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ECONOMIC FORECASTING WITH DEEP LEARNING: CRUDE OIL

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Abstract

Crude oil plays a big role in determining the world economy today. The increase in the oil price leads to an increase in inflation and hence reduces economic growth. More to that from crude oil, different products reduce. Therefore, a change in oil prices will directly affect these products. Because of this, it is very important to determine the future price of crude oil for better economy budgeting and future planning. Knowing the future price of oil is very challenging. Investors, business people, and the government need accurate prediction models for their decision-making. The main challenge of predicting the price of crude oil is the instability of the price of crude oil. In this paper, the study will use the deep learning techniques to capture the behavior of the crude oil price with a comparison with the other three techniques. The study will use Long Short Term Memory (LSTM) with a comparison with the Moving average (MA), linear regression (LR) and Autoregressive integrated moving average (ARIMA). Using the data from West Texas Index Intermediate (WTI), and measurement performance RMSE and R-Square, this research has proved

that deep learning model (LSTM) is the best in capturing nonlinear data for the aim of predicting the future price of crude oil price.

Keywords

Forecasting, LSTM, Moving Average, Linear Regression, ARIMA

1. Introduction

Crude oil is one of the most important commodities in the world. It is one of the key elements in the economy of the world. Most of the energy in the world depend on crude oil. Approximately two-thirds of energy demand in the world is met through crude oil (Alvarez-Ramirez, Soriano, Cisneros, & Suarez, 2003). Crude oil is occurring naturally as unrefined oil and can be refined to produce different important products such as petroleum, diesel, and other petrochemical materials. It is obtained from drilling under the earth's surface (underwater or land). It can be found with other materials such as natural gas and others before refined to produce usable oil and other usable petrochemical products. Others can define Crude oil as a mixture of hydrocarbons and also composed with some accessory compounds that able to give some specific properties to such crude oils (Aluvihara & Premachandra, 2019).

Crude oil price is a crucial indicator of the economic world. Investors, international organizations, governments are the key players in determining the oil price in the markets. Crude oil price is affected by different factors such as political events, speculation of the price in the financial market, demand and supply and among others. These factors contribute much to changing elements of oil prices. More to that the fluctuation of crude oil price extends much to the commodities and services such as food and transport fare. At the beginning of the year 2018, India experienced an unstable increase in prices of oil prices where the oil prices are dependent on the crude oil prices of Dubai and Saudi-Arabia, in which the transportation fare was affected, (Keerthan, Nagasai, & Shaik, 2019).

All of these price changes bring an impact on the economic as well as communities. Oil price inflation plays a role in the global economy, (Husain et al., 2015). There major benchmark oil price in the world as West Texas Intermediate (WTI), Brent crude oil price and Dubai crude oil price. In this benchmark, anyone can obtain the daily price of crude oil in the world market.

Because of these vicissitudes movement of the crude oil price, it is necessary to predict the future price to know where and how the economy will be moving as well as planning of the future. Predicting the future of crude oil price is very important in different aspects of economic, political and industrial areas (Khamehchi & Mahdiani, 2017). Prediction of the oil price has been very challenging due to the instability of the prices. The nonlinearity of the price data has encouraged more researchers to conduct research on how to predict the future price of crude oil. Different models have been suggested, and in this study, we will look at the prediction model using the Deep learning method.

In previous years predictions of oil and prices were done using traditions statistical and economic methods (Coppola, 2008). Different methods have been experimented to accommodate the behavior of oil prices in forecasting the price (Weigend & Gershenfeld, 1994). In recent years, different new techniques have been imposed and put into practice in order to make better predictions. Deep learning methods such as Deep Believe Network and artificial neural network have performed this task well(Chen, He, & Tso, 2017), (Fan, Liang, & Wei, 2008), (Jun, Zhi-bin, & Qiong, 2009). These new techniques accommodated the non-linearity of the movement of the price and hence make the prediction more accurate

Deep learning is a branch of machine learning that is about learning multiple presentations of data to perform a specific algorithm task. It is encouraged by the deep structure of the brain. It mostly consists of an input layer, the hidden layer where manipulation of data takes place and the output layer as shown in figure1.1 below.

