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Predicting Oil Prices: A Comparative Study of Machine Learning and Deep Learning Methods

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Abstract

Crude oil, often referred to as "black gold," is an essential component of the global economy due to its significant contribution to the world's energy requirements. Numerous countries, regardless of their development status, rely significantly on its importation for transportation, heating, power generation, industrial production, agricultural output, and other applications. Energy security for all stakeholders, particularly oil-importing nations, will invariably rely on the sustained flow and provision of crude oil at competitive prices. The prices of crude oil substantially influence governmental decision-making. Consequently, variations in oil prices can incite social unrest and economic turmoil. Consequently, there is an increasing demand for methodologies that can accurately and efficiently forecast the future behavior of oil prices, considering their significant influence on the economy. To accurately predict oil prices, this study will make use of machine learning techniques such as Support Vector Machine (SVM), K-Nearest Neighbors (K-NN), Random Forest (RF), and Decision Tree (DT). Furthermore. long short-term memory network (LSTM) method as deep learning model is also used. The incapacity of recurrent neural networks (RNNs) to recognize long-range dependencies between distant data instances was a major drawback that LSTM was created to overcome. Despite its simplicity, the LSTM framework has remarkable performance across a wide range of applications. The LSTM models achieve a 99.99% prediction accuracy, outperforming other methods.

Keywords: Oil price predictions, Support Vector Machine, Decision Tree, Random Forest, K-NN, Recurrent Neural Network (LSTM).

Article history:

1. Introduction

Crude oil is the viscous, unrefined liquid extracted from oil reservoirs situated hundreds of meters beneath the Earth's surface. It is essential to every economy and cannot be replaced. Crude oil is among the earliest energy sources and plays a significant role in the commodities markets. Crude oil is categorized into many types according to its quality and production origin. Its expenses substantially influence global security and the economy because of its extensive applications. A significant portion of some nations' exports is sourced from crude oil; thus, a swift fluctuation in crude oil prices can exert a considerable financial influence, with price declines resulting in sluggish economic growth and price surges causing acute inflation [1].

Over the past few decades, there have been several wild swings in the world oil market. Every abrupt shock has greatly impacted the world economy, monetary policy, fiscal policy, and energy strategy. Both fundamental and non-fundamental factors influence crude oil's price because of its dual status as a financial asset and a commodity. Fundamental factors include oil consumption, stockpiles, supply, and demand. However, it is difficult to quantify and characterize the exact impact of some non-fundamental elements on oil prices, such as breaking news on the Internet, geopolitical risk indices, and other geopolitical events [2]. The COVID-19

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coronavirus pandemic and the dispute over oil prices between Saudi Arabia and Russia are two examples of these variables. The COVID-19 pandemic's effects on the global economy have resulted in a decline in the demand for oil globally [3].

Consequently, non-linearity, unpredictability, and dynamics reacting to unanticipated events have made it challenging to estimate crude oil prices well. Thus, developing a reliable and accurate way to estimate extremely complex and volatile pricing, such as that of crude oil, is an important and difficult task for a nation's economy [4].

Crude oil price forecasting is a huge field of study that has been going on for a very long time. Many techniques have been proposed. Research on crude oil price prediction strategies can be broadly classified into three categories: econometric, statistical, and artificial intelligence modeling techniques [5]. The most popular techniques for forecasting crude oil prices in recent years have been econometric techniques, which include vector autoregressive and auto-regressive average moving approaches. These strategies outperformed no-change methods in terms of forecast accuracy, at least for some timeframes. It was observed that most econometric techniques were linear, meaning they could not account for the non-linear crude oil prices. Recently, several artificial intelligence methods for oil price prediction have been introduced. Since these methods are non-linear, they can yield more precise forecasts, particularly in situations where the data on crude oil prices exhibit significant non-linearity [6].

Artificial intelligence is essentially the replication of human intelligence in computers that are designed to think like humans and behave like them. In particular, an area of computer science makes it possible for a machine to mimic human intelligence. Since machine learning is a subset of artificial intelligence and deep learning is a subset of machine learning, both are used to achieve artificial intelligence [7]. Energy economics research has made extensive use of artificial intelligence techniques because econometric techniques are not suitable for handling complex non-linear issues. In addition, many AI methods, including deep learning, machine learning, fuzzy inference system models, and others, are used to anticipate crude oil prices. The ability to capture non-linear features is a significant benefit of machine learning and deep learning classification approaches over econometric models. Furthermore, these classification techniques establish the association between input and output, thereby preventing prediction errors, such as the emergence of additional nodes in complex network models [8].

Brent crude oil is used to price two-thirds of the world's traded crude oil supplies, and it is considered one of the most important sources of crude oil pricing on the international market. Consequently, the goal of this study is to outperform similar models in terms of forecasting Brent crude oil prices [9] and [10].

This work's primary contribution is the recommendations it makes for various methods that yield the most accurate oil price forecasts. It is common knowledge that estimating the price of crude oil is a challenging undertaking due to its chaotic and non-linear behavior. We try to truly capture this non-linear behavior by using only historical crude oil prices because there are a variety of factors influencing crude oil prices. Using a number of machine and deep learning algorithms is one of the recommended approaches. The experimental results are very appealing, and these methods provide a fresh viewpoint on improving the accuracy of oil price estimates.

2. Related Works

Oil price, production profile, and related event forecasting have always been wonderful but difficult tasks for researchers. These forecasts are not only a kind of suggestion to economic decision makers, but they are also the driving forces behind the new energy policy, global emission reduction, and the trade-off of the global ecosystem as a result of refining and petrochemical industries. However, recent artificial intelligence and machine learning technologies have significantly changed our approach to these complex tasks by affording us tools that better discover regular patterns and analyze large amounts of data.

Zhao et al. [10] look into the viability of Long Short-Term Memory (LSTM) models for predicting Brent crude oil prices during the universal transition phase towards decarburization. By making use of the data on spot price measured on a day-to-day basis for two years (2018-2019), the authors of the work establish a uniform model of three-layer LSTM afterward. The preprocessed data was log-normalized with the first layer of the model. The model performs well in capturing the overall price trend, but the accuracy falls off during the rapid price changes. The research emphasized the research of LSTM in energy market prediction while at the same time updating further the model by integrating some more elements and with modulus the accuracy in unstable conditions.

In the previous work of Guan and Gong [11], the authors suggest the significance of crude oil price predictions for researchers and investors, emphasizing the growing application of deep learning methods. It presents Mod-VMD-BiLSTM, a novel hybrid deep learning model that combines the Bidirectional Long Short-Term Memory (BiLSTM) and Variational Mode Decomposition (VMD) techniques. By breaking down time series data to uncover hidden temporal patterns in sub-series, the methodology seeks to increase predicting accuracy. The suggested model performs better than benchmark models in terms of accuracy and resilience in a variety of scenarios, according to empirical research and statistical analyses. The dependability of the outcomes is strengthened by the assessment measures' passing statistical tests.

