Cascade networks model to predict the crude oil prices in Iraq

Suhair A. Al-Hilfi, Maysaa Abd Ulkareem Naser
Department of Computer Information System, University of Basrah, Basrah, Iraq

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ABSTRACT

Oil prices are inherently volatile, and they used to suffer from many fluctuations and changes. Therefore, oil prices prediction is the subject of many studies in the field, some researchers concentrated on the key factors that could influence the prediction accuracy, while the others focused on designing models that forecast the prices with high accuracy. To help the institutions and companies to hedge against any sudden changes and develop right decisions that support the global economy, in this project the concept of cascade networks model to predict the crude oil prices has been adopted, that can be considered relatively as new initiative in the field. The model is used to predict the Iraqi oil prices since as its commonly known that the economy in Iraq is totally depend on oil. Therefore, it is vital to develop a better perception about the crude oil price dynamics because its volatility can cause a sudden economic crisis.

Corresponding Author:

Suhair A. Al-Hilfi
Department of Computer Information System, University of Basrah
The Site of Karma Ali, Basrah, Iraq
Email: suhair.alhilfi@gmail.com

1. INTRODUCTION

Oil is the depletable random wealth that distributed all over the earth. Oil is the main energy source; it represents the essential raw material in many industrial processes. It used as fuel for cars, aircraft, trucks, ships, factories equipment, electric power generation and in many other places [1]. Therefore, it is expected that the total world oil consumption will be doubled during the next two decades, with actual energy alternative sources decades away [2], [3].

As it is known that the crude oil is the backbone of the Iraqi economy; in another words the economy in Iraq is overly reliant on the oil industry [4]. In 2019, oil accounted for approximately 96% of Iraqi exports [5]. This total reliance definitely has its own drawback especially during the global crisis that affect the oil prices significantly for example during the last pandemic coronavirus disease (COVID-19) this crisis had a substantial effect on the oil prices in which the Iraqi revenues declined. An overreliance on oil revenues made the Iraqi economy vulnerable to oil price fluctuations [6].

Crude oil prices fluctuations consider as the main concern for both market participants and financial practitioners. Since, crude oil price model is very difficult and complex because of the variations of the oil prices that make it nonlinear, nonstationary, irregular and having high volatility the matter that affects both the global economics and the oil enterprises [7]. Therefore, accurate predication of the oil prices is one of the biggest challenges and the most crucial difficulties that faces the energy economists toward making best decisions in many levels, also it is important for both the industry and the investors in terms of reducing and determining and the risks at the same time it helps producers to make powerful strategic plans that manage their own oil industry and the forward contracts of the oil trade [8]. For all these reasons, an urgent need is required for measuring the oil prices volatility and modeling its chaotic behavior. Therefore, many studies have devoted significant efforts to develop different model types for crude oil prices forecasting.

One of the studies, Naser [9] realized that the dynamic model averaging (DMA) had better performance to forecast the prices of crude oil than the whole other models, also this model can obtain better results to predict the current prices than the future prices. Azevedo and Campos [10] used both the exponential smoothing method and the dynamic regression for predicting Brent & West Texas Intermediate spot oil prices, and the result showed that using this combined model is promising to forecasting the prices of crude oil. Gupta and Pandey [11] used long short term memory (LSTM) based recurrent neural networks to test the volatility of oil prices. The obtained results show an accurate prediction for the crude oil price in near future. Salvi [12] conducted forecasting of crude oil Brent using the LSTM method. The results show that LSTM produces good performance with a root mean square error (RMSE) value of 1.91 for the training and 2.82 and for the testing. A hybrid learning model has been proposed by Shabri and Samsudin [13] an integrating wavelet and multiple linear regressions (MLR) is chosen for decomposing an original time series into various sub-series with different scale. Then, the principal component analysis (PCA) is used in processing sub-series data to forecast the prices of crude oil. And the empirical results showed that the suggested model better than the individual models in prediction prices of the crude oil series. Yu *et al.* [14] proposed a hybrid model, a certain artificial intelligence predicting tools and incorporating compressed sensing based de-noising (CSD) model the proposed combined model showed the best even with different samples at different time range, proving that the proposed CSD-AI model is a robust and effective approach for crude oil prices prediction. Recently in 2021, Yang *et al.* [15] proposed a new hybrid approach, a Kernel Principal component analysis (KPCA), K-means and Kernel-based ELM (KELM) are used to predict crude oil price. In the study, they applied a multi-scale data that including both Google search volume index (GSVI) data and traditional economic data reflecting micro and macro mechanisms that impacting crude oil price respectively, to improve the prediction accuracy, and reduce the predicting deviation.

