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ACTIVATION FUNCTION IN LSTM FOR IMPROVED FORECASTING OF CLOSING NATURAL GAS STOCK PRICES

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Abstract— *The closing price of natural gas stocks greatly influences investment decisions and the energy industry. Predicting prices correctly can greatly help investors, market participants, and all parties involved, as it allows for making better decisions and optimizing investment portfolios. By using deep learning methods to role model various LSTM activation functions, such as Sigmoid, ReLU, and Tanh, this exploration will hopefully help understand complex patterns in time series data. By finding an appropriate forecasting method, all parties involved can reduce the environmental impact. The experimental results show that the model with ReLU activation function has the highest R2 value of 0.960 in both the training and test sets, and the model with Tanh activation function is also successful, with R2 values of 0.950 in the training set and 0.949 in the test set, and an MSE of 0.002. The model with the sigmoid activation function was slightly lower, with R2 values of 0.931 in the training set and 0.943 in the test set, and an MSE of 0.003. These findings indicate that the LSTM model with the ReLU activation function is considered better for predicting the closing price of natural gas stocks. These findings may help investors, stakeholders, and market participants choose the most accurate model to predict the closing price of natural gas stocks.*

Keywords: *LSTM, natural gas, ReLU, sigmoid, tanh.*

Intisari— *Harga penutupan saham gas bumi sangat mempengaruhi keputusan investasi dan industri energi. Memprediksi harga dengan benar dapat sangat membantu investor, pelaku pasar, dan semua pihak yang terlibat karena memungkinkan untuk membuat keputusan yang lebih baik dan mengoptimalkan portofolio investasi. Dengan menggunakan metode pembelajaran mendalam untuk model peran berbagai fungsi aktivasi LSTM, seperti Sigmoid, ReLU, dan Tanh, eksplorasi ini diharapkan akan membantu memahami pola kompleks dalam data set waktu. Dengan menemukan metode peramalan yang tepat semua pihak yang terlibat dapat mengurangi dampak lingkungan. Hasil eksperimen menunjukkan bahwa model dengan fungsi aktivasi ReLU memiliki nilai R2 tertinggi sebesar 0.960 baik pada set pelatihan maupun uji, dan model dengan fungsi aktivasi Tanh juga berhasil, dengan nilai R2 sebesar 0.950 pada set pelatihan dan 0.949 pada set uji, dan MSE sebesar 0.002. Model dengan fungsi aktivasi Sigmoid sedikit lebih rendah, dengan nilai R2 sebesar 0,931 pada set pelatihan dan 0.943 pada set uji, dan MSE sebesar 0.003. Penemuan ini menunjukkan bahwa model LSTM dengan fungsi aktivasi ReLU dianggap lebih baik untuk memprediksi harga penutupan saham gas bumi. Penemuan ini dapat membantu investor, pemangku kepentingan, dan pelaku pasar dalam memilih model yang paling akurat untuk memprediksi harga penutupan saham gas bumi.*

Kata Kunci: *LSTM, gas bumi, ReLU, sigmoid, tanh.*

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INTRODUCTION

Natural gas price predictions are very important for market participants of all types [1]. A general increase in demand can create growth opportunities for the natural gas industry, which in turn affects the stock prices of companies involved in the sector [2]. The closing price of natural gas stocks significantly impacts the energy industry and investment decisions; successfully predicting this price can greatly benefit market participants and parties involved, allowing them to make smarter decisions and optimise their investment portfolios. [3], [4].

It is crucial to determine appropriate forecasting techniques to maximize energy consumption and reduce the negative impact on the environment. Forecasting natural gas demand and consumption with a high degree of accuracy can be done with the Long Short-Term Memory (LSTM) method [4], as demonstrated by comparative analyses with existing Artificial Neural Network (ANN) models [5]. One of the advantages of the LSTM method is that it can project the trend of natural gas prices in the global market with a higher degree of accuracy than ordinary machine learning algorithms [6]. By thoroughly detailing the non-linear relationships between gas composition and various factors affecting it, the LSTM artificial neural network model can produce highly accurate predictions [7],[8]. Predictions made using this model have also been shown to be more precise than predictions made by conventional artificial neural network models [9], [10], [11].

