2025 International Conference on Computer Sciences, Engineering, and Technology Innovation (ICoCSETI) | 979-8-3315-0861-6/25/$31.00 ©2025 IEEE | DOI: 10.1109/ICoCSETI63724.2025.11019594

Comparison of Deep Learning Algorithms (LSTM & GRU) for Predicting Product Stocks

Darmawan Lahru Riatma
Vocational School
of March 11th University
Surakarta, Indonesia
darmawanlr@staff.uns.ac.id

Trisna Ari Roshinta
Vocational School
Sebelas Maret University
Surakarta, Indonesia
trisna.roshinta@staff.uns.ac.id

Masbahah
Vocational School
Sebelas Maret University
Surakarta, Indonesia
masbahah@staff.uns.ac.id

Yusuf Fadhila Rachman
Vocational School
Sebelas Maret University
Surakarta, Indonesia
yusuf_fadil@staff.uns.ac.id

Nur Azizul Hakimi
Vocational School
Sebelas Maret University
Surakarta, Indonesia
n.azizul.haqimi @staff.uns.ac.id

Rayya Alika
Vocational School
Sebelas Maret University
Surakarta, Indonesia
rayya.alika@student.uns.ac.id

***Abstract*— The retail sales sector plays a significant role in the global economy, contributing over 15% of global GDP. The rapid growth of e-commerce has made business forecasting increasingly crucial for-profit planning and operational management in the retail sector. Inaccurate predictions can lead to either stock shortages or excess inventory. If demand is underestimated, stockouts may occur, resulting in lost revenue that often cannot be recovered, as dissatisfied customers may turn to other retail options. This research aims to compare the performance of Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) algorithms for sales prediction. The methodology involves data collection from sales databases, data preprocessing, and stock prediction using the LSTM and GRU algorithms. The model results are then denormalized, and algorithm performance is evaluated. Findings indicate that the LSTM algorithm outperforms GRU regarding RMSE, MAE, and MAPE, demonstrating greater accuracy in the dataset used. Specifically, LSTM achieved an R^2 of 0.83, explaining 83% of the data variance, while GRU achieved an R^2 of 0.70. While both algorithms are effective, GRU's performance is slightly weaker compared to LSTM.**

Keywords*— *Forecasting, LSTM, GRU, Business Analysis

I. Introduction

E-commerce today is experiencing a trend of increasing users and sales, prompting more resellers to seek partnerships and adopt strategic marketing approaches. This trend also impacts the management of purchasing, logistics, and real-time product storage [1], [2], [3]. The retail sales sector holds a substantial role in the global economy, contributing over 15% of global GDP [4]. According to a survey by [5], the combined revenue of the top 250 retail companies worldwide reached US$4.85 trillion in 2019, with an average revenue of US$19.4 billion per company. North America accounted for 47% of this revenue, followed by Europe with 33%, and Asia-Pacific with 16%.

The rapid development of retail business is very fast, making forecasting business very important due to consumer services and careful planning [6]. Predictions that are not accurate can result in a lack or excess of supply [7]. In other words, if the forecast is lower than customer demand, there will be stock-outs that result in lost revenue that is often irreparable, as dissatisfied customers may switch to other retail chains. Conversely, if the forecast is higher than customer demand, there will be excess stock and inventory losses.

Improving forecast accuracy has an impact on inventory and improving customer service [8]. Many methods have been used for forecasting, including deep learning. Deep learning has enabled scientists to extract patterns from various types of data [9]. Deep learning has been applied in predicting time series data, including Recurrent Neural Networks (RNN). RNN excels in areas that require sequential information, such as time series, text, audio, and video [10]. RNN was introduced as an extension of the feedforward network so it can process sequences of varying or even infinite length. Some of the most popular RNN architectures are Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) [11]. LSTM and GRU are RNN networks that are commonly used to predict future components [12] [13] [14] [14], [15], [16], [17], [18]. Work by [19][20] mentions some examples of future prediction cases using LSTM and GRU. While LSTM and GRU are commonly used in forecasting application, there still lack of study about comparison between LSTM and GRU, especially for prediction produck stock.