Liu et al. [12] come up with a new prediction model that is capable of predicting mud loss at pre-operational drilling stages in Southwest Chinese oil fields. The model is a unique blend of a new implementation of the Whale Optimization Algorithm (WOA) along with a Bidirectional Long Short-Term Memory (BiLSTM) neural network to enhance prediction accuracy by the process of optimizing hyperparameters. Data collected from the well was treated by first-level wavelet denoising to get rid of the noise, and then, the seven key parameters were selected on the basis of a result of Spearman's rank analysis. The enhanced WOA-BiLSTM showed a better performance than traditional LSTM, BiLSTM, and WOA-BiLSTM models with 22.3%, 18.7%, and 4.9% higher prediction accuracy, respectively. The model successfully predicted mud loss 10 minutes in advance, thus allowing timely preventive measures.

In this study of Ahmad et al. [13], the authors show the potential of adding optimization algorithms behind deep learning to enhance innovation constantly reconfigure the structures. Successfully merged machine learning with genetic algorithms in the optimization processes of biodiesel to achieve computational efficiency and sustainable energy targets.

Nath et al. [14], suggest study the application of deep learning models, specifically LSTM and Bidirectional LSTM (Bi-LSTM), to predict hydrocarbon production in heterogeneous reservoirs. Their work proves that Bi-LSTM can perform better than conventional models, which can even work effectively when lacking data, as a result, would be provided to production engineers for them to be able to manage complex reservoirs with them.

Isaac et al. [15], the authors take into consideration the use of machine learning techniques for predicting and CRUDE OIL prices and the assessment of their impact on energy stock markets. By using the ensemble hybrid approach with the SVR and K-Nearest Neighbors Regression (KNR), the study shows better results in comparison to the single model, which proves to be the more precise way to forecast the price of oil. The schematic diagram of the research also depicted the input-output relationships between the crude oil prices, exchange rates, and demand-supply gaps in the GLOBAL stock market and the outputs, such as significant correlations.

Jiménez et al. [16], reveal SRCNet that uses Smooth Residual Connections Network (SRCNet), a breakthrough deep learning architecture for transformer oil temperature prediction. SRCNet has brought about remarkable advances in two aspects, which are the Mean Squared Error (MSE) and computational efficiency. Thus, this piece is a big breakthrough in that reducing the inductive bias could result in a model experiencing a higher efficacy at a lower computational cost.

Fan et al. [17], came up with the novel RF-CEEMDAN-TGMA model for oil production prediction, RF being a Random Forest for the selection of features, CEEMDAN for decomposition of data, and TCN-GRU-MA for the forecasting process. The benefits derived from this model are its superiority in performance terms and its stability, which make it also a reliable solution for oil production prediction.

Ren et al. [18], emphasize the significance of deep learning methodologies in the prediction and tracking accuracy of marine oil spill drift and diffusion. They also point out that the integration of deep learning with ocean environmental knowledge is a bright vision for future research and that it provides a wide area of ocean environmental protection applications at the same time.

Kanchymalay et al. [19] maintain that in their research, they have used LSTM networks and news sentiment analysis for prediction. The study shows a six-month sliding window to be the most accurate result in forecasting, with news sentiment being the cause of CPO prices with a six-month lag. The paper proves the power of deep advanced learning methods in predicting agricultural commodity prices.

3. Proposed Methods

The proposed method uses a number of machine and deep learning models to try and predict oil prices. The

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suggested system's steps are the culmination of:

A. Inputting the HBOPD dataset and transforming unprocessed data into a standard.
B. Preparing the data for the model (training and testing).
C. Divided the data into training and testing and selecting the appropriate window.
D. Training the machine and deep learning models using the following models (DT, RF, K-NN, SVR, and Deep LSTM).
E. Prediction of Oil prices.
F. Comparing the performance of trained models.

Several deep learning and machine learning models were used in this work. These models are trained on Microsoft Windows 10 OS using the open-source IDE environment Jupiter notebook. The main programming language was Python, which made use of a wide range of tools and libraries, including Pandas, TensorFlow, Sklearn, NumPy, and Matplotlib [20].

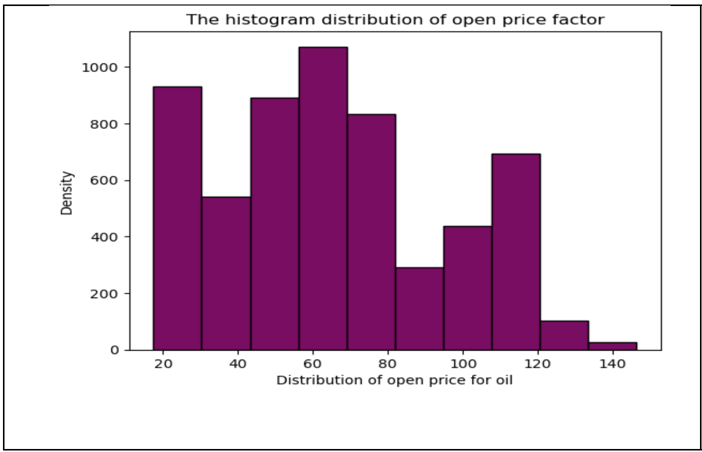
3.1 Testing Dataset

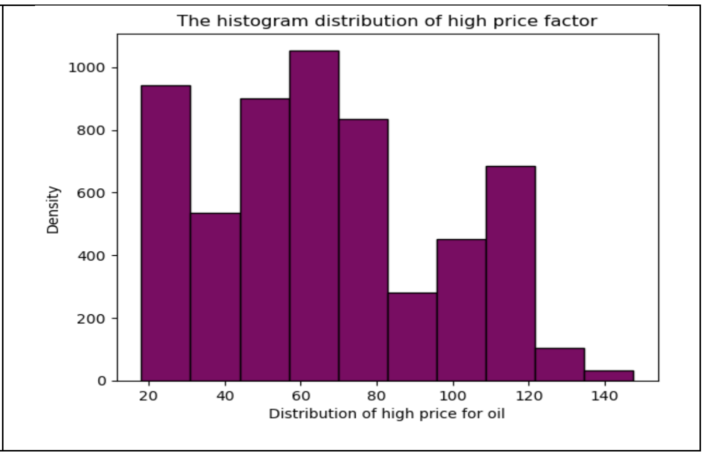
The suggesting system uses the Historical Brent Oil Price Dataset (HBOPD). The Kaggle website has this dataset available. Informally, the price of the Brent Oil futures contract or a comparable instrument is frequently referred to as Brent Crude [21] and [22].