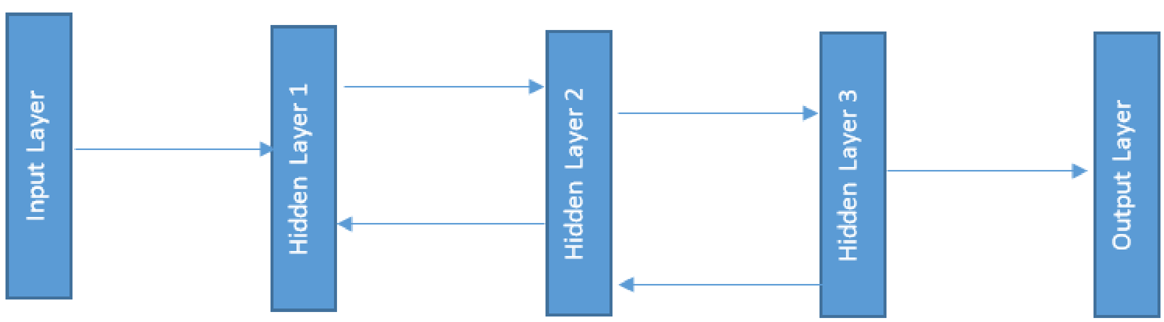

Figure 1: *Error! No text of specified style in document.***:** *Layer in Deep Learning Model (Three Hidden Layers)*

Deep learning performs very well in voice recognition as well as self-care driven. In addition to that, successfully, deep learning has also performed very well in image recognition and in the market and stock analysis (Price prediction of stocks), (Yu & Yan, 2019). In addition, Deep leaning technology has been widely used in image classification and in medicine in the detection and classification of abnormal medical images. A good example is the integration of algorithms such as Gray Level Co-occurrence Matrix (GLCM) with Multivariate Support Vector Machine (MSVM) and K-Nearest Neighbour (KNN) classifiers approaches which producing effective results in spinal cord tumor classification, (Mary S. & Sasikala, 2019). These days investors have been using Deep Learning models in financial advisor as well as decision-making.

This paper adds value to the future researches and studies in prediction technology by studying and analyses Long Short Term Memory along with other three techniques, Moving average (MA), linear regression (LR) and Autoregressive integrated moving average (ARIMA) and compare them to get the best technique in the prediction of prices. Using data from West Texas intermediate, the study measures performance using performance measurement tool R - Square and Root mean Square Error.

2. Literature Review

Many types of research and studies have been conducted in the area of using deep learning in economic and Finance. Much more are continuing to be conducted in predicting the future price of different commodities and stock markets such as gold prices. The increase of this investigation is due to many data have been put in public as well as the increase of advance usage of technology. This proposed research has aimed at doing an analysis of oil prices by using deep learning with the LSTM network (Long Short Term Memory). Therefore, the related work has been explained in this chapter based on the prediction of different commodities.

Kamil and Janisha (Kamil & A, 20018), using data from WTI spanning 16 years from January 2000 to December 2016 study and compare a traditional method ARIMA with the two-deep learning models Long Short Term Memory and Support Vector Regression. Using performance measurement MSE (regression loss function) and r2 score (regression score function) LSTM model performed better compared to the other two models.

Li et al conducted a study on the forecasting of crude oil price base on online media text. The main goal was to capture the quickest and genuine of the price. To archive this, they use a convolutional neural network (CNN) to extract hidden patterns within online news media. More they propose a feature grouping method based on the Latent Dirichlet Allocation (LDA) topic model for distinguishing effects from various online news topics. Their results suggested that the proposed model performed better than the older models (Li, Shang, & Wang, 2019).

Abramson and Finizza (Abramson & Finizza, 1995), use a probabilistic model for the determination of the future oil price at that time. They use of inherently probabilistic belief network models to produce probabilistic forecasts of average annual oil prices. The probabilistic forecasts generated by running Monte Carlo analyses on these scenario networks provide corporate decision-makers with useful insights and recommendations. Guillen follows them by using WTI price in 1998. He uses the data from March 1983 to October 1995.

Using 25 instances of data in forecasting food prices in India, Malhotra and Maloo 2017(Malhotra & Maloo, 2017), they use ANN approach in their experiment and their result suggested ANN be better after yield R-Square of 99.1. Their result aligned with an early study of Nowrouz Kohzadi et al 1993, whereby monthly data of monthly live cattle and wheat prices from 1950 to 1990 were compared using ARIMA technique and ANN. The Artificial Neural Network model achieved 26% lower MAPE (Kohzadi, Boyd, Kermanshahi, & Kaastra, 1996).

