCTION

The stock market serves as a vital mechanism within the global economy, acting as a barometer for economic health and providing a platform for capital allocation [1]. It attracts a diverse range of participants, including individual investors, institutional investors, and financial analysts, all vying for insights that can inform their investment decisions[2]. The intricacies of stock price movements—characterized by high volatility and complex interdependencies—underscore the need for sophisticated prediction methodologies that can offer a competitive edge in an increasingly dynamic environment[3].

Effective stock price prediction has become essential in today's financial landscape, where rapid fluctuations can lead to significant gains or losses[4]. Investors seek to harness predictive analytics not only to enhance their returns but also to manage risks associated with market uncertainties. Consequently, there is a growing emphasis on developing and refining predictive models that leverage advanced techniques to improve forecasting accuracy and reliability[5], [6].

One notable company for analysis is ReconAfrica (RECAF), an energy firm operating in the South African market. RECAF's stock price is influenced by a confluence of factors, including the company's operational performance, broader macroeconomic indicators, and the shifting dynamics within the energy sector. Understanding these influences is critical for developing a robust predictive model that can effectively gauge future price movements[7], [8].

In recent years, deep learning methods have emerged as powerful tools for various predictive tasks, including stock price forecasting [9], [10]. Among these techniques, the Gated Recurrent Unit (GRU) stands out for its effectiveness in handling sequential data and capturing long-term dependencies [9]. As a specialized variant of Recurrent Neural Networks (RNNs), GRU addresses the limitations of traditional RNNs, particularly the vanishing and exploding gradient problems that can impede learning in deeper networks [11]. This makes GRU particularly well-suited for analyzing financial time series data.

This research aims to construct a comprehensive stock price prediction model for RECAF utilizing the GRU architecture. The study will not only delve into the theoretical underpinnings of GRU but also explore its practical application in the context of stock price forecasting. By training and validating the model on historical stock price data, this research will assess its predictive accuracy and reliability in anticipating future market movements.

Previous studies have highlighted the advantages of deep learning techniques, including GRU, over traditional statistical methods in stock price prediction [12]–[14]. However, a gap persists in the existing literature regarding the specific application of GRU to RECAF and the South African stock market as a whole [6]. Addressing this gap is essential for advancing the field of stock price prediction and enhancing the applicability of deep learning techniques in diverse market contexts[15]–[18].

Through this research, we aim to contribute to the existing body of knowledge by providing insights into the effectiveness of GRU in predicting stock prices. By focusing on RECAF, this study will not only enhance our understanding of the factors influencing its stock performance but also offer a framework that can be adapted for other companies within the South African market. Ultimately, the findings will have implications for investors and market analysts seeking to leverage advanced predictive models in their investment strategies.

2. METHOD

This research employs the Gated Recurrent Unit (GRU) to predict the stock price of ReconAfrica (RECAF). The methodology is structured into several critical stages: data collection, data preprocessing, GRU model architecture development, model training, and model performance evaluation.

2.1. Data Collection

Historical stock price data for RECAF was sourced from reputable financial platforms such as Yahoo Finance. The dataset comprises essential variables, including the opening price, closing price, highest price, lowest price, and daily trading volume. The chosen time frame spans the last five years to ensure a comprehensive dataset that sufficiently represents market behavior, allowing for effective model training.

