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Predicting Public Budget Surplus and Deficit Using a Hybrid 1D-CNN–LSTM Model

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Abstract The fiscal position of governments in rentier economies depends heavily on oil revenues. The relationship between oil prices and the budget surplus or deficit is often nonlinear and characterized by complex temporal dependencies, which may limit the predictive capability of conventional econometric models. Accordingly, this study aims to forecast the Iraqi budget surplus and deficit and compare the predictive performance of the ARDL, NARDL, LSTM, 1D-CNN, and hybrid 1D-CNN-LSTM models using oil prices as the primary predictive variable. The hybrid model integrates the feature-extraction capability of One-Dimensional Convolutional Neural Networks (1D-CNN) with the ability of Long Short-Term Memory (LSTM) networks to capture long-term temporal dependencies. The analysis is based on monthly Iraqi data covering the period 2008-2025 (216 observations), with the final year reserved for out-of-sample testing. Model performance was evaluated using the Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Directional Accuracy (DA), and the Diebold-Mariano test. The results confirm the existence of a long-run equilibrium relationship between oil prices and the fiscal surplus/deficit under both the ARDL and NARDL models. The NARDL model further reveals asymmetric effects of positive and negative oil price shocks. In terms of predictive performance, the hybrid 1D-CNN–LSTM model outperformed all competing models, achieving the lowest out-of-sample RMSE(4.008) and the highest DA (0.636). The Diebold-Mariano test also indicates statistically significant superiority of the hybrid model over the NARDL and 1D-CNN models. These findings suggest that the hybrid 1D-CNN-LSTM model provides a more effective framework for modeling the nonlinear and dynamic relationship between oil prices and the fiscal surplus/deficit, making it a promising tool for fiscal forecasting and policy support in oil-dependent rentier economies such as Iraq.

Keywords deep learning forecasting, predicting surplus and deficit, oil price, 1D-CNN, LSTM, 1D-CNN-LSTM

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1. Introduction

In oil-dependent economies, fiscal policy plays a pivotal role in mitigating economic fluctuations and enhancing overall macroeconomic stability. The public government budget represents the main backbone and fundamental pillar of this policy, as it can be regarded as a key instrument for guiding economic activity, achieving fiscal stability, and driving the development process. Accordingly, forward-looking planning of the public budget is of crucial importance for understanding the government's fiscal performance, particularly in terms of budget surpluses and deficits [1]. A deficit is defined as the gap between expenditures and revenues over a specific period and occurs when spending exceeds revenues for the same period. Conversely, a surplus occurs when revenues exceed expenditures [2]. The issue of budget surplus and deficit acquires an exceptional dimension and becomes a top priority for rentier economies, as the government's fiscal position depends heavily on oil revenues, which are characterized by high volatility due to fluctuations in oil prices, in addition to changes in market shares and export-allocated quantities. This, in turn, is directly reflected in the stability of the public government budget [3]. In this respect, volatility of oil prices and ineffective management of resources, especially in instances of increasing items of ineffective and unproductive expenditures, can be said to be the causes of budget deficits of the rentier economies [1]. As a special

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case of rentier economies, the Iraqi economy has, for decades, relied heavily on oil revenues to finance government obligations as well as to provide foreign exchange. The public government budget is planned on the basis of a benchmark crude oil price and specified quantities in line with the market shares determined by the Organization of the Petroleum Exporting Countries (OPEC). However, such planning is often carried out without sufficient attention to the development of other economic sectors that could contribute to maximizing non-oil revenues. As a result, the Iraqi economy has remained persistently exposed to the risks associated with oil price volatility, which in turn have far-reaching effects on fiscal operations and macroeconomic policies. Within this framework, successive governments often face fundamental challenges in managing expenditures and financial obligations, as fluctuations in oil prices are directly reflected in the level of public revenues and, consequently, in the realization of a surplus or the occurrence of a deficit. Moreover, the heavy dependence of public revenues on the oil sector, together with the dominance of relatively rigid current expenditures, such as wages, subsidies, and transfers, within the structure of the public budget, generates complex and nonlinear dynamics in the surplus/deficit series. Such interactions increase the difficulty of accurately modeling and forecasting the government's fiscal position using conventional econometric approaches.

This fact raises questions about the nature of the fiscal response to such fluctuations and about how the relationship between oil prices and budget surpluses or deficits can be modeled? The dynamics of oil prices and their impacts on fiscal policy have been modelled in many studies under the assumption of symmetric relationships. However, recent evidence suggests that macroeconomic variables often exhibit nonlinear and asymmetric responses to oil price changes, which may generate either expansionary or contractionary effects on a country's fiscal position. Accordingly, the common assumption that increases in oil prices necessarily lead to improvements in the fiscal position of oil-exporting countries may not always be true [4]. The government can react to positive shocks (increasing oil prices) with excessive optimism, increasing spending and loosening fiscal restraint on the assumption that these will continue. Such a tendency may eventually result in fiscal deterioration and fiscal deficits in the event of unexpected negative shocks. On the other hand, the decreases in oil prices can lead to more prudent and responsive policy actions to prevent fiscal deficits and reduce dependence on public debt instruments, which will raise government balances and possibly lead to a surplus. Based on this, it can be concluded that the association between oil prices and the fiscal stance of the general government budget might not be stable and symmetric because the shape of the association-or the fiscal policy reaction-changes with the direction and character of oil price shocks. Against this complex backdrop, the inadequacy of classical econometric models, including the Autoregressive Distributed Lag (ARDL) model, becomes evident in explaining the relationship between oil prices and the fiscal position or in predicting its trajectory. This inadequacy stems from assumptions of linearity, parameter stability, symmetric responses, and restrictive error-term properties, as well as from the limited capacity of such models to capture the intricate interactions and behavioral dynamics between oil prices and the government's fiscal stance [5]. However, these restrictions can be partially lifted by using the Nonlinear Autoregressive Distributed Lag (NARDL) model [6], which can be used to decompose the changes in oil prices into positive and negative components, and thus test the asymmetric effects in both the short and long-term. The rationale behind the inclusion of this model is both theoretically and empirically justified because both theoretical and empirical evidence have indicated that the fiscal policy reaction in rentier economies such as Iraq could differ with the direction of oil price shocks. It should be noted that the NARDL model and the hybrid 1D-CNN-LSTM model perform different analytical roles within the framework of the study. While the NARDL model is primarily employed to analyze the asymmetric responses of the fiscal position to positive and negative oil price shocks, the hybrid model is used as a flexible forecasting framework aimed at learning nonlinear temporal patterns and complex dynamics directly from the data, without imposing a predefined asymmetric structure.