All or part of the elements of the Brent Complex, a physically and monetarily traded oil market situated close to the North Sea in Northwest Europe, can be referred to as Brent Oil. Using a variety of indicators, such as volume, close, high, low, and open, users can create a prediction model for historical Brent oil prices from 2000 to 2022 using the data in the HBOPD dataset. It is possible to examine and use one of these indications to forecast oil prices. Table 1, shows the data content and the specific information. The HBOPD dataset is composed of six columns and 8162 rows with no missing data. The data for the HBOPD indicators' histogram distribution is shown in Fig. 1.

Table 1: Some samples from the HBOPD dataset.

Date	Open	High	Low	Close	Volume
2021-11-25	82.24	82.58	81.70	82.22	80445
2021-11-24	81.88	83.00	81.74	82.25	231071
2021-11-23	79.51	82.60	78.55	82.31	366596
2021-11-22	78.58	80.07	77.58	79.70	350902
2021-11-19	81.00	82.24	78.05	78.89	479928
2022-09-04	24.25	24.37	23.70	23.73	30310
2022-09-05	2000-01-04	23.90	24.70	23.89	24.39





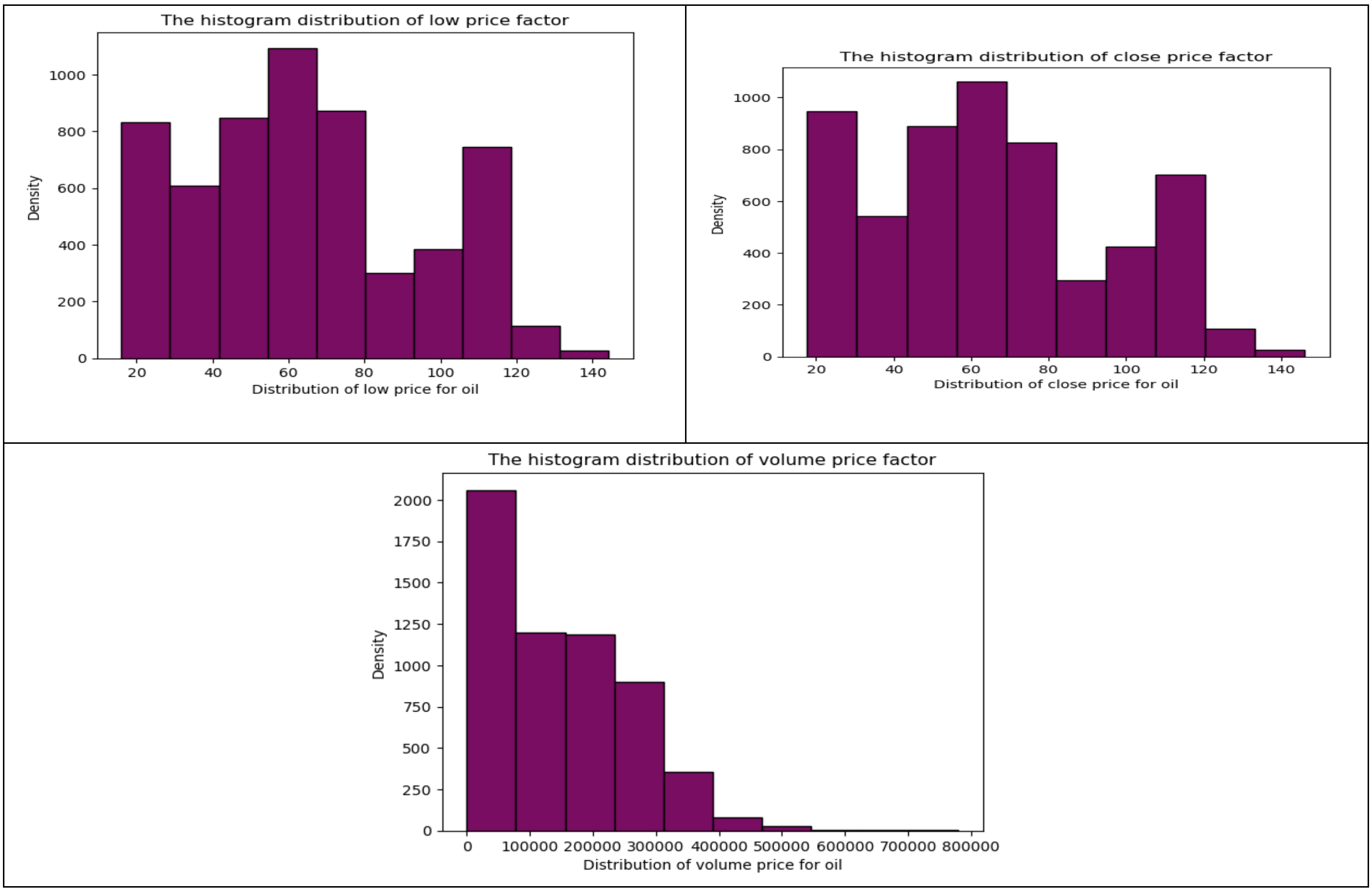


Fig. 1 The Histogram plotting for Oil price.

The degree to which features are associated with one another is shown by their correlation. The correlation matrix indicating the features with higher correlation values is displayed in Table. 2.

Table 2: The HBOPD dataset features correlation matrix.

	Open	High	Low	Close	Volume
Open	1.000000	0.999516	0.999368	0.998940	0.304272
High	0.999516	1.000000	0.999163	0.999417	0.308214
Low	0.999368	0.999163	1.000000	0.999567	0.298417
Close	0.998940	0.999417	0.999567	1.000000	0.302249
Volume	0.304272	0.308214	0.298417	0.302249	1.000000

3.2 Normalizing Raw Data

Effective data organization within a database is achieved through the normalization process. More precisely, normalization is the process of scaling data. Each dataset contains features for which low-value characteristics might not have as much of an impact on the cost function as large-value characteristics. The attributes will be normalized to ensure that their values remain within the same range in order to remedy this issue. All data is placed between one and zero via the normalization process. Various statistical methods have been proposed to achieve data normalization. This work has applied the min-max strategy as shown in the following formula [23]:

$$X = \frac{X - X_{Min}}{X_{Max} - X_{Min}} \tag{1}$$

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3.3 Choosing the Optimal Dataset Splitting Ratio and Window Size

The raw data are normalized after the dataset is input. Subsequently, the ratio of training to testing data is ascertained through experimentation (the best outcomes were achieved by dividing the dataset into 80% training and 20% testing sets). For the purpose of training and testing models, appropriate signal windows that sufficiently incorporate the signal's complete dynamics should be selected [24]. For the training and testing procedures, a window length of sixty was selected for input and one for output in this work. The effects on the model's accuracy are more naturally favorable the older the range that is selected. The selected time, as mentioned in the preceding sections, spans 22 years, from January 2000 to September 2022.

