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Navigating the Dynamics of Brent Crude Oil Prices: Factors, Trends, and Insights

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Abstract
Accurate Brent Crude Oil price prediction is essential for informed decision-making and risk control in the global energy market. This paper examines the dynamics of Brent Crude Oil prices over the previous 35 years, utilizing predictive modelling techniques to project future prices and analyzing historical trends and relationships with the GDPs of major economies. The statistical methods used in this paper include the moving average and Pearson correlation coefficient. While correlation studies show significant positive links between Brent Crude Oil prices and the GDPs of major economies like China, Saudi Arabia, Europe, Russia, and the United States, historical data analysis reveals large price volatility. Highly accurate price forecasting using LSTM (Long Short-Term Memory) modelling approaches provides detailed risk management and decision-making information in the global energy market. The application of the Neural Network and the ARIMA model shows an increase in the price of Brent crude oil in the next year, 2024. Identifying the importance of the Brent crude oil price forecast and its effect on the international market is highly needed. This paper thus might help to increase economic growth. These results highlight the importance of advanced modelling techniques and economic indicators in managing oil price changes and help make informed decisions in the energy industry.

Keywords
Brent Crude Oil, Energy, Moving Average, Correlation, Neural Network, LSTM, ARIMA, Prediction.

Introduction

Crude oil is one of the most significant energy sources, and price changes significantly affect several aspects of the global economy (Deng et al., 2021). Forecasting crude oil prices in the global bulk commodity market has become a topical issue, but the complexity and nonlinearity of price movements are exacerbated by the growing number of various risk variables (Li et al., 2021; Skare et al. 2024). According to Abdollahi and Ebrahimi (2020), oil price forecasting continues to be challenging due to the unique characteristics of the oil price and its enormous influence on many economic sectors. Aamir, Shabri, and Ishaq (2018) imply that, due to unpredictable events, speculative activity, the state of the global economy, and political and social developments, the future of crude oil prices has recently been extremely unclear and challenging to predict.

Like investors, the whole society faces the same challenges in accurately predicting crude oil prices (Tkacova and Gavurova, 2023; Wu et al., 2019). The importance of predicting crude oil has gained momentum, making it the most important and irreplaceable energy source, playing a major role in economic life (Qiu et al., 2018). Gerogiorgis (2009) argues that a fractal scaling law, like a power law that governs the mean size of the absolute values of price changes, can be described as a function of the analysis period. Karasu et al. (2020) present a novel forecasting model based on support vector regression and a wrapper-based feature selection method using multi-objective optimization to tackle the problem of accurately forecasting the future price of crude oil, a key component of the global economy that shows complex nonlinear dynamics. According to Bara et al. (2024), Brent crude oil accounts for two-thirds of the oil market, and the price volatility of Brent crude oil has a major impact on environmental, transportation, mobility, economic, and social variables that influence sustainability. Increased volatility is strongly correlated with disruptions in oil supply and demand, with levels exceeding the usual levels during economic or financial crises, highlighting that volatility remains a major issue when uncertainty stems from global economic and financial instability (Zavadska et al., 2020). After analyzing the impact of the conflict between Russia and Ukraine on the global crude oil market, Zhang et al. (2024) suggest implementing an emergency management system in the oil industry, encouraging diversification of imports of oil and gas by oil-dependent countries, enhancing energy transition initiatives, and effective financial risk mitigation by companies.

According to Kang, Kang, and Yoon (2009), GARCH and IGARCH models are less effective in terms of capturing persistence compared to component-GARCH (CGARCH) and fractionally integrated GARCH (FIGARCH) models. To significantly improve crude oil price prediction accuracy, especially for complex, nonlinear, and irregular data, a new ensemble learning paradigm that combines complementary ensemble empirical mode decomposition (CEEMD) and extended extreme learning machine (EELM) outperforms traditional benchmarks in empirical testing (Tang et al., 2015). For crude oil price modelling and forecasting, a hybrid model combining wavelet transform and artificial neural network (ANN) outperforms ANN alone by a large margin, with the wavelet transform technique proving to be especially useful for data preprocessing and input generation for the ANN model (Shabri & Samsudin, 2014). Karasu and Altan (2022) point out that several variables, including exchange rate, interest rate, supply and demand, OPEC decisions, stock market, gold, speculative trading, significant unforeseen events, political events, government interventions, and others, influence the price of crude oil. To address all of these features, Cheng et al. (2019) propose a new hybrid model of vector error correction and nonlinear autoregressive neural network (VEC-NAR).

Based on past price trends, the paper seeks to predict how the time series of Brent crude oil prices will grow through 2024. Before predicting this, it is necessary to understand the flow of the Brent Crude Oil Price clearly. Therefore, the first Research Question can be formulated as follows:

RQ1: What are the historical trends and patterns in the Brent Crude Oil price over the past 35 years?

According to Mati et al. (2023), the Brent crude oil price is a critical economic indicator significantly influencing the global economy. Establishing the relationship between the economies of selected countries/continents and the Brent Crude Oil price leads to the second research question:

RQ2: Which of the selected countries/continents have the highest correlation between GDP and Brent Crude Oil prices, and how can it be used in predictive modelling?

Forecasting the Brent crude oil price represents important research in the international commodity market (Iftikhar et al., 2023). For this, it is necessary to forecast the future price of Brent Crude oil in the next year. Therefore, the final research question is formulated as follows:

RQ3: How effective is the selected predictive modelling approach in forecasting the future price trends of Brent crude oil, and what are the implications of these forecasts for stakeholders in the global energy market?

Literature Review

The price of crude oil time series data is hard to predict due to its nonstationary and nonlinear behaviour (Iftikhar et al., 2023). According to T. Li et al. (2018), conventional approaches like statistical methods and AI-based models frequently fall short of expectations when projecting crude oil prices. This irregularity of the data may cause false or inaccurate predictions. The erratic behaviour of crude oil prices may be caused by risk factors

(R. Li et al., 2021), including supply and demand, geopolitical events, OPEC and non-OPEC policies, currency exchange rates, technological advances, and environmental regulations. In addition to macroeconomic concerns and linkages with financial markets, participants in the crude oil market are at risk of significant losses due to price volatility (Cheong, 2009). According to Abdollahi & Ebrahimi (2020), the nonlinearity of the price of Brent crude oil can be captured using the combination of Adaptive Neuro-Fuzzy Inference System (ANFIS), Autoregressive Fractionally Integrated Moving Average (ARFIMA), and Markov switching models. The LSTM model with transfer learning shows significant generalization abilities and delivers good prediction accuracy (C. Deng et al., 2021). Xiao et al. (2012) depict that most current models for predicting oil prices solely use the data from the predicted time series.