Nevertheless, even though it is more developed than the linear ARDL model, the NARDL model still belongs to the category of parametric econometric models, although in a nonlinear form, since it presupposes a certain functional form of the relationship between variables [7]. Since the relationship between oil prices and the fiscal position of the government is complex and nonlinear, especially when trying to predict the series of budget surplus/deficit, such models might not be adequate to represent time-varying dynamics and the complex interactions between economic variables [8]. Accordingly, there is a need to adopt more flexible modeling approaches with a stronger capacity to learn from data, in order to improve the accuracy of forecasting the government's fiscal position based on oil

price fluctuations. This, in turn, paves the way for the use of deep learning models such as the 1D CNN–LSTM. Based on this, the present study adopts a comparative framework that includes linear models (ARDL), nonlinear parametric models (NARDL), and machine learning models, with the aim of evaluating their ability to forecast the budget surplus/deficit series and identifying the most efficient model in capturing the relationship between oil prices and the government's fiscal position. In light of these challenges, machine learning (ML) models such as the Long Short-Term Memory (LSTM) model have emerged as powerful tools that have reshaped the landscape of macroeconomic forecasting by addressing many of the limitations of conventional econometric models. A key advantage of these approaches lies in their ability to identify nonlinear patterns and complex interactions among economic variables, particularly in dynamic environments, without relying on restrictive parametric assumptions, as is typically required in traditional models [9, 10], Moreover, Convolutional Neural Networks (CNNs) are considered one of the effective tools for modeling complex short-term features and patterns in time series data [11].
Based on the above, this study is based on the existence of a structural economic relationship between oil prices and the surplus/deficit of the Iraqi economy due to the high dependence of public revenues on the oil sector. Against this backdrop, this study proposes to enhance the forecasting performance of the government budget surplus/deficit series by designing a hybrid model that combines a One-Dimensional Convolutional Neural Network (1D-CNN) to capture short-term temporal patterns from oil prices and model the volatility and impact of oil prices on the government's fiscal position, with a Long Short-Term Memory (LSTM) network to capture cumulative effects and long-term temporal dependency using both the short-term temporal pattern features extracted by 1D-CNN and the historical values of the government budget surplus/deficit series. Accordingly, the research question focuses on evaluating the forecasting ability of conventional econometric models and different deep learning models, namely the ARDL model, the NARDL model, the 1D-CNN model, the LSTM model, and the hybrid 1D-CNN-LSTM model, in forecasting the government budget surplus/deficit series in Iraq. To achieve this objective, these models are compared using a set of forecasting performance measures and evaluation tests, including Root Mean Squared Error (RMSE), the Directional Accuracy Test, and the Diebold–Mariano test, with the aim of identifying the model that is most capable of providing accurate and effective forecasts.

2. Literature review

According to the literature, there is increasing attention towards studying the relationship between the oil revenues and financial variables in the oil-dependent nations. A study by (Monjazeb et al.) revealed the effect of oil revenues on budget deficit in several oil-exporting countries, and the results revealed that oil revenues had a negative impact on the deficit and the impact was statistically significant in certain countries. The role of the gross domestic product (GDP) in cutting the deficit was also emphasized in the study with the effect of taxes being relatively weak [12]. Similarly, (Fasano & Wang) investigated how government expenditure and public revenues are related in the Gulf Cooperation Council (GCC) states. The results proved that there was a long run equilibrium relationship and causality of one way, i.e., revenues to expenditure, which showed that government spending depends on oil revenues [13]. Similarly, a study by (Vohra) examined the impact of oil price fluctuations on the budget deficit and economic growth, showing that a decline in oil prices leads to a widening deficit and a deterioration in the current account [14]. In Iraq, (Kadhim) conducted a study to establish the effect of oil price changes on the populace budget by using a multiple regression model. The outcomes indicated that a one-dollar fall in the price of a barrel of oil produces a loss of more than a billion dollars, thereby exacerbating the budget deficit and negatively affecting investment expenditure [15]. Another study conducted by (Makhanets) aimed to forecast the budget deficit in Ukraine using exponential smoothing and acceleration analysis methods. It was observed that inadequate public financial management contributes to increased deficit which underscores the need to use forecasting models to ensure the fiscal policy decisions are made and the adverse impacts prevented [16]. While the literature has shed light on the link between oil revenues and budget deficits through a number of econometric models and forecasting techniques, most of the studies in the literature were based on traditional parametric models that assume stability of the economic relationship or the specification of the functional form. In recent years, the complexity of the economic and financial interactions, the appearance of nonlinear patterns and recurrent changes in the structure of the relationships, have focused the attention on the development of more flexible models, both in the advanced parametric models and in nonparametric models, to better represent the evolving dynamics of economic and financial relationships. These methods include the Time-Varying Parameter (TVP) models which allow for the variation of the model parameters as a function of time, instead of being constant. This is done in a dynamic probabilistic framework that allows to monitor the evolution of the parameters over time [17]. As an extension of these approaches, models combining regime switching and dynamic parameter variation were developed, such as Markov-Switching (MS) models [18], and hybrid models such as the Markov-Switching Autoregressive (MSAR) model. These models allow for economic relationships to switch between regimes (such as normal and crisis) with certain probabilities, allowing for abrupt changes [19]. Furthermore, models like (MSAR-TVP) combine dynamic changes within regimes with sudden shifts between regimes, in order to better capture the dynamics of the economy and to enhance forecasting accuracy [20]. Other research has also tackled the representation of Structural instability based on the (Bai-Perron) test for structural breaks in time series, by assuming that parameters are changing at some dates, where changes are assumed to be abrupt at some dates [21]. However, though these methods are very important in modelling nonlinearity, asymmetry and structural change, they have yet to be used widely outside the context of the traditional econometric model, which assumes the structure of the economic relationship or the mechanism of the time-varying parameters a priori. This can impair their capacity to capture the multi-faceted and ever-changing nature of economic time series, especially in rentier economies that rely on oil and are highly volatile and dynamic. Moreover, these models demand, to different extents, an a priori specification of the mathematical form of the relationship to be estimated, which may not be adequate when the temporal patterns are complex and nonlinear, and hard to describe in the traditional econometric framework. Given these constraints, recent studies have increasingly focused on the use of machine learning and deep learning models as more flexible and data-driven methods which can better capture the complexity of economic relationships and nonlinear temporal patterns while also improving forecasting accuracy over traditional models.

As the methods of quantitative modeling have rapidly developed, the recent literature has shifted towards the use of machine learning and deep learning models to enhance the precision of predictions of financial and economical phenomena. An experiment conducted by (Hellwig) assessed the predictive capability of econometric models and machine learning methods of financial crisis based on data of 188 countries between the (1979-2015). The results indicated that machine learning models, especially random forests and gradient boosting, are more effective in predicting out-of-sample than the traditional econometric models [22]. A recent literature review by (Chen et al.) highlights that hybrid deep learning models (e.g., CNN-LSTM and CNN-LSTM-AM) tend to achieve better results than standalone models in predicting financial time series [23]. A research study by (Moodi et al.) suggests a hybrid model to predict stock price fluctuations, comprising of deep learning architecture CNN, GRU, and LSTM, by enhancing feature extraction with modeling of short- and long-term temporal relationships. The results indicated that the proposed model performed better compared to standalone models which shows its effectiveness in enhancing the accuracy of financial market trend prediction [24]. Similarly, (Hoa et al.) proposed a hybrid model combining one-dimensional convolutional neural networks (1D-CNN) and long short-term memory (LSTM) networks to forecast the closing prices of Ethereum. The model tries to focus on the non-linear and dynamic characteristics of crypto currency data by modelling local trends and time-dependent relationships. The experimental results revealed that the hybrid model was much more effective in comparison to standalone models (LSTM and 1D-CNN), which demonstrated that the hybrid model is highly efficient in enhancing the accuracy of predictions in highly volatile financial markets [25].