This research focused on the concept of the cascade networks model to predict the crude oil prices, that can be considered relatively as new initiative in the field. Our model has been used to predict oil prices in Iraq since as its commonly known that the economy in Iraq is totally depend on oil. Therefore, it is vital to develop a better perception about the crude oil price dynamics because its volatility can cause a sudden economic crisis. The main aim of this model is improving the accuracy of long-term crude oil prices predictions as well as assist the decision makers to minimize the risks that related to crude oil market. This paper contains the following main contributions: we are proposing the concept of a cascade neural networks model framework to predict crude oil prices that can be considered a relatively new initiative in the field. The adopted model takes full advantage of using gradient boosting (GB) feature selection to highlight how a single factor contributes to the other key features. Since multiple features are included and have different weights, the GBNet output provides the influence of each feature rather than selecting the feature only. The ConvLSTM employs convolution filters for capturing local relationship values, an LSTM can more efficiently carry the overall relationship of a whole sequence. This transforms ConvLSTM into a powerful architecture for capturing long-term dependencies between features extracted by convolution. The experimental results showed that the suggested method went beyond the other deep learning model and traditional methods (ARIMA) as well as that the approach proposed is beneficial for forecasting crude oil prices.

2. RESEARCH METHOD

2.1. Convolutional recurrent neural network

It is a recurrent layer. The internal matrix multiplications are interchanged by the convolution operations. This approach has proven very effective for time series classification and can be adapted for use in multi-step time series forecasting [16]. The ConvLSTM core consistent with the LSTM. The convolutional structures extract the embedded spatial features and process its space correlation embedded within the LSTM cell that process their time correlation thus improving the prediction accuracy. It is not only able to model time series, but also it can describe the spatial features. Note that the original ConvLSTM contains many parameters because of the convolution operation. Therefore, reduce the convolution operation for the three gates may gain better accuracy since it means less parameters and low computational cost [17]. The main equations that controlling the ConvLSTM cells are shown in (1) to (5), where * identifies the element-wise multiplication, ∘ identifies the convolution operation, and *W, b* are parameters of the network [18].

$$i_g(t_s) = sigma(W(i_g) \circ x(t_s) + U(i_g) \circ h(t_{s-1}) + W_i\ (c) * c_{ts-1} + b(i_g)) \quad (1)$$

$$f_g(t_s) = sigma(W(f_g) \circ x(t_s) + U(f_g) \circ h(t_{s-1}) + W_f(c) * c_{ts-1} + b(f_g)) \quad (2)$$

$$c_g(t_s) = f_g(t_s) * c(t_{s-1}) + i_g(t_s) * tanh(W(c) \circ x(t_s) + U(f_g) \circ h(t_{s-1}) + b(c)) \quad (3)$$

$$o_g(t_s) = sigma(W(o_g) \circ x(t_s) + U(o_g) \circ h(t_{s-1}) + W_o(c) * c_{ts-1} + b(o_g))) \quad (4)$$

$$h(t_s) = o_g(t_s) * tanh(c(t_s)) \quad (5)$$

2.2. The proposed cascade neural networks prediction model

The proposed method involves using the concept of cascade neural network model. It consists of the following steps: data collection, training phase to build the model that consists of two neural networks, feedforward neural network and recurrent neural network. This model has been used to predict the crude oil prices over long-term period with high accuracy and the final step was evaluating the created models through testing data. All of these steps are illustrated in Figure 1, and the carried-out steps are explicated in the sections that follow.