Despite this study concentrate on aiming using deep learning in forecasting the price of oil, many kinds of research have conducted to forecast the price of different commodities and other issues such as weather. Xiongwen et al developed a neural network to predict the stock market. They used long short term memory network to predict the stock market. The experimented result shows that LSTM with an embedded layer performed better (Pang, Zhou, Wang, Lin, & Chang, 2018).

(Lee, Kang, & Shin, 2017) Studies in using deep learning technology in the environmental field to predict the status of pro-environmental consumption. They use the Recurrent Neural Network model to archive their results. Their results were compared with the ordinary least square and artificial neural network model the RNN performed better than the other models because the traditional method of forecasting (econometric methods) does not be able to capture the nonlinear data and the deep learning models are good in capturing complex and nonlinear characteristic of oil price movements. The studies suggest that deep learning models produce better and accurate results in forecasting.

3. Methodology

Forecasting models have been developed for a long time. In the past, the models were developed using tradition methods. These traditional methods consider only linear data in making the prediction. Examples of these traditional methods include the Moving Average Method. The introduction of Deep Learning in forecasting is a game-changer since Deep learning models consider nonlinearity of the data. The most common deep learning method models include Convolutional Neural Network (CNN), Deep Believe Network (DBN) and Long Short Term Memory (LSTM) (Hinton, Osindero, & Teh, 2006), (Chen et al., 2017).

3.1 Data Collection

One of the important keys in doing research is the collection of data. Deep learning methods need a larger volume of data, therefore the large the volume of data the better results. This study focused on predicting crude oil price, using the daily price from West Texas Intermediate (WTI), for the period of 11 years from March 2009 to March 2019, having 2519 observations. The study will use LSTM with a comparison with moving average, Linear Regression, and ARIMA models.

3.2 Data Processing

After collection of the data, the Cleaning of data follows. Each date must have corresponding data value and eliminate unwanted data. This also involves filling the missing data and integration. Generally, the processing of data is done here.

Then the cleaned data is divided into training data and testing data. Training data is used to train the model of the historical movement of the data. Testing data is compared with the predicted results to obtain how accurate the prediction is. After dividing data, training data fed into the system and train for the prediction. The data passes through hidden layers before reaching out layer. The out data are matched with the testing data, and performance evaluation is done using performance metrics. In this study, R square and RMSE are used.

In this paper, four models have been tested and analyzed. Then the result of each technique is compared to get a better technique in prediction analysis.

3.3 Linear Regression

Linear regression shows the relationship between two variables (simple regression) or many variables (multiple regression) by fitting a linear equation to observed data. For single regression one being dependent variable Y and other independent variable X. therefore it is a method used for predicting a certain value depending on another variable. It shows the relation between X and Y. generally, a simple regression can be presented mathematically as

$$Y \approx a + ß X + \varepsilon \qquad (1)$$

Whereby a = constant value and ß are the unknown value that present intercept and slope. It is the coefficient value of X. ε Present error estimation. Y and X are out the value or the target value and independent value respectively.

Multiple linear regression is regression whereby independent variables (more than one variable) are used to predict the independent variable. Most of the regression models are multiple regression. Mathematical can be presented as:

$$Y \approx a + ß_1 X_1 + ß_2 X_2 + ... + ß_n X_n + \varepsilon \qquad (2)$$

Where X_1, X_2, and X_n are independent values. Y is predicted value (dependent value), a = constant value, and ß coefficient of independent value and ε Present error estimation.

According to Data camp, Linear regression is one of very primitive statistical logarithm and yet very old, but never to be old to be used in building data science models (Paul, 2018). According to the University of Pittsburgh, linear regression plays an important role in the field of artificial intelligence such as machine learning. The linear regression algorithm is one of the fundamental supervised machine-learning algorithms due to its relative simplicity and well-known properties (Hauskrecht).

3.4 Moving Average

It is sometimes known as a rolling average. It is calculated by creating a series of average from one point to another within the data set. Some people term it as moving mean. It is one of the most method used in forecasting the prices of commodities. The moving average indicators (methods) have been while used in the prediction of the price of products. It has also been used for the determination of trading points. There are two commonly used moving average, namely

a. **Simple Moving Average** can be calculated as

$$SMA = (A_1 + A_2 + .. + A_n) \div n \qquad (3)$$

A = the average value in a period n, and n is the number of times. It calculates the arithmetic mean of the value over the period of time.

b. **Exponential Moving Average:** This type of moving average reacts more significantly to a recent change of value. This means that it places a greater weight and significance of the most recent data value. In order to calculate EMA, it required to calculate SMA, Multiplier for smooth (factor weight for previous) and then compute the current EMA.