Although hybrid deep learning models are widely adopted for forecasting financial time series, especially in the stock and crypto currency markets, their application to the public finance sector is still relatively small, especially in studying the predictive relationship between oil price fluctuations and the fiscal position balance (surplus or deficit), particularly in rentier economies that depend heavily on oil revenues. Therefore, the study gap is the few applied studies that have investigated this relationship with hybrid deep learning models. The aim of this research is to fill this gap by proposing a more accurate forecasting framework that considers the nonlinear and dynamic nature of these variables.

3. Methodology

3.1. Deep learning models

In deep learning models, Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are among the most common and most effective deep learning algorithms. The Long Short-Term Memory (LSTM) model is the most prominent architecture within recurrent neural networks [26]. Experimental studies have also shown that hybrid deep learning models achieve higher predictive performance compared to traditional statistical models or classical machine learning models [27].

3.1.1. Convolutional Neural Networks – CNN

The CNN structure was designed by(LeCun et al.) [28], for automatic pattern recognition, especially for handwritten characters and digits by the automatic capture of latent aspects of the data. The architecture processes data in the form of two-dimensional (2D) grids (images and videos). Therefore, 2D-CNNs cannot be used in order to forecast or analyze the time series-like one-dimensional signals. To address this limitation, a class of one-dimensional convolutional neural networks (1D-CNNs) emerged. The typical architecture of the one-dimensional convolutional neural network (1D-CNN) illustrated in Figure (1) consists of three main layers: one-dimensional convolutional layers (1D convolutional layers), pooling layers, and fully connected layers, along with two fundamental components, namely the dropout layer and the activation function [29], as follows:

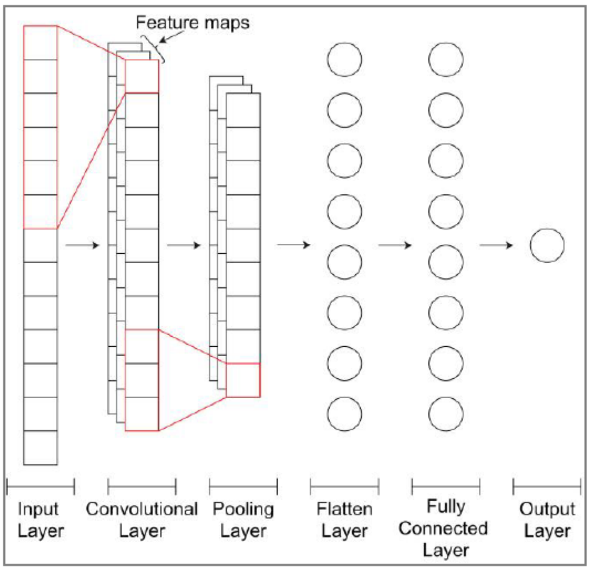


Figure 1. The structural architecture of a one-dimensional Convolutional Neural Network (1D-CNN) [30]

- The one-dimensional convolutional layer operates by detecting features and patterns in the input data represented as a vector $X[n]$, where $n = 0, 1, \ldots, N-1$. The operation of this layer depends on the following parameters:

1. Filters or kernels: generate feature maps, where feature maps are the outputs obtained by applying a single filter to the previous layer through performing the convolution operation on the input data. The size and number of kernels influence the feature extraction process. Assuming that $k[n]$ represents a convolution kernel of size ϑ , the convolution output $\zeta[n]$ is computed according to the following expression [29, 31]:

$$\zeta[n] = x[n] * k[n] = \sum_{m=0}^{\vartheta-1} k[m].x[n-m] \ \ , \ n = 0, 1, ..., N-1 \tag{1}$$

The convolution operation is represented by the symbol $(*)$.Overall, the extracted features at the output of layer l can be mathematically represented as follows:

$$\zeta_i^l = \sigma\left(b_i^l + \sum_j \zeta_j^{l-1} . k_{ij}^l\right) \tag{2}$$

Where ζ_i^l refers to the i-th feature in layer l, while ζ_j^{l-1} denotes the j-th feature in layer $l-1$. The term k_{ij}^l represents the kernel that connects the i-th feature to the j-th feature, and b_i^l denotes the bias term associated with these features. The symbol σ refers to the activation function.

2. Activation function: The activation function is used to learn and approximate any type of continuous, complex, and extended relationships among the network variables. There are several types of activation functions, the most prominent of which are the Rectified Linear Unit (ReLU), Softmax and Sigmoid functions. In this study, the Exponential Linear Unit (ELU) activation function is adopted, which is derived from the ReLU function. It includes an additional constant αthat controls the smoothness of the function when the inputs are negative. ELU is also characterized by its ability to accelerate the convergence of the loss function toward zero, in addition to providing more accurate results. It is mathematically defined as follows [32]:

$$R(\zeta) = \begin{cases} \zeta & if \;\; \zeta > \; 0 \\ \alpha . \exp(\zeta - 1) & if \;\; \zeta \leq \; 0 \end{cases} \quad , \alpha > 0 \tag{3}$$

- Stride: It determines how the convolution kernel moves over the input data. The most common value is one, which means that the kernel moves across the input data by one column at each iteration [33].
- Pooling Layer: This layer is placed immediately after the convolutional layer. Its function is to reduce the size of the feature map produced by the convolution operation, which means retaining the most informative features without redundancy. Moreover, this reduction contributes to accelerating the training process. There are several types of pooling operations, such as max pooling, average pooling, and sum pooling [34].
- Flatten layer & dropout layer: The flattening layer converts the input data into a one-dimensional vector to be passed to the fully connected layers. The dropout layer is used to overcome the problem of Overfitting when connecting all features to the flattening layer. During the dropout process, a number of neurons are randomly deactivated during training according to the rate specified by the dropout parameter. The purpose of this procedure is to reduce model complexity and improve its generalization capability [31].
- Dense fully connected layer: The inputs to this layer are the outputs from the previous layer (the flattened output). It processes the flattened representation and re-maps it in a way that is suitable for the nature of the problem. This layer can be regarded as the output layer if it is the final layer in the CNN architecture. In general, the operation of this layer can be represented as follows:

$$\text{output} = \sigma\left(< input, w_d > + b_d\right) \tag{4}$$

Here $<$ input, $w_d >$ refers to the inner product between the weight vector w_d and the input vector, b_d represents the bias vector of this layer, and the symbol σ refers to the activation function [31].

3.1.2. Long Short-Term Memory - LSTM

Long short-term memory LSTM model is an extension of Recurrent Neural Networks (RNN), which was first proposed by (Hochreiter & Schmidhuber) [35], and was later improved by(Gers & Schraudolph) [36], and further refined by (Greff et al.) [37]. The LSTM model was created to solve the vanishing gradient problem, which is caused by neural network weights variation as training progresses, and hence, makes traditional Recurrent Neural Networks (RNNs) unsuitable to learn long and sequential temporal dependencies in data. Contrarily, LSTM networks have the capacity to handle sequential data and they are able to remember information at a previous step along the sequence thus making them quite effective in predicting the next steps. This characteristic renders LSTM especially ideal in modeling and extracting long-term time information [38].