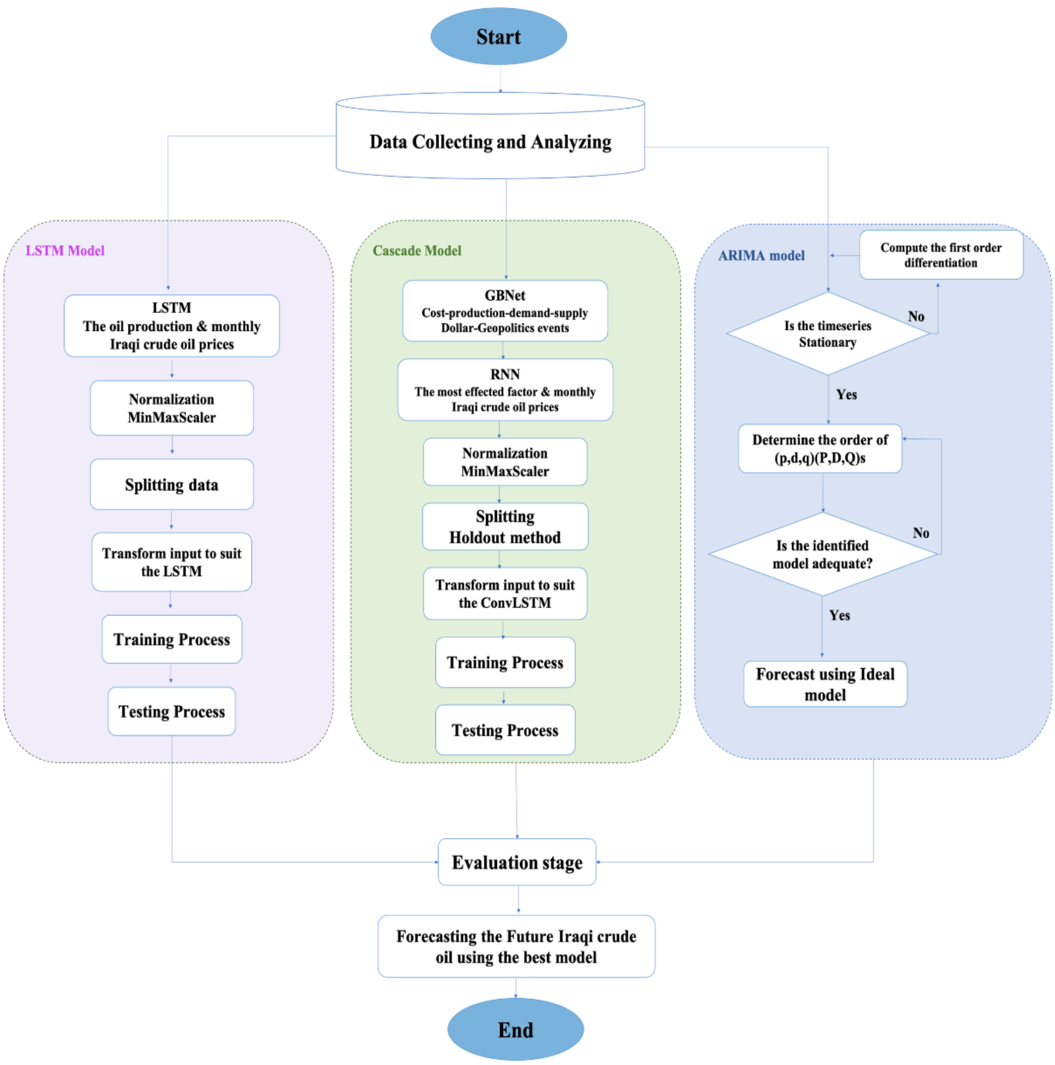

Figure 1. Proposed method for the prediction models

2.3. Data set collection and description

The first step started by collecting and analyzing the data, that implemented in parallel to crude oil prices analyze and situations prediction through observations and documentation. The next step was preprocessing the raw data to select the suitable required datasets. In this paper, we examine whether using several factors effecting the crude oil prices can help to improve the forecasting performance. We select the monthly Iraqi crude oil prices as research object and the sample period ranges from January 2009 to

December 2020. Iraqi crude oil prices are obtained from the Organization of the Petroleum Exporting Countries (OPEC), and the attributes as listed in Table 1.

Table 1. The data set description

Feature	Description	Source
Oil price	The monthly prices of the Iraqi crude oil in USD	[19]
World oil demand	Annual average of oil demand, Million barrel per a day	[19]
World oil supply	Annual average of oil supply, Million barrel per a day	[19]
Financial factor DOLLAR	The exchange rate of the Iraqi Diner against the US Dollar price	[20]
The Iraq oil production	Monthly average of oil barrel production, 1000 barrel per a day	[19]
Upstream cost	Producing cost of a single crude oil barrel	[21]
Geopolitical events	Outbreak of oil crises, major wars, and economic recession: 1: exciting; 0 : nothing	[22]

2.4. Training the proposed cascade neural networks

This research attempts to accurately predict the crude oil prices particularly the prices of the Iraqi oil by adopting in the two phases. First phase, in our model the irrelevant features can cause greater computational costs, greater utilization, also greater training time that may lead to over-fitting issues. Therefore, choosing good features is significant to reduce data dimensionality that will reduce the training time and the storage requirements.