This study was conducted to compare the performance of the RNN algorithm, namely LSTM and GRU, to predict products sold based on the available dataset and train data. This is important to ensure the supply chain and product availability so that it is expected to have an impact on consumer services and careful planning. The article enriches the body of knowledge in machine learning by providing a comparative analysis of LSTM and GRU in the context of product stock prediction, a relatively underexplored area in prior research. By evaluating the strengths and limitations of both algorithms, this study promotes further research into optimizing existing methods or developing new approaches.

II. Methodology

The workflow of this research is divided into five steps, data collection, data processing, model generation, denormalization and evaluation. The number of hidden layers used in this study is 1 to 3, while the hidden units used are 10 to 30. The workflow can be seen in Figure 1.

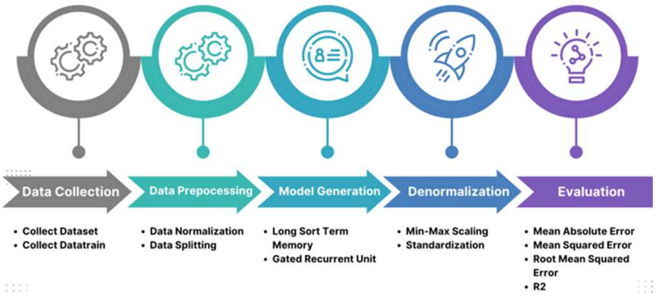

Fig. 1. Proposed Framework for Experiments

A. Data Collection

This step involves gathering datasets and training data that will be used to develop the prediction model. The limitations of this study are, data collection in this study is done by extracting data bread sales data from January 2021 to September 2022 from a marketplace in Taiwan. The total data used was 129,270 data. The example of sales data is presented in Table 1.

Table 1. Example of Bread Sales Data

No	Date	Products	QTY	Price
1	2021-01-02	BAGUETTE	1	0.90 €
2	2021-01-02	PAIN AND CHOCOLATE	3	1.20 €
3	2021-01-02	CROISSANT	3	1.10 €

B. Data Preprocessing

Data normalization is performed to ensure all variables are on the same scale. Subsequently, the data is split into training and testing sets for model training and validation. This stage aims to produce a valid dataset and is ready to use in machine learning models by normalizing and splitting the data.

- Data Normalization

The data is normalized into two intervals: [-1,1] and [0,1] to determine which interval produces the best value. The purpose of normalization is to eliminate duplicate data, to reduce complexity, and to make it easier to modify data.

$$x_n = \frac{x_0 - x_{min}}{x_{max} - x_{min}} \quad (1)$$

Where x_n is the mark results normalization, x_0 actual data value, x_{min} is the minimum value of actual data, and x_{max} is the mark maximum from actual data.

- Data Splitting

The dataset that has been normalized will be divided into training data and test data according to the expected prediction period.

C. Prediction Stock

Two algorithms, LSTM and GRU, are employed to build a stock prediction model based on historical data patterns.

- Long Short Term Memory

Long Short Term Memory (LSTM) algorithm is often implemented for prediction and forecasting. LSTM has proven to give results powerful, efficient, and predictable forecasting reliable for problem prediction [21].

The LSTM architecture is shown in Figure 2, consisting of an input layer, an output layer, and a hidden layer. The hidden layer consists of an input gate, a forget gate, and an output gate.

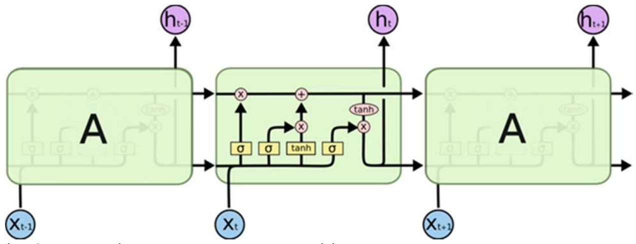

Fig. 2. Long Short Term Memory Architecture

$$I_t = \sigma(W_i S_{t-1} + W_i X_t) \quad (2)$$

$$\hat{C} = \tanh(W_c S_{t-1} + W_c X_t) \quad (3)$$

$$f_t = \sigma(W_f S_{t-1} + W_f X_t) \quad (4)$$

$$O_t = \sigma(W_o S_{t-1} + W_o X_t) \quad (5)$$

Where I_t is the input gate, f_t is the forget gate, $\hat{C}$ is the memory cell, O_t is the output gate.

