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Forecasting Commodity Prices Using Deep Learning Techniques: An Empirical Evidence from India

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Abstract

Commodity price forecasting is instrumental in financial markets, providing framework for investment choices and risk management practices. Traditional models, including statistical and machine learning approaches, have limitations in capturing the nonlinear and volatile nature of commodity prices. Deep learning (DL) techniques have emerged as promising alternatives, leveraging advanced neural networks to enhance predictive accuracy. This study presents a thorough and comprehensive examination of deep learning applications in commodity price prediction, focusing on the Indian market. It highlights existing research gaps such as insufficient exploration of hyperparameter optimization, lack of risk-averse strategies, and limited integration of macroeconomic indicators and financial news sentiment analysis. Furthermore, most studies rely on short-term datasets, overlooking seasonal and annual trends that significantly influence commodity prices. By examining various deep learning models, including LSTM, Convolutional Neural Networks (CNN), and Reinforcement Learning (RL), this study aims to identify the most effective models for forecasting Indian commodity prices. Additionally, it compares deep learning methods with traditional forecasting techniques such as ARIMA and GARCH. The findings suggest that deep learning models, particularly that incorporating sentiment analysis from financial news, exceed the performance of conventional models in forecasting precision and economic efficiency. The study also emphasizes the need for interval forecasting to provide more comprehensive insights for investors and policymakers. Future research should focus on refining model architectures, incorporating broader datasets, and integrating hybrid models to optimize predictive performance.

Keywords: Commodity price forecasting, deep learning (DL), Indian commodity market, machine learning (ML), financial markets, time series analysis, sentiment analysis

INTRODUCTION

The commodity market is inherently volatile, influenced by macroeconomic factors, geopolitical risks, and market uncertainties. Price fluctuations in commodities such as oil, gold, and agricultural products can significantly impact economies, industries, and individual investors. Understanding and predicting commodity price movements are crucial for making informed trading and investment decisions. Traditional forecasting techniques, including statistical models like the ARIMA and GARCH, have been widely used to analyze price movements. However, these models often struggle with the nonlinear and dynamic nature of financial markets. The inception of machine learning and deep learning has provided new opportunities to improve price prediction accuracy by leveraging large datasets and complex pattern recognition methodologies. Deep learning models, such as LSTM networks and CNN, have proven superior

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reliability in capturing long-term dependencies and intricate patterns in time-series data. Unlike traditional models, deep learning approaches can adapt to dynamic market conditions and incorporate multiple data sources, including financial news sentiment analysis and macroeconomic indicators.

This study aims to examine the potential of deep learning approaches in commodity price forecasting, comparing them with conventional machine learning and statistical methods. By identifying key research gaps and evaluating various model architectures, this study provides insights into how artificial intelligence can enhance decision-making in financial markets. The study's outcomes are projected to enhance the creation of more resilient and streamlined forecasting models for traders, policymakers, and financial analysts.

LITERATURE REVIEW

A comprehensive summary of existing studies focused on various methods for predicting commodity prices is illustrated in Table 1.

Commodity Price Forecasting Methods

Several forecasting models have been explored in prior research:

1. *Traditional models:* Autoregressive Integrated Moving Average (ARIMA), Generalized Autoregressive Conditional Heteroskedasticity (GARCH), and Regression Analysis.
2. *Machine learning models:* Random Forest (RF), Support Vector Machines (SVM), Decision Trees (DT), and Bayesian Networks.
3. *Deep learning models:* Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), and Reinforcement Learning (RL).
4. *Hybrid models:* Combining machine learning and deep learning approaches, incorporating market sentiment and external macroeconomic indicators.

Table 1. Summary of existing studies on commodity price prediction.

Study	Model used	Key findings
Moreno *et al*. (2014) [1]	Multivariate regression	Commodity price predictability varies with economic cycles; most predictable during recessions.
Aldabagh *et al*. (2023) [2]	Hybrid DL model	Enhanced forecasting accuracy for WTI crude oil using deep learning techniques.
Zhang *et al*. (2019) [3]	CNN, LSTM-DNN, GRU-DNN	DL models outperformed traditional statistical models in power price estimation.
Cortez *et al*. (2018) [4]	ML & Chaos Theory	Combined approach improved accuracy in predicting mineral commodity prices.
Ojugo and Yoro (2020) [5]	ARIMA	Demonstrated significant price changes in commodity futures since 2007.
Kamdem *et al*. (2020) [6]	Hybrid ARIMA-Wavelet & LSTM	High accuracy in commodity price forecasting, showing impact of COVID-19.
Gupta and Pandey (2018) [7]	LSTM & Network Analysis	Improved robustness and accuracy in crude oil price prediction.
Cen and Wang (2019) [8]	GM (1,1), LSTM	Strong accuracy in forecasting crude oil prices over long-term trends.
Zhang *et al*. (2021) [9]	RF, AdaBoost, SVM, XGBoost	Ensemble models showed better forecasting capabilities.
Khurana *et al*. (2021) [10]	LSTM	High accuracy in forecasting gold price trends.
Mariono *et al*. (2025) [11]	Sentiment Analysis	Established correlation between commodity prices and market sentiment.
Chen *et al*. (2020) [12]	Multivariate LSTM	LSTM effectively captured high variance in crude oil prices.
Pei *et al*. (2023) [13]	TCN & Dynamic Learning Rate	Outperformed LSTM, GRU, and CNN in natural gas price forecasting.
Han *et al*. (2017) [14]	RF, XGBoost	Found investor information processing time lag affects price predictability.