Feedforward neural network (GBNet) has been used with six inputs (cost, production, world demand and supply, USD exchange rate and Geopolitics event) to address the most affecting factor on the prediction process, the architecture of the proposed GBNet consists of four layers, the mean square error has been set as fitness function. The transfer functions are the sigmoid function that used at the hidden layer and the linear function that used at the output layer. The final output produced the most affecting factor.

The adopted architecture in this project produces a sequential layer's structure in which the first layer is the input, and the last layer is the output. The first layer weights are not randomly initialized, but they are the feature importance of the gradient boosted tree that trained at the model initialization. In training model, data is fed completely as forward, while the layers weights are updated with respect to the gradient descent as backward propagation. After that instead of going to the following epoch of training process the algorithm moves through all the network layers and again updates the weights depending on the feature importance of the gradient boosted tree that trained at the network layers respectively. Furthermore, the trees are trained at the hidden layers during the forward propagation of the CBNet and their feature importance is stored which has been updated after the backward pass [23]. The proposed architecture of the Feedforward neural network consists of four layers as: input layer, two hidden layers, and an output layer as explained in Figure 2.

Second phase, the recurrent neural network (RNN) has been used to forecast the future Iraqi crude oil prices through using the most affecting factors that obtained from the first phase along with monthly oil prices. The architecture for the adopted model consists of ConvLSTM for memorizing and extracting the information of the input data, the ADAM optimizer [24] has been adopted for updating weights and bias, also mean square error has been set as fitness function, ReLU is the transfer function of the hidden layer and the linear function at the output layer. The structure of the model depicted in Figure 3. This phase has several steps.

2.4.1. Data preprocessing

Forecasting complex data such as crude oil prices is one of the numerous tasks in machine learning due to the irregularity, complexity, and non-linear nature of the data. Before building the model, data processing is carried out by selecting several aspects such as normalization and data partitioning that have been used to prepare the inputs.

- Normalization: many models work well with the normalized datasets. The normalized data also known as Min-Max scaler that adjusts data into (0 to 1) by using the minimum and the maximum value of the data [25] as obtained using (6). That scaling the instance to the range (0 and 1) in order to avoid the parameters of the model being dominated by small or large data range and to improve the accuracy and the CPU processing time [26].

$$\text{Normalized}_{\text{dataset}} = \frac{Raw_{dataset} - Minimum_{datasetvalue}}{Maximum_{datasetvalue} - Minimum_{datasetvalue}} \tag{6}$$

- Transforming the datasets to suit the model: convert the values array into data matrix using the timeseries data, the sequence of values is very important. Transform the sequence of crude oil prices into a matrix suitable for ConvLSTM training, the input data (X) expects in form (filters, kernel size, input shape, lookback) each oil prices transform to image, where the colors represent different oil prices, the lookback which is the number of the previous time steps that used as input variables for predicting the next time, in this project three and five time steps have been used [27].

– Data partition: the train-test split technique is used to build the predictor that estimate the performance of the model, since it used to give predictions on data that not used to train the used model before the Hold-out process has been used and according to this, the dataset has divided into two parts, one for training and the other part for testing. Predictions that obtained from the model compared with the actual data from the test set to evaluate the prediction accuracy [28].