The (LSTM) model is characterized by having a more complex architectural structure compared with traditional neural networks. As shown in Figure (2), every LSTM unit in the model includes a Memory Cell, which is represented by the symbol (C_t) , as well as three types of gates, the forget gate (f_t), the input gate (i_t), and the output gate (o_t). All these gates work together to regulate the flow of information both in and out of the unit. This process allows to manage the long-term dependencies in the time series through selective information updating or information retention over time [39]. The mathematical formulas for the gates and the LSTM structure can be expressed as follows [40]:

$$f_t = \sigma(W_{fx}x_t + W_{fh}h_{t-1} + b_f) \quad (5)$$

$$i_t = \sigma(W_{ix}x_t + W_{ih}h_{t-1} + b_i) \quad (6)$$

$$o_t = \sigma(W_{ox}x_t + W_{oh}h_{t-1} + b_o) \quad (7)$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \quad (8)$$

$$\tilde{C}_t = \tanh(W_{cx}x_t + W_{ch}h_{t-1} + b_c \quad (9)$$

$$h_t = o_t \odot \tanh(C_t) \quad (10)$$

The (f_t, i_t, o_t) represents the forgetting gate, the input gate and the output gate respectively, and the symbol σ represents the sigmoid activation function and is defined as follows:

$$\sigma(x) = 1/1{+}\mathrm{e}^{-\mathrm{x}} \quad (11)$$

$(W_{fh}, W_{ih}, W_{oh}, W_{ch})$ represent the correlated weight matrices for the three gates and the cell state, respectively; $(W_{fx}, W_{ix}, W_{ox}, W_{cx})$ represent the input weight matrices for the three gates and the cell state, respectively; (b_f, b_i, b_o, b_c) are bias coefficients associated with each gate and the cell state and $(C_t, C_{t-1}, \tilde{C}_t)$ represent the current cell state, the previous cell state, and the candidate cell state respectively. The forget gate defines how much historical information to forget of the previous cell state C_{t-1}, the input gate defines how much it should extract out of the current candidate cell state $(\tilde{C}_t)$ and pass it to the current cell state C_t, and the output gate defines how much the cell outputs should be passed to the rest of the network.

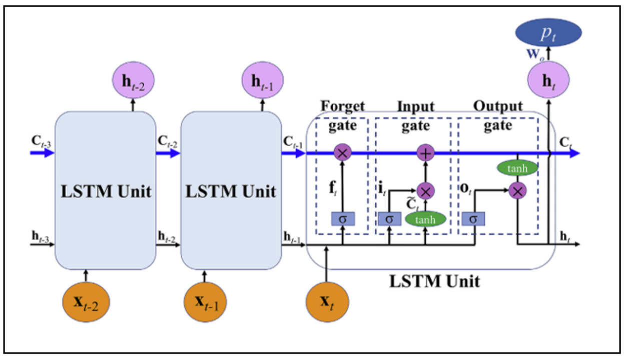


Figure 2. Structures of long short-term memory (LSTM) [41]

3.2. Proposed model 1D-CNN-LSTM

The proposed model is based on integrating a CNN model with an LSTM architecture through three consecutive stages. The first stage involves employing one-dimensional convolutional neural networks (1D-CNNs), in which the convolutional layers of the CNN, with the aid of convolutional kernels, perform short-term linear convolution operations. The outputs of the convolutional layer are then represented as feature maps, which constitute a compact representation capturing local latent and nonlinear patterns in the input time series. These patterns include oil price shocks and the manner in which the fiscal position responds to such shocks or fluctuations, as well as short-term dynamics that are unlikely to be adequately modeled using conventional econometric methods. Subsequently, the feature maps are passed to a pooling layer, with the aim of transforming them into a more structured and less noisy

feature space, in preparation for feeding this space into the LSTM architecture.
Mathematically, after applying the convolution operation in Equation (1), the extracted local features are represented as feature maps generated by the convolution kernels. The output of the convolutional layer can therefore be expressed as:

$$H = [h_1, h_2, h_3, \ldots, h_T] \tag{12}$$

Where H denotes the sequence of extracted feature maps, and T' represents the transformed temporal dimension after the convolution and pooling operations. Since multiple convolution filters are employed, each temporal feature vector contains the responses of all convolution filters and can be represented as:

$$H = [h_{t1}, h_{t2}, h_{t3}, \ldots, h_{tF}] \tag{13}$$

Where F denotes the number of convolutional filters, and each element h_{tf} represents the extracted response of filter $f - th$ filter at time step t Accordingly, the generated feature maps are reorganized into a sequential temporal representation before being passed to the LSTM architecture. Thus, the input to the LSTM layer is represented as:

$$(h_1, h_2, h_3, \ldots, h_T) \rightarrow \textit{LSTM} \tag{14}$$

This allows the LSTM network to capture long-term temporal dependencies and cumulative dynamic effects based on the local temporal patterns extracted by the 1D-CNN component.
The second stage involves feeding the aforementioned features into the LSTM architecture to model long-term temporal dependence and the dynamic relationship between oil prices and the government's fiscal position. This process is carried out through the structural framework of the LSTM network, which consists of internal memory and control gates, allowing the cumulative effects of oil price fluctuations on the fiscal position to be tracked and selectively retained. At the same time, the LSTM mechanism filters out information that is irrelevant or less important. The last step of the hybrid model concludes by transforming the temporal representations and patterns learned during the training process into final predictive value(s) for the budget surplus and deficit series. This is accomplished by projecting the outputs of the LSTM network onto a dense output layer, which performs a linear transformation of the learned temporal representation using an ELU activation function, subject to the Mean Squared Error (MSE) objective function. The following diagram illustrates the working mechanism of the proposed CNN–LSTM model.

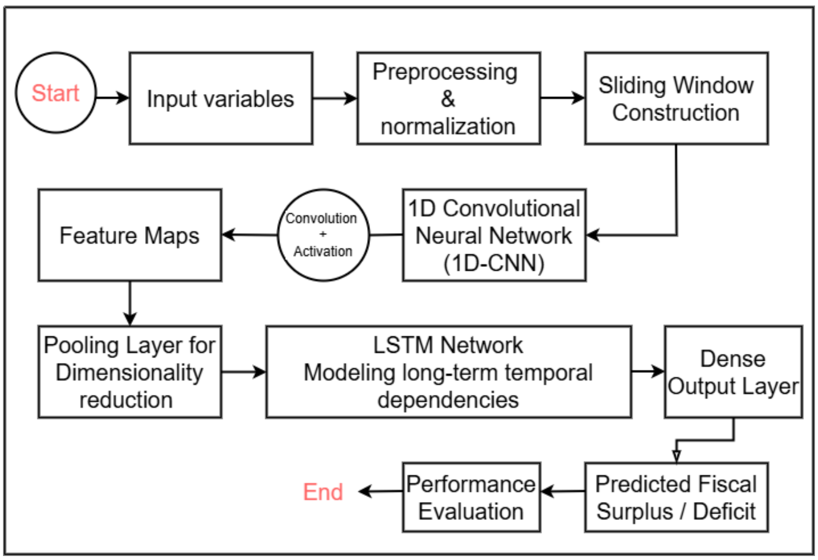


Figure 3. illustrates the methodology of the CNN-LSTM hybrid model

4. Result and discussion

4.1. Data

This study employs monthly data from the Iraqi economy covering the period 2008-2025, yielding 216 observations. The analysis is based on two variables: oil prices (measured in U.S. dollars) as the explanatory variable and the budget surplus/deficit (measured in trillion Iraqi dinars) as the response variable. The data were collected from the official database of the Central Bank of Iraq.For the purpose of developing and evaluating the forecasting models, the dataset was divided into three subsets: 86% for training, 8% for validation, and the final year of the sample (2025) was reserved as an out-of-sample testing period, representing approximately 6% of the total observations. The same data-splitting procedure was applied consistently across all competing models, namely ARDL, NARDL, LSTM, 1D-CNN, and the hybrid 1D-CNN-LSTM model.