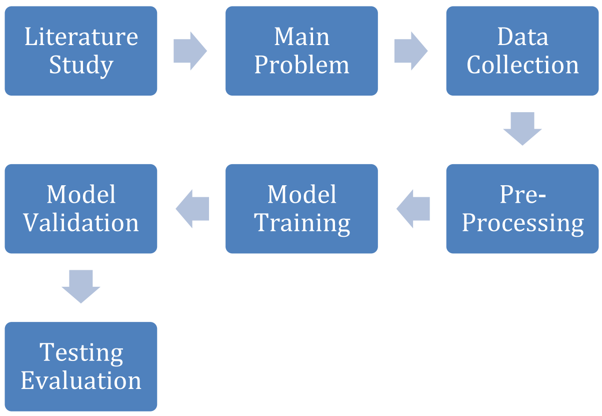
Activation functions are essential in improving LSTMs' understanding of complex patterns in time series data. The success of the activation function in LSTM lies in its ability to overcome the vanishing gradient problem, which allows the model to retain the memory of important information over a long period. The activation function is a critical element of the LSTM architecture, as revealed in several studies [12], [13].

Several frequently used activation functions, such as Sigmoid, ReLU, and Tanh, also strengthen the performance of LSTM. Exploration to find a more optimal activation function is expected to positively contribute to the learning performance of artificial neural networks [14]. The purpose of using the ReLU activation function is to increase computational capability, while the application of Dropout is intended to prevent the possibility of overfitting [15], [16]. Sigmoid and Tanh activation functions are an integral part of LSTM, an artificial neural network specifically designed to analyze and understand long-term relationships in data through deep learning methods [17].

This study aims to examine the performance and role of various activation functions in LSTM, such as Sigmoid, ReLU, and Tanh. By understanding the critical role of activation functions in solving the vanishing gradient problem and maintaining the memory of information over a long period, this research aims to determine the best activation function to improve the learning performance and performance of artificial neural networks. By using deep learning methods such as LSTM, this exploration is expected to positively contribute to understanding complex patterns in time series data. By finding the proper forecasting technique, they can improve energy consumption efficiency and reduce the adverse impact on the environment.

MATERIALS AND METHODS

The research design includes the critical elements in understanding and implementing the research phase using the LSTM structure. Figure 1 presents an overview of the proposed research framework:



Source: (Research Results, 2024)
Figure 1. Proposed Method

Based on the illustration in Figure 1, this research framework has several critical elements.

A. Literature Study

In this stage, literature related to the research topic, such as activation functions and LSTM architecture in natural gas stock price closure, is collected and analyzed. The purpose of this stage is to broaden the understanding of the current technology on which the research is based, find research gaps, evaluate the activation functions used, and describe the LSTM designs used in previous studies and their evaluation methods.

B. Main Problem

At this stage, the problem to be solved by improving the performance of LSTM through an appropriate activation function is identified.

C. Data Collection

Currently, the data used comes from Kaggle and provides current and comprehensive information on the futures of gas, oil, and other fuels [18]. One type of futures contract is a contract that obliges the seller to sell a certain amount of fuel to the buyer at a predetermined price and date in the future. Natural gas is the main subject of this research. The natural gas dataset consists of 7 features as shown in Table 1.

Table 1. Natural Gas Dataset

No	Feature	Description
1	Date	The date when the data was documented. Format: YYYY-MM-DD
2	Open	Market's opening price for the day.
3	High	Peak price during the trading window.
4	Low	Lowest traded price during the day
6	Close	Price at which the market closed.
7	Volume	Number of contracts exchanged during the trading period.