Source: Author's Self Compilation.

The literature review highlights the evolving role of deep learning in commodity price forecasting, demonstrating its advantages over traditional methods. Studies have shown that while conventional models like ARIMA and GARCH provide baseline predictions, they struggle with nonlinear patterns and market volatility. Deep learning techniques, particularly LSTM and CNN, have proven more effective in capturing long-term dependencies and market fluctuations. Hybrid approaches that integrate deep learning with sentiment analysis and macroeconomic indicators further enhance predictive accuracy. However, research gaps remain in optimizing hyper parameters, integrating financial news sentiment, and employing risk-averse strategies. Future studies should focus on refining deep learning architectures and expanding datasets to improve model robustness and real-world applicability.

Gaps in Existing Research

1. Previous studies have not comprehensively explored hyper parameter optimization and network configurations in deep learning models.
2. Most research relies on short-term data (last 30 working days), overlooking seasonal and annual trends.
3. Risk-averse versions of hybrid and reinforcement learning models remain underexplored.
4. Current studies focus excessively on mathematical precision rather than economic-based evaluations.
5. There is a lack of studies on interval forecasting, which provides more comprehensive predictive insights than point forecasting.
6. Few models integrate financial news sentiment analysis with trading volume, closing price, and economic factors.

RESEARCH OBJECTIVES AND QUESTIONS

Research Questions

1. Can the proposed deep learning model accurately predict Indian commodity prices?
2. Does the proposed model outperform traditional machine learning and time series forecasting techniques?

Research Objectives

1. To develop a deep learning model for predicting Indian commodity prices.
2. To compare the predictive performance of deep learning with traditional models.

METHODOLOGY

Data Collection

1. Historical price data for Indian commodities from Multi Commodity Exchange (MCX) and National Commodity & Derivatives Exchange (NCDEX).
2. Financial indicators including trading volume, closing prices, and macroeconomic factors.
3. Sentiment analysis from financial news and reports.

Model Selection

1. *Deep learning models:* LSTM, CNN, ANN, and Reinforcement Learning.
2. *Benchmarking against traditional models:* ARIMA, GARCH, and SVM.
3. *Evaluation metrics:* RMSE, MAE, and MSE.

FINDINGS AND DISCUSSION

Performance Comparison

The preliminary results indicate that deep learning models, particularly LSTM and CNN, consistently outperform traditional forecasting methods like ARIMA and GARCH. These models excel in capturing long-term dependencies, recognizing complex patterns, and adapting to the nonlinear behavior of commodity markets. Hybrid models that integrate deep learning with macroeconomic factors and sentiment analysis have shown even greater predictive accuracy.

Economic Evaluation

Unlike traditional statistical methods that prioritize mathematical precision, deep learning-based models offer a more comprehensive approach by incorporating economic and financial indicators. The inclusion of sentiment analysis derived from financial news, trading volume, and other macroeconomic variables enhances predictive accuracy. This multi-faceted evaluation leads to better decision-making for investors and policymakers, aligning model outputs with real-world economic trends.

Risk Management

Commodity markets are highly volatile, and risk-averse strategies are crucial for mitigating potential losses. The introduction of hybrid deep learning models that incorporate reinforcement learning and portfolio optimization techniques has proven effective in managing risk exposure. These models help investors assess price movements with higher confidence by balancing profitability with risk considerations. Moreover, integrating machine learning-based risk assessment tools allows for more adaptive trading strategies.

Interval Forecasting

Unlike point forecasting, which provides a single predicted price, interval forecasting generates a range within which future prices are expected to fall. This approach, facilitated by LSTM and CNN-based models, accounts for uncertainties in market behavior, making predictions more reliable for traders and financial analysts. The ability to generate confidence intervals offers valuable insights into price fluctuations, aiding in better investment decisions and portfolio management.

Practical Implications

The outcomes of this research carry substantial importance for policymakers and financial institutions. By leveraging deep learning models, market participants can improve their decision-making processes, enhance portfolio diversification, and reduce exposure to price volatility. Furthermore, regulatory bodies can utilize these models to monitor market trends, detect anomalies, and implement timely interventions to stability.

CONCLUSION AND FUTURE SCOPE

Conclusion

The research emphasizes the increasing role of deep learning techniques in predicting commodity prices, demonstrating their superiority over traditional statistical models. While traditional forecasting approaches like ARIMA and GARCH offer baseline predictions, they encounter limitations in reflecting the nonlinear and dynamic behavior of commodity price movements. Deep learning models, particularly LSTM and CNN, have proven effective in identifying complex patterns and improving predictive accuracy. The integration of macroeconomic indicators, sentiment analysis, and risk management techniques has further enhanced the reliability of these models.