- Gated Recurrent Unit

Gated Recurrent Unit (GRU) networks have a similar cell structure to LSTM networks. However, their simpler regulation mechanism compared to LSTM networks allows the system to perform complex calculations with fewer resources and in less time. Thus, training of these networks is done at a higher speed. [22].

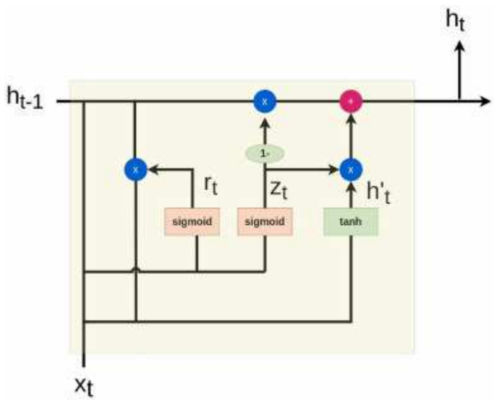

Fig. 3. Gated Recurrent Unit Framework

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t] + b_z) \quad (6)$$
$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t] + b_r) \quad (7)$$
$$h't = \tan h(W_h \cdot [r_t \odot h_{t-1}, x_t] + b_h) \quad (8)$$
$$h_t = (1 - z_t \odot h_{t-1} + z_t \odot h'_t) \quad (9)$$

Where h_t is the hidden layer vector, x_t is the input vector, b_z, b_r, and bh are the bias vectors, W_z, W_r, and W_h are the parameter matrices [23].

D. Data Denormalization

After the prediction is made, the results are translated back to their original scale using methods such as min-max scaling or standardization. The output generated from the prediction process is still in the form of normalized data, so denormalization is carried out, namely changing the data back to real values. After that, the percentage of training data and testing data will be produced, which can then be used to calculate the error or percentage of error. Because the data is still in the form of an interval range that has previously been normalized. Min-max scaler is used to normalize data, and Equation 10 is a mathematical representation of min-max scaler [24].

$$dn_i = (n_i + 1)(x_{max} - x_{min}) + \left(\frac{2(x_{min})}{2}\right) \quad (10)$$

Where dni is the denormalized data, ni is the normalized data, x_{min} is the minimum value of the real data and x_{max} is the maximum value of the real data. The purpose of denormalization is to make it easier to read the resulting output values.

E. Evaluation

The model is evaluated using metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2) to measure prediction performance. Error Measurement is calculated to ensure that the model predicts with good accuracy and minimizes errors. Error analysis of the LSTM and GRU algorithms uses Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MPAE). R square is also known as the coefficient of determination which explains how far dependent data can be explained by independent data. The formulas can be seen as follows [25].

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y_i - \hat{Y}_i}{Y_i}\right| \times 100\% \quad (11)$$

$$RSME = \sqrt{\sum \frac{(Y' - Y)^2}{n}} \quad (12)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|Y_i - \hat{Y}_i\right| \quad (13)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2}{\sum_{i=1}^{n}\left(Y_i - \bar{Y}\right)^2} \quad (14)$$

In this context, "yi" is the actual output, "yˆ" is the predicted output, and "n" indicates the number of existing examples.

IV. Results and Discussion

A. Experiment Data

The data was obtained from Taiwan's marketplace. The experiment only used the bread sales data from January 2021 to September 2022, with a total of 129,270 data. The data is cleaned, filtered based on user input, and processed into normalized monthly sales data. In this study, the prediction of next month used the previous 12 months of data. The LSTM model is built, compiled, and trained with ModelCheckpoint to save the best model. After training, the model is used to make predictions on the test data, and evaluation is carried out with RMSE, MAE, and MAPE. This process uses Tensorflow Keras tools and Python programming language.

B. Evaluation of LSTM and GRU

In this study, the evaluation uses RMSE (Root Mean Squared Error), MAPE (Mean Absolute Percentage Error), and MAE (Mean Absolute Error). Testing is done by trying several epochs, namely 20, 50, 75, 100, 125, 150, and 200. Table 2 and Figure 3 show the performance of the model on the LSTM and GRU algorithms.