4.2. ARDL Model Results

Since testing is deemed in order to determine the stationarity prior to the development of econometric models, (KPSS) was tested on the oil price series as well as the surplus/ deficit series. Table (1) indicates that both the level test values of both variables are less than the critical values at the (%5) level and hence the null hypothesis of stationarity is not rejected. Based on this, both variables will be stationary at level, i.e. they will be integrated of order zero, $I(0)$, which will enable the variables to be used directly in the further analysis.

Table 1. KPSS Test Results for the State's Fiscal Position and Oil Prices Variables

Variables	**Level**		**Integration Degree**
	LM-Stat.	**Critical Value**	
Oil Price	0.308	0.463	I(0)
Surplus/Deficit	0.351	0.463	I(0)

Note: The critical value is reported at the 5% significance level.

The ARDL model was estimated to form a conventional econometric method of estimating and modeling the relationship between oil prices and the fiscal surplus/deficit, with the purpose of predictions and comparison with the 1D-CNN-LSTM model and evaluating the performance efficiency of both models. According to the Akaike Information Criterion (AIC), the ARDL(2, 3) model was chosen under a constant term as the best specification. The coefficient of determination R^2 was (0.26) which had a weak explanatory power of the model. The F-Bounds test statistic value was (88.88), and this is more than the critical values at the 5% significance level, and this implies that there is a long-run equilibrium relationship that exists between the variables. The estimation outcomes also indicated a positive and statistically significant impact of oil prices in long run. Alongside, the estimated value of the error correction coefficient reached (-1.615) at a statistical significance level of (0.000), indicating the presence of a strong adjustment mechanism. However, the fact that the coefficient exceeds unity in absolute value suggests an overshooting adjustment pattern. This can be interpreted within the context of the Iraqi economy, where sharp fluctuations in oil revenues lead to non-gradual fiscal responses characterized by rapid expansion in public spending during periods of high oil prices, followed by the adoption of sharp corrective measures when prices decline. Such a pattern of fiscal adjustment may result in a temporary overshooting of the equilibrium level before returning to it again, reflecting the cyclical and irregular nature of fiscal policy in rentier economies, particularly the Iraqi economy. To assess the adequacy of the estimation and verify that the assumptions of the econometric model are satisfied, Table (2) presents the results of the diagnostic tests, as follows:
The results reported in Table (2) indicate the absence of residual serial correlation based on the Breusch-Godfrey test. In addition, The results of both the Breusch-Pagan-Godfrey and White heteroskedasticity tests indicated the presence

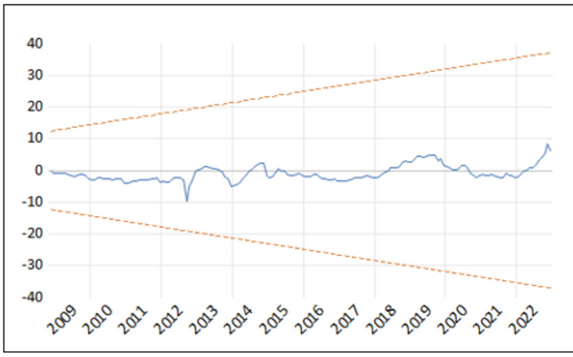
of heteroskedasticity in the model residuals, as the associated probability values were below the 5% significance level. Consequently, the null hypothesis of homoskedasticity was rejected, confirming that the residual.

variance is not constant across observations. Also, the null hypothesis of normality of the residuals was rejected based on the Jarque-Bera test. Therefore, robust standard errors based on the HAC (Newey-West) estimator were employed in order to improve the reliability of statistical inference under the potential violation of some conventional residual assumptions. It should be noted that the use of robust standard errors does not alter the estimated parameter values or the forecasting performance of the model, but rather affects the estimation of standard errors, t-statistics, and their associated probability values. Furthermore, Figure (4) presents the CUSUM and CUSUM-Square tests, which indicate the presence of some potential fluctuations in the stability of the model parameters over time. Overall, these results suggest that the ARDL model is capable of explaining the fundamental relationship between the variables; however, it may be limited in capturing nonlinear behavior.

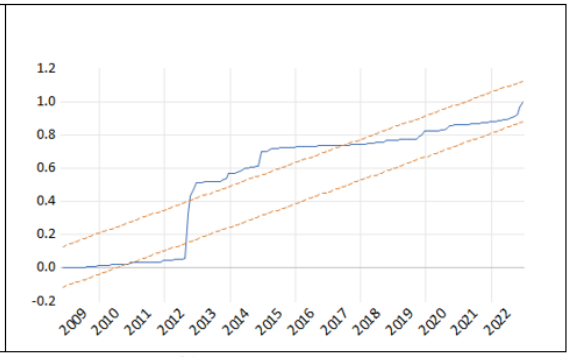
Note: Probability values are reported at the 5% significance level.

Table 2. presents the results of the diagnostic tests for the ARDL model.

Diagnostic Test	**Statistic**	**Value**	**Probability**
Breusch–Godfrey Serial Correlation LM Test			
F-Statistic	Prob(F)	0.360	0.698
Obs*R-squared	Prob(χ^2)	0.755	0.685
Ramsey RESET Test			
F-Statistic	Prob(F)	0.0.392	0.148
Likelihood Ratio	Prob(χ^2)	46.750	< 0.0001
Breusch–Pagan–Godfrey Heteroskedasticity Test			
F-Statistic	Prob(F)	5.417	< 0.0001
Obs*R-squared	Prob(χ^2)	28.409	< 0.0001
Scaled Explained SS	Prob(χ^2)	300.2	< 0.0001
White Heteroskedasticity Test			
F-Statistic	Prob(F)	11.788	< 0.0001
Obs*R-squared	Prob(χ^2)	120.562	< 0.0001
Scaled Explained SS	Prob(χ^2)	1274.236	< 0.0001
Jarque–Bera Normality Test			
JB-Statistic	Prob(JB)	3353.276	< 0.0001