Source: (Kaggle Portal[18], 2024)

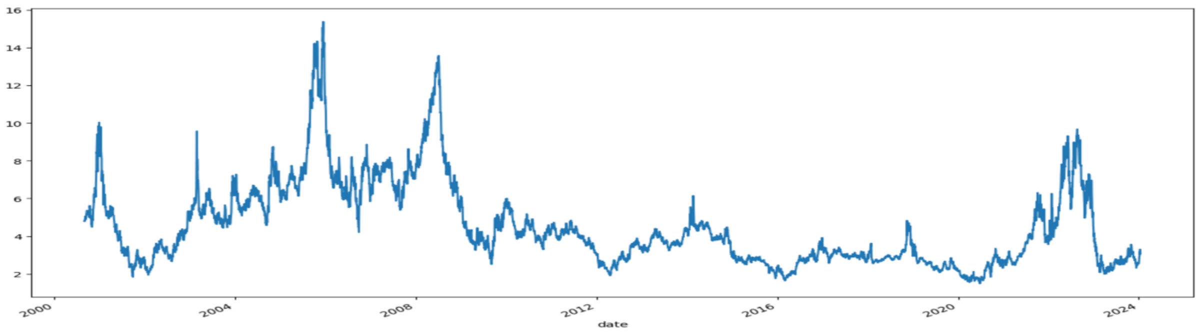
Table 2 shows that this dataset contains natural gas stock price data from 30 August 2000 to 15 January 2024 and consists of 5,780 total records. The natural gas stock price dataset can be utilized to develop a stock price prediction model using LSTM architecture. LSTM is an artificial neural network model known for handling long-term time and dependency problems. Using LSTM can utilize historical stock price data to predict future closing prices. The process involves training the model using historical data that includes stock price information from the past. The LSTM model will learn patterns and trends from the historical data, predicting future natural gas stock prices. Thus, developing LSTM models using natural gas stock price datasets can be valuable for investors to gain additional insights when making investment decisions.

Table 2. Natural Gas Stock Price Datasets

date	open	high	low	close	volume
30/08/2000	4.65	4.81	4.63	4.80	34954
31/08/2000	4.82	4.86	4.73	4.78	25787
01/09/2000	4.75	4.86	4.75	4.83	113
05/09/2000	4.84	4.97	4.84	4.96	26096
06/09/2000	4.98	5.11	4.96	5.06	32764
.....	.....	.....	.....	.....	.....
11/01/2024	3.02	3.23	2.94	3.09	235033
12/01/2024	3.11	3.37	3.10	3.31	235033
15/01/2024	3.11	3.18	3.03	3.08	52838

Source: (Kaggle Portal[18], 2024)

In this research, forecasting will be done on the closing price of natural gas stocks. Figure 2 is the time series data used.



Source: (Kaggle Portal[18], 2024)

Figure 2 Time Series Data of Natural Gas Stock Closing Prices

Data on the closing prices of natural gas stocks in the United States from 2000 to 2024 are presented in Figure 2. The graph shows the direction of movement of natural gas stock prices in the long term. The price of natural gas stocks appears to be steadily increasing. The upward trend in natural gas prices can be attributed to variables such as increased demand for natural gas for power generation, transportation, and industry. On the other hand, significant price variations may indicate short-term price changes. Several variables, including economic conditions, demand and availability of natural gas, and other unexpected variables, can cause these fluctuations. The highest and lowest natural gas stock prices over some time are used to identify price peaks and valleys. Natural gas stock prices peaked in 2008 and 2023 and reached their lowest in 2001 and 2020. Conversely, an increase in natural gas stock prices could be due to the rise in demand and natural gas supply.

D. Pre-processing

At this stage, the steps applied are as follows:

1. Data Cleaning

   At this stage, checks are made to find incomplete or low-quality data.
2. Eliminating Duplication

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At this stage, we will find and resolve redundant or duplicate data.

