Bitlis Eren Üniversitesi Fen Bilimleri Dergisi
BİTLİS EREN UNIVERSITY JOURNAL OF SCIENCE
ISSN: 2147-3129/e-ISSN: 2147-3188
VOLUME: 13 NO: 4 PAGE: 1013-1022 YEAR: 2024
DOI: 10.17798/bitlisfen.1494090

Enhancing Currency, Commodity and Energy Price Forecasting Using the LSTM Model: A Case Study of EUR/NZD, GAS and SUGAR Prices

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Keywords: Time series analysis, EUR/NZDUSD exchange rate, deep learning.

Abstract
Forecasts from machine and deep learning models are vital for traders and investors in the global financial markets. Many different forecasting methods rely on technical patterns. In this study, the LSTM model based on candlesticks and financial variables was used to improve trading forecasts of different types. Japanese candlesticks are among the most widely used tools for evaluating financial markets. Therefore, these candlesticks, which show price patterns and differences between buying and selling, provide important data for predicting future price fluctuations. A 15-minute candlestick or 15-minute frame is used. The model showed excellent performance in predicting currency rates (EUR/NZDUSD), with an accuracy based on mean square error (MSE = 1.377e-07). The model also showed better accuracy in predicting sugar prices compared to other models, reaching (MSE = 1.419836). The same results were obtained with the GAS model, where the value was (MSE = 0.000173). This superior performance of the model indicates its ability to generate historical patterns and use them effectively in forecasting financial markets. These results provide promising opportunities for traders and investors to make more guided and intelligent investment decisions based on future trends based on these patterns. By using historical patterns and financial data, LSTM's deep learning model shows exceptional predictive performance. It outperforms traditional machine learning methods such as XGBoost. XGBoost achieved a score on the EUR/NZDUSD exchange rate (MSE = 9.537e-07). The error rate for the presented model is considered to be high. This confirms the success of the represented approach and its ability to enable traders and investors to make more informed and strategic decisions. This ultimately contributes to improving trading conditions and investment outcomes in global financial markets.

1. Introduction

Forecasting asset prices in financial markets is essential for making informed investment decisions, managing risks, and formulating policies. With the increasing availability of financial data and advancements in computational techniques, researchers and practitioners in economics and finance have turned to sophisticated machine learning models to enhance the accuracy of price forecasts. In recent years, artificial intelligence models such as the Long Short-Term Memory (LSTM) model have garnered significant attention due to their ability to capture complex temporal dependencies in sequential data. Originally developed for natural language processing tasks, LSTM has been successfully applied to various time series prediction problems, including financial markets forecasting.

This study aims to explore the effectiveness of the LSTM model in improving the forecasting accuracy of currency, commodity, and energy prices. The study focuses on three distinct markets: the EUR/NZDUSD currency pair, natural gas (GAS) futures, and sugar (SUGAR) futures. These markets represent different asset classes with unique

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Received: 01.06.2024, Accepted: 26.12.2024

characteristics, providing a diverse set of challenges and opportunities for forecasting.