It is clear from a closer look at metrics like Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE) that the method that combines the reconstruction of Intrinsic Mode Functions (IMFs) with the ARIMA (Autoregressive Integrated Moving Average) model is suitable (Aamir et al., 2018). This approach offers several benefits, including insights into the factors that affect crude oil prices through Empirical Mode Decomposition (EEMD), mitigation of non-zero mean challenges within IMFs, streamlined forecasting using only relevant data, reduced computational requirements, and a simplified model selection for improved precision and stability in forecasting. According to S. Deng et al. (2020), a hybrid model of the Hidden Markov Model (HMM) and Dynamic Time Warping (DTW) was proposed for forecasting changes in the price of crude oil and trading. This model outperforms benchmark methods in terms of forecasting and trading performance, with a goodness of fit of approx. 62.74%, an annual profit return of 34.3%, and a Sharpe ratio value of 2.274 in the WTI market. To accurately predict nonstationary and nonlinear crude oil price time series, an adaptive hybrid ensemble learning paradigm called CEEMD-A&S-SBL that combines complementary ensemble empirical mode decomposition (CEEMD), autoregressive integrated moving average (ARIMA), and sparse Bayesian learning (SBL) is proven to significantly outperform state-of-the-art models in terms of root mean squared error (RMSE), the mean absolute error (MAPE), and the directional statistic (Dstat) (Wu et al., 2019).To confirm the existence of a fractal scaling law based on the mean size of absolute price changes as a function of the analysis time interval, Gerogiorgis (2009) investigates the fractal scaling behaviour of crude oil price variation across multiple time resolutions and calculates the drift exponent for both the pre-and post-2008 periods. Using technical indicators like simple moving average (SMA), exponential moving average (EMA), and Kaufman's adaptive moving average (KAMA) on Brent crude oil closing prices, Karasu et al. (2020) propose a novel forecasting model using support vector regression (SVR) with a wrapper-based feature selection approach using multi-objective optimization, demonstrating superior performance in capturing the nonlinear dynamics and enhancing forecasting precision and volatility. Bekiros et al. (2020) show that wavelet-based volatility forecasting outperforms random walk forecasting in the crude oil market, especially when compared to wavelet-based return forecasting, emphasizing the implications for market efficiency and price prediction.

Zhang et al. (2019) examined the forecasting of crude oil price volatility using various GARCH-type models, including single-regime models (GARCH, GJR-GARCH, and EGARCH) and regime-switching models (MMGARCH and MRS-GARCH), within-sample results favouring MRS-GARCH in weekly data, yet out-of-sample results indicating limited improvement from regime switching, thus suggesting that single-regime GARCH models perform similarly across different time horizons for Brent crude oil. Bildirici et al. (2020) studied the erratic behaviour of crude oil prices during the COVID-19 pandemic and the Russia-Saudi Arabia oil conflict and proposed the ground-breaking LSTARGARCHLSTM hybrid model. This model outperforms conventional GARCH and LSTARGARCH models by dividing data into two regimes and achieving better RMSE and MAE performance metrics for crude oil price prediction. G. Li et al. (2022) introduce a novel forecasting model called ICEEMDAN-SSCE-TVMD-GTO-KELM, which employs parameter-optimized kernel-based extreme learning machine (KELM) and a secondary decomposition through an improved complementary ensemble empirical mode decomposition with adaptive noise (ICEEMDAN), state space correlation entropy (SSCE), and improved variational Mode Decomposition by tunicate swarm algorithm (TVMD) to identify highly complex components and further decompose the most complex component to address nonstationary and nonlinear patterns. West Texas Intermediate (WTI) and Brent oil experimental results show excellent accuracy, with RMSE, MAE, MAPE, and R2 for WTI at 0.2947, 0.2133, 0.3665, and 0.9939, respectively, outperforming nine other models and demonstrating its promising potential in crude oil price forecasting.

The cutting-edge WANN model combining a discrete wavelet transform and artificial neural networks outperforms conventional ANN models in terms of accuracy in predicting daily crude oil prices, as demonstrated by a comparison of West Texas Intermediate (WTI) and Brent crude oil spot prices at a one-day lead time (Shabri and Samsudin, 2014). Altan & Karasu (2022) present an innovative crude oil price prediction model that incorporates long short-term memory (LSTM), trend, volatility, and momentum technical indicators, utilizing features derived from various indicators such as exponential moving average (EMA), simple moving average (SMA), Kaufman's adaptive moving average (KAMA), commodity channel index (CCI), rate of change (ROC), relative strength index (RSI), average true range (ATR), volatility ratio (VR), and highest high-lowest low (HHLL), while employing the chaotic Henry gas solubility optimization (CHGSO) technique, ultimately demonstrating its effectiveness in successfully addressing the chaotic and nonlinear characteristics of the West Texas Intermediate (WTI) and Brent crude oil time series (COTS), as evidenced by the Theil's U and mean absolute percentage error (MAPE) metrics during optimization.

Oyuna & Yaobin (2021) highlighted the strategic importance of crude oil price volatility and the potential for future research to explore jump-diffusion models in this context while introducing the Heston stochastic volatility model for forecasting crude oil price volatility and revealing its high predictive accuracy compared to improved GARCH models. Cheng et al. (2019) introduce a novel hybrid VEC-NAR model that combines vector error correction (VEC) for addressing lag and correlation issues in crude oil prices with a nonlinear autoregressive neural network (NAR) component for capturing nonlinearity. Based on empirical data from 1 January 2003 to 31 December 2014 and compared with established models, Diebold-Mariano tests show that this model shows high short-term forecasting accuracy. H.-L. Zhang et al. (2018) develop crude oil price models for long-term price forecasts and quantitatively examine the contribution ratios of six significant variables, including the Dow Jones Indexes, OECD oil stocks, US rotary rig count, US dollar index, total open interest, and geopolitical instability. These models were found to predict annual averaged Brent crude oil prices ranging from $53.0 to $120.7 per barrel for the period 2017-2022, with qualitative analysis supporting a co-integration relationship among the variables. Using multivariate time series of significant S&P 500 stock prices, Gaussian process modelling, deep learning, vine copula regression, Bayesian variable selection, and nonlinear principal component analysis (NLPCA), Kim et al. (2022) presents a methodology for forecasting Brent and WTI oil prices. The methodology shows that vine copula regression with NLPCA outperforms other approaches in predicting changes in oil prices. Xu & Wang (2023) introduce rolling window integration into EEMD-based (ensemble empirical mode decomposition) modelling for crude oil price forecasting, revealing that EEMD's impact on forecast accuracy is limited when applied exclusively to in-sample data by the efficient market hypothesis, but demonstrate the superiority of the suggested rolling window EEMD-denoising model for long-term predictions.

Using 310 economic series as exogenous factors from 1993 to 2021, Boubaker et al. (2022) introduce a change point-adaptive-RNN (CP-ADARNN) framework for forecasting crude oil prices with high-dimensional monthly variables. The CP-ADARNN show superior predictive performance compared to benchmarks, with a 12.5% lower root mean square error and a correlation of 0.706 between predicted and actual returns. CP-ADARNN's superiority is robust to Brent oil prices even during the COVID-19 pandemic, offering valuable insights into the relationship between oil market stakeholders and researchers. Ahmad et al. (2021) present a novel hybrid forecasting approach called Median Ensemble Empirical Mode Decomposition and Group Method of Data Handling (MEEMD-GMDH), which successfully addresses mood-splitting issues and exhibits superior performance in forecasting crude oil prices when evaluated against various benchmarks. This is reflected in improved accuracy metrics like Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Diebold-Mariano (DM) test results. Utilizing data on Brent crude oil and gas prices from January 1991 to December 2016, Nyangarika & Tang (2018) modified the ARIMA model by adding exponential smoothing to estimate parameters and increase forecast accuracy. The results show improved predictions, especially near the time series end, with little impact on other emissions, indicating the potential for investors to forecast prices and assess risks in oil futures markets.