a) CUSUM



b) CUSUM Square

Figure 4. Illustrates the structural stability test of the ARDL model

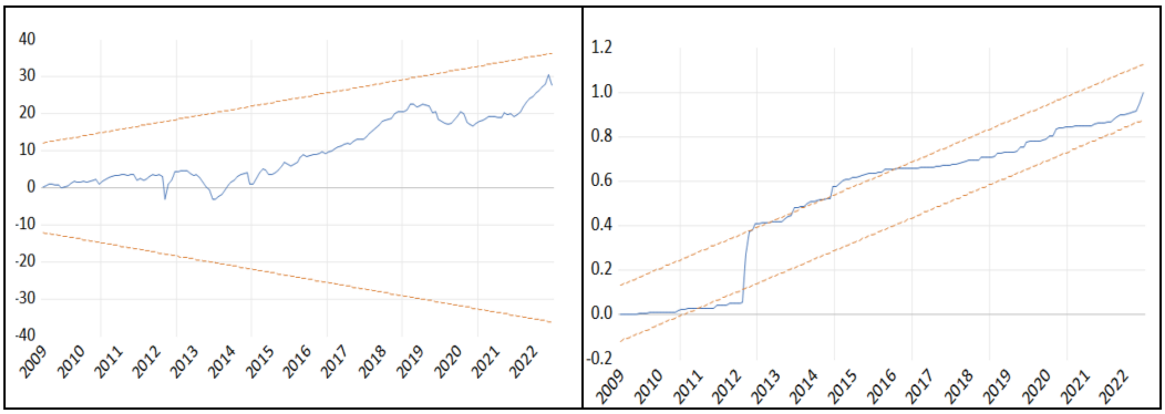
4.3. NARDL Model Results

As the possible presence of asymmetric effect of oil price fluctuations on the fiscal surplus/deficit, the NARDL model was used as a nonlinear extension of the ARDL model. This approach separates oil price changes into positive and negative partial shocks so that the fiscal surplus/deficit could react differently to positive and negative oil price shocks. The Akaike Information Criterion (AIC) was used to determine the model that best fits the data, and the NARDL(2,1,5) model was chosen under a constant term as the optimum model. This specification includes the dependent variable with two lagged terms, the positive and negative oil price components with one and five lagged terms, respectively.

The estimation results indicate the presence of a long-run equilibrium relationship among the variables, as the F-Bounds Test statistic reached (58.6), exceeding the critical value even at the 1% significance level, thereby confirming the existence of co-integration. The error correction coefficient was found to be (-1.640) with a p-value less than (0.0001), indicating a rapid speed of adjustment toward equilibrium following shocks. The coefficient exceeding unity in absolute value suggests an overshooting adjustment pattern, consistent with the interpretation discussed in the conventional ARDL model. Further, the coefficient of determination R^2 value reached approximately (0.30), indicating a weak explanatory power of the model, which is relatively close to that of the conventional ARDL model. The F-statistic was (7.16) and the significant level is (0.008) indicating that the model as a whole is statistically significant, The Wald test results also revealed a statistically significant asymmetry in the effects of positive and negative oil price shocks on the fiscal surplus/deficit. The test yielded an F-statistic of (8.5107) with a p-value of (0.0040), leading to the rejection of the symmetry hypothesis at the (5%) significance level. This finding indicates that the impact of an increase in oil prices on the fiscal surplus/deficit is not equal to the impact of a decrease in oil prices. In other words, the government's fiscal position responds differently to positive oil price shocks than it does to negative oil price shocks. Table (3) presents the results of the diagnostic tests for the NARDL model.

Table 3. Diagnostic Tests for the Estimated NARDL Model

Diagnostic Test	**Statistic**	**Value**	**Probability**
Breusch–Godfrey Serial Correlation LM Test			
F-Statistic	Prob(F)	0.3514	0.7042
Obs*R-squared	Prob(χ^2)	0.7562	0.6851
Ramsey RESET Test			
F-Statistic	Prob(F)	0.685	0.423
Breusch–Pagan–Godfrey Heteroskedasticity Test			
F-Statistic	Prob(F)	4.991	< 0.0001
Obs*R-squared	Prob(χ^2)	40.7888	< 0.0001
Scaled Explained SS	Prob(χ^2)	333.0826	< 0.0001
White Heteroskedasticity Test			
F-Statistic	Prob(F)	10.3959	< 0.0001
Obs*R-squared	Prob(χ^2)	149.5067	< 0.0001
Scaled Explained SS	Prob(χ^2)	1220.877	< 0.0001
Jarque-Bera Normality Test			
JB-Statistic	Prob(JB)	2104.561	< 0.0001



a) CUSUM b) CUSUM Square

Figure 5. Illustrates the structural stability test of the NARDL model.

According to Table (3) the Breusch-Godfrey test, there is no serial correlation in the residuals, indicating that they are independent. In addition, the Ramsey RESET test does not indicate any evidence of model misspecification or incorrect functional form. The Breusch-Pagan-Godfrey and White heteroskedasticity tests both indicated the presence of heteroskedasticity in the model residuals, as all associated p-values were less than 0.001, leading to the rejection of the null hypothesis of constant error variance. Moreover, the Jarque-Bera test rejects the null hypothesis of normality, implying that the residuals are not normally distributed. Therefore, HAC (Newey-West) robust standard errors were employed to improve the reliability of statistical inference under possible violations of the classical residual assumptions.

As shown in Figure (5), the results of the CUSUM and CUSUM-Square tests indicate that the CUSUM plot remains within the critical bounds throughout the study period, suggesting parameter stability of the model. The CUSUM-Square plot also lies within the critical bounds, although it approaches the upper bound in some periods, reflecting limited fluctuations without undermining the overall stability of the model.

Overall, these results indicate that the NARDL model provides greater flexibility in representing the relationship between oil prices and the surplus/deficit compared with the linear ARDL model, by allowing for asymmetric effects of positive and negative oil price shocks. Nevertheless, the explanatory power of the model remained weak and relatively close to that of the conventional ARDL model, in addition to the presence of some potential fluctuations in parameter stability over time. Moreover, the model still relies on a set of assumptions associated with conventional econometric models, including residual properties and the functional form of the relationship. This further reinforces the need to employ more flexible models, such as the 1D-CNN-LSTM model, which is capable of representing nonlinear relationships and complex temporal dynamics more effectively without strict reliance on the assumptions of conventional econometric models.

4.4. Application of the Hybrid 1D-CNN – LSTM

After confirming the existence of a long-run relationship between oil prices and the fiscal surplus/deficit using the ARDL and NARDL models, the study proceeded to the forecasting stage to evaluate the ability of different models to capture the dynamics of the dependent variable and predict its future values. Given that economic and financial data often exhibit complex patterns and nonlinear relationships that may not be fully represented by conventional econometric models, a set of deep learning models was employed, including the Long Short-Term Memory (LSTM) model, the One-Dimensional Convolutional Neural Network (1D-CNN) model, and the hybrid 1D-CNN-LSTM model. These models were considered alongside the traditional econometric models, namely ARDL and NARDL, to compare their predictive performance and assess the extent to which prediction accuracy could be improved by exploiting the capability of deep learning techniques to model nonlinear relationships and complex temporal patterns. The empirical analysis was implemented in the R programming environment using the Keras and TensorFlow libraries for constructing and training the neural network models, together with several supporting packages for data processing and result analysis. Furthermore, the data-partitioning scheme described previously in 4.1 was adopted to ensure a fair and objective comparison among all competing models. To ensure the best possible architecture for each model, the hyper-parameters were not selected arbitrarily; instead, they were optimized using the Bayesian Optimization algorithm. This approach systematically searches for the optimal combination of hyper-parameters capable of achieving the lowest forecasting error on the validation dataset. In addition, the Early Stopping technique was employed during the training process, whereby the learning procedure is automatically terminated when no further improvement in the validation loss function is observed over a specified number of training epochs. This strategy helps mitigate the problem of overfitting and enhances the models' ability to generalize when applied to new and unseen data. Table (4) presents the optimal hyper-parameter configurations obtained for each model using the Bayesian Optimization algorithm. The results indicate that the Long Short-Term Memory (LSTM) model achieved its best performance with 82 LSTM units and 32 neurons in the dense layer, together with a dropout rate of 0.38. This configuration may reflect the need for greater capacity to capture long-term temporal dependencies while maintaining an appropriate level of regularization to mitigate overfitting. For the One-Dimensional Convolutional Neural Network (1D-CNN) model, the optimal architecture consisted of 30 filters and a kernel size of 3, along with a relatively small number of neurons in the dense layer. This suggests that extracting local patterns from the time series was sufficient to achieve the model's best predictive performance. In contrast, the Bayesian Optimization procedure selected a relatively large architecture for the hybrid 1D-CNN-LSTM model, comprising 31 filters, 72 LSTM units, and 29 neurons in the dense layer, with a low dropout rate of 0.10. This configuration indicates that the hybrid model required a richer network structure to effectively capture both local and temporal patterns in the data and thereby achieve superior predictive performance.