2. Related Works

There are many studies in the literature stating that deep learning is widely used in financial market forecasting such as volatility forecasting, price forecasting and trend forecasting for various financial assets such as stock transactions, futures, and interests. In 2019, Yan Hu and his colleagues conducted a study entitled A hybrid deep learning approach by integrating LSTM-ANN networks with GARCH model for copper price volatility prediction about copper prices. The classical GARCH model is combined with a deep neural network based on LSTM and ANN. In turn, the researchers point out that the challenges and limitations they faced in the research are related to the non-linear nature and change over time of the factors affecting copper prices. This is important to understand the prediction capabilities and potential limitations of the model. This study concluded that the hybrid model achieves a significant improvement in the ability to predict copper prices [1]. In 2021, both M.S. Islam, Hossainb. By conducting a study on Forex market data and massive daily trading volume of over $5.1 trillion for major currency pairs (EUR/USD, GBP/USD, USD/CAD, USD/CHF) and specific history for analysis. It was titled Foreign exchange currency rate prediction using a GRU-LSTM hybrid network, where a new model combining GRU and LSTM is presented to predict currency rates was used. With 20 cells selected for the first GRU layer and 256 cells for the second LSTM layer. The model is applied over different time periods (10 minutes and 30 minutes) using data from the different time periods to show effectiveness. However, the study indicates that the market remains difficult and unstable, as well as the specific time period for the analysis and the specific currencies on which the model was tested. However, in this study it was shown that the performed model outperforms the individual models GRU and LSTM, and also outperforms the simple moving average (SMA) model. The new model achieves relatively good performance using different metrics such as MSE, RMSE, MAE, and R^2. It is the least risky based on its R^2 score, making it a good choice for investors who want to reduce risk in the Forex market [2]. In 2021, Mohammad J. Hamayel and Amani Yousef Owda conducted a study entitled A Novel Cryptocurrency Price Prediction Model Using GRU, LSTM and bi-LSTM Machine Learning Algorithms on three different cryptocurrencies: Bitcoin (BTC), Litecoin (LTC), And Ethereum (ETH). Three models, RNN, GRU, and Bidirectional LSTM (bi-LSTM), were used to predict cryptocurrency prices. Emphasis is placed on forecast accuracy using the Mean Percentage Error (MAPE) criterion. However, researchers point out that current models do not take into account other factors that may affect cryptocurrency prices, such as social media and trading volume. However, the GRU model showed the advantage in predicting cryptocurrency prices, as it showed better accuracy based on MAPE. In the future, additional research is suggested to explore other factors that may influence cryptocurrency prices such as social media, user tweets, and trading volume [3]. In 2022, the Hachmi Ben Ameur Group conducted a study on daily data for commodity markets extending from January 2002 to December 2020. The Bloomberg Commodity Index and five other sub-indices are used. The use of artificial intelligence analysis and deep learning techniques has been used to predict commodity prices. The focus was on using the LSTM algorithm. The focus was solely on using the Bloomberg Commodity Index (to which the Global Aggregate Index refers) and its five sub-indices: the Agricultural Wealth Index, the Precious Metals Index, the Livestock Index, the Industrial Minerals Index, and the Energy Index. The research successfully demonstrated the effectiveness of the Long Short Memory Method (LSTM) as a tool for forecasting commodity prices. The superiority of the Bloomberg Livestock Sub-Index and the Bloomberg Industrial Metals Sub-Index is evident in evaluating other commodity indices. These results are important for investors in terms of risk management as well as for policy makers in adjusting public policy, especially during the Russian-Ukrainian war [4]. In 2023, FEI LI and colleagues conducted a study entitled A Medium to Long-Term Multi-Influencing Factor Copper Price Prediction Method Based on CNN-LSTM on copper prices with 11 factors affecting copper price fluctuations selected as explanatory variables. CNN was used to extract spatial features of the data and LSTM to extract temporal features, and these features are fed into the CNN-LSTM network to predict monthly copper prices. The explanatory variables were carefully selected based on an analysis of the characteristics of the variables and quantitative relationships with influencing factors. The researchers point out the challenges of analyzing primary data using traditional methods, which may require adjustment to the selected influencing factors and final results. However, our approach outperforms existing methods by using the effective ability to extract space features of CNNs and extract temporal features of LSTMs. In improving the predictive power of copper prices [5].

In the same year 2023, Carlo Mari and Emiliano Mari conducted a study on a variety of time series data for US energy prices, including a daily time series for electricity prices, a time series for natural gas prices, and a time series for crude oil prices. In that study, they used the method of describing the primary system through the process of back propagation, and the second system is driven by predictions of a deep neural network trained on time series of market returns. A statistical technique based on the moments simulation method was also proposed to estimate the model on market data. Although there may be challenges in applying this model to real market data because market changes are not accurately predicted. However, the researchers find that the proposed model produces results that agree well with the empirical data, as it appears to reproduce the first four central means of the empirical distributions of log returns well, and it models the observed price series well as well [6]. Another noteworthy study was presented by Fischer and Krauss in 2018. In their study, they implemented the application of LSTM networks to financial market predictions [7]. Chong, Han, and Park merged deep learning networks with three unsupervised feature extraction methods. As a result, they improved the financial forecasting performance, but it is not yet sufficient to achieve high accuracy. However, it has application advantages over traditional methods that are not naturally generated in financial market data [8]. Li and Tam developed a hybrid model in 2017. The authors combined LSTM with real-time wavelet denoising functions to predict stock indices. Here, a sliding window mechanism was adopted for wavelet denoising. Experimental results showed that their proposed model outperformed the LSTM model without wavelet denoising module [9].