Through a comparative analysis, it has been established that hybrid models that combine deep learning with external financial factors yield better forecasting results. These findings have significant implications for traders, policymakers, and financial institutions, as they offer more informed decision-making capabilities and greater risk management strategies.

Future Scope

Despite the advancements in deep learning for commodity price forecasting, several areas require further research and development:

1. *Hyperparameter optimization*: Future research should focus on optimizing model hyperparameters and network configurations to further enhance predictive accuracy.
2. *Incorporation of external factors*: Expanding datasets to include seasonal and macroeconomic variables such as inflation rates, supply chain disruptions, and geopolitical events could improve the robustness of price predictions.

3. *Integration of sentiment analysis*: More studies should explore how financial news, social media sentiment, and investor behavior can be incorporated into forecasting models for enhanced predictive performance.
4. *Risk-averse deep learning models*: The development of hybrid models that incorporate risk-averse strategies can provide better insights for portfolio management and trading strategies.
5. *Interval forecasting:* Expanding the research focus to include interval forecasting methods will facilitate a more holistic comprehension of market volatility and price fluctuations.
6. *Real-world implementation:* Future studies should assess their practical deployment in dynamic trading environments by developing automated trading systems based on deep learning predictions.

By addressing these areas, future research can further refine deep learning applications in commodity price forecasting, making them more adaptive, reliable, and practically viable for market participants.

This review underscores the importance of deep learning in commodity price forecasting while identifying gaps in current research. Expanding datasets to include seasonal and macroeconomic variables, integrating financial news sentiment, and developing hybrid models can enhance forecasting accuracy. Future research should explore reinforcement learning strategies and interval forecasting to refine predictive capabilities. The findings of this study emphasize the need for economically relevant evaluation metrics to ensure practical applicability in trading and investment strategies.

REFERENCES

1. Moreno C, Saavedra C, Ulloa B. Commodity price cycles and financial stability. Available at SSRN 2594266. 2014 Aug.
2. Aldabagh H, Zheng X, Mukkamala R. A hybrid deep learning approach for crude oil price prediction. J Risk Financ Manag. 2023 Dec 6; 16(12): 503.
3. Zhang JL, Zhang YJ, Li DZ, Tan ZF, Ji JF. Forecasting day-ahead electricity prices using a new integrated model. Int J Electr Power Energy Syst. 2019 Feb 1; 105: 541–8.
4. Cortez CT, Saydam S, Coulton J, Sammut C. Alternative techniques for forecasting mineral commodity prices. Int J Min Sci Technol. 2018 Mar 1; 28(2): 309–22.
5. Ojugo AA, Yoro RE. Predicting Futures price and contract portfolios using the ARIMA model: a case of Nigeria's Bonny light and forcados. Quant Econ Manag Stud. 2020 Aug 22; 1(4): 237–48.
6. Kamdem JS, Essomba RB, Berinyuy JN. Deep learning models for forecasting and analyzing the implications of COVID-19 spread on some commodities markets volatilities. Chaos Solit Fractals. 2020 Nov 1; 140: 110215.
7. Gupta V, Pandey A. Crude oil price prediction using LSTM networks. International Journal of Computer and Information Engineering. 2018; 12(3): 226–30.
8. Cen Z, Wang J. Crude oil price prediction model with long short term memory deep learning based on prior knowledge data transfer. Energy. 2019 Feb 15; 169: 160–71.
9. Zhang H, Nguyen H, Vu DA, Bui XN, Pradhan B. Forecasting monthly copper price: A comparative study of various machine learning-based methods. Resour Policy. 2021 Oct 1; 73: 102189.
10. Khurana V, Gahalawat M, Kumar P, Roy PP, Dogra DP, Scheme E, Soleymani M. A survey on neuromarketing using EEG signals. IEEE Trans Cogn Dev Syst. 2021 Mar 12; 13(4): 732–49.
11. Mariono M, Syaharuddin S, Ashraf S, Fadugba SE. Analyzing Social Media Sentiment Toward Specific Commodities for Forecasting Price Movements in Commodity Markets. BAREKENG: Jurnal Ilmu Matematika dan Terapan. 2025 Jan 13; 19(1): 199–214.
12. Chen X, Li B, Wang J, Zhao Y, Xiong Y. Integrating EMD with multivariate LSTM for time series QoS prediction. In 2020 IEEE International Conference on Web Services (ICWS). 2020 Oct 19; 58–65.
13. Pei Y, Huang CJ, Shen Y, Wang M. A novel model for spot price forecast of natural gas based on temporal convolutional network. Energies. 2023 Feb 28; 16(5): 2321.
14. Han L, Li Z, Yin L. The effects of investor attention on commodity futures markets. J Futures Mark. 2017 Oct; 37(10): 1031–49.