Mathematically it is presented by:

$$EMA_t = [V_t \times (S \div (1+d))] + EMA_y \times [1 - (s \div (1+d))] \qquad (4)$$

EMA_t = Exponential Moving Average today,

V_t = Value today, EMA_y = Exponential moving Average yesterday, S = Smoothing Factor and d = number of days

Moving average methods use historical data in prediction. The longer the time period for the moving average, the greater the lag. Thus, 500 days moving average will have better results than the one with 50 days. Some researches indicate to have different type of moving average such as simple moving average (SMA), weighted moving average (WMA), exponential moving average (EMA), adaptive moving average (AMA), typical price moving average (TPMA), and triangular moving average (TMA) (Wang,, et al., 2014).

3.5 Autoregressive Integrated Moving Average (ARIMA)

The model has become more popular to predict the future value for non-linearity data. ARIMA's name comes from the key aspect of the model. AR means autoregression, I stand for integrated and MA stands for Moving average. The mode generally upgrades the version of the autoregressive moving average (ARMA). It most terms as ARIMA (p, d, q), whereby

P = number of autoregressive (lag order), d = integrated part (also known as the degree of difference) and q is moving average. In addition, these value p, d, q are non-negative integers

ARIMA came to solve the problem of ARMA failed to capture non-stationary data. ARMA only considered stationary data. Therefore, ARIMA models are the best in some cases where data show the evidence of non-stationary. In order to choose the ARIMA model parameters, Akaike Information Criterion (AIC) is considered. In ARIMA the forecasting equation is constructed as follows. First, let y denote the d^{th} difference of Y, which means:

$$\text{If } d = 0: \quad y_t = Y_t \qquad (5)$$

$$\text{If } d = 1: \quad y_t = Y_t - Y_{t-1} \qquad (6)$$

$$\text{If } d = 2: \quad y_t = (Y_t - Y_{t-1}) - (Y_{t-1} - Y_{t-2}) \qquad (7)$$

$$= Y_t - 2Y_{t-1} + Y_{t-2} \qquad (8)$$

George Box and Gwilym Jenkins developed a mathematic model for forecast data from a specified time series. The model is known as the Box-Jenkins model. This is the same as the

ARIMA model with the season. RIMA model with seasonality is denoted as SARIMA (*p*,*d*,*q*)(*P*, *D*,*Q*).

More to that, The Box-Jenkins Model forecasts data using three principles, autoregression, differencing and moving average. These three principles are known as p, d, and q respectively. Each principle is used in the Box-Jenkins analysis and together they are collectively shown as ARIMA (p, d, q)(Kamil & A, 20018),(Gordon Scott, 2019).

3.6 Long Short Term Memory (LSTM)

Long short Term Memory network was introduced by Hachreiter and Schmidhuber in the late 1990s. LSTM is basically an improvement of the recurrent neural network. Due to some shortfall in RNN in losing memory, LSTM was introduced to tackle the issue of memory loss. LSTM can process single data such as image an entire sequence of data such as video. Because of this capability of the processing sequence of data, LSTM has been very well applicable in speech recognition as well as handwriting recognition. The flow of information in LSTM is as in Figure 2. LSTM is composed of the cell, which remembers values over a period, input gate, output gate and forget gate. The aim of these gates is to keep the flow of information. In figure 3.2, X_t passes the information from previous block cell. Then new information from the input gate and information from previous cell combined (x), and pass through cell (C_t) and new information are created. f_t is a function decision for storing information, and h_t is out from current cell.