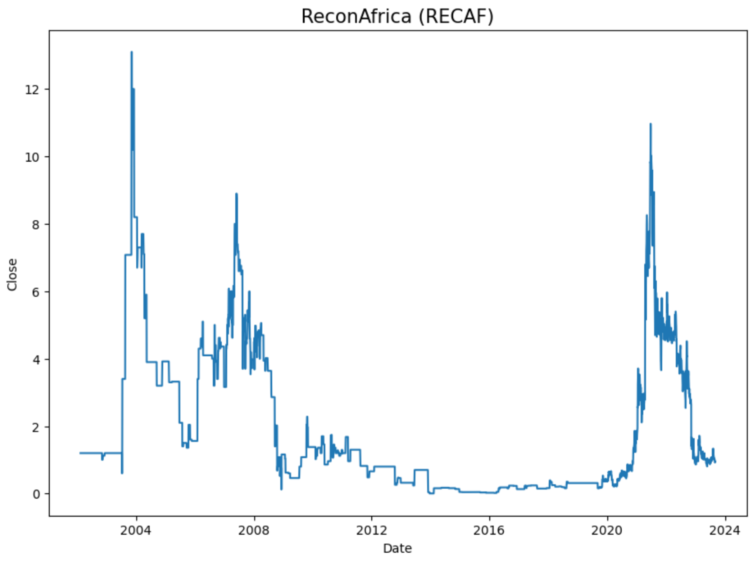

Figure 1. Historical stock price data for RECAF

2.2. Data Preprocessing

Prior to training the GRU model, the raw data undergoes a series of preprocessing steps to ensure its quality and suitability for analysis [19]. The preprocessing stages include: Handling Missing Values: Missing values in the dataset are addressed through deletion or imputation methods to maintain data integrity, Data Normalization: Normalization techniques, specifically Min-Max Scaling, are employed to rescale the data within the range [0, 1]. This step is crucial for improving the model's convergence during training, Sequence Generation: The stock price data is transformed into sequences of a specified length, which serve as inputs for the GRU model. This allows the model to learn from historical trends effectively, Data Division: The dataset is split into training and testing sets in an 80:20 ratio. The training set is used to fit the model, while the testing set evaluates its performance.

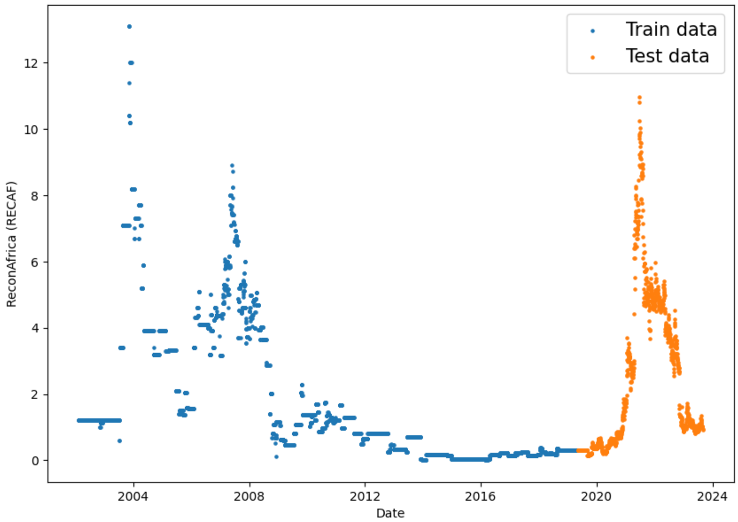

Figure 2. Graph of train and test data split

2.3. GRU Model Architecture

The architecture of the GRU model is designed to capture temporal patterns inherent in stock price data. The model comprises several key layers [20]:

1. Input Layer: This layer receives input sequences of stock price data, structured as (sequence_length, features).
2. GRU Layer: A GRU layer is included to extract temporal features from the input sequences. The number of units in this layer is optimized to enhance feature extraction.
3. Dense Layers: Several fully connected dense layers follow the GRU layer, facilitating the combination of extracted features and further learning.
4. Output Layer: The output layer consists of a single neuron that generates predictions for future stock prices.

