Deep Learning as a Decision Financial Tool in the Oil and Gas Industry

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Abstract

The global oil and gas sector drives high-value projects with significant financial exposure. Effective corporate and industrial planning requires closely monitoring the evolution of oil barrel prices and generating accurate forecasts. Deep Learning models can provide decision-makers with greater security in mitigating financial risks. This research presents an advanced model that employs Deep Learning techniques alongside traditional statistical models to select the most effective model for each dataset. Additionally, the study emphasizes the need to present results visually, offering decision-makers increased clarity and confidence in models generated by artificial intelligence techniques. In computer science, this study highlights the importance of Deep Learning models in enhancing the predictive capabilities of software systems. Interdisciplinary collaboration between industry experts and AI specialists is essential to achieving optimal results and driving innovation across industries, particularly in financial decision-making. The findings of this research demonstrate that Deep Learning provides a forward-looking, strategic tool to manage products highly exposed to oil price volatility, delivering a more resilient approach to financial planning and risk management in the oil and gas industry.

1 Introduction

When addressing low-complexity problems, human cognition is typically sufficient to execute mathematical modeling and identify optimal solutions efficiently without delaying decision-making processes within the desired timeframe. However, as the complexity of the problem increases, the need for computational tools becomes apparent, particularly when simulations are required to evaluate and select the most effective solution. In this context, the role of new technologies is fundamental, especially in developing financial models where the interaction between users and data significantly influences the outcomes.

In the Oil & Gas supply chain, monitoring global oil price fluctuations is critical for operational and strategic decision-making. Accurate forecasts of future oil prices enable suppliers to plan their budgets

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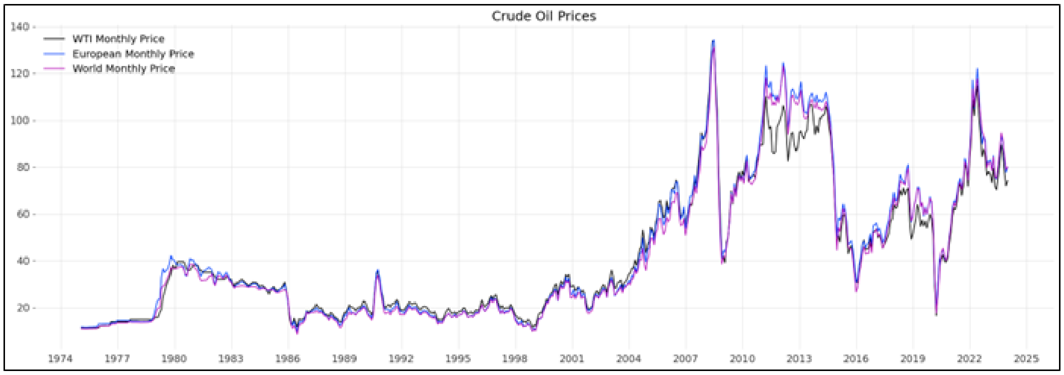

Figure 1: Historical oil price dynamics.

and finances effectively, as oil prices directly impact revenue and profitability. By leveraging reliable price predictions, companies can make well-informed investment decisions, control expenses, and mitigate financial risks. As illustrated in Fig. 1, the volatility in oil markets is evident, highlighting the importance of this study.

Beyond short-term operational needs, companies producing subsea oil extraction systems must develop medium- to long-term strategies for market forecasting, raw material inventory management, and cash flow optimization to maintain financial stability. In the Brazilian Oil & Gas sector, fluctuations in oil barrel prices serve as key indicators for future investment decisions, particularly for major industry players. This underscores the closest relationship between market dynamics and the volatility of other commodities used in the oil extraction process, such as metals and steel, which are vital to producing subsea systems [10, 19].

The green energy sector has increasingly adopted comparative time series models, including both hybrid approaches, combining classical statistical methods with deep learning techniques [7], and purely comparative models [19, 18]. This research focuses on the predictability of oil prices through the analysis of price curve dynamics, particularly about the daily distributions of key oil barrel price benchmarks in the Brazilian market: WTI, which is widely used as a standard in global markets, and Brent Oil, produced in Europe, the United Kingdom, and Norway. Additionally, the study considers the average global price based on the Organization of the Petroleum Exporting Countries (OPEC).