Table 4. Optimal Hyperparameter Settings for the Deep Learning Models

Hyperparameter	1D-CNN	LSTM	1D-CNN-LSTM
Filters	30	–	31
Kernel Size	3	–	3
LSTM Units	–	82	72
Dense Units	8	32	29
Dropout Rate	0.3960	0.3801	0.1000
Epochs	150	150	150
Batch Size	9	10	5
Learning Rate	0.0082	0.0095	0.0100
Flatten Layer	Enabled	–	Disabled

Note: "–" indicates that the hyperparameter is not applicable to the corresponding model. Pooling layers were not used in any of the proposed architectures.

It is important to note that the Flatten layer was intentionally omitted from the hybrid 1D-CNN-LSTM model, representing one of the key distinctions between this architecture and certain conventional convolutional neural network structures. This decision was made because the objective of the hybrid model extends beyond merely extracting local features through the 1D-CNN layers; it also requires preserving the temporal structure and sequential dependencies of the data before passing it to the LSTM layer. The use of a Flatten layer transforms multidimensional feature maps into a one-dimensional vector, which results in the loss of temporal information and sequential relationships among observations. Since LSTM layers fundamentally rely on learning long-term temporal dependencies within time-series data, the loss of this temporal structure would limit their ability to capture the underlying dynamics of the series effectively. Accordingly, the feature maps generated by the convolutional layer were passed directly to the LSTM layer as a sequence of feature vectors, thereby preserving the temporal ordering of the extracted information. This design enhances the model's ability to capture complex temporal patterns and cumulative relationships embedded in the oil price and fiscal surplus/deficit data, ultimately improving its prediction capability. To evaluate the predictive performance of the different models, a set of statistical measures was employed, including the Root Mean Squared Error (RMSE), the Mean Absolute Error (MAE), and Directional Accuracy (DA). Table (5) presents the results of these measures for the in-sample and out-of-sample forecasts.

Table 5. Forecasting Performance Measures for the Competing Models

Model	In-Sample Performance		Out-of-Sample Performance		
	RMSE	MAE	RMSE	MAE	DA
ARDL	4.631658	2.629207	4.308934	3.227648	0.181818
NARDL	4.525520	2.726443	5.054588	4.249737	0.454546
LSTM	5.166716	2.633738	4.099187	2.987492	0.454546
1D-CNN	5.119617	2.635256	4.654221	3.942018	0.363636
1D-CNN-LSTM	4.785901	2.517234	4.008143	2.929263	0.636364

The results indicate that the NARDL model achieved the lowest RMSE value, suggesting its superiority in reducing large forecasting errors within the sample. In contrast, the hybrid 1D-CNN-LSTM model recorded the lowest MAE value among all competing models, reflecting its ability to minimize the average magnitude of forecasting errors. Overall, the results reveal a relatively close performance among the different models within the sample. Consequently, out-of-sample forecasting results constitute the more important criterion for assessing model efficiency and their ability to generalize, which is a fundamental consideration in forecasting studies. The out-of-sample forecasting results, constitute the most important criterion for evaluating the effectiveness of prediction models, as they reflect a model's ability to generalize and generate accurate predictions for observations that were not used during the training phase. The results indicate the superiority of the hybrid 1D-CNN–LSTM model over the competing models, as it achieved the lowest values for both the Root Mean Squared Error (RMSE) and the Mean Absolute Error

(MAE), demonstrating its high efficiency in minimizing forecasting errors when applied to new data. To provide a visual assessment of predictive performance, Figure (6) presents the actual fiscal surplus/deficit series alongside the out-of-sample predicted values generated by the competing models.

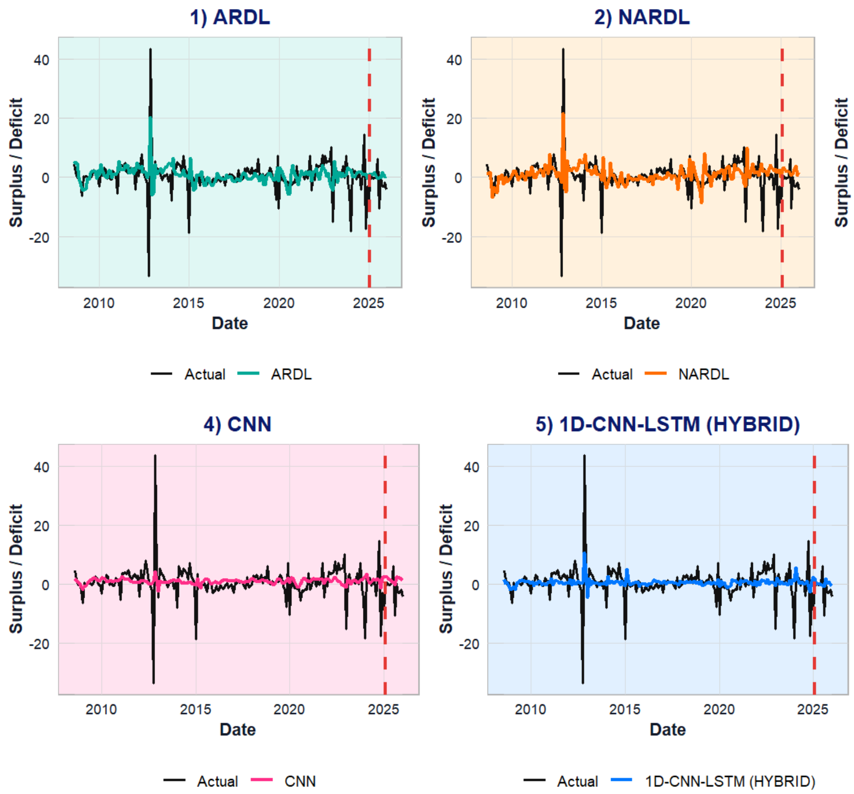


Figure 6. Actual and Predicted Fiscal Surplus/Deficit Values for the Competing Models: In-Sample and Out-of-Sample Predictions.