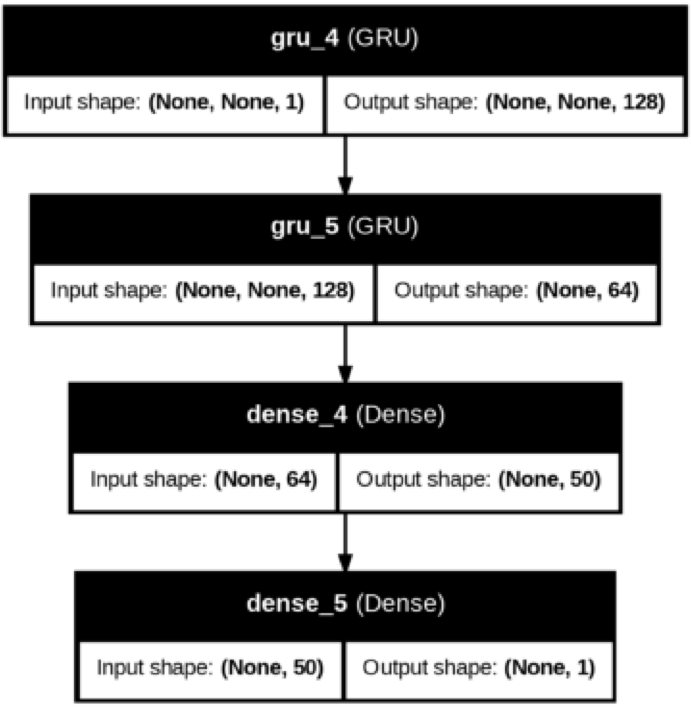

Figure 3. GRU Model Architecture

2.4. Model Training

The GRU model is trained using the preprocessed training data through a series of systematic steps:

1. Model Compilation: The model is compiled with the Adam optimizer and utilizes the Mean Squared Error (MSE) as the loss function, which is suitable for regression tasks.
2. Early Stopping: Early stopping techniques are implemented to mitigate overfitting by monitoring the model's performance on a validation set. This approach ensures that training halts once performance ceases to improve.
3. Model Training: The model is trained over a predetermined number of epochs, with a defined batch size. During this process, the model's weights are adjusted iteratively to minimize the loss function.

2.4. Model Performance Evaluation

Upon completion of the training process, the model's performance is assessed using the test data. The evaluation employs several metrics [10]:

1. Mean Absolute Error (MAE): This metric calculates the average absolute error between the model's predictions and actual stock prices.
2. Mean Squared Error (MSE): MSE assesses the average squared error between the predicted and actual values, providing insight into prediction accuracy.
3. Root Mean Squared Error (RMSE): RMSE quantifies the extent of error between the predicted and actual values, serving as a crucial indicator of model performance.
4. Mean Absolute Percentage Error (MAPE): This metric measures the average absolute percentage error, offering a relative measure of prediction accuracy.
5. Prediction vs. Actual Plotting: A comparative visualization is generated to juxtapose predicted stock prices against actual values, allowing for an intuitive assessment of the model's performance.

3. RESULTS AND DISCUSSION

3.1. Result

The Gated Recurrent Unit (GRU) model developed in this study was rigorously trained and tested using historical stock price data for ReconAfrica (RECAF). To evaluate the model’s performance, several key metrics were employed: Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). The evaluation results indicate that the GRU model demonstrates robust performance in predicting RECAF stock prices, with metric values of MAE at 0.09921739, MSE at 0.039725516, RMSE at 0.19931261, and MAPE at 4.2703176. These low values reflect a small prediction error in absolute terms, as well as minimal error rates when assessed through their squared and square root forms. This outcome illustrates the model's high level of accuracy in predicting stock prices, supported by the relatively low percentage error reflected in the MAPE values.

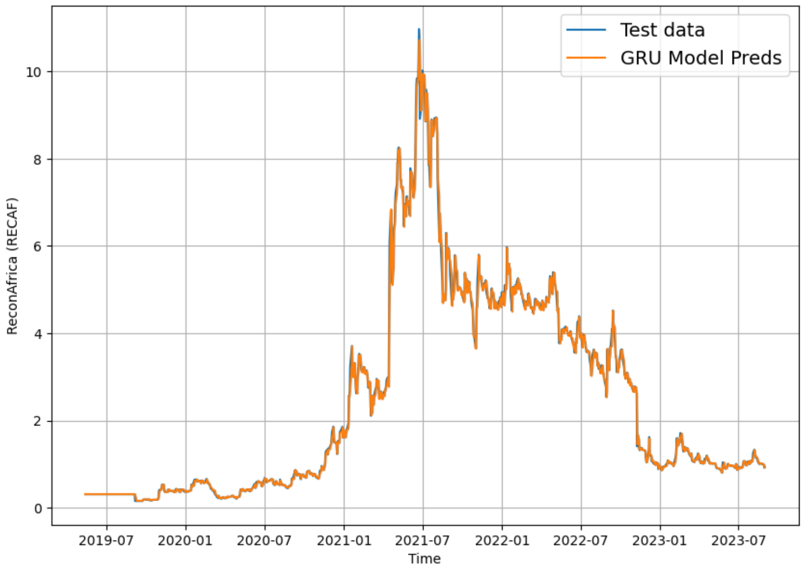

Figure 4. Comparison graph between test data and GRU prediction model

To further substantiate these findings, a graph comparing the actual stock prices with those predicted by the GRU model visually demonstrates that the predictions closely align with the actual values. This graphical representation reinforces the model's ability to capture essential patterns in RECAF's historical stock price data, thereby validating its predictive capabilities.