3.4 Implementing ML and DL Models

In this work, these algorithms are trained to predict the Brent crude oil price using a closing price indicator in the developed oil price forecasting system. The models were implemented based on the steps highlighted in Fig. 3.

A. Decision Tree (DT)

Decision Trees are a robust paradigm for including extraneous features while offering an interpretable framework. Nonetheless, it can be precise at times, yet it is susceptible to overfitting since it expands excessively. In this predictor, the criterion employed was Mean Square Error (MSE), which quantifies the quality of the split. The random state, which served as the seed for the random number generator, was thirty-three, and the maximum depth of the tree was twenty.

B. Random Forest (RF)

The ensemble-based predictor known as RF uses several DTs; in order for the predictor to function, 4000 trees must be planted. Once the forest of trees is established, the predictor uses a voting system to combine the predictions of the trees, with each tree's vote having the same weight. The maximum tree depth in the random forest was ten, the random state was thirty-three, and the criterion utilized was "mean squared error.

C. K-Nearest Neighbors (K-NN)

Regression and classification both use KNN. It is predicated on the notion of selecting from a group of previously identified patterns or observations the K patterns that are most similar to the intended pattern. Ten neighbors made up this predictor, and "distance" was chosen as the weight.

D. Support Vector Machine (SVM)

The support vectors of the SVM show the vectors or points that shape the hyper-plane, and the SVM predicts the data points in a hyper-planar manner. This learning model produces precise predictions. Moreover, it is less susceptible to the risk of overfitting. However, because it uses a greater dimensions technique, computing it takes longer. This model used a cash size of 200, a "non-linear" kernel type, and a regularization parameter of 3.

E. Long Short-Term Memory (LSTM)

The LSTM model is used in the suggested deep learning model as a particular type of Recurrent Neural Network (RNN), which is widely used to handle temporal data. Layered support vector machines (LSTM) are node layers that enable multi-stage data processing and effective recognition. As Table 2 illustrates, the LSTM model's suggested structure consists of multiple layers. For the validation studies, much care was taken in selecting the hyper-parameters. These hyper-parameters include (hidden layers =5, number of neurons = (512, 256, 128, 64, 25), learning rate= 0.001, optimizer= NAdam, loss function =MSE, time step= 60, number of epochs= 80, batch size=64).

Table 2: The LSTM model layers details.

Layer (type)	**Output Shape**	**No. of Parameters**
lstm_2 (LSTM)	(None, 60, 256)	71210
lstm_3 (LSTM)	(None, 60, 128)	55681
lstm_4 (LSTM)	(None, 64)	14626
dense_2 (Dense)	(None, 32)	532
dense_3 (Dense)	(None, 1)	16
Total parameters: 142,516 Trainable parameters: 142.516 Non-trainable parameters: 0		

3.5 Evaluation Measures

In order to evaluate the model's forecasting accuracy, many metrics are selected to analyze trend performance and inaccuracy. In the following formulas, F^t denotes the expected value of t^{th}, A^t denotes the actual value of t^{th}, and U is the number of evaluated samples. The element F^t for the matching element A^t of the ground truth dataset is predicted by the machine learning and deep learning models [17].

The coefficient of determination, or R-squared or R2, is a number that goes from zero to one that represents the portion of the variability of the dependent variable that can be predicted by the non-dependent variables. Based on the average of the actual values ($\bar{A} = \frac{1}{U}\sum_{t=1}^{U} A^t$), the R2 formula can be expressed as follows [17] and [24]:

$$R^2 = 1 - \frac{\sum_{t=1}^{U}(F^t - A^t)^2}{\sum_{t=1}^{U}(\bar{A} - A^t)^2} \qquad (2)$$

When it is necessary to identify outliers, the Mean Square Error (MSE) measurement can be applied. The formula for the MSE measurement is as follows [20]:

$$MSE = \frac{1}{U}\sum_{t=1}^{U}(F^t - A^t)^2 \qquad (3)$$

However, the square root procedure establishes a monotonic relationship between MSE and Root Mean Square Error (RMSE). The following is the formula for RMSE [18]:

$$RMSE = \sqrt{\frac{1}{U}\sum_{t=1}^{U}(F^t - A^t)^2} \qquad (4)$$

The average total of all absolute mistakes is represented by the Mean Absolute Error (MAE), which has the following formula [14]:

$$MAE = \frac{1}{U}\sum_{t=1}^{U}|F^t - A^t| \qquad (5)$$

The following represents the Median Absolute Error (Median-AE) [24]:

$$Median - AE = \underset{t = 1, U}{Median}(|F^t - A^t|) \quad (6)$$

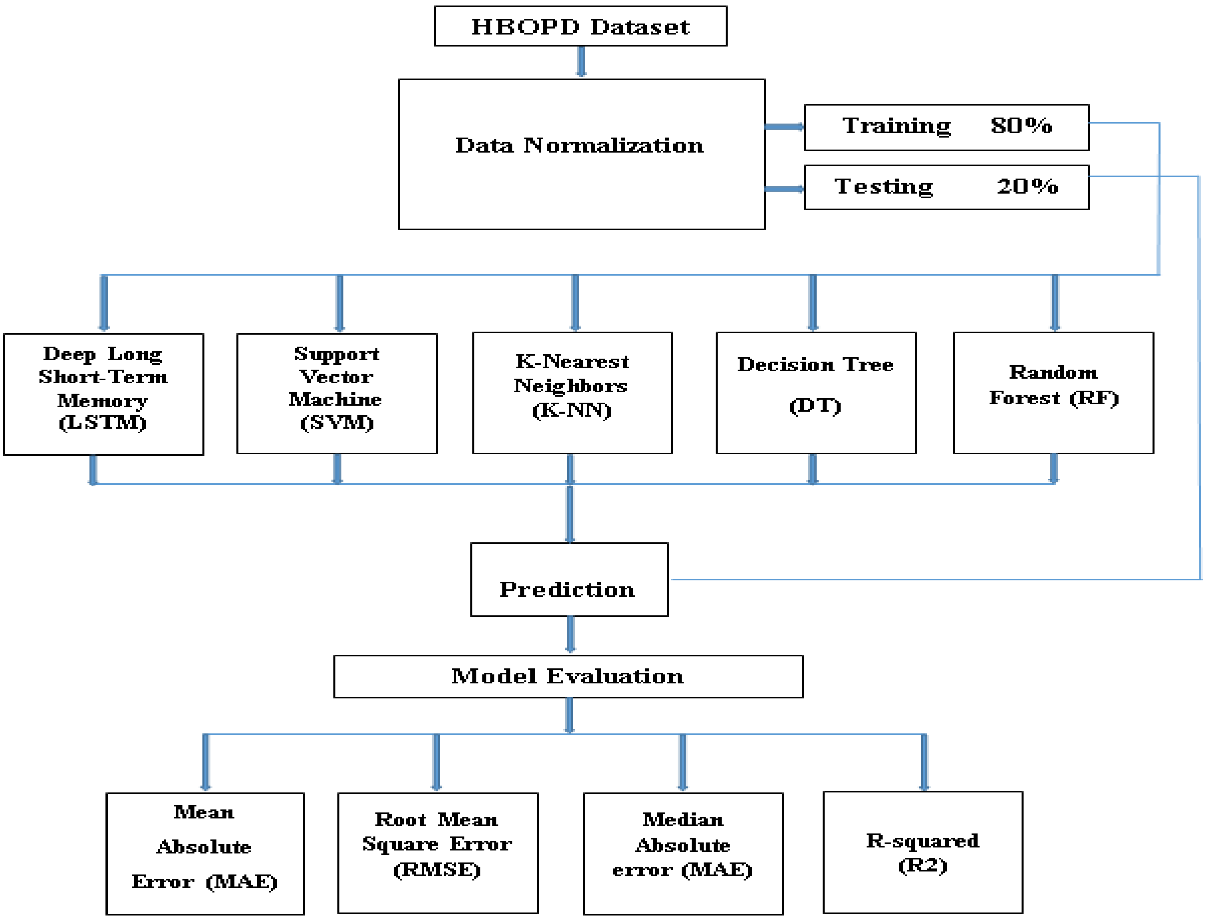

Fig. 3 The proposal model stages.

4. Results and Discussions

Initially, DT, RF, K-NN, and SVM employ 80% of the close price data (January 2000–September 2022) as training data and the remaining 20% as testing data. The obtained prediction results for the deployed machine learning models are displayed in Figs. 4 to 7.

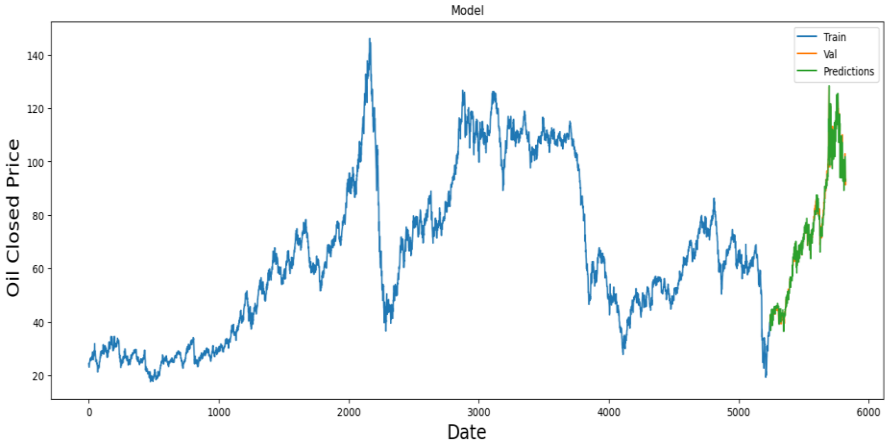

Fig. 4 Prediction model plot for Decision Tree

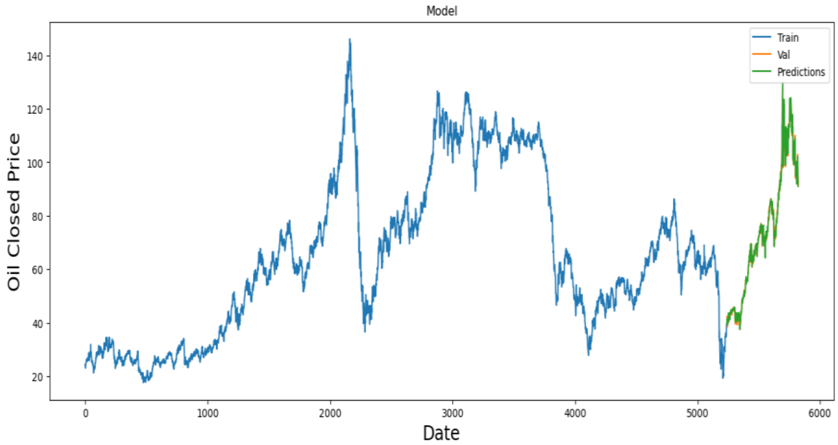

Fig. 5 Prediction model plot for random Forest.

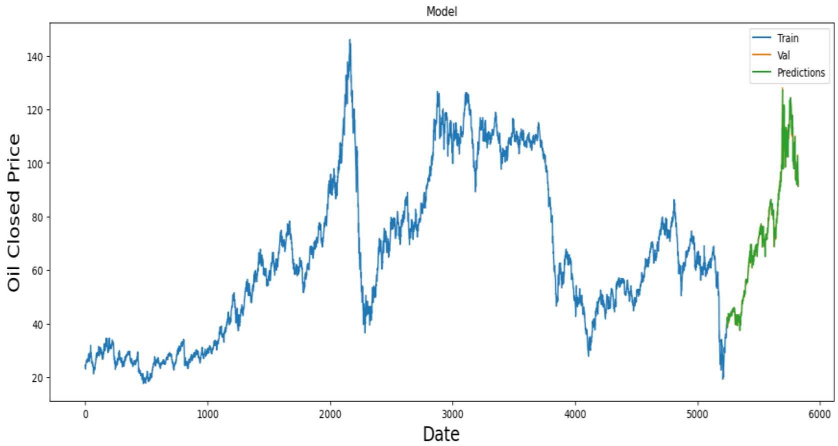

Fig. 6 Prediction model plot for K-NN.