Lu et al. (2022) introduce a novel CEEMDAN-GA-SVR hybrid model that combines a genetic algorithm (GA), support vector regression machine (SVR), and complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN), which, after extensive testing and comparison with benchmark models, shows higher accuracy in predicting crude oil prices, as demonstrated in a case study using weekly Brent crude oil prices. Xu & Niu (2022) question the effectiveness of the ensemble empirical mode decomposition (EEMD) for crude oil futures price prediction, proposing a sliding decomposition-ensemble paradigm (SW-EEMD-RVFL) that conducts decomposition within a sliding window to use only historical series. They found that while hybrid models perform well in in-sample data, SW-EEMD-based models do not outperform EEMD-based models or individual models in out-of-sample data, providing possible explanations, along with a demonstration of the Efficient Markets Hypothesis (EMH) in the context of methods based on artificial intelligence.

Ortiz Arango (2017) shows that the use of neural network differentials (DNN) for forecasting future prices of financial assets, specifically West Texas International and Brent crude oil barrels, provides comparable accuracy to the threshold generalized autoregressive conditional heteroskedasticity (TGARCH) models and outperforms GARCH models in the specified periods from 2 January 2013 to 24 February 2015 and from 25 February to 10 March 2015, with the additional benefit of not requiring the use of a priori information. To improve the accuracy of energy market forecasting, Cen & Wang (2018) created a novel neural network architecture called CID-STNN, which combines a stochastic time strength neural network (STNN) and a complexity invariant distance (CID)-controlled learning rate and its performance with STNN using ensemble empirical mode decomposition (EEMD) on WTI and Brent time series data, demonstrating its improved predictive abilities. Based on these findings, it can be stated that neural networks play a significant role in predicting Brent crude oil.

Plotting a line graph and a one-year moving average will provide a clear answer to the first research question. Basis descriptive statistics like mean, median, standard deviation, etc., will provide an additional advantage for

RQ1. For RQ2, we will select the GDP of five countries/continents and find the relationship between them by using the Karl Pearson correlation coefficient. LSTM NN will be used to predict the Brent crude oil price for 2024, based on 35 years of historical data, which will lead to answering the final research question.

Material and Methods

For the purpose of the analysis, historical data on Brent crude oil was taken from the investing.com website for the period 1989 - 2023. Of this time series data, we focus primarily on two variables, "Date" and "Price". There are 8942 rows of daily stock price values of Brent Crude Oil from 1989 - 2023. The price of Brent Crude Oil is expressed in USD. To find the correlation between the price of Brent Crude Oil and the GDP of some countries, the GDP of four countries (China, Russia, USA, Saudi Arabia) and one continent (Europe) were selected. Each GDP figure is for 35 years of annual GDP in billions of USD.

First, the characteristics of the price of Brent Crude Oil were determined by descriptive statistics along with the direction and flow of the price trend by plotting line graphs. Next, the price trend is determined by smoothing the data using the moving average statistical method. Here, the moving average is found for one-year trading data, which will help to determine the trend of the price and to forecast the price. The mathematical expression for the moving average is as follows:

Suppose the number of trading days is 256 days per year $\left(\frac{8942}{35} \approx 256\right)$. A represents the i-th data point, where $i = 1, 2, \dots, 8942$. The j-th value of the 256-day moving average (MA_{256}) is calculated as follows:

$$MA_{256}(j) = \frac{1}{256} \sum_{k=j}^{j=255} x_k \tag{1}$$

where j values range from 1 to 8942-256+1=8687. The above formula is used to calculate the average of 256 consecutive data points beginning at index j and finishing at index j+255, then proceeding one step at a time until all data points are covered. The divisor 256 denotes the number of data points used in the average.

The GDP of China, Russia, Saudi Arabia, the USA, and Europe were plotted using Line Plot. Then, the relationship between the annual Brent Crude Oil Price and GDP was determined using Pearson's Correlation Coefficient. For plotting the correlation coefficient, the slope must be used:

$$m = \frac{r \times \sigma_{GPP}}{\sigma_{meanprice}} \tag{2}$$

where:

m	slope
r	the correlation coefficient
σ_{GPP}	the standard deviation of GDP of each country/continent
$\sigma_{meanprice}$	the standard deviation of annual mean price of Brent crude oil

An artificial neural network (NN) approach called Long Short-Term Memory (LSTM) is used to forecast the future average price trend of Brent Crude Oil. Several parameters are needed to create the Neural Network, including:

a. The number of Elements in the Neural Network Model depends on the model's configuration and input data. The input data is of the matrix size $m\ x\ n$; in this case, it varies depending on the input data, i.e., $'252\ x\ 1', '252\ x\ 2'$, etc.
b. Diverse Activation functions (utilizing Elementwise Layer) will be employed to facilitate signal propagation among NN layers. The selection of activation functions will encompass the following options: Sine, Ramp (also recognized as ReLu – Rectified Linear Unit), and ArcTan.
c. Time series lag is a sequence of prior values that is used to predict future values. The considered lag is 252 days.

The NN structure will be identical in all cases (except for the parameter changes). Figure 1 shows a schematic of the NN.

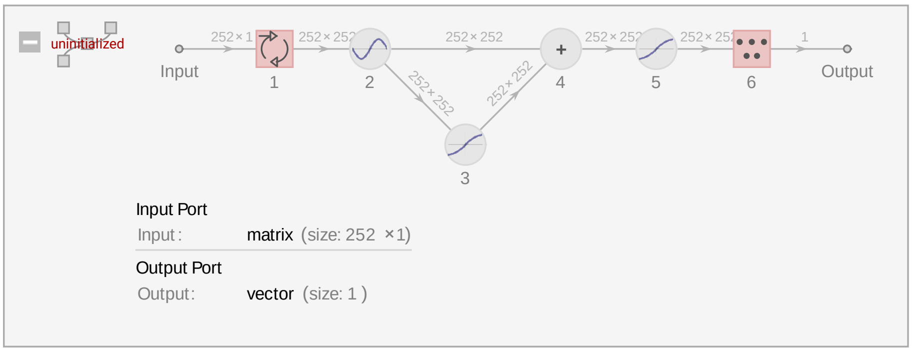

Fig. 1. Structure of the LSTM NN.

The neural network consists of six main layers, excluding the input and output. The six layers between the input and output layers are hidden.

a. Input Layer: A matrix representing the price of Brent crude oil is provided in the input layer. Different sizes of matrices will be investigated in the experiment (based on the input data). Here, the size of the matrix is "252 x 1". The value '*m*' in the matrix represents the number of consecutive variables required to compute the following variable.
b. 1st Hidden Layer (LSTM Layer): The first hidden layer is an LSTM layer. It generates an output matrix of dimensions *m* x *n*,' where '*m*' is the time series lag and '*n*' is chosen empirically. Here, the matrix at the input layer of size 252 x 1 will generate a matrix of size 252 x 252 at the output). The '*n*' value grows by one.
c. 2nd Hidden Layer (Elementwise Layer - Perceptron): This layer is built as an Elementwise Layer, which is a simple network that functions as a perceptron. The activation functions of these layers will be randomly chosen from a specified list of activation functions.
d. 3rd Hidden Layer (Elementwise Layer): This layer is an Elementwise Layer with the same activation function selection criteria as the second hidden layer.
e. 4th Hidden Layer (Plus Layer): The fourth hidden layer, known as the "Plus" layer, accomplishes summing. It accepts input from the second and third hidden levels and transmits the output to the fifth hidden layer.
f. 5th Hidden Layer (Elementwise Layer): This layer is an Elementwise Layer that uses the same activation function selection criteria as the second and third hidden layers.
g. 6th Hidden Layer (Linear Layer): The sixth hidden layer is a Linear Layer, which acts on a data matrix at the input (a 252 x 252 matrix is shown in the picture). It generates a vector with one element as output.
h. Output Layer: The output layer predicts the average annual price of Brent crude oil.