Table 1. Evaluation result table of GRU model

Evaluation Method	Value
MAE	0.09921739
MSE	0.039725516
RMSE	0.19931261
MAPE	4.2703176

3.2. Discussion

The results of this research indicate that the GRU model is effective in forecasting RECAF stock prices. The low MAE, MSE, RMSE, and MAPE values signify that the model produces reliable and accurate predictions. A critical aspect of the GRU model is its capacity to discern temporal patterns in stock price data, which may be challenging for traditional predictive methods to identify. This advantage arises from the GRU architecture, specifically designed to address issues related to vanishing and exploding gradients, which are common pitfalls in conventional Recurrent Neural Networks (RNNs).

When juxtaposed with alternative stock prediction methodologies such as ARIMA or linear regression, the GRU model exhibits superior performance in capturing the nonlinear fluctuations of stock prices. This finding aligns with previous studies that advocate for the efficacy of deep learning techniques in financial forecasting. Given the model's high predictive accuracy, it serves as a valuable tool for investors and market analysts, aiding them in making informed decisions. Accurate predictions can help identify market trends and enable timely actions to maximize returns or mitigate risks.

However, despite the GRU model's commendable performance, certain limitations must be acknowledged. The model requires substantial amounts of data for effective training and is computationally intensive. Future research could focus on optimizing the model's architecture and exploring innovative techniques such as transfer learning to enhance predictive accuracy. Additionally, it is essential to recognize that stock price predictions are influenced not only by historical data but also by various external factors, including economic conditions, political events, and market sentiment. Therefore, integrating external data into stock prediction models presents an intriguing avenue for future exploration.

In conclusion, this study validates the GRU model as an effective tool for predicting RECAF stock prices. With favorable evaluation outcomes, the model contributes significantly to the field of stock market analysis and provides valuable insights for market participants seeking to refine their investment strategies.

4. CONCLUSION

This research successfully developed a stock price prediction model for ReconAfrica (RECAF) using the Gated Recurrent Unit (GRU), demonstrating excellent performance with a Mean Absolute Error (MAE) of 0.0992, Mean Squared Error (MSE) of 0.0397, Root Mean Squared Error (RMSE) of 0.1993, and Mean Absolute Percentage Error (MAPE) of 4.27. These results highlight the model's strong capability to capture complex and non-linear patterns in stock price data, making it a valuable tool for investors and market analysts in making informed decisions and identifying trends. However, the study acknowledges the potential for improvement by integrating external data such as macroeconomic indicators and exploring other deep learning architectures like Convolutional Neural Networks (CNN) or Long Short-Term Memory (LSTM) models. Additionally, limitations include dependence on the quality of historical data and significant computational requirements, suggesting that optimizing model architecture and utilizing more efficient computational techniques should be priorities for future research.

REFERENCES

[1] A. C. Bhavani, A. V. Ramana, and A. S. N. Chakravarthy, "Comparative Analysis between LSTM and GRU in Stock Price Prediction," 2022, pp. 532–537. doi: 10.1109/ICECAA55415.2022.9936434.

[2] A. Chintam, G. R. R. Kumar, D. Chandramouli, J. A. Rani, and M. A. Praveen, "Accurate stock prices prediction on Grouped Time Series Data using Recurrent Neural Network Variants," 2022, pp. 1–6. doi: 10.1109/ICAECT54875.2022.9807842.

[3] D. Murekachiro, T. M. Mokoteli, and H. Vadapalli, "Predicting Emerging and Frontier Stock Markets Using Deep Neural Networks," 2019, pp. 899–918. doi: 10.1007/978-3-030-29516-5_68.