Table 2. Evaluation Results LSTM and GRU Algorithms

		EPOCH						
Algorithm	**Metric**	**20**	**50**	**75**	**100**	**125**	**150**	**200**
LSTM	RMSE	1241.60	613.55	613.55	613.55	537.93	537.93	461.09
	MAE	1149.65	454.19	454.19	454.19	464.20	464.20	366.06
	MAPE	0.68	0.60	0.60	0.60	0.23	0.23	0.15
GRU	RMSE	1104.90	855.20	763.75	762.48	762.48	757.86	622.94
	MAE	985.01	676.52	590.55	562.26	562.26	589.41	451.04
	MAPE	0.54	0.28	0.20	0.20	0.20	0.24	0.15

RMSE testing is done to measure the root of the mean square error between the predicted value and the actual value. The smaller the RMSE value, the better the model is at predicting results that are close to the actual value. Table 2 shows the LSTM algorithm with the smallest value at epoch 200 with a value of 461.09, which means that the LSTM model prediction has an average error of 461.09 units from the actual value. In the GRU algorithm, the smallest value is at epoch 200 with a value of 622.94, which means that the GRU model prediction has an average error of 622.94 units from the actual value. LSTM has a lower RMSE value than GRU, which is 461.09, while GRU is 622.94, this shows that LSTM produces more accurate predictions in the existing dataset compared to GRU.

Figure 3 shows the LSTM RMSE test at epoch 100 is 613.55, at epoch 150 it decreases to 537.93, and at epoch 200 it reaches 461.09. This shows that increasing epochs in LSTM improves model performance, as seen from the decrease in RMSE value as the epoch increases. Meanwhile, in the GRU algorithm, the RMSE at epoch 100 is 762.48, a little decrease to 757.86 at epoch 150, and decreased further to 622.94 at epoch 200. Although there is an RMSE decrease in GRU, its value is larger than LSTM, which means that GRU has underperformance for this dataset at each epoch.

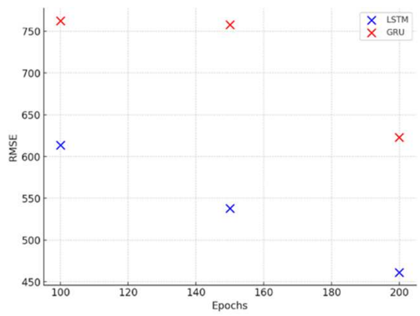

Fig. 3. RMSE vs Epoch for LSTM And GRU Algorithms

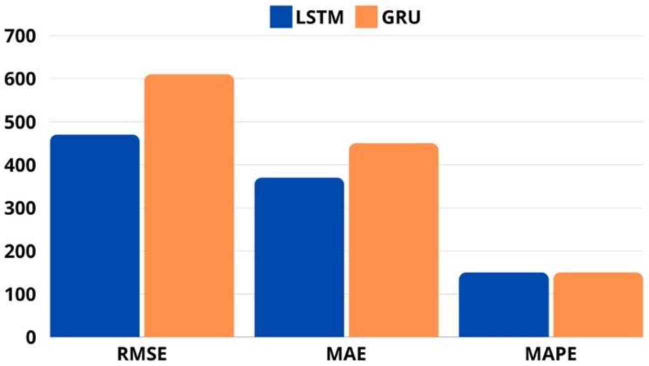

Fig. 4. Comparison of GRU and LSTM Algorithms Performance

Figure 4 shows the results of the MAE (Mean Absolute Error) test on the LSTM algorithm showing a value of 366.06 at epoch 200, while on GRU, the MAE value is 451.04 at the same epoch, this shows that LSTM shows a lower MAE value than GRU, with a difference of about 85 units. MAE treats all errors equally, regardless of magnitude. Like RMSE, lower MAE values indicate better accuracy, and MAE is also in the same units as the data. This shows that the LSTM model is more accurate than GRU in predicting the dataset used.