Furthermore, the hybrid model recorded the highest value of Directional Accuracy (DA), indicating a greater ability to correctly predict the direction of future changes in the fiscal surplus or deficit. These findings suggest that integrating convolutional and recurrent neural network structures enables the model to capture both local and long-term temporal patterns more effectively, thereby enhancing its predictive performance in out-of-sample applications. Based on the improvement percentages reported in Table (6), the hybrid 1D-CNN-LSTM model reduced the out-of-sample RMSE by 6.98% compared with the ARDL model, by 20.70% compared with the NARDL model, by 2.22% compared with the LSTM model, and by 13.88% compared with the 1D-CNN model. The hybrid model also achieved substantial improvements in Directional Accuracy (DA), recording increases of 250% relative to the ARDL model, 40% relative to both the NARDL and LSTM models, and 75% relative to the 1D-CNN model.

Table 6. Out-of-Sample Percentage Improvement of the 1D-CNN-LSTM Model Relative to the Competing Models.

Competing Model	RMSE (%)	MAE (%)	DA (%)
ARDL	6.98	9.24	250
NARDL	20.70	31.07	40
LSTM	2.22	1.95	40
1D-CNN	13.88	25.69	75

These findings indicate that the hybrid model not only improved prediction accuracy but also demonstrated a superior ability to correctly predict the direction of future changes in the fiscal surplus/deficit variable. Although

some competing models outperformed others on certain in-sample performance measures, the hybrid model proved to be the most efficient in out-of-sample forecasting. This reflects a stronger capacity for generalization and a better ability to capture the underlying patterns in the data while mitigating the effects of overfitting, making it a more suitable model for future forecasting purposes.
To examine the statistical significance of differences in predictive performance among the competing models, the Diebold–Mariano test was employed, and its results are reported in Table (7).

Table 7. Diebold–Mariano Test Results for the Competing Forecasting Models

Comparison	DM Statistic	P-Value
1D-CNN-LSTM vs ARDL	-1.6426	0.1287
1D-CNN-LSTM vs NARDL	-2.3419	0.0390
1D-CNN-LSTM vs LSTM	-0.7117	0.4915
1D-CNN-LSTM vs 1D-CNN	-2.6032	0.0246

As shown in Table (7) The findings reveal that the hybrid 1D-CNN-LSTM model significantly outperformed both the NARDL model and the 1D-CNN model, thereby reinforcing the conclusions drawn from the out-of-sample prediction accuracy measures. In contrast, no statistically significant differences were detected between the hybrid model and either the ARDL or LSTM models, despite the hybrid model achieving the best values across the out-of-sample performance indicators. These results suggest that the hybrid model maintained a consistently superior predictive performance relative to all competing models, with sufficient statistical evidence supporting its superiority over the NARDL and 1D-CNN models.
Overall, the empirical findings confirm that the hybrid 1D-CNN-LSTM model represents the most efficient framework among the competing models for forecasting the fiscal surplus/deficit. The model was able to simultaneously exploit the capability of convolutional layers to extract local patterns and features from the data, as well as the ability of Long Short-Term Memory (LSTM) layers to capture long-term temporal dependencies. This integration was reflected in superior out-of-sample predictive performance and a substantial improvement in directional prediction accuracy. These results suggest that combining feature-extraction mechanisms with temporal learning provides a more effective framework for modeling and forecasting the dynamics of the relationship between oil prices and the fiscal surplus/deficit. From an economic perspective, the findings suggest that improving the accuracy of fiscal surplus/deficit predictions can provide an important tool for supporting financial planning in the Iraqi economy, which is heavily dependent on oil revenues. The superior predictive performance achieved by the hybrid 1D-CNN–LSTM model implies the possibility of obtaining more accurate estimates of future developments in the government's fiscal position compared with traditional models. This, in turn, may assist policymakers in assessing the potential impacts of oil price fluctuations and preparing for them more effectively. Moreover, the model's enhanced ability to correctly predict the direction of future changes in the fiscal surplus or deficit provides early signals that can be utilized in budget preparation, public expenditure management, and the formulation of appropriate fiscal policy responses to oil-related shocks. Therefore, the importance of the hybrid model extends beyond its superior statistical performance to providing a more efficient quantitative tool for supporting fiscal decision-making in oil-dependent rentier economies, including the Iraqi economy.

5. Conclusion

The objective of this study was to predict the fiscal surplus/deficit series of the Iraqi economy using oil prices as the principal explanatory variable. To achieve this objective, a comparative analysis was conducted among a set of econometric and deep learning models, namely ARDL, NARDL, LSTM, 1D-CNN, and the hybrid 1D-CNN–LSTM model. The findings revealed the existence of a long-run equilibrium relationship between oil prices and the fiscal surplus/deficit. Furthermore, the results of the NARDL model indicated the presence of asymmetric effects of positive and negative oil price shocks on the government's fiscal position. Although the ARDL and NARDL models contributed to explaining the economic relationship between the variables, their explanatory and predictive capabilities remained relatively limited due to their reliance on conventional econometric assumptions that may not adequately capture the complexity and nonlinear dynamics inherent in economic data.

In contrast, the results demonstrated the superiority of the hybrid 1D-CNN–LSTM model over all competing models in out-of-sample prediction. The hybrid model achieved the lowest prediction error measures and the highest Directional Accuracy (DA), reflecting its ability to exploit the strengths of both one-dimensional convolutional neural networks in extracting short-term local patterns and Long Short-Term Memory networks in capturing long-term temporal dependencies. Moreover, the results of the Diebold–Mariano test supported the efficiency of the hybrid model relative to several competing models, confirming its superiority in modeling the relationship between oil prices and the fiscal surplus/deficit and in predicting its future developments.
From an economic perspective, the findings suggest that improving the accuracy of fiscal surplus/deficit predictions can provide an important tool for supporting financial planning in the Iraqi economy, which is heavily dependent on oil revenues. More accurate predictions regarding the government's fiscal position can assist policymakers in assessing the potential impacts of oil price fluctuations and preparing for them more effectively. In addition, such predictions provide early indicators that can support budget preparation, public expenditure management, and the formulation of appropriate fiscal policy responses to oil-related shocks. Accordingly, it can be concluded that the hybrid 1D-CNN–LSTM model represents a promising and more efficient framework for predicting fiscal variables in oil-dependent rentier economies. The study also recommends extending future research by incorporating additional economic and financial variables, which may further enhance the explanatory and predictive capabilities of the proposed models.

Study Limitations and Future Directions

Although the proposed models achieved satisfactory forecasting performance, this study focused primarily on oil prices as the main explanatory variable of the fiscal surplus/deficit, consistent with the rentier nature of the Iraqi economy. In addition, the sample size of 216 monthly observations, together with the need to maintain a balanced modeling framework when comparing conventional econometric models with deep learning models, necessitated the use of a limited number of variables. Therefore, future studies may extend the scope of the analysis by incorporating additional economic and financial variables, such as government expenditure, non-oil revenues, exchange rates, and inflation, which could enhance the economic interpretation of the results and improve forecasting accuracy. Furthermore, more advanced deep learning architectures or new hybrid models may be explored to capitalize on the advantages of both conventional econometric approaches and modern artificial intelligence techniques in forecasting fiscal and financial variables.

Code Availability

The complete R implementation used in this study, including data, model estimation procedures, deep learning architectures, hyperparameter optimization, predictive evaluation, and Diebold–Mariano tests, is publicly available at: https://github.com/suliamanhussien83-ux/1D-CNN-LSTM

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