Among deep learning architectures, long short-term memory (LSTM) networks, which represent a specific type of recurrent neural network (RNN), are particularly well-suited for modeling temporal patterns in various time series tasks [10-12]. In this study, LSTM model based on candlesticks and financial variables was used to improve various types of price predictions. Using this data showing price patterns and differences between buy and sell, an existing model was applied to predict future price fluctuations. The model was used to predict exchange rates, sugar prices and GAS values. The deep learning technique was compared with some traditional models. The rest of the study consists of material and methods, methodology, experimental findings and conclusions-recommendations sections.

2.1. Literature Gap

Despite advances in predictive models for analysing market data, there is a gap in understanding the limitations associated with the non-linear nature and temporal volatility of factors affecting commodity prices, particularly in highly volatile and dynamic markets such as cryptocurrencies. Existing research focuses primarily on traditional methods and does not take into account emerging factors such as social media and trading volumes. In addition, relying on deep neural networks for prediction poses challenges due to potential statistical constraints and reliance on training data that may not accurately reflect real market dynamics. This gap in the literature highlights the need for further research and development of models that address these challenges and provide more robust predictions for market analysis.

3. Material and Methods

3.1. Dataset

Time series type data were used in the financial variables category for the date and time of each trading session, in the commodities category for sugar trading prices, in the energy category for gas trading prices and in the currencies category for New Zealand dollar trading prices. They are displayed in the form of Japanese candlesticks. Each time period is defined by the opening price, the high price, the low price and the closing price. The time period is 15 minutes per frame.

3.2. Performance Evaluation Criteria

Accuracy and performance measures is crucial step for experimental results. The following performance metrics were used to evaluate the performance of the LSTM model and to measure error rates [13]. The evaluation criteria used in this study are frequently preferred and these are Mean Squared Error (MSE) [14], Mean Absolute Error (MAE) [15], Root Mean Squared Error (RMSE) [16], Mean Absolute Percentage Error (MAPE) [17], Coefficient of Determination (R-squared).

3.3 Machine Learning and Deep Learning Algorithms

In this section, the approaches compared to the presented model are explained. The relevant techniques are classified as machine learning or deep learning algorithms.

Machine Learning Algorithms encompass a diverse set of techniques and tools employed for training models to comprehend data and leverage this comprehension for predictive or classification purposes. What distinguishes machine learning is its inherent ability to learn from data, continuously enhancing model performance over time. In the context of this study, various machine learning algorithms were employed as models to predict exchange rates using the dataset under examination. These algorithms are then compared with the outcomes derived from the offered algorithm. Noteworthy among them are Random Forest (RF), Adaptive Boosting (AdaBoost) and eXtreme Gradient Boosting (XGBoost), each contributing to the comparative analysis [18]. RF is a machine learning model grounded in the concept of random trees. It is a powerful tool extensively employed for classification and forecasting purposes. This model operates by utilizing multiple independent decision trees, a characteristic that enhances accuracy and mitigates the overfitting problem, contributing to its effectiveness in diverse applications [19]. XGBoost is a robust machine learning framework designed for predictive and classification tasks. Renowned for its exceptional performance, XGBoost excels in handling large datasets. This framework operates on the principle of ensemble learning, leveraging the strengths of multiple models to construct a powerful predictive model [20]. AdaBoost is a traditional machine learning model that aims to enhance performance by creating a set of weak models. It can also be used in deep machine learning [21].