The reference price for the Brazilian oil barrel is established by ANP Resolution 874 of April 18, 2022, as specified in Article 2, Clause XIII, with pricing determined in U.S. dollars per barrel. This pricing is based on a blend of North Sea oils that feed into the Brent pipeline system and are loaded onto oil tankers at the Sullom Voe Terminal in the United Kingdom.

The findings of this research underscore that, in sectors characterized by significant financial risk and complexity, artificial intelligence (AI) offers a powerful tool to support strategic and financial decision-making. In the Oil & Gas industry, Deep Learning has proven to be an effective and reliable method for addressing high-risk scenarios that involve potential loss of shareholder value. Strengthening the connection between academia and industry in this sector could be a pivotal step toward modernizing how financial aspects are monitored and managed.

For reproducibility of the experiment there is a GitHub link in the footnote of this paper. [2]

2 Methodology

Although the literature presents previous studies on the application of Deep Learning in several commodity price databases, the main objective of this research is to evaluate the use of the Simple-FeedForward (SFF), Deep Non-Parametric Time Series (DNPTS) and Temporal Fusion Transformer (TFT) models in crude oil price series that dictate the trend of medium and long-term investments throughout the Oil and Gas sector in Brazil. All these complex models were compared to the traditional statistical models, ARIMA, and Exponential Smoothing.

[2] https://github.com/aguinaldoflor/LXAI_neurIPS_2024

The Temporal Fusion Transformer (TFT) model combines the transformers' ability to capture long-range dependencies in the data with a specific architecture to fuse two different architectures: self-attention with Long Short-Term Memory (LSTM). The TFT also efficiently handles multiple data sources, integrating information from past time series, static attributes that do not change over time, and exogenous variables that may affect the predictions.

The Simple Feed Forward (SFF) model is a neural network for time series forecasting. The SFF model, as the name suggests, is a simple feedforward neural network structure, meaning that the connections between the nodes do not form cycles. This model comprises several layers, where each layer receives input from the previous layer, processes this input, and passes the output to the next layer.

Finally, the DNPTS model does not assume a specific parametric form for the series. Instead, it utilizes data-based methods to identify patterns, trends, and seasonality without imposing a pre-defined structure like parametric models (ARIMA, SARIMA). It represents an innovative approach to time series forecasting, integrating the flexibility of non-parametric methods with the deep learning capability of neural networks.

3 Related Work

Industries that are part of any market niche in the oil and gas sector will always be directly exposed to the price of a barrel of oil, whether for short, medium, or long-term financial planning; exposure to this commodity can impact the financial health of even large corporations. Monitoring commodity price fluctuations and making projections are a major challenge for the financial sector of industries. New technologies can act as decision support for investments or for the financial management of large projects.

Artificial Intelligence is a technology emerging in Corporate Finance and Financial Risk Analysis studies. To improve the efficacy of new studies in the financial field. Deep Learning models have been used for predicting financial disasters [34] and evaluating financial risk in various sectors of the economy: Electric Energy [21] using models capable of projecting consumption [29, 16]; Medicine [26, 24, 22], tourism, economy, retail, demography, among others [4].

The importance of oil for the economic development of a nation generates a search for coverage against the uncertainty in the price of the commodity. In addition to the effect of the volatility of the price itself, there is also the high variation over time of the raw materials used by suppliers who are part of the first link in the chain of significant oil operators.

From more traditional research, techniques in price prediction studies for oil include ARIMA, vector autoregressive models, and Monte Carlo Simulation, among others. In the context of nonlinear scenarios, these models tend to perform poorly despite having good efficacy for handling linear and stationary time series.

Contemporary literature has shown a shift in studies on oil pricing from traditional econometric and statistical models to more advanced, nonlinear models with machine learning and Deep Learning techniques to capture the high volatility in oil price curves. This period of change has brought about some studies by researchers [2, 36, 9] who are now using artificial intelligence and deep learning techniques for oil price projection. This sector is relatively archaic but has been updated through new technologies. This includes explaining price fluctuations during COVID-19 [35] or discussing regional prices, such as in China [13].