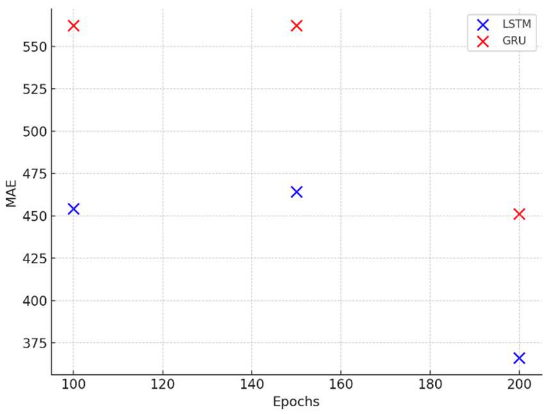

Fig. 5. MAE vs Epoch for LSTM And GRU Algorithms

From Figure 5, the MAE of LSTM epoch 100 is 454.19, slightly increasing to 464.20 at epoch 150, but significantly decreasing to 366.06 at epoch 200. This shows that although there is a slight increase in error at epoch 150, the overall performance of LSTM improves with more epochs, especially at epoch 200. The MAE at epochs 100 and 150 remains 562.26, unchanged, and only decreases to 451.04 at epoch 200. Although there is a decrease at epoch 200, the MAE value of GRU is still higher than that of LSTM, indicating that LSTM is more efficient in reducing errors.

The MAPE (Mean Absolute Percentage Error) test results with epoch 200 on the LSTM and GRU algorithms show the same value, which is 0.15 or 15%. MAPE measures the average prediction error in percentage terms. A value of 0.15 means that the average prediction error for both algorithms is 15% of the actual value. The lower the MAPE value, the better the model is at making accurate predictions. In this case, a prediction error of 15% is considered quite good, especially if the expected predicted value is within an acceptable margin of error.

C. *Coefficient Test Determination*

In this study, R^2 measures how well the model can explain the variation in data or how well the model fits the actual data. The R^2 value ranges from 0 to 1, where 1 indicates that the model can predict the value perfectly, and 0 means the model cannot explain the variability in the data at all. Table 3 shows the results of the comparison of the determination coefficients at epochs 20 to 200.

Table 3. R^2 Measures for LSTM and GRU

Metric	**Epoch**						
R^2	**20**	**50**	**75**	**100**	**125**	**150**	**200**
LSTM	-0.16	0.71	0.71	0.71	0.78	0.78	0.83
GRU	0.074	0.44	0.55	0.55	0.55	0.56	0.70

Epoch 200 compared to GRU, LSTM is superior with an R^2 value of 0.83, which means that this model can explain 83% of the data variation and is more suitable for this prediction problem, while in GRU with an R^2 value of 0.70, it is still a good model, but its performance is slightly weaker than LSTM. Figure 6 shows that LSTM performance increases with increasing epochs. From a poor start at epoch 20 with a negative R^2, the model continues to improve and reaches optimal results at epoch 200 with a very good R^2 value of 0.83.

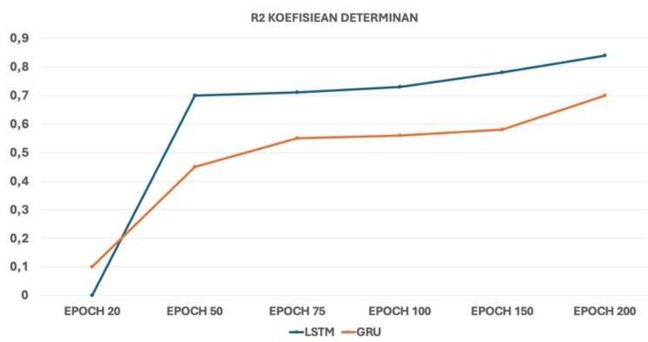

Fig. 6. Coefficient Determinant vs Epoch for LSTM and GRU

GRU starts training with better performance than LSTM, but the improvement is much slower. Although there is an increase to $R^2 = 0.70$ at epoch 200, GRU lags behind compared to LSTM, which is already reaching $R^2 = 0.83$.

IV CONCLUSION

This study compares the performance of LSTM (Long Short-Term Memory) and GRU (Gated Recurrent Unit) algorithms in the context of product stock prediction, offering valuable insights into their strengths and weaknesses based on evaluation metrics such as RMSE, MAE, MAPE, and R^2. While both algorithms are widely used in prediction tasks, the findings highlight how their performance varies with specific datasets and epoch numbers. Unlike many previous studies that focus on a single evaluation metric, this research provides a more comprehensive analysis by evaluating multiple metrics, enabling a deeper understanding of the models' behavior.

The results offer practical recommendations for industry decision-makers to choose the most suitable algorithm for stock prediction. LSTM, with its higher R^2 value of 0.83 and more accurate predictions (lower MAE), emerges as the preferred choice for scenarios requiring high precision. Although GRU is simpler, its performance on this dataset is slightly inferior to LSTM. This finding is crucial for companies aiming to balance prediction accuracy and processing efficiency.