Long-Short Term Memory Layer $[\boldsymbol{n}]$ represents a network that receives an input matrix representing a sequence of vectors. The output is a sequence of the same length. Each input sequence element is a vector of size k, and each output sequence element is a vector of size *n*. LSTM consists of four blocks: Input gate, output gate, forget gate, and memory gate.

$\{x_1, x_2, \dots, x_T\}$ is the input sequence, and the output of the LSTM is a series of states $\{S_1, S_2, \dots, S_T\}$. The cell state is defined as follows:

$$c_t = f_t * c_{t-1} + i_t * m_t \tag{3}$$

where

c_t	is a new variable state.
f_t	forget gate.
c_{t-1}	the initial state of the variable.
i_t	input gate.
m_i	memory gate.

The input gate is defined as follows:

$$i_t = \sigma[W_{ix}x_t + W_{is}S_{t-1} + b_i] \tag{4}$$

where

$$\sigma(z) = \frac{1}{(1 + exp(-z))} \tag{5}$$

σ	is Logistic Sigmoid.
W_{ix}	is an input weight in the input gate matrix n x k
x_t	is an input variable, matrix n x k.
W_{is}	Weight of the state in the input gate, matrix n x n.
S_{t-1}	The initial state.
b_i	Bias,vector size n.

The state is defined as follows:

$$s_t = o_t * Tanh[c_t] \tag{6}$$

where,

s_t	is a state of the variable.
o_t	output gate.
$Tanh$	Hyperbolic tangent.

Output gate is defined as follows:

$$o_t = \sigma[W_{ox}x_t + W_{os}S_{t-1} + b_o] \tag{7}$$

where,

W_{ox}	Defines the input weight in the output gate, matrix n x k.
W_{os}	Weight of the state in output gate, matrix n x n.
b_o	Bias, vector size n.

When compared to, say, a Gated Recurrent Layer, the benefit of LSTM is in the forget gate:

$$f_t = \sigma[W_{fx}x_t + W_{fs}S_{t-1} + b_f] \tag{8}$$

Where,

W_{fx}	is an input weight in forget gate, matrix n x k.
W_{fs}	is the weight of the state in forget gate, matrix n x n.
b_f	Bias, vector size n.

The main processes of LSTM include memory gate as follows:

$$m_t = Tanh[W_{mx}x_t + W_{ms}S_{t-1} + b_m] \tag{9}$$

Where,

W_{mx}	Defines the input weight in memory gate, matrix n x k.
W_{ms}	Weight of the state in memory gate, matrix n x n.
b_m	Bias, vector size n.

From the 5 NN, the best one will be selected and used for predicting the price for the next year.

The next step is predicting the Brent crude oil price for the whole year 2024 using the Wolfram Mathematica function called "TimeSeriesModelFit". It automates the selection of a time series model from a large class of possible models. Here, the software itself selected the integrated ARMA model family (ARIMA) with an order of (0,1,0).

Autoregressive Integrated Moving Average (ARIMA) is a model used to forecast time series data, which combines autoregression (AR), differencing (I), and moving averages (MA).

The model is denoted as $ARIMA(p, d, q)$,

Where:

p	Is the order of the autoregressive component.
d	Is the degree of differencing.
q	Is the order of the moving average component.

The following is the general equation for $ARIMA(p,d,q)$:

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{p-q+} \varepsilon_t \tag{10}$$

Where:

y_t	is the value of the time series at time *t*.
c	is the constant term.
$\phi_1, \phi_2, \ldots, \phi_p$	are autoregressive parameters.
ε_t	is the white noise error term at time *t*.
$\theta_1, \theta_2, \ldots, \theta_q$	are moving average parameters.
$y_{t-1}, y_{t-2}, \ldots, y_{t-p}$	are past values of the time series.

If differencing is required to achieve stationarity of the series, the d parameter is relevant. Subtracting the series from its d-times-lagged version is a differencing operation. The aim of ARIMA modelling is to find the values of p, d, and q that minimize the residuals and create an efficient model for predicting future time series values. The model is frequently fitted to historical data, and techniques like maximum likelihood estimation are used to estimate the model's parameters. Following the model fitting, future values can be predicted using the patterns found in the time series data.

Results

Figure 2 shows a graph of Brent crude oil prices over 35 years. The graph displays dynamic fluctuations. Prices are generally rising, but this is not a straight line; peaks and valleys are along the curve. For example, a peak in 2008 of about $140 per barrel can be mentioned, followed by a sharp decline to about $40 per barrel in 2009. In addition, there has been increased volatility in recent years, as evidenced by the 2010 spike to over $100 per barrel and a subsequent 2015 decline to about $50 per barrel.

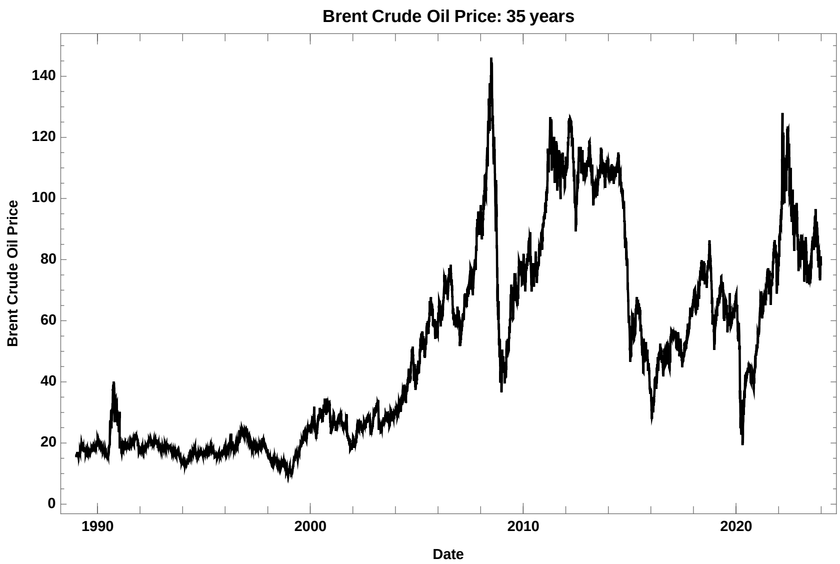

Figure 2: Brent Crude Oil Prices: A 35-Year Perspective

A thorough overview of the price distribution of Brent Crude Oil over the designated period is provided by the descriptive statistics in Table 1. The lowest price recorded was $9.64 per barrel, representing the lowest point; the highest price within the monitored period was a startling $146.08 per barrel, representing the highest value. The average price ($51.6339 per barrel) provides an average benchmark for understanding the dataset. The variance of 1085.07 illustrates the degree of variability within the data by highlighting the extent of dispersion from the mean. We can see how prices are spread around the mean and how volatile things are, with a standard deviation of 32.9404. Further context regarding data distribution within the interquartile range is given by the quartile deviation of 27.53. Different viewpoints on the dispersion of prices from their respective measures of central tendency are provided by the median and mean deviations, which are 26.915 and 28.4613, respectively. When taken as a whole, these data provide a complex picture of the distribution and fluctuation of Brent Crude Oil prices, which is essential for well-informed analysis and decision-making in the energy market.