Recent research using Deep Learning models, such as Convolutional Neural Networks - CNN [20], Temporal Fusion Transformer - TFT [15], and Recurrent Neural Networks - RNNs using LSTM and GRU [28, 32], have datasets with daily closing values of the oil market in China and the United States. Although published between 2023 and 2024, the datasets are from periods up to 2020 - 2021, which may offer distortions with applications carried out between 2022 and 2024, a post-pandemic period with a cooling in the barrel price.

This entire theoretical framework and body of research in Machine Learning, Deep Learning, and Artificial Intelligence must be integrated into fields not directly connected to technology. To facilitate this "connection" between technology and non-technological areas, such as business and finance, meticulous care, and expertise in the field of human-computer interaction are required. The outcomes generated through computational models for complex problems yield an automated analysis with interactive visual means, as discussed by James J. Thomas and Kris Cook [**?**] at the IEEE Computer Graphics and Applications conference. These visual analyses assist decision-makers in choosing safer paths without the need to develop manual mathematical models for the predictability of future events. The literature presents various approaches adapted for specific uses, such as in data science with models developed from machine learning [33]. VisualSynth [11] is a framework that offers a way to employ simple interaction through colors in data science-related activities. Interactive Machine Learning follows a similar path, aiming to complement human intelligence with computational models [8].

Furthermore, in the domain of human-computer interaction, there are numerous studies directed at problem areas such as text [31, 25], images [23, 5], and in the same study area as this research, in Time Series [17, 12]. Many research efforts focus on assisting users in solving complex problems in diverse areas that may be challenging to address without the direct involvement of computational models.

4 Metrics

The accuracy of each model is measured using seven statistical indices calculated by the library itself: Normalized Root Mean Square Error (NRMSE), Symmetric Mean Absolute Percentage Error (SMAPE), and Mean Absolute Scaled Error (MASE). Additionally, we have developed a classification approach that considers the combination of all these metrics through a score, allowing us to determine the best model among all those tested automatically. This automation in the developed model brings more clarity to the interpretation of results, offering a more concise structure to assist decision-makers based on the obtained outcomes.

A model that demonstrates high levels of accuracy in predicting oil prices helps mitigate the imminent risk of financial loss in oil and gas sector projects.

5 Dataset

The global Oil and Gas sector is characterized by three price benchmarks that serve as global references for oil pricing: the American market with WTI (West Texas Intermediate), Brent oil for the European market, and the global average price set by the Organization of the Petroleum Exporting Countries (OPEC). The variable names have been defined succinctly yet clearly for anyone accessing the results. The series containing American oil prices was labeled with "wti_" at the end, followed by "d" for daily price. Similarly, the European oil price was designated as "eur_", and in the same manner, the global oil price was denoted as "wor_".

The daily oil prices in Table 1 is derived from real-world data based on the price per barrel in U.S. dollars. The daily price series begins on January 4, 2016, and ends on February 16, 2024.

For the division between training and testing, the last 300 records were employed in the daily series for the model's testing phase. All the time series were extracted on the New York Time data base.

All datasets underwent an individual preprocessing phase, accounting for observed seasonality and trends and analyzing missing data or any additional irregularities.

Table 1: Statistical Description of Daily Oil Price Dataset

Description	wti_d	eur_d	wor_d
count	2,042	2,042	2,042
mean	67.02	72.05	70.35
Std	21.86	23.85	23.86
Min	8.91	9.12	12.22
25%	49.59	53.80	51.04
50%	63.29	68.79	67.24
75%	83.27	88.07	88.40
max	123.64	133.18	128.27

After structuring the time series, the Dickey-Fuller (ADF) test was applied to check the stationarity of each variable. It was necessary first to transform the data using logarithms, which showed a high p-value. In the second phase, the technique of log differentiation by a twelve-month moving average was applied to make the series stationary. From this point, the experimental phase began.

6 Experiment and Analysis

All models and their requirements were installed correctly in a virtual environment dedicated to the project using Python 3.12.0. The Visual Studio Code 1.85.1 code editor was employed on the Windows 11 operating system. About hardware, the models were executed on a PC equipped with an ASUS ROG Strix Z590-A motherboard, 64 GB of RAM, an NVIDIA GeForce RTX 4070 Ti Super GPU, and an Intel Core i7-10700K CPU 3.8GHz processor with eight cores.