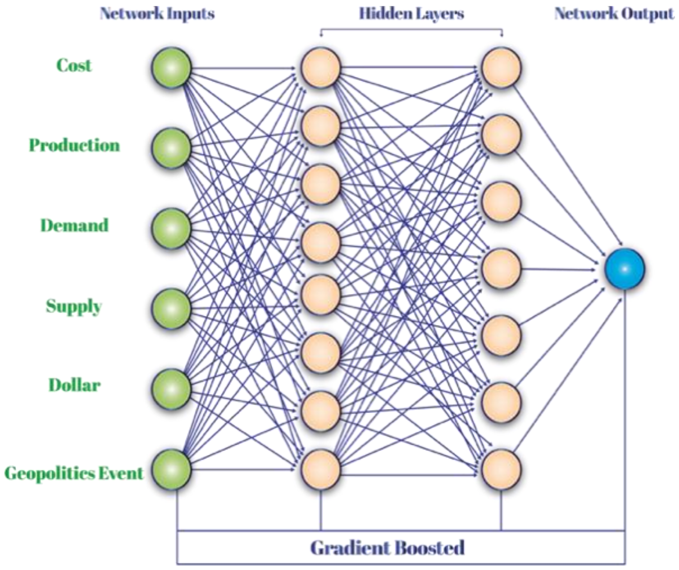

Figure 2. Sketch map of the proposed GBNet

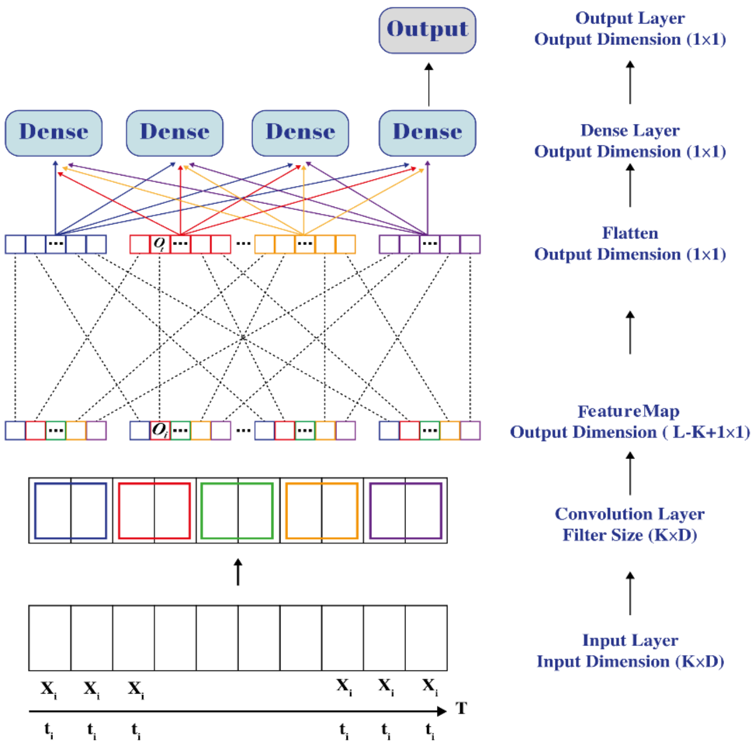

Figure 3. ConvLSTM neural network structure

2.4.2. Fitting the model to the training data

The model's composed of three main functional layers; the first is convolutional followed by flatten layer and the last layer is a fully-connected layers, the output of the first convolutional layer is the input of the fully-connected layer and neurons in the fully-connected layers are connected to all neurons. The outputs of the fully-connected layer which produces the predicted oil values over the true values. Following the model's construction, we move on to the training/learning step. The training process in this research using a convolutional layer with 64 filters using kernel size=1, flatten layer, and fully connected layer. Both the optimizer Adam and the loss function are used to evaluate and optimize the model during the training process to achieve the purpose of model optimization. Figure 4 depicts the training process's workflow.

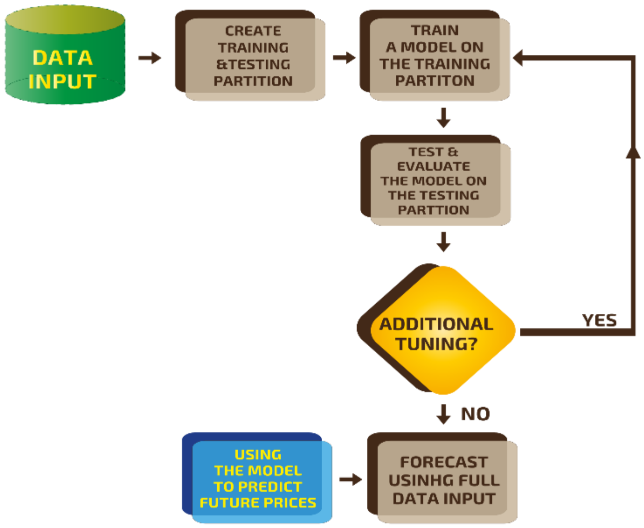

Figure 4. The training processes

2.5. Evaluating the models on the test data

There are several criteria for evaluating the learning result, which are related to the out-of-sample performance prediction. These criteria are involved in different aspects of the measuring techniques to ensure the model final performance that are important in predicting the crude oil prices. To evaluate the predictive performance of the model we employ mean absolute error (MAE) [29] in (7) and RMSE [30] in (8):

$$MAE = \frac{1}{n}\sum_{i=}^{n}|y_i - \tilde{y}_i| \tag{7}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=}^{n}(y_i - \tilde{y}_i)^2} \tag{8}$$

where (y_i) is actual Iraqi crude oil price values, $(\tilde{y}_i)$ the predicted Iraqi crude oil price values at time (i) and (n) is the numbers of predicted values.