Table 1: Descriptive Statistics of Brent Crude Oil Prices

Description	Descriptive Statistics (Brent Crude Oil)
Minimum	9.64
Maximum	146.08
Mean	51.6339
Variance	1085.07
Standard Deviation	32.9404
Quartile Deviation	27.53
Median Deviation	26.915
Mean Deviation	28.4613

Figure 3 illustrates the 35-year history of Brent crude oil prices, which is characterized by a long-term upward trend interspersed with significant fluctuations. Even though there is an overall upward trend, the situation is not good. The graph shows periods when prices rose sharply, reaching a peak of $140 per barrel in 2008, followed by a sharp decline, as illustrated by the drop to $40 per barrel in 2009. More of this volatility has been seen in recent years, with a spike above $100 per barrel in 2014 and a sharp drop back to $50 in 2015.

More context is given by the orange line, which is a moving average. An upward slope indicates a long-term bias towards higher prices despite short-term fluctuations, which indicates an underlying trend. On the other hand, a downward slope could indicate a downward trend. The strength of the trend can be inferred from the slope's steepness. Flatter slopes indicate a weaker trend or periods of consolidation, while steeper slopes indicate a more noticeable upward or downward trend. Additionally, the moving average can serve as a support or resistance level. Prices that are getting close to the line may encourage buyers (support), but prices approaching it may lead to selling pressure (resistance).

In summary, we gain a deeper understanding of the oil market by combining the moving average's insights with the overall price trend. There may be a long-term upward trend, but there is always short-term volatility. Therefore, in addition to other technical indicators and fundamental analysis of factors influencing the oil market, it is imperative to consider the moving average's slope and potential support/resistance levels to make well-informed decisions.

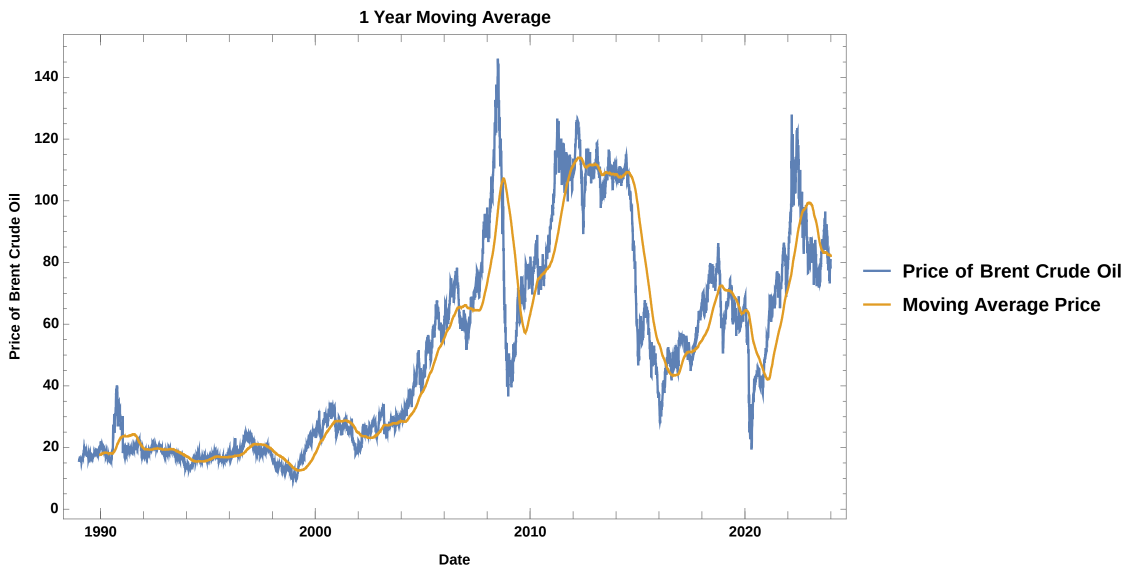

Figure 3: Brent Crude: A Long-Term View with Short-Term Swings (Past 35 Years)

Using GDP growth rates from 1989 to 2023, this graph shows the economic path of Saudi Arabia, China, Russia, the United States, and Europe (the European Union). China is a notable example of a consistently strong performer and continues on a positive trajectory, albeit with a slowdown. Greater volatility is seen in similar patterns in the US and Europe. Both countries experienced booms in the late 1990s and mid-2000s before seeing more muted growth from the late 2000s onward. Small changes mark Russia's history compared to others.

In summary, China has been a leader in steady economic growth over the previous 35 years. While the US and Europe saw positive growth despite greater volatility, Russia's path was characterized by sharp fluctuations, perhaps as a result of historical events and its dependence on oil. The history of Saudi Arabia appears to be closely linked to the world's oil market. It is critical to keep in mind that the GDP growth rate is only one element of the whole picture (Figure 4).

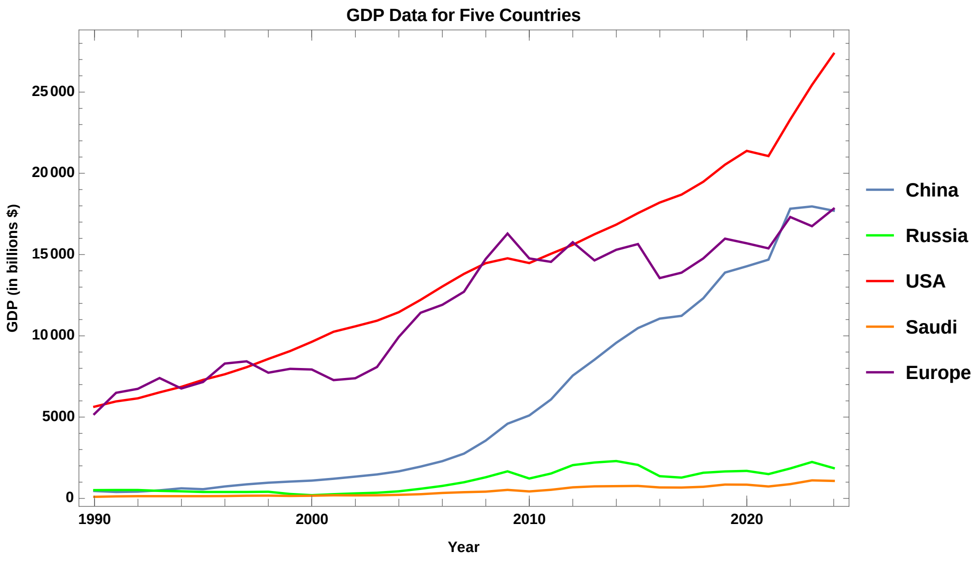

Figure 4: Growth Paths Diverge: A Comparison of GDP Growth Rates (1989-2023)

Figure 5 shows the average annual price of crude oil for the previous 35 years. The year is shown on the x-axis, while the y-axis shows the price per barrel of oil. On the graph, there are four data points. The data points for the years 1989 and 2023 are located on the left and right, respectively. Figure 5 indicates that although there have been some fluctuations in the price of crude oil over the last ten years, an upward trend is generally observed. By 2009, the price had increased from $20 per barrel in 1991 to about $100.