3. Data Transformation
In this step, the data is sorted by date to make it more organized. In the Date feature, the data type is converted into the date-time form using the to_datetime() function; then, the data is transformed using the MinMaxScaler() function with a range of -1 to 1. This function is shown in equation (1):

$$X_{\text{scaled}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{1}$$

4. Data Validation
In this step, the dataset is divided into two parts. The first consists of training data, consisting of 4,348 data, which will be used to train the model, and the second consists of testing data, composed of 1,523 data, which will be used to assess the accuracy and robustness of the model that has been created.

E. Model Training

This stage involves training the pre-processed dataset using the LSTM architecture by applying ReLU, Tanh, and Sigmoid activation functions. The training process includes adjusting the model parameters to optimize performance based on the choice of loss and optimiser functions.

F. Model validation

At this stage, the dataset will be used to evaluate the performance of the trained model. Validation is done to ensure that the model can understand specific patterns in the training data and be applied to different data.

G. Testing Evaluation

At this stage, the trained model will be tested on independent test datasets to assess its performance objectively. This will involve using performance metrics such as R^2 and Mean Squared Error (MSE).

RESULTS AND DISCUSSION

The training model in this study uses the Long Short-Term Memory (LSTM) architecture, which consists of three main layers: the input layer, the hidden layer, and the output layer. The input layer receives input data that can be a sequence of time, text, or other sequential data. This data is then processed in the hidden layer, which consists of LSTM memory blocks. Each LSTM memory block has several vital components: input gates, forget gates, output gates, and one or more memory cells. The input gate determines which information to input into the memory cell. In contrast, the forget gate governs which information should be removed from the memory cell based on its relevance for prediction. Information deemed irrelevant is removed to prevent noise, while vital information is kept in the memory cell—the output gate controls which information will be output from the LSTM memory block at each step. Finally, the output layer produces the final result of the network based on the information processed through the hidden layer. This structure allows the LSTM to retain important long-term information, remove irrelevant information, and use relevant information to make predictions or generate the output needed in this study. Equation (2) describes the output gate activation function mathematically:

$$f_t = \sigma(W_{xf}X_t + W_{hf}H_{t-1} + b_f) \tag{2}$$

W_{xf} and W_{hf} Are the weight parameters for the forget gate, while b_f It is the bias parameter for the forget gate. The sigmoid function, represented by σ(), is used with a range of values from 0 to 1. Next, equations (3) and (4) are used to formulate the input gate activation function:

$$\tilde{C}_t = \tanh(W_{xc}X_t + W_{hc}H_{t-1} + b_c) \tag{3}$$

$$i_t = \sigma(W_{xi}X_t + W_{hi}H_{t-1} + b_i) \tag{4}$$

Where W_{xc} and W_{hc} are the memory cell weight parameters, W_{xi} and W_{hi} are the gate weight parameters, b_i and b_c Are the memory cell and gate bias parameters, respectively. The next step is to update the state of the memory cell at time t via dot product based on the previous state of the memory cell C_{t-1} and the candidate value $\tilde{C}_t$ at the current time, t. The memory cell state update function is described by the following equation (5):

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t) \tag{5}$$

After the memory cell state completion process is complete, the results are sent via the control output gate. Output gates organize information in memory cells to achieve desired results. Formula (6) is used to calculate the gate output value:

$$o_t = \sigma(W_{xo}X_t + W_{ho}H_{t-1} + b_o) \tag{6}$$

In the final step, the gate output weight parameters of the LSTM hidden layer states are calculated using equation (7):

$$h_t = o_t * \tanh(C_t) \tag{7}$$

The results of model training using the ReLU activation function on LSTM with natural gas datasets show significant progress in optimizing predictions. The value of the decreasing function falls consistently on nine occasions, reaching 0.00094156 on the last event. The low loss function indicates that the model can accurately model the relationships between variables in the data set, especially in the case of natural gas. These results suggest that ReLU activation in LSTM helps learn and fit models to complex data patterns. This shows that the model has achieved the best prediction level without overfitting the training data, even though the training was stopped at the 9th epoch with an initial delay. A model capable of optimizing predictions with a high level of accuracy was created using the ReLU activation function in LSTM with a natural gas dataset.