Given LSTM's superior results, companies can confidently adopt this algorithm to enhance operational efficiency and improve stock management processes. These findings are particularly relevant for industries such as retail and logistics, where real-time predictions are essential to minimize losses and optimize inventory. With a MAPE of 15%, both models demonstrate sufficient accuracy for real-world applications. However, the recommendation to use LSTM is further supported by its ability to explain up to 83% of data variability, making it a more reliable option for practical use.

The novelty of this study lies in its in-depth analysis of LSTM and GRU algorithms for stock prediction, bridging the gap between theoretical research and practical application. By providing actionable insights, this research supports better decision-making in the industry, enhances operational efficiency, and encourages the adoption of machine learning-based predictive technologies. The consistent performance of LSTM across multiple metrics solidifies its role as the preferred choice for stock prediction problems requiring high accuracy and robust generalization capabilities.

REFERENCES

[1] N. Chaudhuri, G. Gupta, V. Vamsi, and I. Bose, "On the platform but will they buy? Predicting customers' purchase behavior using deep learning," *Decis Support Syst* , vol. 149, p. 113622, Oct. 2021, doi : 10.1016/j.dss.2021.113622.

[2] RM van Steenbergen and MRK Mes , "Forecasting demand profiles of new products," *Decis Support Syst* , vol. 139, p. 113401, Dec. 2020, doi : 10.1016/j.dss.2020.113401.

[3] M. Zeng, H. Cao, M. Chen, and Y. Li, "User behavior modeling, recommendations, and purchase predictions during shopping festivals," *Electronic Markets* , vol. 29, no. 2, pp. 263–274, Jun. 2019, doi : 10.1007/s12525-018-0311-8.

[4] World Economic Forum, "How turning retail stores into e-commerce centers can avoid massive emissions," https://www.weforum.org/agenda/2022/09/retail-stores-into-ecommerce-centres-avoid -carbon-emissions/.

[5] Deloitte Touche Tohmatsu Limited, "Global powers of retailing," https://scholar.google.com/scholar_lookup?title=Global%20powers%20of%20retailing&publication_year=2021&author=Deloitte%20Touche%20Tohmatsu%20Limited.

[6] D. Corsten and T. Gruen, "Desperately seeking shelf availability: an examination of the extent, the causes, and the efforts to address retail out-of-stocks," *International Journal of Retail & Distribution Management* , vol. 31, no. 12, pp. 605–617, Dec. 2003, doi : 10.1108/09590550310507731.

[7] LACG Andrade and CB Cunha, "Disaggregated retail forecasting: A gradient boosting approach," *Appl Soft Comput* , vol. 141, p. 110283, Jul. 2023, doi : 10.1016/j.asoc.2023.110283.

[8] L. Tiacci and S. Saetta, "An approach to evaluate the impact of interaction between demand forecasting method and stock control policy on the inventory system performances," *Int J Prod Econ* , vol. 118, no. 1, pp. 63–71, March. 2009, doi : 10.1016/j.ijpe.2008.08.010.

[9] MM Najafabadi , F. Villanustre , TM Khoshgoftaar , N. Seliya , R. Wald, and E. Muharemagic , "Deep learning applications and challenges in big data analytics," *J Big Data* , vol. 2, no. 1, p. 1, Dec. 2015, doi : 10.1186/s40537-014-0007-7.

[10] J. Yu, A. de Antonio, and E. Villalba -Mora, "Deep Learning (CNN, RNN) Applications for Smart Homes: A Systematic Review," *Computers* , vol. 11, no. 2, p. 26, Feb. 2022, doi : 10.3390/computers11020026.

[11] R. DiPietro and G.D. Hager, "Deep learning: RNNs and LSTM," in *Handbook of Medical Image Computing and Computer Assisted Intervention* , Elsevier, 2020, pp. 503–519. doi : 10.1016/B978-0-12-816176-0.00026-0.

[12] M. Waqas and UW Humphries, "A critical review of RNN and LSTM variants in hydrological time series predictions," *MethodsX* , vol. 13, p. 102946, Dec. 2024, doi : 10.1016/j.mex.2024.102946.