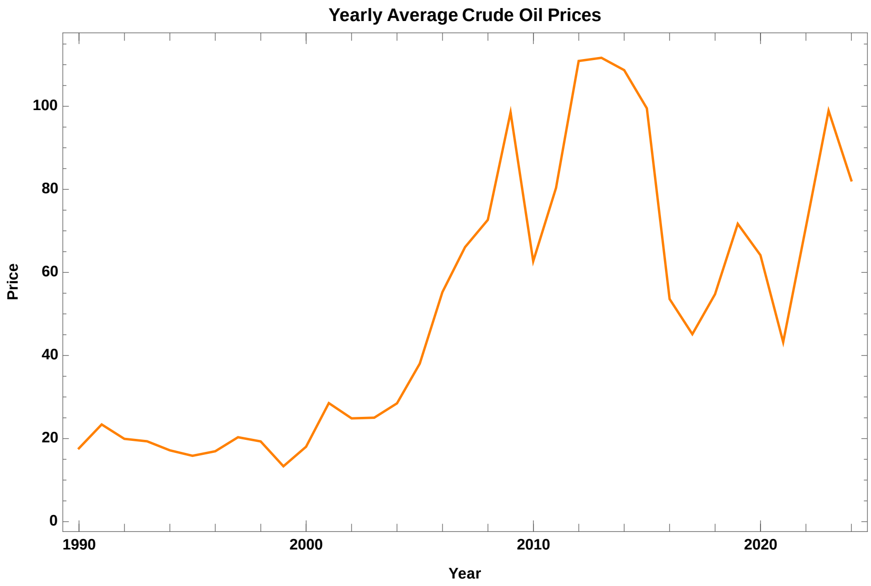

Figure 5: Average Annual Brent Crude Oil Prices

Figure 6 presents an intriguing trend: the price of Brent crude oil (on the x-axis) and China's GDP (on the y-axis) show a positive correlation, with Pearson correlation coefficient of 0.651. This implies that oil prices typically rise when China's GDP grows and vice versa. However, it should be noted that correlation does not imply causation, as other factors can influence both variables. For instance, there is no clear causal relationship between the observed positive correlation and the global economic downturn, which could simultaneously reduce China's GDP and the global oil demand. This relationship can be due to several possible reasons. China's economic growth is frequently accompanied by rising oil consumption, which can increase costs. On the other hand, a slowdown in the Chinese economy might result in lower oil demand, leading to lower prices.

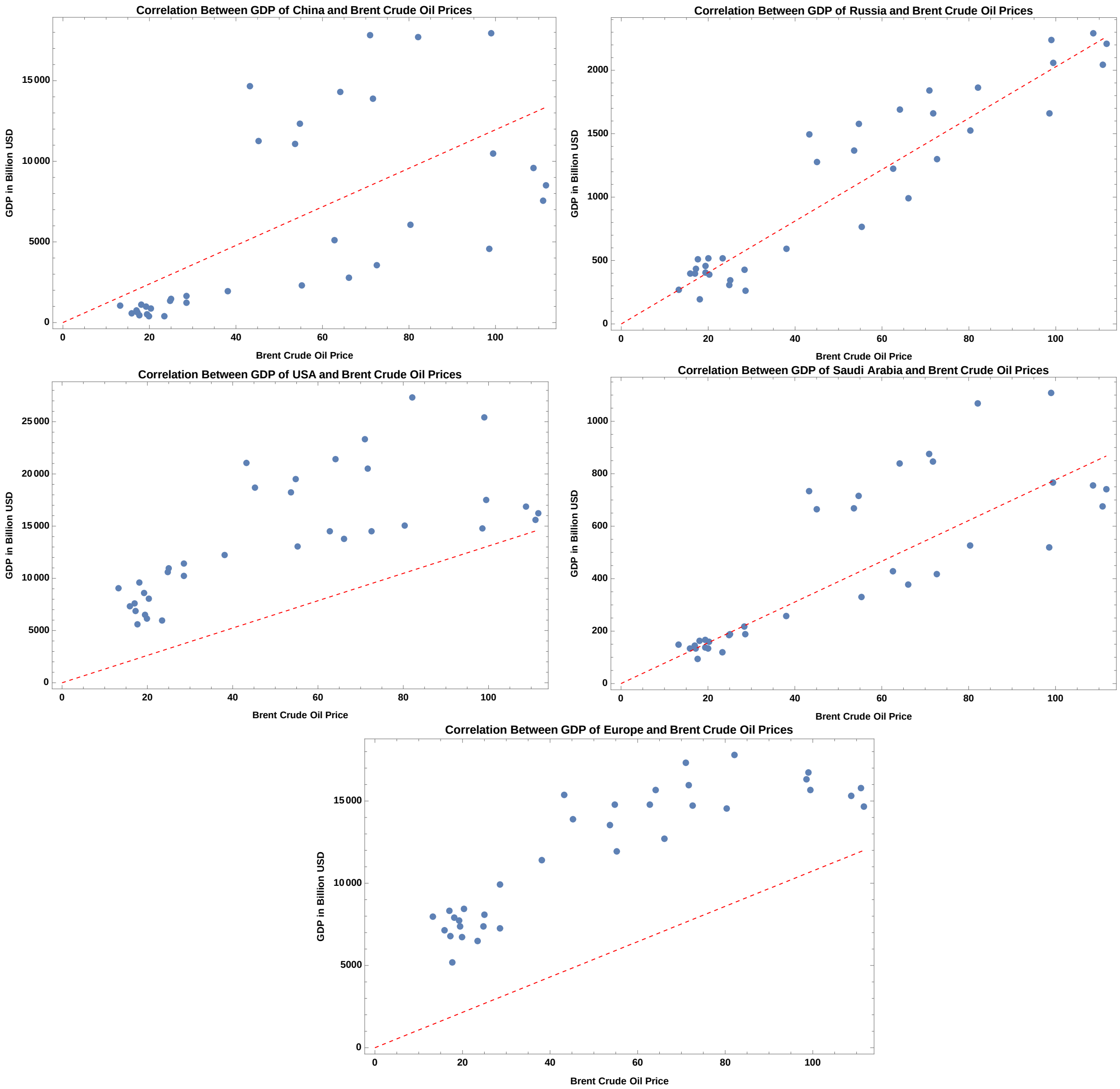

Fig 6. Correlation Between the GDP of selected countries and the Historical Brent Crude Oil Prices.

A closer look at the correlation between Russia's GDP and Brent crude oil prices shows an *R*-value of 0.9385 and a positive correlation, which means that Russia's GDP and crude oil prices are interdependent. Similarly, the correlation between US GDP and Brent crude oil prices shows an *R*-value of 0.7187 and a moderately strong positive correlation, which means that the variables of US GDP and the price of Crude Oil are interdependent. The correlation values between the price of Brent crude oil and Saudi Arabia and Europe's GDP are 0.8103 and 0.8734, respectively. This implies that they have a strong positive correlation. In conclusion, it can be stated that all of the correlation coefficients show positive correlations, albeit in varying degrees of strength.