2.6. Experimental setup

The training time that the proposed model takes for the first phase is around 3 minutes and around 2 minutes for the second phase. The number of epochs was set to 150 epochs and an early stopping technique was used to prevent over-fitting. The experiment in this research was implemented using Python version 3.8 and the Keras framework and runs on a MacBook Pro with an Intel Core i7 processor and 16 GB of memory.

3. RESULTS AND DISCUSSION

Here, we will evaluate our proposed effectiveness for improving forecasting accuracy. The compared models included, one classical time series method of ARIMA, and popular deep learning model of LSTM. To arrive at our result, the experiments were implemented using 150 epochs. First, before conducting the experiments we checked the dataset's volatility behavior, the result is illustrated in Figure 5.

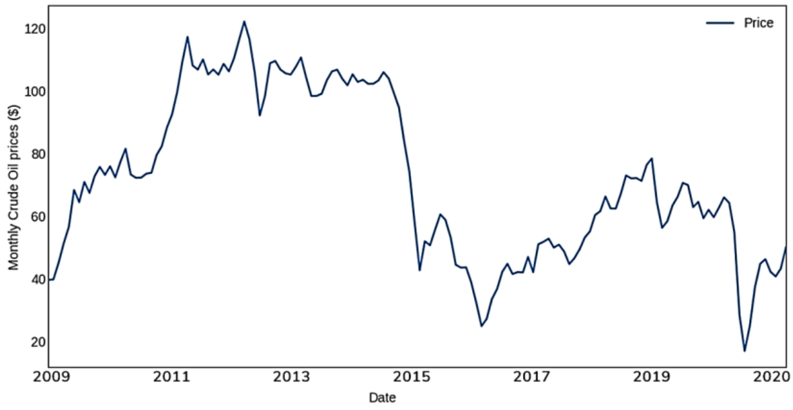

Figure 5. Fluctuations of Iraqi crude oil prices

3.1. Overall results

This section shows the result of the proposed model. At the first phase the model trained using Feedforward neural network and an optimization technique known as boosted gradient descent which initialized depending on the feature importance of the gradient boosted trees. That gives the idea to determine which attribute in a given set of features is the most useful. The result that obtains after training the model show the feature that has the biggest impact on the prediction process of Iraqi crude oil is the production. The feature importance of each factor shown in Figure 6.

After finding the most affecting factors that obtained from the first phase. We trained the model using the monthly Iraqi oil production amount along with the monthly Iraqi oil prices. Three percentages for splitting training and testing were used as shown in Table 2. We strictly followed the sequential order to split training and testing sets to avoid the data leaking problem.