Deep Learning algorithms constitute a specialized category within the broader field of machine learning, and they belong to the family of deep neural networks. Specifically designed to tackle complex data and structures with intricate details, these algorithms excel in extracting valuable features from such data. Their remarkable capability lies in learning from diverse datasets, recognizing intricate patterns, and constructing accurate predictive models. In the context of this study, we will compare the LSTM algorithm with the following noteworthy deep learning algorithms [22]. Gated Recurrent Unit (GRU) stands as a prevalent deep neural network model tailored for processing sequential data, including text and audio. Recognized for its efficiency in handling temporal patterns, GRU finds applications in machine translation and voice recognition [23]. Gradient Boosting Decision Trees (GBDT) is considered a model for traditional machine learning, it is also used in deep machine learning. It is based on decision trees and is widely used in classification and prediction [24]. Long Short-Term Memory (LSTM) is a deep neural network that is specifically used to process data sequences such as time sequences. It has the ability to handle both long and short delays in data, making it suitable for forecasting temporal data such as currency exchange rates.

4. Methodology

The study aims to predict time series data for each trade of commodities, energy and currencies based on the time series data represented. The overall process includes several key stages, each of which contributes to the development of an accurate predictive model, as shown in Figure 1

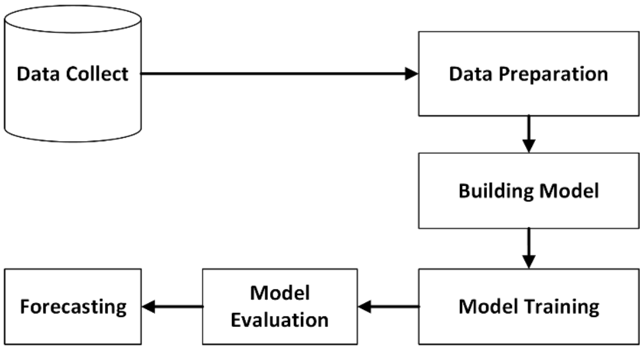

Figure 1. Flowchart of the offered system

4.1 Data collection and Data preparation

Data collection and preparation is a very important step in the study methodology. Raw data must be processed to ensure it is ready for training and evaluation. This involves the following steps:

4.1.1 Reading data from the source

In this step, raw data is obtained from the forex market for real-time and live trading. It includes a time series dataset for three categories of data: date and time of each trading session, sugar trading prices from the commodity category, gas trading prices from the energy category, and New Zealand dollar trading prices from the currency category. Each category consists of the highest price, lowest price, opening price, closing price, and trading volume. Which is retrieved from Dukascopy website, one of the most prominent forex and online trading sites. (https://www.dukascopy.com/swiss/english/marketwatch/historical/). The site provides many useful services and tools for traders, including historical price data and is a popular Swiss site.

4.1.2 Time and date formatting

Since time and date can be critical factors in temporal data analysis, the columns for time and date must be properly formatted to enable the model to accurately understand temporal patterns. Therefore, some data mining techniques such as data cleaning, data merging and data transformation were applied. The time zone facility for each session for the GMT date and time was removed, as with it, the field for each session was considered as a string. After removing it as a whole, we were able to apply operations to this field comfortably and treat it as a date and time field. Then, the direction or position of the date and time for each session was modified to match the style used.

4.1.3 Data organization

In this step, the initial financial data for each of the three types of data is prepared to be suitable for training and evaluation of the LSTM model. A package of 20 pre-readings is chosen, which consists of 20 candles. Each candle is a 15-minute price period per candle. The data is organized in a format consistent with time for the time series.

4.2 Building Model

The structure of the LSTM model is built through a deep study of the key parameters. The number of LSTM units was set to 20 in each layer, allowing the model to capture complex temporal patterns within the data. Activation functions, such as the sigmoid function, are automatically configured within each LSTM module to organize the flow of information, and by arranging the layers in a sequential manner, we created an information flow through the network.

4.3 Training Model

After establishing the structure of the LSTM model, we move to the critical and sensitive phase of training the model. In this stage, we prepare the model to make accurate predictions by exposing it to pre-processed training data. This process involves several key steps, each of which contributes to the model's ability to learn from historical patterns and make informed predictions.

Important training parameters are configured before starting the training process. The batch size, set to 120, controls the amount of training data that is processed before the model's internal weights are changed. We also specify the number of training periods, which is 20 in this case. This refers to the number of times the full training data set is applied to the model. Through this iterative approach, the model can enhance internal representations and reveal hidden patterns. Choosing a loss function is a critical step in the training process. The mean square error (MSE) loss function was used because it calculates the difference between the predicted and actual values of the target variable. The model adjusts its parameters to enhance the predicted accuracy by minimizing this loss.