After dividing the dataset into training and testing, we used the data series applied method of differentiating the log by the moving average in a 12-month window, significantly improving results compared to a prior test without this function.

Before starting the simulations, all hyperparameters were tested with slight variations to analyze their impact on the results of each dataset. Then, for best results, the most sensitive hyperparameters in each model.

At the end of the code for each dataset, an individual score was calculated for the positioning of each model based on the metrics presented, with the last column of the tables showing a score sum. This optimized approach makes it possible to verify the best model in a more balanced way.

The results presented in Table 2 compare five forecasting models applied to three daily oil barrel prices datasets: World Daily Price, Europe Daily Price, and WTI. The evaluated models include the Temporal Fusion Transformer (TFT), SimpleFeed-Forward (SSF), Deep Non-Parametric Time Series (DNPTS), ARIMA, and Exponential Smoothing. The metrics used for evaluation were NRMSE (Normalized Root Mean Squared Error), SMAPE (Symmetric Mean Absolute Percentage Error), and MASE (Mean Absolute Scaled Error), with a final score (Score) derived from the sum of rankings assigned to each metric. The results are discussed individually for each dataset and in a general comparison across models.

The performance on the World Daily Price dataset, the TFT model exhibited the best overall performance in the World Daily Price dataset. It achieved the lowest NRMSE (0.0801), SMAPE (0.0631), and MASE (1.8015), resulting in the highest total score (15 points). These results indicate that the

Table 2: Results of Daily Oil Price

Model	**NRMSE**		**SMAPE**		**MASE**		**Score**
	Result	Scr	Result	Scr	Result	Scr	
World Daily Price							
Temporal Fusion Transformer - TFT	0,0801	5	0,0631	5	1,8015	5	15
SimpleFeed-Forward - SSF	0,0816	4	0,0641	4	1,8322	4	12
Deep Non-Parametric TS - DNPTS	0,0876	3	0,0723	3	2,0611	2	8
ARIMA	0,1270	2	1,9850	1	2,0028	3	6
Exponential Smoothing	0,1308	1	1,5433	2	2,0690	1	4
Europe Daily Price							
Temporal Fusion Transformer - TFT	0,0494	5	0,0386	5	1,5916	5	15
SimpleFeed-Forward - SSF	0,0558	4	0,0438	4	1,8145	4	12
Deep Non-Parametric TS - DNPTS	0,0638	3	0,0537	3	2,2023	1	7
ARIMA	0,1386	2	1,9701	1	1,8410	3	6
Exponential Smoothing	0,1435	1	1,5670	2	1,9282	2	5
WTI Daily Price							
SimpleFeed-Forward - SSF	0,0462	5	0,0372	4	1,6101	4	13
Temporal Fusion Transformer - TFT	0,0463	4	0,0364	5	1,5769	5	14
Deep Non-Parametric TS - DNPTS	0,0564	3	0,0474	3	2,0450	1	7
ARIMA	0,1382	2	1,6770	1	1,7622	3	6
Exponential Smoothing	0,1412	1	1,5880	2	1,8142	2	5

TFT is highly effective at capturing complex temporal patterns present in global daily oil prices, offering forecasts with lower absolute, percentage, and scaled errors.

The SimpleFeed-Forward (SSF) model also demonstrated competitive performance, with an NRMSE of 0.0816 and a total score of 12, positioning itself as the second-best alternative to the TFT. The DNPTS model showed intermediate performance, while traditional models such as ARIMA and Exponential Smoothing performed worse. Notably, Exponential Smoothing had the highest NRMSE (0.1308) and the worst SMAPE (1.5433), highlighting its limitations in modeling the complexity of the data in this dataset.

In the Europe Daily Price dataset, the TFT again showed superior performance, with the lowest NRMSE (0.0494), SMAPE (0.0386), and MASE (1.5916), achieving a perfect score of 15 points. These results further reinforce the robustness of the TFT across different datasets, demonstrating its ability to capture seasonal variations and trends in European oil prices. The SSF model ranked second, with results slightly inferior to those of the TFT, highlighting its efficiency with lower computational complexity. The DNPTS model again showed moderate performance, while ARIMA and Exponential Smoothing performed the worst. In particular, Exponential Smoothing exhibited the highest NRMSE (0.1435) and SMAPE (1.5670), reinforcing its unsuitability for complex time series like oil prices.