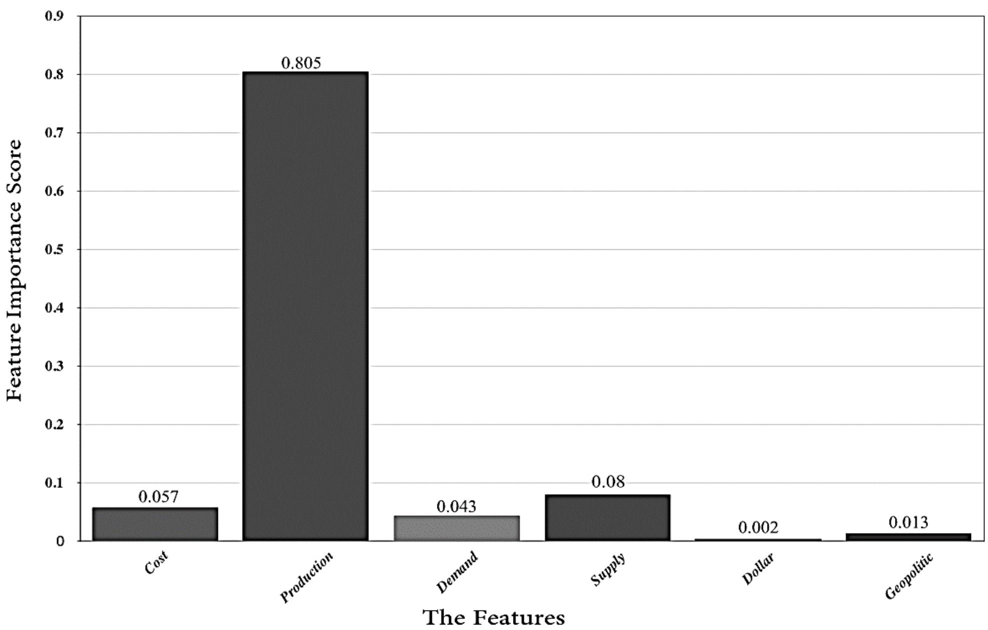

Figure 6. The feature importance of each factor

Table 2. Training and testing percentage

	Training	Testing
A	90%	10%
B	80%	20%
C	70%	30%

The results shown in Table 3 was obtained with the model using 3 previous time steps to predict the next month. The results shown in Table 4 was obtained with the model using 5 previous time steps to predict the next month. From Tables 3 and 4, we can see that the best result obtained from using 3 previous time steps to predict the next step. The loss function of model training and evaluation was calculated for every epoch. It describes the error in predictions. Plotting a graph gives us a good idea as to what is the benefit of each epoch. The loss function curve's trend from the first to the 150th iteration is depicted in Figure 7. The crude oil price is predicted using the cascade neural network model and the actual prices depicted in Figure 8. It can be inferred that the model adapts to the trend of the actual value. The model cannot predict sudden changes to the price value. This problem is faced during any of the time series forecasting issues. These changes likely happen due to the occurrence of some event in the real world.

Table 3. Metrics comparison for 3-time steps

Metrics	Cascade model-A	Cascade model-B	Cascade model-C
MAE	**0.05759**	0.07904	0.07904
RMSE	**0.08510**	0.09369	0.09369

Table 4. Metrics comparison for 5-time steps

Metrics	Cascade model-A	Cascade model-B	Cascade model-C
MAE	**0.05869**	0.09168	0.09228
RMSE	**0.09781**	0.12787	0.11795