[4] D. Murekachiro, T. M. Mokoteli, and H. Vadapalli, "Stock Market Trend Prediction in Sub-Saharan Africa Using Generalized Additive Models (GAMs)," 2019, pp. 9–19. doi: 10.1007/978-3-030-30465-2_2.

[5] D. V. Trivedi and P. S. Patel, "An Analysis of GRU-LSTM Hybrid Deep Learning Models for Stock

Price Prediction," *Int. J. Sci. Res. Sci. Eng. Technol.*, pp. 47–51, 2022, doi: 10.32628/ijsrset229264.
[6] W. Lu, W. Ge, R. Li, and L. Yang, "A Comparative Study on the Individual Stock Price Prediction with the Application of Neural Network Models," 2021. doi: 10.1109/ICCEAI52939.2021.00046.
[7] J. Leng, W. Liu, and Q. Guo, "Stock movement prediction model based on gated orthogonal recurrent units," *Intell. Syst. with Appl.*, vol. 16, p. 200156, 2022, doi: 10.1016/j.iswa.2022.200156.
[8] Z. Bao, Q. Wei, Q. Wei, T. Zhou, X. Jiang, and T. Watanabe, "Predicting stock high price using forecast error with recurrent neural network," vol. 6, no. 1, pp. 283–292, 2021, doi: 10.2478/AMNS.2021.2.00009.
[9] H. Zhu, "Stock Price Prediction Using GRU and BiLSTM Models," 2023, pp. 95–105. doi: 10.1007/978-981-99-0483-9_9.
[10] Y. Chi-Hun, "Deep learning-based stock price prediction system and method using recurrent neural network." 2019.
[11] R. Mangalampalli, P. Khetre, V. Malviya, and V. Pandey, "Stock Prediction using Hybrid ARIMA and GRU Models," *Int. J. Eng. Res.*, vol. 9, no. 05, 2020, doi: 10.17577/IJERTV9IS050550.
[12] P. Dey *et al.*, "Comparative Analysis of Recurrent Neural Networks in Stock Price Prediction for Different Frequency Domains," *Algorithms*, vol. 14, no. 8, 2021, doi: 10.3390/A14080251.
[13] J. Liu, F. Chao, Y.-C. Lin, and C.-M. Lin, "Stock Prices Prediction using Deep Learning Models.," *arXiv: Learning*. 2019. [Online]. Available: https://arxiv.org/pdf/1909.12227.pdf
[14] "A Stock Price Prediction Model Based on Investor Sentiment and Optimized Deep Learning," *IEEE Access*, vol. 11, pp. 51353–51367, 2023, doi: 10.1109/access.2023.3278790.
[15] W. Yujie, L. Hui, Z. Caiming, G. Qiang, and L. Xin, "Stock price fluctuation prediction method of convolutional neural network combining financial news." 2018.
[16] M. Guan, Y. Zhu, and B. Xiao, "Unveiling the Predictive Power: Comparative Analysis of Cutting-Edge Deep Learning Models for Stock Price Forecasting," 2023, doi: 10.54097/hbem.v19i.11747.
[17] R. H. Kusumodestoni and S. Sarwido, "Komparasi Model Support Vector Machines (Svm) Dan Neural Network Untuk Mengetahui Tingkat Akurasi Prediksi Tertinggi Harga Saham," *J. Inform. Upgris*, vol. 3, no. 1, 2017, doi: 10.26877/jiu.v3i1.1536.
[18] Y. Srivastava, A. S. Chauhan, R. Vaishnav, and K. Bharadwaj, "Forecasting Market Price of Stock Using Artificial Neural Network," 2023, pp. 544–547. doi: 10.1109/icseiet58677.2023.10303500.
[19] Y. S. Khodke, "Stock Price Prediction Using LSTM and GRU," *Int. J. Sci. Technol. Eng.*, vol. 11, no. 6, pp. 1163–1167, 2023, doi: 10.22214/ijraset.2023.53826.
[20] W. Wu, Y. Zhao, Y. Wang, and X. Wang, "Stock Price Forecasting and Rule Extraction Based on L1-Orthogonal Regularized GRU Decision Tree Interpretation Model," 2020, pp. 309–328. doi: 10.1007/978-981-15-7984-4_23.