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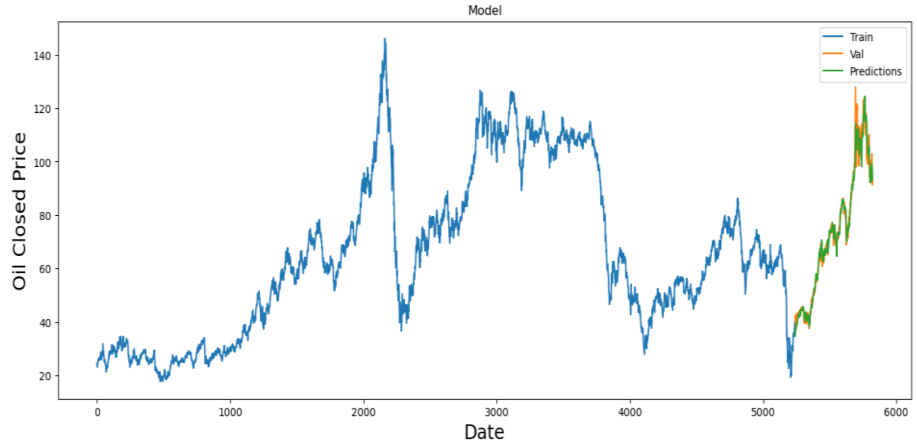

Fig. 7 Prediction model plot for SVR**.**

Scatter plots are one kind of graph that is used in data visualization to show and examine the relationship between two variables. Each point on the graph is a data observation, and its location is defined by two coordinates: one on the x-axis and one on the y-axis. In this study, the relationship between testing and prediction values of the implemented machine learning models is shown in Figs. 8 to 11.

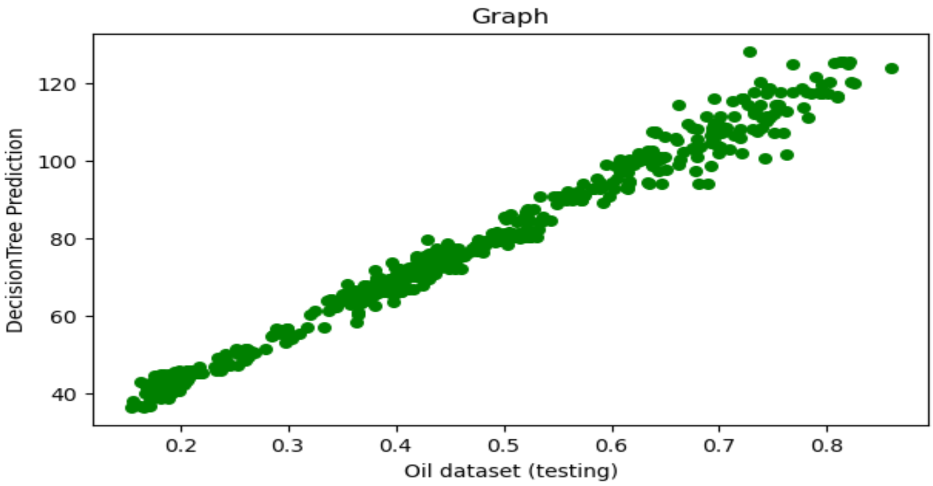

Fig. 8 Scatter plots between testing and prediction values of DT Repressor model.

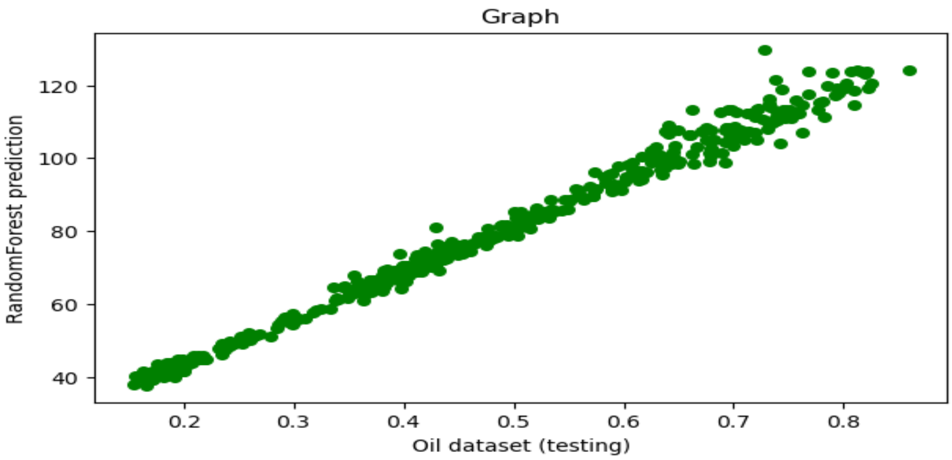

Fig. 9 Scatter plots between testing and prediction values for RF Repressor model.

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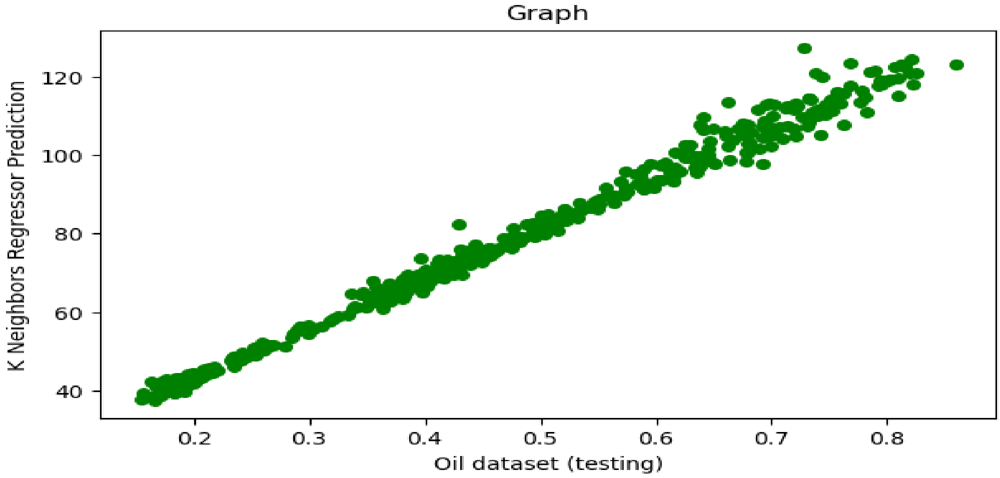

Fig. 10 Scatter plots between testing and prediction values for K-NN Repressor model