Prediction using LSTM Models

The performance of LSTM-based neural network models and activation function configurations for prediction tasks can be seen in Table 2. The networks 1NN252 to 5NN252 use different combinations of Ramp, Sin, and ArcTan activation functions. All models show good accuracy, with variances between 0.988 and 0.992. This implies the adaptability of LSTM architectures and the importance of experimenting with activation functions to maximize predictive modelling performance.

Among these 5 NNs, the 5NN252, with the combination of the activation functions Ramp, Ramp and Sin, shows the best accuracy of 99.21%.

Table 2: LSTM Model Performance and Activation Functions

Network	Performance	Activation Function	Activation Function	Activation Function
1NN252	0.991797	Ramp	Sin	Sin
2NN252	0.988628	Sin	ArcTan	ArcTan
3NN252	0.990139	ArcTan	ArcTan	Sin
4NN252	0.991391	Sin	ArcTan	Sin
5NN252	0.992067	Ramp	Ramp	Sin

Figure 7 shows the comparison of predicted average crude oil prices in the last 35 years. Five curves (1NN Predicted, 2NN Predicted, 3NN Predicted, 4NN Predicted, and 5NN Predicted) can be seen on the graph, each of which represents a different prediction model with a curve for the annual average. Between 1990 and 2009, an increase in GDP was seen, followed by a fluctuation in every predicted curve. Of the curves presented, 5NN Predicted shows the highest accuracy and values closest to the original Value/Actual Value.

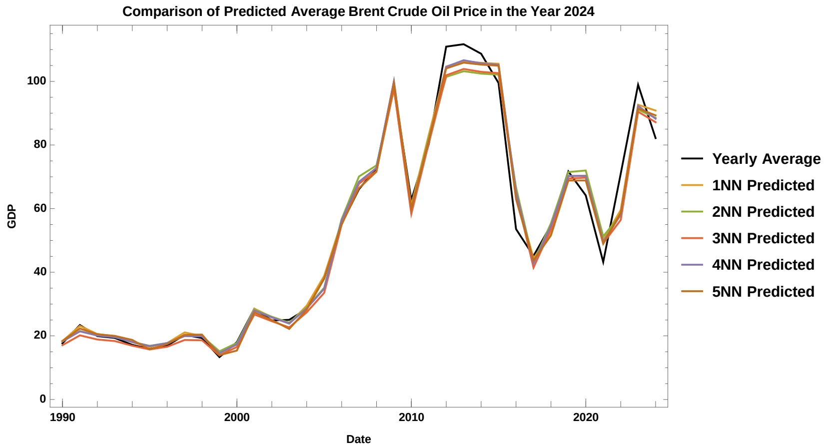

Figure 7: Comparison of Predicted Average Brent Crude Oil Price (1990-2024)

Figure 8 shows the comparison between average annual crude oil prices with the best predicted crude oil price. This shows that the average yearly crude oil prices are very similar to predicted prices.

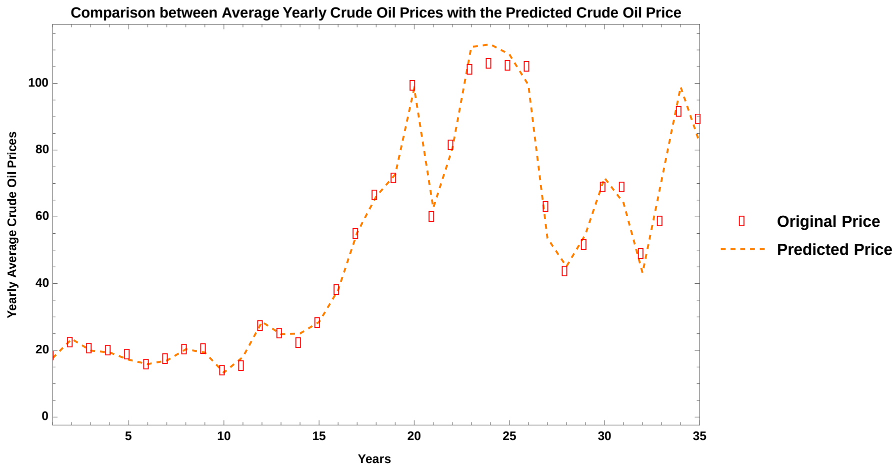

Figure 8: Comparison Between Average Yearly Crude oil Prices with the Predicted Crude oil Price

Thus, based on the model used for the 5NN, it is possible to predict the next year's average Brent crude oil price. Figure 9 shows the predicted average crude oil prices in the year 2024. In January 2024, the price starts at 82.3 and increases until next January, reaching nearly a value of 85.2. According to the 5NN model, the average predicted Brent crude oil price for 2024 is 85.18.

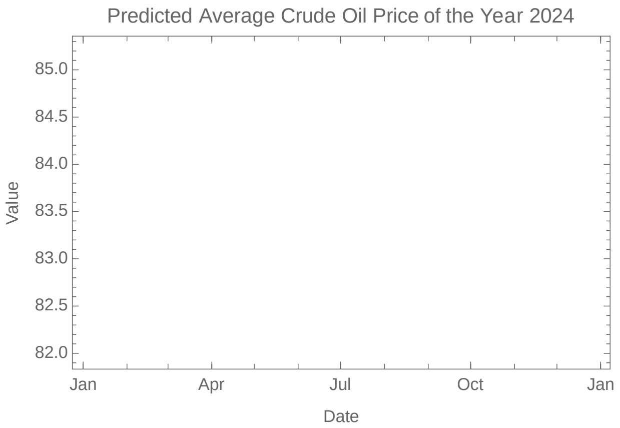

Figure 9: Predicted Average Crude Oil Price of the Year 2024

Figure 10 shows the predicted price for a period of one year. In 2024, the GDP value slowly increased to the value in 2023.

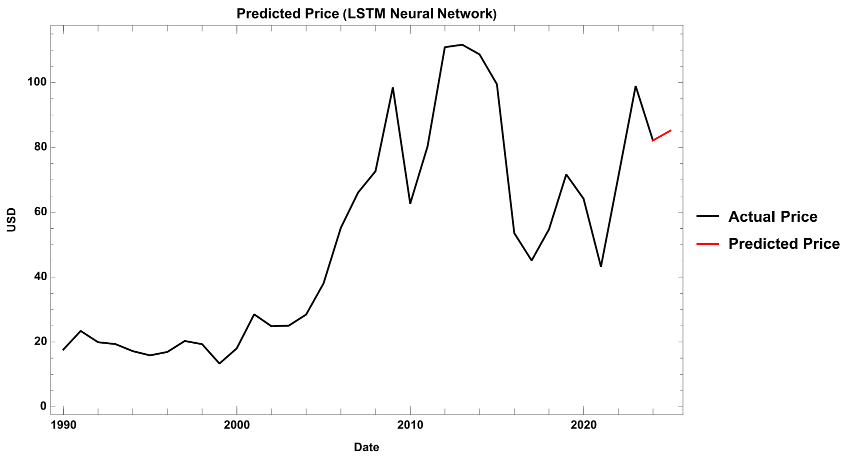

Figure 10: Predicted Price of Brent Crude Oil (2024)

A closer look at the one-year prediction of Brent crude oil values using a Wolfram Mathematica function called "TimeSeriesForecast" shows a predicted series of data, which are given as 252 values. The average value is 81.01, which is quite different from the above predicted NN values.