In the WTI Daily Price dataset, the SimpleFeed-Forward model achieved the best NRMSE (0.0462) performance, followed closely by the TFT, which showed an NRMSE of 0.0463 and the lowest SMAPE (0.0364). The slight difference between the two models suggests that both are effective in forecasting the WTI market, with SSF having a slight edge in NRMSE, while TFT outperforms in percentage-based errors. The DNPTS model performed moderately, with an NRMSE of 0.0564, while traditional models such as ARIMA and Exponential Smoothing again performed poorly. Exponential Smoothing showed the least effective results, with an NRMSE of 0.1412 and SMAPE of 1.5880.

Overall, the TFT stands out as the most consistent and robust model across all three datasets, achieving the highest total score in two of the three datasets and consistently ranking among the top two models regarding NRMSE, SMAPE, and MASE. The consistent performance of the TFT can be attributed to its ability to capture seasonal patterns and complex dynamics in time series data. This highlights the potential of deep learning-based models, such as the TFT, for more accurate forecasting of volatile and high-dimensional time series, such as oil prices.

The SimpleFeed-Forward model also demonstrated notable performance, consistently ranking second in all datasets. Its simplicity and efficiency make it a viable alternative to the TFT, especially when seeking a balance between accuracy and computational cost. The DNPTS model showed intermediate performance, not surpassing the deep learning-based models but still providing respectable results.

Traditional models, such as ARIMA and Exponential Smoothing, showed significantly poorer performance than the more advanced models. These models consistently recorded the highest error margins across all datasets. Exponential Smoothing, in particular, exhibited the worst overall performance, with high NRMSE and SMAPE values, indicating its limitations in modeling the complexity and volatility of oil prices.

7 What can be Learned?

Although based on simple mathematical approaches, the computational models selected for this research become impractical to apply manually due to the large volume of data and the number of iterations involved. However, the choices related to tools and types of models result from well-founded human decisions, highlighting the need for human-machine interaction. The selection of models, tools, libraries, and computational infrastructure directly impacts the quality of the results and is based on previous scientific studies, not on assumptions or intuition.

Applying artificial intelligence techniques like Deep Learning enables more efficient data processing, significantly enhancing the developed models. However, this advancement is only possible through human intervention and knowledge. The success of these approaches depends not only on computational power but also on human intellectual effort and the collaboration between academia and industry.

Although the experimental results are organized in tables, graphical visualization can further facilitate decision-making in a bar chart commonly used in corporate environments, as shown in Fig. 2. These

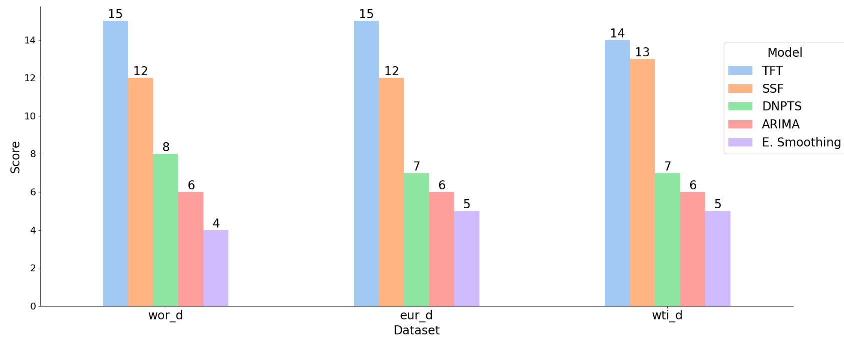

Figure 2: Model Performance per Dataset represented by bar chart.

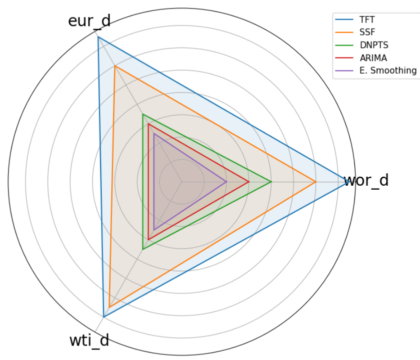

Figure 3: Model Performance per Dataset represented by radar chart.

graphical representations enable faster and more focused analysis, highlighting the best model for each dataset with information relevant to the user.