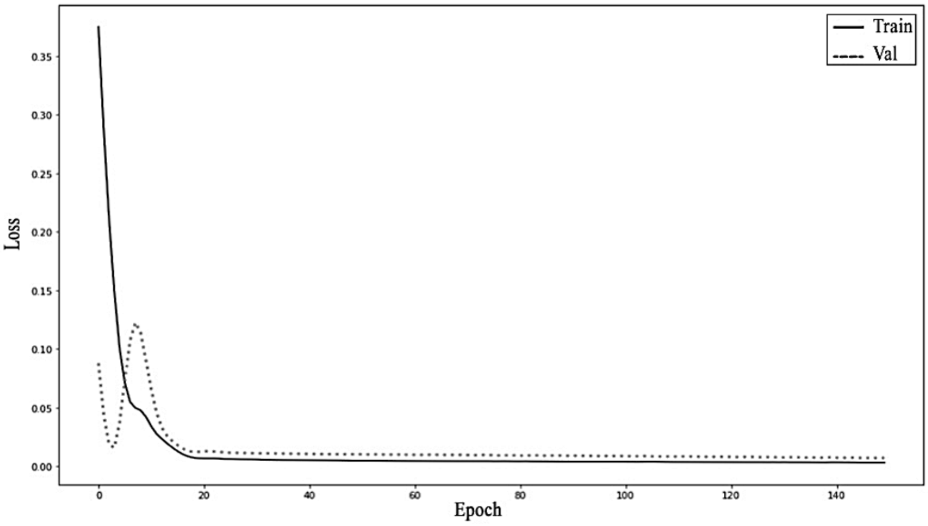

Figure 7. The training and validation loss per epoch

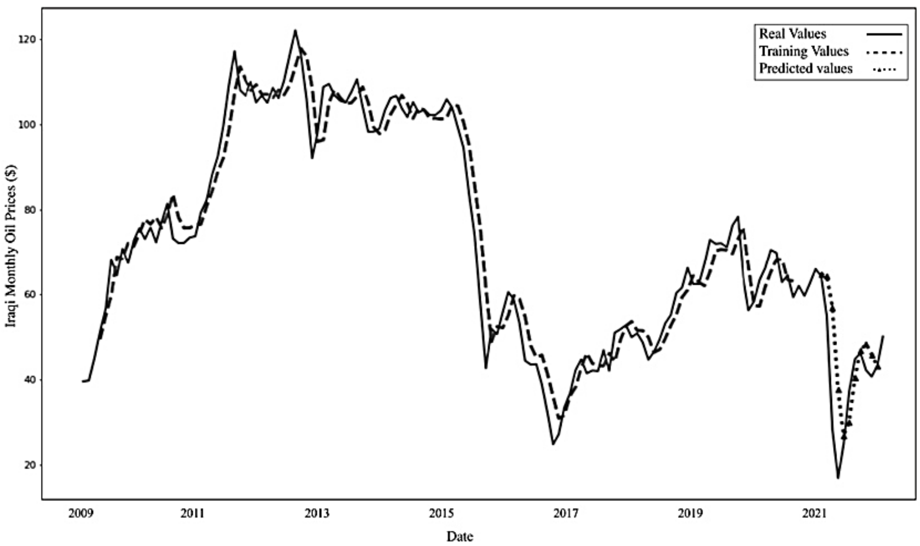

Figure 8. The forecasted and the actual crude oil price

3.2. Comparative the different models results

Our proposed model has been compared to other models using the same data samples. The performance results for predicting Iraqi crude oil prices using the three models are shown in Table 5, while Table 6 shows the effectiveness results. According to our findings, the proposed model obtains encouraging results and outperforms the previous state-of-the-art in all criteria. The prediction for Iraqi crude oil prices for 2021 using Cascade neural network are shown in Table 7.

From Tables 5 and 6, we can see that among all these models, the cascade model has the best performance on of MAE and RMSE metrics, which proves that this model can be used to solve difficult issues. Table 6 indicates that our cascade model has higher efficiency than LSTM during the training process, because it requires 70% less hyperparameters that need to be learned than the LSTM model. As a result, our cascade neural network model uses less training parameters comparing to the LSTM, which means it uses less resources of computing and storage as well as it executes and trains faster than LSTM's. While the ARIMA model has the worst performance and the results further confirmed that this model, does not perform well at both nonlinear and non-stationary time series problems.

Table 5. Predictive performance comparison

Metrics	Cascade model	LSTM model	ARIMA model
MAE	**0.05759**	0.16123	1.065
RMSE	**0.08510**	0.16587	1.181

Table 6. Comparison in the number of parameters

Method	Total Params
Cascade model	27,457
LSTM	83,265

Table 7. Iraqi crude oil prices forecasting for 2021 (Unit: $/Bbl)

Month	Crude oil price $	Month	Crude oil price $
Jan.	52.274345	Jul.	62.359043
Fab.	77.70367	Aug.	66.33245
Mar.	58.135868	Sep.	63.92885
Apr.	73.10502	Oct.	63.81816
May	60.927467	Nov.	64.59536
Jun.	69.12265	Dec.	61.882626

4. CONCLUSION

In this research the proposed solution to forecast the accurate Iraqi crude oil prices has been focused on investigating the effect of the other factors on the prediction process. The main purpose of the research was to deliver the idea of the cascade neural network model that uses the structure of the oil market (which will change in the present or future) as the prior information for determining the parameters. The adopted model takes the full advantages of using the convolution recurrent unit networks since the cascade model uses the LSTM for solving the problem of non-stationarity crude oil prices dataset and propagates non-linear crude oil prices dataset by adopting multi-layer neural networks. The main aim of this model is improving the accuracy of long-term crude oil prices predictions as well as assist the decision makers to minimize the risks that related to crude oil market. For future research activities can be expanded to investigate forecasting short-term price trends. To analyze the non-stationarity problem of daily data this method can be combined with complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) for solving the problem of non-stationarity crude oil price data, since the daily data is more complicated, because it is noisier than the monthly data.

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BIOGRAPHIES OF AUTHORS

Suhair A. Al-Hilfi received her B.Sc. degree in Computer Science from University of Basrah, Iraq in 2010. Currently, she is a Master's student in Computer Information System Department, College of Computer Science and Information Technology, University of Basrah, Iraq. Her research interest is data mining and machine learning. She can be contacted at email: suhair.alhilfi@gmail.com.

Maysaa Abd Ulkareem Naser is currently, a professor in Computer Information System Department, College of Computer Science and Information Technology, University of Basrah, Iraq. In 2001, she received her M.Sc. degree in Computer Science from Basrah University. She had lots of research published in scientific journals in the fields of natural language processing, image processing, and expert systems, machine learning. Her research interests include artificial intelligence. She can be contacted at email: maysaa.naser@uobasrah.edu.iq.