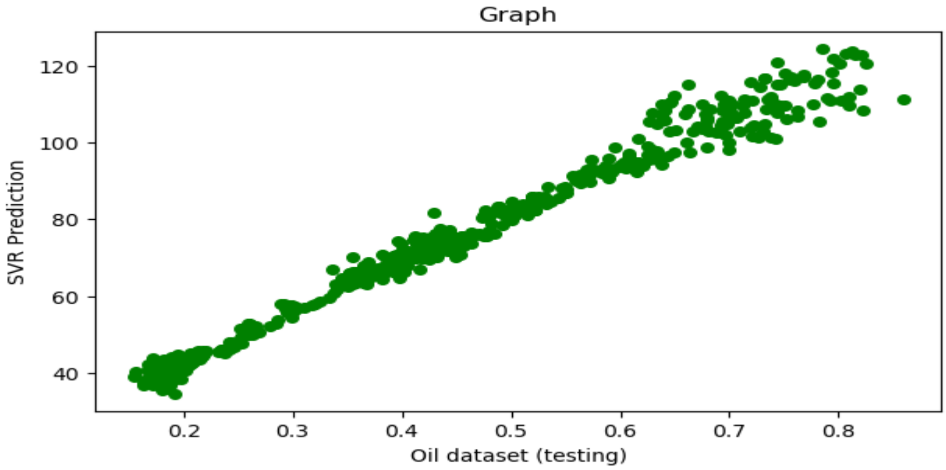

Fig. 11 Scatter plots between testing and prediction values for SVR model.

Thereafter, in the proposed LSTM-based predictor using the Adam optimizer, 80% of closing price data ranging from January 2000 to September 2022 is used as training data while reserving the remaining 20% for testing. Figure 12: Predicted output from the proposed LSTM model. Figure 13: Scatter plots defining the relationship between the testing values and the predictions made by the model.

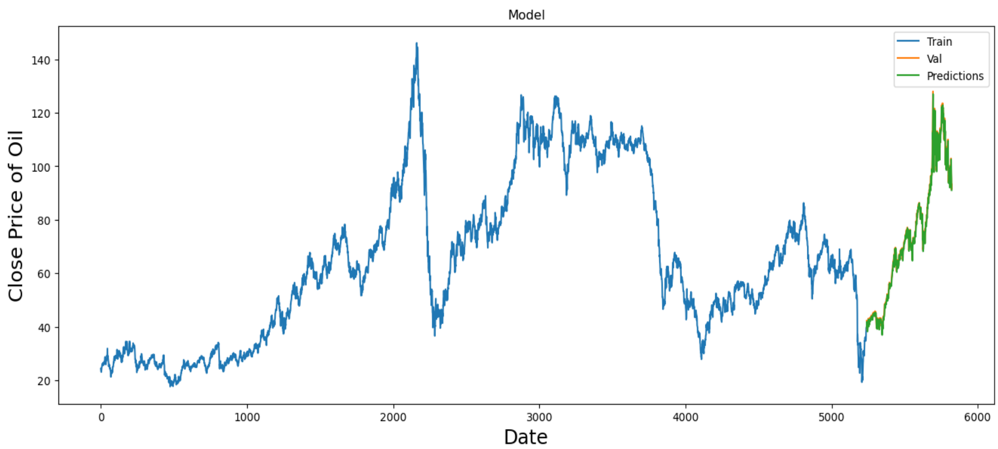

Fig. 12 Prediction model plot for Deep LSTM

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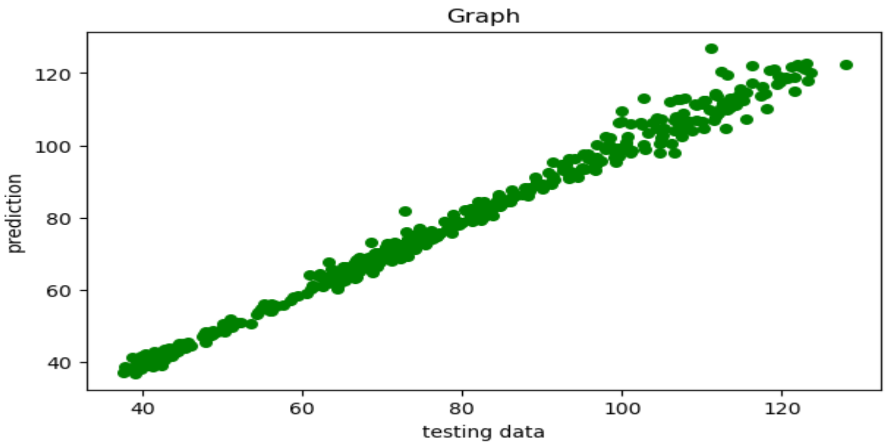

Fig. 13 Scatter plots between the values for testing and prediction for the Deep LSTM model.

Table 3. Results of proposed algorithms.

Implemented Models	**Train Score %**	**Mean Absolute Error (MAE)**	**Root Mean Square Error (RMSE)**	**Median Absolute Error (Median-AE)**	**R2 score**
D.T.	0.9889	0.0154	0.0218	0.0112	0.986
R.F.	0.9991	0.0151	0.0173	0.0073	0.9912
K-NN	0.9769	0.0280	0.0303	0.0213	0.9612
S.V.M	0.9942	0.0167	0.0246	0.0115	0.9823
RNN (LSTM)	0.9999	0.0147	0.0124	0.0066	0.9915

In particular, the suggested LSTM, DT, RF, K-NN, and SVM are used as benchmarking models to confirm the precision of model predictions for oil prices. R-squared, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Median Absolute Error (Median-AE) are used in this study to assess the performance of the implemented models. With an R2 score of 0.9912, an MAE of 0.0151, an RMSE of 0.0173, and a median-AE of 0.0073, RF fared better than the other machine learning models employed.

The results indicate that the suggested LSTM model has an MAE of 0.0147, an RMSE of 0.0124, a median-AE of 0.0066, and an R2 score of 0.9915. The outcomes of other machine learning models are surpassed by these acquired findings. The evaluation's produced results based on the testing set are displayed in Table 3. Based on the various outcomes from testing the implemented models, we concluded that the recommended LSTM layers yielded the best results and were thus approved as the last and trustworthy design of the suggested oil price prediction system.

Based on the aforementioned study, it is clear that the proposed LSTM model differs from existing models in that it can accurately represent the non-linear aspects of the creation of crude oil prices. Predicting crude oil prices has proven to be a strong suit for machine learning models. This method is useful for identifying the short- and long-term variables influencing the price of crude oil, which allows for risk mitigation and opportunity capture during price swings. In the area of oil price prediction, there is still a great deal of room for growth as deep learning methods progress.