For example, Fig. 3 presents a radar chart, an effective tool for comparing multiple models. In this chart, each line represents a model, while the axes correspond to the datasets (e.g., "wor_d," "eur_d," "wti_d"). Larger areas indicate better performance, making it easier to identify more balanced and robust models or stand out in specific criteria.

Fig. 4, a heatmap chart, complements this analysis by visually highlighting model performance differences. Darker shades indicate higher scores, while lighter tones point to inferior performance. This type of visualization helps identify performance patterns immediately without needing to scrutinize the numbers. Models like TFT and SSF stand out with the highest scores, while Exponential Smoothing shows lower results. Moreover, using color gradients in the heatmap allows capturing performance nuances that might go unnoticed.

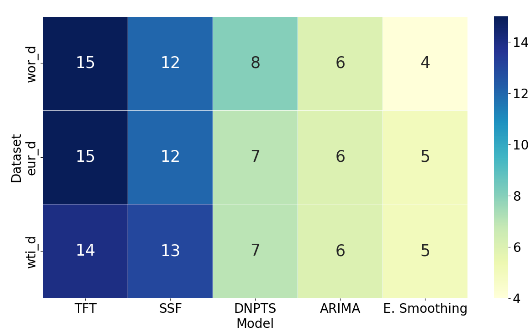

Figure 4: Model Performance per Dataset represented by heatmap chart.

Through these visualizations, decision-makers can quickly identify the most suitable model, streamlining the selection process and maximizing the accuracy of decisions. This modeling process was structured by professionals with expertise in technology and business contexts, ensuring that the solutions align with the company's needs.

Finally, the technological advances driven by artificial intelligence foster profound transformations in companies, breaking traditional paradigms and creating new opportunities. Studies indicate that contrary to the fear that automation and AI will eliminate jobs, these changes can preserve them, reconfiguring the nature of work rather than replacing it [27, 3, 1].

8 Discussion

Several studies have explored the use of Deep Learning techniques as new approaches for forecasting steel and other metal prices, focusing on comparisons that show superior results from these models compared to traditional statistical or regression methods [30, 10, 19]. At the same time, academic literature also examines the application of Deep Learning in building Value at Risk (VaR) models, particularly in the context of currency fluctuations, investment portfolios, and stocks [6, 37, 14].

This study goes beyond these approaches by proposing a model that bridges academic theory with the industrial sector, with a special focus on the financial area of these industries. By integrating artificial intelligence techniques with financial time series forecasts, a well-established methodology in the financial market, the research aims to demonstrate how collaboration between academic research and industry is crucial for driving profitability, promoting sustainability, and generating value for various stakeholders.

9 Limitations

A key limitation of this study is restricted access to specific datasets, often available only through subscriptions, which poses challenges for smaller companies. Including these datasets would significantly improve the model's value for forecasting commodity prices. The model can be calibrated and adapted to new datasets, including those for other commodities. Still, the cost of subscriptions to large commodity databases may make it impossible to implement models of this nature in companies that do not have a high turnover to compensate for the investment.

By aligning academic knowledge with the practical needs of the sector, innovative solutions are created that enhance competitiveness and efficiency, highlighting the importance of continuous synergy between research and industry for the development of strategic and sustainable solutions in support of corporate decision-making.

10 Conclusion

The results demonstrate the superiority of Deep Learning techniques in predicting oil prices, especially compared to traditional methods such as ARIMA and Exponential Smoothing. Models like TFT, SFF, and DNPTS consistently outperform the others in terms of accuracy of error metrics in oil price forecasting. This high level of accuracy allows for a more reliable assessment of financial risk scenarios, which is essential for decision-making in corporate environments.

Advanced Deep Learning techniques offer a clear advantage in analyzing complex time series, such as commodity prices, due to their ability to capture non-linear patterns and volatile market dynamics. By reducing forecast errors, these models provide more solid support for strategic decision-making, allowing companies to anticipate potential financial risks, such as fluctuations in oil prices, and proactively adjust their operations. This way, organizations can optimize their planning and financial management processes, avoiding significant losses.