Using the Tanh activation function on the natural gas dataset, several conclusions can be drawn from the results of LSTM model training. Over 49 epochs, training is performed, and model parameters are updated to optimize performance based on the measured loss function. The initial loss value was significant, around 0.0144 in the first epoch, but gradually decreased rapidly in the following epoch. At the 49th epoch, the LSTM model with the ReLU activation function showed the ability to reduce loss up to 0.000963. This improvement shows that the model can model complex relationships in the natural gas dataset because it has learned well from the training data.

Additionally, it is worth noting that training is stopped at the 49th epoch with the early delay strategy, which indicates that the model has reached the optimal level for minimizing loss. After that, no significant improvement was seen. Using the Tanh activation function in LSTM on the natural gas dataset has resulted in a model capable of predicting with a high degree of accuracy, and the initial delay strategy helps prevent overfitting to the training data. This model is good enough to show patterns and trends in natural gas data.

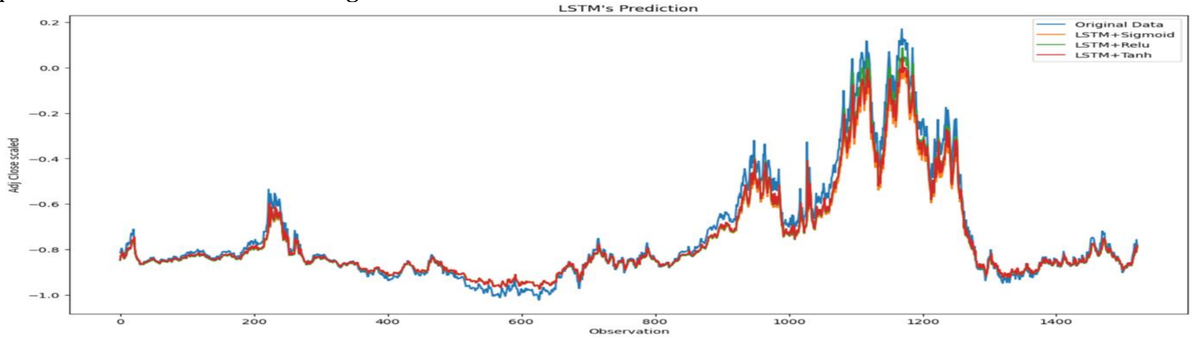
The results of model training using the Sigmoid activation function in the LSTM model with the natural gas dataset show significant changes over several epochs. The loss value of the initial model was relatively high, namely 0.0136 in the first epoch, but the loss value continued to fall until it reached a minimum value of 0.00097503 in the 33rd epoch. This indicates that the model effectively learns and adjusts its internal parameters to improve its performance. Non-linear relations non-linear natural gas time series data can be modeled well by the LSTM model through a model training process using the Tanh activation function. The purpose of using the Sigmoid activation function was to increase the computational capabilities of the model, and the results appear to be successful in reducing the prediction error rate. To prevent overfitting of the training data, the training process was stopped at the beginning of the 35th epoch because there was no significant increase in model performance after that. These results show that using the Sigmoid activation function in LSTM with natural gas datasets can produce accurate and effective prediction models for future natural gas trends or behavior.

Table 3. Comparison of the Number of Epochs and Losses

Activation Function	Final Epoch	Loss Amount
ReLU	9	0.00094156
Tanh	49	0.000963
Sigmoid	35	0.00097503

Source: (Research Result, 2024)

A comparison of the performance of the LSTM model with the ReLU, Tanh, and Sigmoid activation functions is shown in Table 3. All three models managed to achieve a high level of accuracy. The ReLU activation function provides optimal results at the 9th, 49th, and 35th epochs. To avoid overfitting the training data, all models correctly use an early stopping strategy.