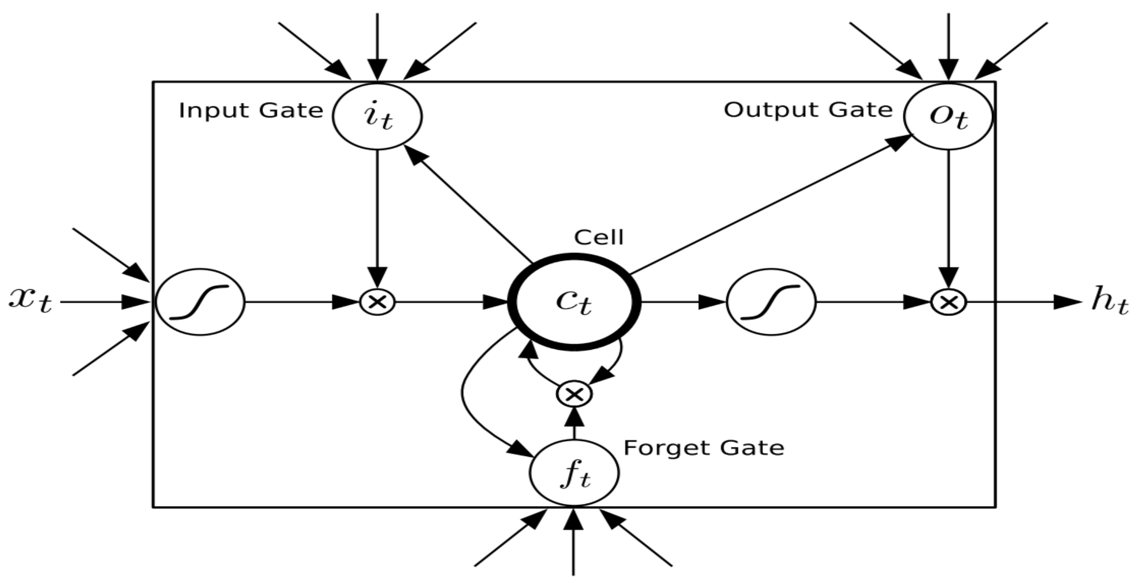

Figure 2: *A Single LSTM Memory Block Showing the Gates and Memory Cell* (FastML, 2016)

LSTM has been widely used in different areas because of the capability of storing information. This can be achieved because of the existing memory in the gates. LSTM can pass information that has been captured in the early stages and keep that information for a long time, which enable the LSTM to generate the long-distance dependencies(Ugurlu, Tas, Kaya, & Oksuz, 2018), (Chung, Gulcehre, Cho, & Bengio, 2014).

4. Experiment and Results

This study experiment is based on measuring the performance of the LSTM model compare with the other three methods using performance metrics Root Mean Square Error and R-square. RMSE is the difference between the predicted value and the value observed. It measures the accuracy to compare the forecasting error. The less the value RMSE the perfect the prediction.

R- Square is a statically measurement which measures how close the data fit in the regression line. Some of the research termed it as the coefficient of determination. R –square value is between 0 to 100% (0 to 1), being closer to 1 is the perfect one.

The distribution of the data is distributed as indicated in figure 3. These data are the daily oil price from WTI for the period of March 2009 to March 2019

Figure 3: *Real Observation of Crude Oil Price 2009 - 2019*

Form the above figure 3, one can conclude and say the data are non-stationary. However, in this study, the researcher uses the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) to determine whether the data series used are non-stationary or not. Usually if data series are stationaries, the ACF goes to zero in a quicker way, while for non-stationaries decreases very slow. The total number of observations is 2519. The data was spilled into training data and testing data. Approximately 68% of data was used in training and the rest as testing. Then the data were tested under the platform of the tensor flow environment using python