[13] M. Wang and F. Ying, "Point and interval prediction for significant wave height based on LSTM-GRU and KDE," *Ocean Engineering* , vol. 289, p. 116247, Dec. 2023, doi : 10.1016/j.oceaneng.2023.116247.

[14] A. Ait Mansour, A. Tilioua , and M. Touzani , "Bi-LSTM, GRU and 1D-CNN models for short-term photovoltaic panel efficiency forecasting case amorphous silicon grid-connected PV system," *Results in Engineering* , vol. 21, p. 101886, March. 2024, doi : 10.1016/j.rineng.2024.101886.

[15] MS Islam and E. Hossain, "Foreign exchange currency rate prediction using a GRU-LSTM hybrid network," *Soft Computing Letters* , vol. 3, p. 100009, Dec. 2021, doi : 10.1016/j.socl.2020.100009.

[16] K. Zarzycki and M. Ławryńczuk , "Advanced predictive control for GRU and LSTM networks," *Inf Sci (NY)* , vol. 616, pp. 229–254, Nov. 2022, doi : 10.1016/j.ins.2022.10.078.

[17] Z. Yao, Z. Wang, D. Wang, J. Wu, and L. Chen, "An ensemble CNN-LSTM and GRU adaptive weighting model based improved sparrow search algorithm for predicting runoff using historical meteorological and runoff data as input," *J Hydrol (Amst)* , vol. 625, p. 129977, Oct. 2023, doi : 10.1016/j.jhydrol.2023.129977.

[18] L. Zhao, Z. Li, L. Qu, J. Zhang, and B. Teng, "A hybrid VMD-LSTM/GRU model to predict non-stationary and irregular waves on the east coast of China," *Ocean Engineering* , vol. 276, p. 114136, May 2023, doi : 10.1016/j.oceaneng.2023.114136.

[19] K. Johny, ML Pai, and AS, "A multivariate EMD-LSTM model aided with Time Dependent Intrinsic Cross-Correlation for monthly rainfall prediction,"

Appl Soft Comput , vol. 123, p. 108941, Jul. 2022, doi : 10.1016/j.asoc.2022.108941.

[20] A. C. Ozdemir , K. Buluş , and K. Zor , "Medium- to long-term nickel price forecasting using LSTM and GRU networks," *Resources Policy* , vol. 78, p. 102906, Sept. 2022, doi : 10.1016/j.resourpol.2022.102906.

[21] Y. Liu, C. Yang, K. Huang, and W. Gui, "Non-ferrous metals price forecasting based on variational mode decomposition and LSTM network," *Knowl Based Syst* , vol. 188, p. 105006, Jan. 2020, doi : 10.1016/j.knosys.2019.105006.

[22] A. C. Ozdemir , K. Buluş , and K. Zor , "Medium- to long-term nickel price forecasting using LSTM and GRU networks," *Resources Policy* , vol. 78, p. 102906, Sept. 2022, doi : 10.1016/j.resourpol.2022.102906.

[23] K. Zor and K. Bulus , "A benchmark of GRU and LSTM networks for short-term electric load forecasting," in *2021 International Conference on Innovation and Intelligence for Informatics, Computing, and Technologies (3ICT)* , IEEE, Sep . 2021, pp. 598–602. doi : 10.1109/3ICT53449.2021.9581373.

[24] KE ArunKumar , DV Kalaga , Ch. Mohan Sai Kumar, M. Kawaji , and TM Brenza , "Comparative analysis of Gated Recurrent Units (GRU), long Short-Term memory (LSTM) cells, autoregressive Integrated moving average (ARIMA), seasonal autoregressive Integrated moving average (SARIMA) for forecasting COVID-19 trends," *Alexandria Engineering Journal* , vol. 61, no. 10, pp. 7585–7603, Oct. 2022, doi : 10.1016/j.aej.2022.01.011.

[25] A. C. Ozdemir , K. Buluş , and K. Zor , "Medium- to long-term nickel price forecasting using LSTM and GRU networks," *Resources Policy* , vol. 78, p. 102906, Sept. 2022, doi : 10.1016/j.resourpol.2022.102906.

[26] J. Tang, C. Liu, D. Yang, and M. Ding, "Prediction of ionospheric TEC using a GRU mechanism method," *Advances in Space Research* , vol. 74, no. 1, pp. 260–270, Jul. 2024, doi : 10.1016/j.asr.2024.03.050.