4.4 Model evaluation

After the training phase, the model moves to the main evaluation phase, where its performance is carefully examined. To measure a model's ability to predict outcomes based on unseen data. A wide range of rating scales are used. These metrics include mean square error (MSE), mean absolute error (MAE), root mean square error (RMSE), mean absolute percentage error (MAPE), and coefficient of determination (R-squared). Based on the values of the resulting metrics, if the results are acceptable for those metrics, one can move to the prediction stage, and if unacceptable results are achieved, one can move to the data preparation stage again and carry out the rest of the stages until acceptable results are obtained.

4.5 Forecasting

The final step is to predict future data points using the trained LSTM model. In order to achieve this, new data must be prepared in a manner similar to the training data, predictions must be produced using the trained model, and it may be necessary to undo any changes to the data in order to obtain predictions in their original size. The accuracy of the predictions is then evaluated after further analysis using pre-defined performance criteria.

5. Experimental Results and Discussion

In this section, the results are discussed in two parts. While the first part focuses on the results of machine learning models on the three previously mentioned data categories, the second part discusses the results of deep learning models on energy, commodity and foreign exchange trading prices.

5.1. Results of machine learning models

AdaBoost, XGBoost and RF machine learning models were used with time series data on commodities, energy and currencies. In this study, the accuracy of machine learning models was tested using error and performance measurements. Table1 indicates performance and error metrics for the machine learning algorithms.

Table 1. Performance and error metrics for the AdaBoost, XGBoost, and RF

MODELS	MSE	MAE	RMSE	MAPE	R-SQUARED	Type of Data
AdaBoost	0.0034	0.05658	0.0583	0.37185	0.995697	EUR/NZDUSD
	4.8513	2.1766	2.2025	78.9842	-38.914	GAS
	23848.7	147.688	154.43	21.3163	-10.905	SUGAR
XGBoost	9.537e-07	0.00069	0.00097	0.11674	0.99536	EUR/NZDUSD
	0.000405	0.01059	0.0201	0.395931	0.99642	GAS
	48.4896	4.34413	6.9634	0.61338	0.97619	SUGAR
RF	0.00456	0.05392	0.0675	8.95	-21.2112	EUR/NZDUSD
	6.43851	1.77175	2.5374	66.12	-55.73	GAS
	25661.06	138.550	160.19	19.95	-11.59863	SUGAR

Details in Table 1, the best model is XGBoost as it has the lowest percentage error. The MSE for EUR/NZDUSD was 9.537e-07. Furthermore, for GAS, the MSE is 0.000405, which is considered to be one of the best results obtained by the XGBoost model for GAS. The similarly resluslts for SUGAR, where MSE=48.4896 was obtained. This is also true for other error measurements for the same model. Figure 2 shows the plot patterns for the actual and predicted predictive model performance of AdaBoost on SUGAR prices. Figure 3 and Figure 4 show the actual and predicted chart patterns for GAS and NZDUSD prices respectively for the same models. Based on the charts showing the chart patterns of SUGAR, GAS, and NZDUSD prices for the performance of machine learning prediction models, the best model that shows almost the same pattern of actual value is the XGBoost model across all of them. Thus, it can be said that the XGBoost machine learning model can compete with the LSTM deep learning model.

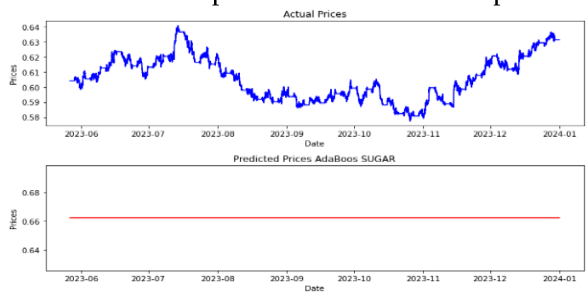

Figure 2. Chart of actual values and predicted values of SUGAR prices with AdaBoost