Source: (Research Result, 2024)

Figure 3 Prediction of Closing Stock Prices Using the LSTM Model with ReLU, Tanh, and Sigmoid Activation Functions

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Using the LSTM model with ReLU, Tanh, and Sigmoid activation functions, the closing stock price shows that the stock price will close at a higher price than the original data price. This can be seen from the prediction graph above the actual data graph, where the price of the ReLU activation function is always favorable. In contrast, the price of the Tanh and Sigmoid activation functions can be negative or positive. Based on prediction results, closing stock prices can be caused by many things, such as sound business performance, bright industry prospects, or favorable economic conditions.

The model evaluation results using the LSTM model with the ReLU activation function show excellent performance. The R2 value, which measures how well the model explains data variations, reached 0.960 on the training set and 0.964 on the testing set. An R2 value greater than 1 indicates that the model can effectively explain data variations, both in training data and newly viewed data. Apart from that, MSE has a value of 0.002, which shows that the model can produce predictions that are very close to the actual value in the dataset. A low MSE value indicates that the model can make predictions very close to the actual value. Therefore, it can be concluded that the LSTM model with the ReLU activation function can model relationships in the data very well and provide accurate predictions. The results of this evaluation provide confidence that the model does not experience overfitting and can make accurate predictions in real situations.

The performance evaluation results of the LSTM model using the Tanh activation function on specific datasets show extraordinary performance. An R2 value of 0.950 on the training set indicates that the model successfully explains large variations in the training data and achieves a significant level of accuracy. The R2 value on the test set of 0.959 adds evidence that the model can also effectively generalize and accurately predict data that has never been seen before. The low MSE value of 0.002 indicates that the model predictions have a significant gap. Overall, the results of this evaluation show that the LSTM model with the Tanh activation function can produce very accurate and consistent forecasts on training and testing data.

The evaluation results of the LSTM model using the Sigmoid activation function show excellent performance. On the training dataset, the model shows a high level of goodness-of-fit with an R2 value of 0.931, which shows that the model can explain as much as 93.1% of the variation in the training data. The model also offers excellent performance on the test dataset with an R2 value of 0.943. A high R2 level on the testing dataset indicates the model's ability to understand and model patterns in the testing dataset. In addition, the low MSE value of 0.003 means that the predictions produced by the Sigmoid model have a low error rate. A low MSE value indicates that the model can provide accurate predictions and is close to the actual value. Overall, the results of this evaluation show that the use of the Sigmoid activation function in the LSTM model produces an excellent model for predicting natural gas data; on both training and test data sets, the model fits well and is accurate.

Table 4. Comparison of LSTM Model Training Results

Activation Function	R2 Score (Train)	R2 Score (Test)	MSE
ReLU	0.960	0.964	0.002
Tanh	0.950	0.959	0.002
Sigmoid	0.931	0.943	0.003

Source: (Research Result, 2024)

Table 4 depicts the performance evaluation results of the LSTM model with ReLU, Tanh, and Sigmoid activation functions on the natural gas closing price dataset. The comparison shows that all three models show excellent performance with high R2 scores on training and testing datasets. Apart from that, each of the three models has a low MSE value, which shows that the predictions made have relatively minor errors.

Based on the evaluation provided, the model with the ReLU activation function seems to give better results in terms of prediction accuracy on natural gas datasets. Therefore, the LSTM model with the ReLU activation function is considered better for predicting the closing price of natural gas stocks.

This research contributes significantly to applying the LSTM model with various activation functions in predicting the closing price of natural gas shares. First and foremost, using the ReLU activation function in LSTM shows significant improvements. There is a consistent decrease in the value of the loss function over the nine epochs. The low functional loss values demonstrate the model's ability to model relationships in natural gas datasets accurately, especially in this context. Although the training process was stopped at the 9th epoch with premature termination, the model has reached the ideal level without overfitting the training data.

Furthermore, applying the Tanh activation function to LSTM performs well for 49 epochs. This happens even though the initial loss value is quite significant. Still, the rapid decline in the following epoch shows the model's ability to understand and model complex relationships in natural gas datasets. In addition, the initial delay strategy at the 49th epoch shows that the model has reached the optimal level, and the evaluation of the test dataset shows accurate results.