In a corporate environment where market volatility and uncertainties are constant, adopting Deep Learning techniques for financial risk analysis is not just an option but a necessity. The improved accuracy of these tools directly contributes to better resource allocation and risk mitigation, providing a significant competitive advantage for companies. Therefore, corporate decision-makers must incorporate these technologies into risk analysis processes, ensuring greater resilience and adaptability in an increasingly dynamic market.

References

[1] D. Acemoglu and P. Restrepo. The race between man and machine: Implications of technology for growth, factor shares, and employment. *American economic review*, 108(6):1488–1542, 2018.

[2] A. Ali Salamai. Deep learning framework for predictive modeling of crude oil price for sustainable management in oil markets. *Expert Systems with Applications*, 211:118658, 2023.

[3] M. Arntz, T. Gregory, and U. Zierahn. The risk of automation for jobs in oecd countries: A comparative analysis. 2016.

[4] G. Athanasopoulos, R. J. Hyndman, N. Kourentzes, and A. Panagiotelis. Forecast reconciliation: A review. *International Journal of Forecasting*, 40(2):430–456, 2024.

[5] J. Backman, M. Koistinen, and A. Ronkainen. Agricultural process data as a source for knowledge: Perspective on artificial intelligence. *Smart Agricultural Technology*, 5:100254, 2023.

[6] P. Brugière and G. Turinici. Deep learning of value at risk through generative neural network models: The case of the variational auto encoder. *MethodsX*, 10:102192, 2023.

[7] P. Cihan. Comparative performance analysis of deep learning, classical, and hybrid time series models in ecological footprint forecasting. *Applied Sciences*, 14(4):1479, 2024.

[8] J. J. Dudley and P. O. Kristensson. A review of user interface design for interactive machine learning. *ACM Transactions on Interactive Intelligent Systems (TiiS)*, 8(2):1–37, 2018.

[9] Y. Fang, W. Wang, P. Wu, and Y. Zhao. A sentiment-enhanced hybrid model for crude oil price forecasting. *Expert Systems with Applications*, 215:119329, 2023.

[10] P. Foroutan and S. Lahmiri. Deep learning-based spatial-temporal graph neural networks for price movement classification in crude oil and precious metal markets. *Machine Learning with Applications*, 16:100552, 2024.

[11] C. Gautrais, Y. Dauxais, S. Teso, S. Kolb, G. Verbruggen, and L. De Raedt. Human-machine collaboration for democratizing data science. *arXiv preprint arXiv:2004.11113*, 2020.

[12] J. K. Guo and M. O. Hofmann. Interactive pattern discovery in high-dimensional, multimodal data using manifolds. *Procedia computer science*, 114:258–265, 2017.

[13] L. Guo, X. Huang, Y. Li, and H. Li. Forecasting crude oil futures price using machine learning methods: Evidence from china. *Energy Economics*, 127:107089, 2023.

[14] K. He, L. Ji, G. K. Tso, B. Zhu, and Y. Zou. Forecasting exchange rate value at risk using deep belief network ensemble based approach. *Procedia computer science*, 139:25–32, 2018.

[15] K. He, L. Zheng, Q. Yang, C. Wu, Y. Yu, and Y. Zou. Crude oil price prediction using temporal fusion transformer model. *Procedia Computer Science*, 221:927–932, 2023. Tenth International Conference on Information Technology and Quantitative Management (ITQM 2023).

[16] H. Kazmi, C. Fu, and C. Miller. Ten questions concerning data-driven modelling and forecasting of operational energy demand at building and urban scale. *Building and Environment*, 239:110407, 2023.

[17] S. Kim, D. Tasse, and A. K. Dey. Making machine-learning applications for time-series sensor data graphical and interactive. *ACM Transactions on Interactive Intelligent Systems (TiiS)*, 7(2):1–30, 2017.

[18] R. Maiti, B. G. Menon, and A. Abraham. Ensemble empirical mode decomposition based deep learning models for forecasting river flow time series. *Expert Systems with Applications*, 255:124550, 2024.

[19] M. Mohsin and F. Jamaani. A novel deep-learning technique for forecasting oil price volatility using historical prices of five precious metals in context of green financing–a comparison of deep learning, machine learning, and statistical models. *Resources Policy*, 86:104216, 2023.