Figure 11 shows the Brent crude oil price from 2021-2025. For 2024, the predicted price will show a slightly increasing trend in the next months.

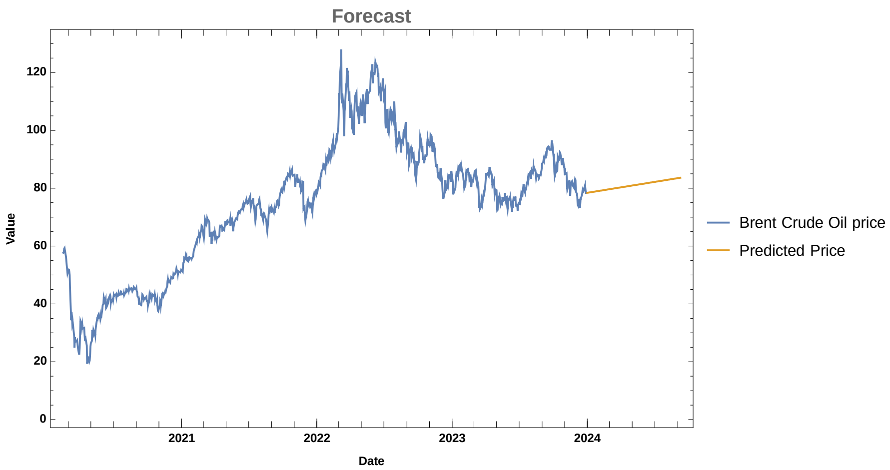

Figure 11: Predicted Price of Brent Crude Oil (2024)

Both predictions provide the same results, and the price of Brent crude oil is expected to increase in 2024.

Discussion

RQ1: What are the historical trends and patterns in the Brent Crude Oil price over the past 35 years?

Historical data on Brent crude oil was analyzed using data from the investing.com website between 1989 and 2023. The data indicate that the historical trends and patterns in Brent crude oil prices over the last 35 years indicate a dynamic environment with significant fluctuations. Notable peaks and falls can be seen in the data, including a high in 2008 at nearly \$140 per barrel and the lowest point in 1999 at approximately \$9.64 per barrel. In addition, there has been increased volatility in recent years, with a rise above \$100 per barrel and subsequent drops. These patterns indicate that although oil prices are generally rising in the long run, there are significant and noticeable short-term fluctuations. The results are in line with Cheong (2009), who states that crude oil market participants are at risk of significant losses due to price volatility.

RQ2: Which of the selected countries/continents have the highest correlation between GDP and Brent Crude Oil prices, and how can it be used in predictive modelling?

To answer this research question, it is necessary to determine the GDP of some countries/continents, including the USA, China, Russia, Saudi Arabia, and Europe. The GDP figures are given annually, so we work with the annual mean of the Brent crude oil price. The determined Karl Pearson's correlation coefficient for each GDP with the Brent crude oil price shows a positive correlation. The price of Brent crude oil and Russia's GDP positively correlate, as indicated by the correlation coefficient (R-value) of 0.9385. This means that an increase or decrease in Russia's GDP is accompanied by a corresponding rise or fall in Brent crude oil price, and vice versa. Similarly, there is a moderately strong positive correlation (correlation coefficient of 0.7187) between the US GDP and the price of Brent crude oil. This indicates that, although to a slightly lesser extent than in Russia, changes in US GDP also correspond to changes in the price of oil. The same applies to the Brent Crude Oil price and GDP of Saudi Arabia and Europe, with correlation coefficients of 0.8103 and 0.8734, respectively. This suggests that there is a strong positive correlation. Based on the above, it can be concluded that there is a strong correlation between the GDPs of Saudi Arabia, the United States, Europe, and Russia and the prices of Brent Crude Oil. This means that changes in these nations' economies impact oil prices. A large volume of historical data on GDP and oil prices was collected to predict future prices. These results align with Sahu et al. (2022), who state that the rise in crude oil prices and the GDP of the United States will increase the use of renewable energy, which will positively impact GDP and crude oil prices. Both variables show the same impact.

Using a simple linear regression, it is possible to predict the Brent Crude Oil price for the next year based on the GDP of the highest-correlated country. However, this can only be done if the GDP for 2024 is given. This means that the Brent Crude Oil price is a univariate figure, and to better predict the time series of the data, a predictive modelling approach such as LSTM is performed. Based on the daily prices of Brent Crude Oil over the past 35 years, the average price for the next year (2024) can be predicted.

RQ3: How effective is the selected predictive modelling approach in forecasting the future price trends of Brent Crude Oil, and what are the implications of these forecasts for stakeholders in the global energy market?

The selected predictive modelling technique has demonstrated excellent accuracy in predicting future price trends of Brent Crude Oil, especially the 5NN252 LSTM model combining Ramp, Ramp, and Sin activation functions. This model outperforms other configurations tested in the experiment, with an accuracy of 99.21%. C. Deng et al. (2021) also recommend using the LSTM model due to its strong generalization ability and high prediction accuracy. Utilizing LSTM architectures in conjunction with different activation functions emphasizes the flexibility and importance of experimenting with different configurations to maximize the performance of predictive modelling. Based on the LSTM NN, the average price of Brent Crude Oil in 2024 is 85.18. When using the Wolfram Mathematica ARIMA model, the predicted price is 81.01. The two predictive prices are different, showing a slight change in the values. However, the trend and direction of the predicted price for the next year are the same, i.e., increasing.

Conclusion

A 35-year study of Brent Crude Oil prices reveals a volatile market with significant ups and downs, which has seen greater volatility recently. Strong positive correlations are evident when comparing the GDPs of major economies, such as Saudi Arabia, the USA, Europe, and Russia with the price of Brent Crude Oil. These correlations suggest that economic factors affect oil prices. Forecasting using sophisticated modelling approaches such as LSTM has shown high accuracy. This model outperforms other configurations tested in the experiment, with an accuracy of 99.21%, thus offering significant insights to global energy market participants. Li & Cao (2018) find that when comparing ARIMA and LSTM models, LSTM is simpler and more effective. These results highlight the value of sophisticated modelling and economic indicators for risk management and well-informed decision-making in the energy industry.

The paper's primary focus was an analysis of past price fluctuations in Brent Crude Oil together with forecasts for the future. The objective was to determine trends that would help businesses and energy sector experts anticipate changes in the market. Forecasting the price and volatility of crude oil is crucial for providing investors with information and enables making informed government policy decisions (Niu et al., 2021). Making informed decisions and plans in a dynamic energy sector requires this understanding. It helps businesses plan better, make smart investments, and manage inflation. In addition, it helps reduce market volatility, facilitate environmental planning for energy transitions, and promote economic stability, all of which eventually support sustainable economic growth at the global level.

The LSTM predicts an upward trend in the year 2024. The predicted annual Brent Crude Oil price for the next year is $85.18. However, the ARIMA model shows a much lower predicted value compared to the LSTM model, specifically, $81.01. Nevertheless, both models show an upward trend, which means that the price of Brent Crude Oil will increase next year.

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