In addition, using the Sigmoid activation function in the LSTM model provides satisfactory results. During the training process, the loss value continues to decrease, and an initial delay at the 35th epoch prevents overfitting of the training data. The evaluation of the test dataset demonstrates the model's ability to make accurate predictions.

The ReLU activation function has a higher R2 score on both datasets, indicating a higher level of accuracy, as shown by the comparison of the three models using Table 4. Therefore, based on the evaluation, the LSTM model with the ReLU activation function can be considered superior. Suitable for predicting the closing price of natural gas stocks. This study increases stakeholder understanding regarding using LSTM and various activation functions in predicting natural gas stock prices. This helps them make more accurate and informed decisions.

CONCLUSION

The research results show that activation functions in the LSTM model, especially ReLU, Tanh, and Sigmoid, can significantly improve the forecasting of closing prices for natural gas commodity shares. The training results show that each activation function has advantages, but overall, ReLU provides more accurate predictions on natural gas datasets. All models achieved high accuracy levels without overfitting the training data despite initial delays at various time points.

On the training and test sets, model performance evaluation using R2 Score and MSE shows that the LSTM model with ReLU activation function is perfect, followed by Tanh and Sigmoid. Prediction of the closing price of natural gas shares using the LSTM model with three activation functions shows a positive trend, indicating that the model can adequately model and understand patterns and behavior from time data.

Therefore, this research significantly contributes to applying Deep Learning techniques, especially LSTM, to improve closing stock price predictions for natural gas commodities. The evaluation results show that the choice of activation function in LSTM can significantly influence the model performance, and using the ReLU activation function seems to be a better choice for this purpose. The results of this research can help practitioners and stakeholders make investment decisions in the natural gas stock market more accurately and precisely.

REFERENCE

[1] L. Zhan and Z. Tang, ‘Natural Gas Price Forecasting by a New Hybrid Model Combining Quadratic Decomposition Technology and LSTM Model’, *Mathematical Problems in Engineering*, vol. 2022, no. 1, p. 5488053, 2022, doi: 10.1155/2022/5488053.

[2] A. Manowska, A. Rybak, A. Dylong, and J. Pielot, ‘Forecasting of Natural Gas Consumption in Poland Based on ARIMA-LSTM Hybrid Model’, *Energies*, vol. 14, no. 24, Art. no. 24, Jan. 2021, doi: 10.3390/en14248597.

[3] J. Liu, S. Wang, N. Wei, X. Chen, H. Xie, and J. Wang, ‘Natural gas consumption forecasting: A discussion on forecasting history and future challenges’, *Journal of Natural Gas Science and Engineering*, vol. 90, p. 103930, Jun. 2021, doi: 10.1016/j.jngse.2021.103930.

[4] S. Devi, S. Warasniasih, and P. Masdiantini, ‘The Impact of COVID-19 Pandemic on the Financial Performance of Firms on the Indonesia Stock Exchange’, *Journal of Economics, Business, & Accountancy Ventura*, vol. 23, Nov. 2020, doi: 10.14414/jebav.v23i2.2313.

[5] I. E. Livieris, E. Pintelas, N. Kiriakidou, and S. Stavroyiannis, ‘An Advanced Deep Learning Model for Short-Term Forecasting U.S. Natural Gas Price and Movement’, in *Artificial Intelligence Applications and Innovations. AIAI 2020 IFIP WG 12.5 International Workshops*, I. Maglogiannis, L. Iliadis, and E. Pimenidis, Eds., Cham: Springer International Publishing, 2020, pp. 165–176. doi: 10.1007/978-3-030-49190-1_15.

[6] W. Qiao, W. Liu, and E. Liu, ‘A combination model based on wavelet transform for predicting the difference between monthly natural gas production and consumption of U.S.’, *Energy*, vol. 235, p. 121216, Nov. 2021, doi: 10.1016/j.energy.2021.121216.