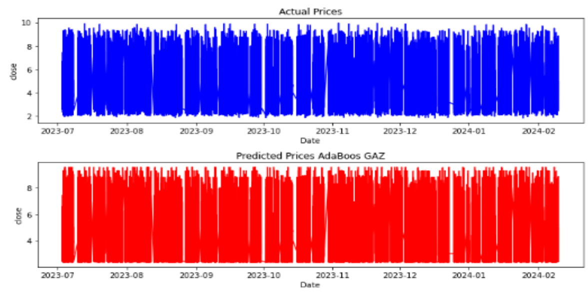

Figure 3. Chart of actual values and predicted values of GAS prices with AdaBoost

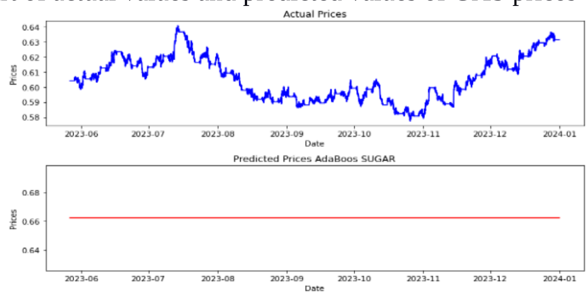

Figure 4. Chart of actual values and predicted values of NZDUSD prices with AdaBoost

5.2 Results of deep learning models

Deep learning models LSTM, GRU and GBDT were used with time series data on commodities, energy and currencies. In this study, the accuracy of deep learning models was tested using error and performance measurements. Table 2 represents the error and performance metrics of deep learning models.

Table 2. Performance and error metrics for the LSTM, GRU and GBDT

MODELS	MSE	MAE	RMSE	MAPE	R-SQUARED	TYPE OF DATA
LSTM	1.377e-07	0.00024	0.0003	0.0411	0.999330	EUR/NZDUSD
	0.000173	0.00754	0.0131	0.2706	0.998470	GAS
	1.419836	0.61444	1.1915	0.0902	0.999302	SUGAR
GRU	1.3772e-07	0.00025	0.0003	0.0414	0.999330	EUR/NZDUSD
	0.00019	0.00961	0.0138	0.3505	0.998308	GAS
	1.537671	0.75178	1.24002	0.1106	0.999245	SUGAR
GBDT	0.002162	0.04175	0.0465	6.4133	-4.093e-05	EUR/NZDUSD
	3.933846	1.66492	1.9833	43.108	-8.96e-05	GAS
	7987.260	73.2919	89.371	13.0054	-1.824e-05	SUGAR

Based on the error and performance metrics resulting from the three previous deep learning model in Table 2. We find that the best model that achieved the lowest error rate in the prediction process is the LSTM model compared to the rest of the other deep learning models. The MAE ratio was = 0.00024 for EUR/NZDUSD. Also, when using the same measure but on the GAS, we found that MAE = 0.00754, which is also considered one of the best results achieved by the LSTM model on the GAS. The same applies to SUGAR, which achieved MAE = 0.61444. This applies to the rest of the error measures for the same model. Noting that the GRU model achieved error measures that were very close to the model. Figure 5 shows the prediction behavior of LSTM, GRU and GBDT models on SUGAR prices.

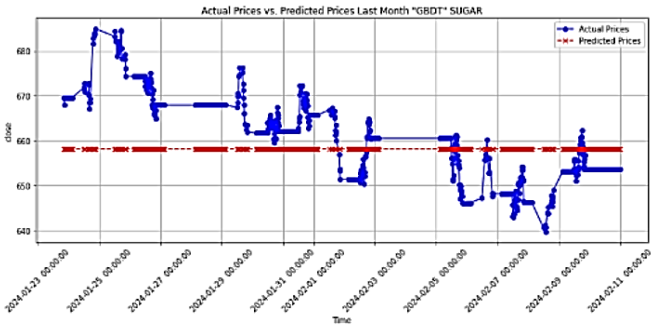

Figure 5. Chart of actual values and predicted values of SUGAR prices with LSTM

This is based on chart patterns for the performance of actual and forecast SUGAR, GAS and NZDUSD price prediction models for deep learning models. The LSTM and GRU model showed remarkable success in achieving perfect matching between actual and expected value in all relevant data categories. The GRU model showed high convergence with the model.