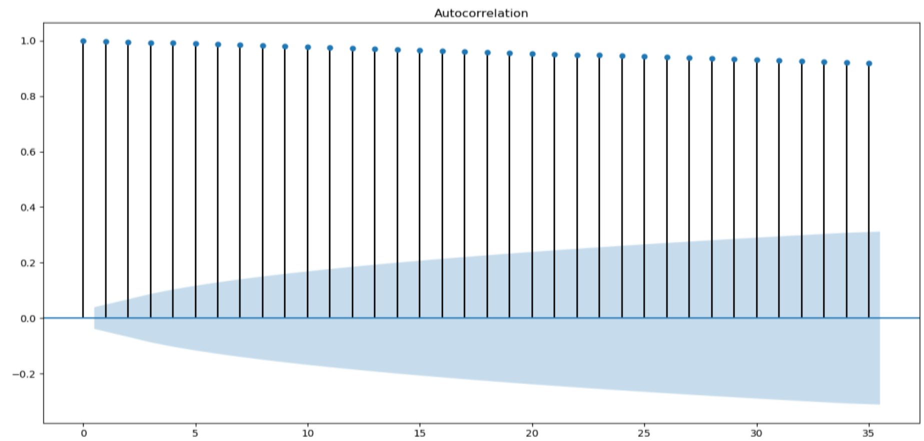

Figure 4: *Showing ACF for the Data Series*

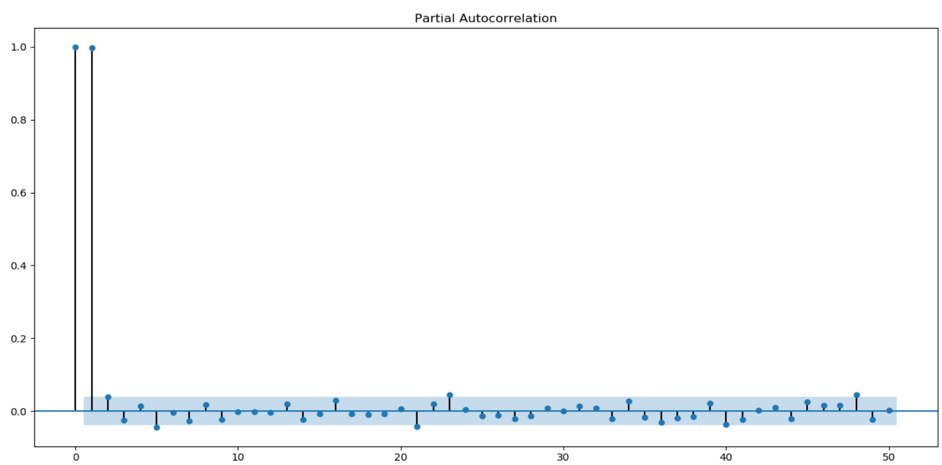

Figure 5: *Showing PACF for the Data Series*

From the above figures 4 and 5, it clear that the data used in this study are non-stationary series. This means there is a presence of seasonality.

Moving Average: In moving average, the data were split into two-part, training data and testing data. Total observation is 2519, and 1709 is used as training data and the remaining as testing data.

The graph of prediction against real data is seen in Figure 6. the RMSE and R square is shown in table 1.

Figure 6: *Showing prediction Vs True price in MA method*

Linear Regression: After splitting the data into training and testing the graph of the prediction against reality movement is shown in Figure 7 and performance matrices are shown in Table 1

Figure 7: *Showing prediction Vs True price in LR method*

ARIMA: First the parameter of the ARIMA (p,d,q) was identified. The best way to identify the ARIMA parameter is to apply the evaluation model function. Then stats models procedure finds a set of parameter that suits the data. The parameters with the lowest AIC value is the best alternative. In our study ARIMA (0, 1, 1) x(0, 0, 1, 12)12 - AIC:6131.36243058826 is selected. Figure 8 shows the results of ARIMA method.

Figure 8: *Showing Prediction Vs True price in ARIMA Method*

LSTM. This is deep learning, so the data are repeated trained in the node. In this study, we set up with two layers of LSTM with 50 units each, epochs 5, and batch size 2. The prediction graph is shown in figure 9.

Figure 9: *Showing Prediction Vs True Price in LSTM Method*

Table 1 shows the performance of each model used, and hence enabling to identify which model has performed better. Using the RMSE and R Square, the least RMSE the better the model and as the R-square approaches to 1 the better the model is. R square is the percentage of a perfect match with real data. Therefore, LSTM shows better performance since it has the least RMSE of 1.18 and R-Square of 0.97. R square shows how the prediction results are close to reality. The moving average has RMSE of 23.79, and R-Square of 0.77. Linear regression has RMSE of 24.77 and an R-square of 0.32. Despite having a good RMSE but the prediction results are very far from reality. ARIMA has performed poorly among the four and it has RMSE and R-square of 106.03 and 0.50 respectively.These performance matrices show that the LSTM is a better method in the forecasting of nonlinear data compare with the rest of the model teste.

Table 1: *Showing Performance of the Models*

		RMSE	R-Square
Models	Moving Average	23.79	0.77
	Linear Regression	24.77	0.32
	ARIMA	106.03	0.50
	LSTM	1.18	0.97

5. Conclusion

Determining the future movement of the oil price is very important since oil plays a major role in the world economy. Having the correct and accurate prediction is an advantage for the country. In this study, four different methods have been tested and analyzed for the aim of getting a better way of prediction crude oil prices. Using the daily price of crude oil from WTI, this study proposed LSTM, a deep learning technology for a better prediction of oil price. The tested results show that LSTM performs the other three-technique by using RMSE and R –Square as a performance measurement instrument. This research gives out a way for more researchers to conduct studies in a better way to make prediction. Coming up with deep learning gives out more chances to have a better way since deep learning techniques deal with volatile data. Deep learning is getting more popular in current world technology. It has been deployed in many complex and sophisticated techniques such as pattern recognition, voice recognition, cancer detection among others.

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