5. Conclusion

Crude oil accounts for a significant amount of the energy produced globally, and even with the availability of alternative energy sources, it is expected that the world's reliance on oil may continue in the near future. Shocks to the price of oil have the ability to swiftly spread through a variety of routes to the macroeconomy, eventually affecting consumers. It is clear that the probability of oil price shocks has a significant impact on a number of important macroeconomic indices, such as growth rate, inflation rate, employment, investment choices, and exchange rate. Energy studies are expected to play a significant influence in economics and policymaking given the recent spike in global energy costs. Naturally, countries' economic policies need to adjust quickly in response to shocks to the price of oil, highlighting the need for many economic stakeholders to monitor the price of oil. As a result, models that enable accurate forecasts of crude oil prices may keep growing in value. After accounting for all of these variables, it is clear that our suggested system for predicting oil prices will be very beneficial to a wide range of economic actors, including investors, industrial producers, governments, countries that export oil, and spot and futures market participants. This is due to the fact that their economic decision-making is significantly impacted by the complex features of crude oil prices.

Machine learning techniques (like decision trees and linear regression) are easier to understand and analyze than deep learning, which often requires large datasets. ML models require less time to train and test because they use simpler techniques, but there is a lot of human labor involved in selecting, creating, and preprocessing features. Deep learning models excel at tasks like audio processing, image recognition, and natural language processing; they eliminate the need for manual feature engineering by automatically learning high-level features from raw data; they achieve exceptional results on complex problems (like computer vision, autonomous vehicles), but they also require large, labeled datasets to train effectively, and they require specialized hardware like GPUs/TPUs.

References

[1] Xu, Z., Mohsin, M., Ullah, K., & Ma, X. (2023). Using econometric and machine learning models to forecast crude oil prices: Insights from economic history. Resources Policy, 83, 103614.

[2] Liang, X., Luo, P., Li, X., Wang, X., & Shu, L. (2023). Crude oil price prediction using deep reinforcement learning. Resources Policy, 81, 103363.

[3] Zhao, Y., Li, J., & Yu, L. (2017). A deep learning ensemble approach for crude oil price forecasting. Energy Economics, 66, 9-16..

[4] Das, S., Sahu, T. P., & Janghel, R. R. (2022). Oil and gold price prediction using optimized fuzzy inference system based extreme learning machine. Resources Policy, 79, 103109.

[5] Gao, S., & Lei, Y. (2017). A new approach for crude oil price prediction based on stream learning. Geoscience Frontiers, 8(1), 183-187.

[6] Mellit, A., & Kalogirou, S. (2022). Artificial intelligence techniques: machine learning and deep learning algorithms. Handbook of artificial intelligence techniques in photovoltaic systems, 43-83.

[7] Santosh, K. C., Das, N., & Ghosh, S. (2021). Deep learning models for medical imaging. Academic Press.

[8] He, H., Sun, M., Li, X., & Mensah, I. A. (2022). A novel crude oil price trend prediction method: Machine learning classification algorithm based on multi-modal data features. Energy, 244, 122706.

[9] Cen, Z., & Wang, J. (2019). Crude oil price prediction model with long short term memory deep learning based on prior knowledge data transfer. Energy, 169, 160-171.

[10] Zhao, Y., Hu, B., & Wang, S. (2024). Prediction of brent crude oil price based on lstm model under the background of low-carbon transition. arXiv preprint arXiv:2409.12376.

[11] Guan, K., & Gong, X. (2023). A new hybrid deep learning model for monthly oil prices forecasting. Energy Economics, 128, 107136.

[12] Liu, X., Jia, W., Li, Z., Wang, C., Guan, F., Chen, K., & Jia, L. (2023). Prediction of Lost Circulation in Southwest Chinese Oil Fields Applying Improved WOA-BiLSTM. Processes, 11(9), 2763.

[13] Ahmad, A., Yadav, A. K., & Singh, A. (2023). Application of machine learning and genetic algorithms to the prediction and optimization of biodiesel yield from waste cooking oil. Korean Journal of Chemical Engineering, 40(12), 2941-2956.

[14] Nath, F., Asish, S., Debi, H. R., Chowdhury, M. O. S., Zamora, Z. J., & Muñoz, S. (2023, August). Predicting hydrocarbon production behavior in heterogeneous reservoir utilizing deep learning models. In Unconventional Resources Technology Conference, 13–15 June 2023 (pp. 506-521). Unconventional Resources Technology Conference (URTeC).

[15] Isaac, S., Lass, B. T., Isiaka, T. M., Bello, U. M., & Peter, M. (2023). Deep Learning Networks for Simultaneous Multiple Crude Oil Price Predictions.

[16] Jiménez-Navarro, M. J., Martínez-Ballesteros, M., Martínez-Álvarez, F., & Asencio-Cortés, G.

(2023). A new deep learning architecture with inductive bias balance for transformer oil temperature forecasting. Journal of Big Data, 10(1), 80.

[17] Fan, Z., Liu, X., Wang, Z., Liu, P., & Wang, Y. (2024). A Novel Ensemble Machine Learning Model for Oil Production Prediction with Two-Stage Data Preprocessing. Processes, 12(3), 587.

[18] Ren, P., Huang, W., & Luo, C. (2024). Prediction and (back) tracking of marine oil spill drift and diffusion. Frontiers in Marine Science, 11, 1427604.

[19] Kanchymalay, K., Hashim, U. R., Krishnan, R., Ikram, R. R. R., & Kuhan, R. R. (2024). Deep Learning Based Prediction Model for Crude Palm Oil Prices Using News Sentiment Analysis with Sliding Window. Journal of Artificial Intelligence and Technology.

[20] Y. Chen, K. He, and G. K. F. Tso, "Forecasting Crude Oil Prices: A Deep Learning based Model," Procedia Comput. Sci., vol. 122, pp. 300–307, 2017, doi: 10.1016/j.procs.2017.11.373.

[21] J. Fang, X. Cheng, H. Gai, S. Lin, and H. Lou, "Development of machine learning algorithms for predicting internal corrosion of crude oil and natural gas pipelines," Comput. Chem. Eng., vol. 177, no. January, p. 108358, 2023, doi: 10.1016/j.compchemeng.2023.108358.

[22] Cvejić, S., Hrnjaković, O., Jocković, M., Kupusinac, A., Doroslovački, K., Gvozdenac, S., ... & Miladinović, D. (2023). Oil yield prediction for sunflower hybrid selection using different machine learning algorithms. Scientific Reports, 13(1), 17611.

[23] Ibrahim, N. M., Alharbi, A. A., Alzahrani, T. A., Abdulkarim, A. M., Alessa, I. A., Hameed, A. M., ... & Almuqhim, A. A. (2022). Well performance classification and prediction: Deep learning and machine learning long term regression experiments on oil, gas, and water production. Sensors, 22(14), 5326.

[24] Jiang, H., Hu, W., Xiao, L., & Dong, Y. (2022). A decomposition ensemble based deep learning approach for crude oil price forecasting. Resources Policy, 78, 102855.