Model is considered to have succeeded in achieving the best results from other deep learning models. Therefore, to prove the strength and accuracy of the presented model, we can observe or compare some other results with the machine learning model that achieved the best results among other models, which is XGBoost. Therefore, error rates and performance rates, as well as charts and price distribution curves, can be compared to find out which is the best deep learning model or machine learning model with these types of data. Table 3 shows the error rates between the two models.

Table 3. Performance and error metrics between both the XGBoost and LSTM

MODELS	MSE	MAE	RMSE	MAPE	R-Squared	Type of Data
LSTM	1.377e-07	0.00024	0.0003	0.0411	0.999330	EUR/NZDUSD
	0.000173	0.00754	0.0131	0.2706	0.998470	GAS
	1.419836	0.61444	1.1915	0.0902	0.999302	SUGAR
XGBoost	9.537e-07	0.00069	0.00097	0.11674	0.99536	EUR/NZDUSD
	0.000405	0.01059	0.0201	0.395931	0.99642	GAS
	48.4896	4.34413	6.9634	0.61338	0.97619	SUGAR

The large differences in error rates can be seen in Table 3 between the LSTM deep learning model and the XGBoost machine learning model on all data types: GAS, EUR/NZDUSD, SUGAR. The LSTM deep learning model has achieved lower results in error rates than the machine learning model.

When the performance metrics are examined in general, LSTM performed better than XGBoost. Especially RMSE provides information about the fit of a regression line to the data points. LSTM created the best fitting line of the predictions and data points. In other words, it predicted better than XGBoost. MSE works according to the same principles as RMSE, the squared value of RMSE. A larger R-squared value means a better regression model since it explains most of the variance in the response variable values. For this reason, LSTM performed better than XGBoost as proven by other metrics.

When analyzing the performance of the models on different datasets, it is clear that LSTM outperforms XGBoost in most metrics, especially in the case of EUR/NZDUSD data. For example, LSTM achieves lower MSE and RMSE values, meaning that LSTM had a better fit to the regression line than XGBoost. This is particularly reflected in the higher R-squared value of the LSTM model, indicating that LSTM explains most of the variance in the dependent variable values.

For GAS and SUGAR data, LSTM remains superior in most metrics such as RMSE and R-Squared, indicating its ability to provide more accurate and reliable forecasts than XGBoost. However, it can be noted that XGBoost is not necessarily performing poorly, but it is less accurate compared to LSTM, especially in forecasts related to complex datasets such as EUR/NZDUSD.Thus, the table shows that LSTM outperforms XGBoost in providing more accurate predictions on different data types, making it the more effective model in these cases.

6. Conclusion and Suggestions

This study has achieved remarkable results in terms of trade forecasting for commodities, energy and currencies using the deep learning model. The LSTM based model showed excellent performance in predicting exchange rates (EUR/NZDUSD) and a high accuracy of around 1.377e-07 based on MSE value. The same measurement was obtained on the price of sugar, where it showed the best accuracy among other models with a value of MSE = 1.419836. This was also achieved with GAS, so the MSE value = 0.000173. In addition, a comparison was made between machine learning and deep learning models in the study. The XGBoost machine learning model produced better results than similar machine learning models in terms of having fewer errors on the three data types. It also achieves patterns of charts for actual and predicted values better than its counterparts. However, when compared with the deep learning model LSTM outperforms all metrics and models as well as the visible model and price distribution curve. This indicates the model's ability to absorb historical patterns and use them effectively to predict the future. These patterns and results provide promising opportunities for traders and investors in global trading markets to make more directed and smarter investment decisions based on the trend taken by these patterns. The success of this study reflects the ability to improve trading forecasts of various types using deep learning techniques and thus can contribute to improving the conditions of traders and investors.

Contributions of the authors

BA conceives twrites the draft of the paper, implements the algorithm, and performs analysis. FT and MK write the revision of the article, analyze the algorithm results in detail, and obtain the results for comparison. All authors read and approved the final manuscript.

Conflict of Interest Statement

There is no conflict of interest between the authors.

Statement of Research and Publication Ethics

The study is complied with research and publication ethics.

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