[20] M. Mohsin and F. Jamaani. A novel deep-learning technique for forecasting oil price volatility using historical prices of five precious metals in context of green financing – a comparison of deep learning, machine learning, and statistical models. *Resources Policy*, 86:104216, 2023.

[21] B. N. Oreshkin, D. Carpov, N. Chapados, and Y. Bengio. N-BEATS: neural basis expansion analysis for interpretable time series forecasting. *CoRR*, abs/1905.10437, 2019.

[22] U. Orji and E. Ukwandu. Machine learning for an explainable cost prediction of medical insurance. *Machine Learning with Applications*, 15:100516, 2024.

[23] W. Pan, J. Yan, H. Chen, J. Yang, Z. Xu, X. Li, and J. Yao. Human-machine interactive tissue prototype learning for label-efficient histopathology image segmentation. In *International Conference on Information Processing in Medical Imaging*, pages 679–691. Springer, 2023.

[24] M. Panja, T. Chakraborty, S. S. Nadim, I. Ghosh, U. Kumar, and N. Liu. An ensemble neural network approach to forecast dengue outbreak based on climatic condition. *Chaos, Solitons Fractals*, 167:113124, 2023.

[25] A. Peris and F. Casacuberta. Online learning for effort reduction in interactive neural machine translation. *Computer Speech & Language*, 58:98–126, 2019.

[26] I. Salehin, M. S. Islam, P. Saha, S. Noman, A. Tuni, M. M. Hasan, and M. A. Baten. Automl: A systematic review on automated machine learning with neural architecture search. *Journal of Information and Intelligence*, 2(1):52–81, 2024.

[27] K. Schwab. *The fourth industrial revolution*. Crown Currency, 2017.

[28] A. Sen and K. Dutta Choudhury. Forecasting the crude oil prices for last four decades using deep learning approach. *Resources Policy*, 88:104438, 2024.

[29] J. B. Thomas and S. K.V. Neural architecture search algorithm to optimize deep transformer model for fault detection in electrical power distribution systems. *Engineering Applications of Artificial Intelligence*, 120:105890, 2023.

[30] A. Varshini, P. Kayal, and M. Maiti. How good are different machine and deep learning models in forecasting the future price of metals? full sample versus sub-sample. *Resources Policy*, 92:105040, 2024.

[31] B. C. Wallace, K. Small, C. E. Brodley, J. Lau, and T. A. Trikalinos. Deploying an interactive machine learning system in an evidence-based practice center: abstrackr. In *Proceedings of the 2nd ACM SIGHIT international health informatics symposium*, pages 819–824, 2012.

[32] J. Wang, W. Zhao, F.-S. Tsai, H. Jin, J. Tan, and C. Su. A study of crude oil futures price volatility based on multi-dimensional data from event-driven and deep learning perspectives. *Applied Soft Computing*, 146:110548, 2023.

[33] K. Wongsuphasawat, Z. Qu, D. Moritz, R. Chang, F. Ouk, A. Anand, J. Mackinlay, B. Howe, and J. Heer. Voyager 2: Augmenting visual analysis with partial view specifications. In *Proceedings of the 2017 chi conference on human factors in computing systems*, pages 2648–2659, 2017.

[34] C. Wu, C. Jiang, Z. Wang, and Y. Ding. Predicting financial distress using current reports: A novel deep learning method based on user-response-guided attention. *Decision Support Systems*, 179:114176, 2024.

[35] Y. Xu, T. Liu, and P. Du. Volatility forecasting of crude oil futures based on bi-lstm-attention model: The dynamic role of the covid-19 pandemic and the russian-ukrainian conflict. *Resources Policy*, 88:104319, 2024.

[36] K. Yang, Z. Cheng, M. Li, S. Wang, and Y. Wei. Fortify the investment performance of crude oil market by integrating sentiment analysis and an interval-based trading strategy. *Applied Energy*, 353:122102, 2024.

[37] C.-X. Zhang, J. Li, X.-F. Huang, J.-S. Zhang, and H.-C. Huang. Forecasting stock volatility and value-at-risk based on temporal convolutional networks. *Expert Systems with Applications*, 207:117951, 2022.