[7] R. Guan, A. Wang, Y. Liang, J. Fu, and X. Han, ‘International Natural Gas Price Trends Prediction with Historical Prices and Related News’, *Energies*, vol. 15, no. 10, Art. no. 10, Jan. 2022, doi: 10.3390/en15103573.

[8] S. Karasu and A. Altan, ‘Crude oil time series prediction model based on LSTM network with chaotic Henry gas solubility optimization’, *Energy*, vol. 242, p. 122964,

Accredited Rank 2 (Sinta 2) based on the Decree of the Dirjen Penguatan RisBang Kemenristekdikti No.225/E/KPT/2022, December 07, 2022. Published by LPPM Universitas Nusa Mandiri

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Mar. 2022, doi: 10.1016/j.energy.2021.122964.

[9] D. Li, Y. Zhang, D. Gong, L. Pan, and Y. Zhao, 'Gas Data Prediction Based on LSTM Neural Network', *IOP Conf. Ser.: Mater. Sci. Eng.*, vol. 750, no. 1, p. 012175, Feb. 2020, doi: 10.1088/1757-899X/750/1/012175.

[10] B. Liu, J. Chen, H. Wang, and Q. Wang, 'Renewable Energy and Material Supply Risks: a Predictive Analysis Based on An LSTM Model', *Frontiers in Energy Research*, vol. 8, 2020, Accessed: Jan. 17, 2024. [Online]. Available: https://www.frontiersin.org/articles/10.3389/fenrg.2020.00163

[11] J. Berrisch and F. Ziel, 'Distributional modeling and forecasting of natural gas prices', *Journal of Forecasting*, vol. 41, no. 6, pp. 1065–1086, 2022, doi: 10.1002/for.2853.

[12] S. Kiliçarslan and M. Celik, 'RSigELU: A nonlinear activation function for deep neural networks', *Expert Systems with Applications*, vol. 174, p. 114805, Jul. 2021, doi: 10.1016/j.eswa.2021.114805.

[13] M. H. Essai Ali, A. B. Abdel-Raman, and E. A. Badry, 'Developing Novel Activation Functions Based Deep Learning LSTM for Classification', *IEEE Access*, vol. 10, pp. 97259–97275, 2022, doi: 10.1109/ACCESS.2022.3205774.

[14] K. Biswas, S. Kumar, S. Banerjee, and A. K. Pandey, 'TanhSoft—Dynamic Trainable Activation Functions for Faster Learning and Better Performance', *IEEE Access*, vol. 9, pp. 120613–120623, 2021, doi: 10.1109/ACCESS.2021.3105355.

[15] N. Alamsyah, T. P. Yoga, and B. Budiman, 'Improving Traffic Density Prediction Using Lstm With Parametric Relu (PRELU) Activation', *JITK (Jurnal Ilmu Pengetahuan dan Teknologi Komputer)*, vol. 9, no. 2, Art. no. 2, Feb. 2024, doi: 10.33480/jitk.v9i2.5046.

[16] S. Mastromichalakis, 'ALReLU: A different approach on Leaky ReLU activation function to improve Neural Networks Performance', *arXiv preprint arXiv:2012.07564*, 2020, doi: 10.48550/arXiv.2012.07564

[17] L. Fernando Santos, M. Gattass, A. Correa Silva, F. Miranda, C. Siedschlag, and R. Ribeiro, 'Natural gas detection in onshore data using transfer learning from a LSTM pre-trained with offshore data', in *SEG Technical Program Expanded Abstracts 2020*, in SEG Technical Program Expanded Abstracts. , Society of Exploration Geophysicists, 2020, pp. 1190–1195. doi: 10.1190/segam2020-3426303.1.

[18] 'Oil, Gas & Other Fuels Futures Data'. Accessed: Jun. 26, 2024. [Online]. Available: https://www.kaggle.com/datasets/guillemservera/fuels-futures-data?resource=download