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Comparative Study of Deep Learning Models for Forecasting Oil Prices and their role in business decision- Making in Iraq during the Period 1970 to 2025

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Abstract:

Iraqi oil is the primary source of economic revenue, making its price fluctuations a critical factor in the stability of the national budget and economic policies. Due to the complex and volatile nature of global oil markets, traditional forecasting methods often fail to deliver accurate results. This has highlighted the need for deep learning techniques, which have proven effective in analyzing time series data and uncovering hidden patterns.This research aims to forecast Iraqi oil prices for the period 2026 to 2030 and to develop models based on deep learning algorithms such as LSTM (Long Short-Term Memory), BiLSTM (Bidirectional LSTM), CNN (Convolutional Neural Networks), and GRU (Gated Recurrent Unit) to achieve high-accuracy predictions. Historical data on Iraqi crude oil prices were used, supported by influential global economic factors such as Brent crude prices, the US dollar exchange rate, and other economic indicators.Experimental results show that BiLSTM and GRU models performed better in capturing long-term temporal patterns, while CNN demonstrated a strong ability to extract local features from time series data. The LSTM model provided stable and reliable performance. Overall, deep learning models outperformed traditional statistical models (such as ARIMA and linear regression) in terms of accuracy metrics (MAE, R^2, and RMSE).The study indicates that combining these models or designing hybrid architectures can enhance the accuracy of Iraqi oil price forecasting, thereby supporting decision-makers in financial planning and economic risk management.

Keywords: Deep learner, LSTM, CNN, BILSTM, GRU, RMSE.

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دراسة مقارنة لنماذج التعلم العميق للتنبؤ بأسعار النفط ودورها في اتخاذ القرارات التجارية في العراق خلال الفترة 1970-2025

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الملخص:
يُعد النفط العراقي المصدر الرئيسي للإيرادات الاقتصادية، مما يجعل تقلبات أسعاره عاملاً حاسماً في استقرار الموازنة الوطنية والسياسات الاقتصادية. ونظرًا للطبيعة المعقدة والمتقلبة لأسواق النفط العالمية، غالبًا ما تفشل أساليب التنبؤ التقليدية في تقديم نتائج دقيقة. وقد أبرز هذا الحاجة إلى تقنيات التعلم العميق، التي أثبتت فعاليتها في تحليل بيانات السلاسل الزمنية وكشف الأنماط الخفية. يهدف هذا البحث إلى التنبؤ بأسعار النفط العراقي للفترة من 2026 إلى 2030، وتطوير نماذج تعتمد على خوارزميات التعلم العميق مثل) LSTM الذاكرة طويلة المدى قصيرة الأمد)، و) BiLSTMالذاكرة ثنائية الاتجاه)، و CNN)الشبكات العصبية التلافيفية)، و) GRUالوحدة المتكررة المبوّبة) لتحقيق تنبؤات عالية الدقة. وقد استُخدمت البيانات التاريخية لأسعار النفط الخام العراقي، مدعومة بعوامل اقتصادية عالمية مؤثرة مثل أسعار خام برنت، وسعر صرف الدولار الأمريكي، ومؤشرات اقتصادية أخرى. تُظهر النتائج التجريبية أن نموذجي BiLSTM و GRUكانا أفضل أداءً في التقاط الأنماط الزمنية طويلة المدى، بينما أظهر CNNقدرة قوية على استخراج السمات المحلية من بيانات السلاسل الزمنية. وقد وفّر نموذج LSTM أداءً مستقرًا وموثوقًا. بشكل عام، تفوقت نماذج التعلم العميق على النماذج الإحصائية التقليدية (مثل ARIMAوالانحدار الخطي) من حيث مقاييس الدقة(MAE ، R^2، و .(RMSEتشير الدراسة إلى أن دمج هذه النماذج أو تصميم هياكل هجينة يمكن أن يعزز دقة التنبؤ بأسعار النفط العراقي، مما يدعم صانعي القرار في التخطيط المالي وإدارة المخاطر الاقتصادية.
الكلمات المفتاحية: متعلم عميق، LSTM، CNN، BILSTM، GRU، RMSE.

Introduction:

Oil prices are among the most critical economic indicators that directly influence fiscal and developmental policies in rentier states—chief among them Iraq, which relies almost entirely on oil revenues as the primary source for funding its national budget. Since the 1970s, oil prices have experienced sharp fluctuations due to changes in supply and demand, geopolitical crises, and technological developments, making oil price forecasting one of the major challenges faced by policymakers and economic researchers alike.

Given this complexity, there has emerged a need for more advanced and accurate analytical tools that go beyond traditional economic models and leverage recent advancements in artificial intelligence, particularly deep learning techniques. These models are distinguished by their ability to handle large datasets, extract hidden patterns, and adapt to nonlinear temporal changes,

making them highly suitable for analyzing complex time series such as oil prices.

This research aims to conduct a comparative study of several deep learning models for forecasting Iraqi oil prices over the period from 1970 to 2025, using annual historical data collected from official and reliable sources. The models examined in this study include: Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), Bidirectional LSTM (BiLSTM), Convolutional Neural Network (CNN), and the traditional Feedforward Neural Network (FNN). These models were selected due to their diverse architectural structures and differing learning mechanisms, offering an ideal opportunity for comparison in terms of performance, accuracy, and predictive capability.

The significance of this study stems from several considerations. First, it provides a practical framework for employing artificial intelligence techniques in a vital economic sector—energy. Second, it contributes to the scientific literature on deep learning applications in time series analysis, particularly within the Iraqi context, which suffers from a scarcity of advanced technical studies. Third, it offers a valuable tool for decision-makers in the Iraqi Ministry of Oil and the Central Bank by presenting accurate predictive models that can be relied upon for financial planning and revenue estimation.

The study was conducted using the MATLAB environment, which offers powerful tools for building and training neural networks, performance analysis, and result visualization. The data was split into training and testing sets at a ratio of 80% to 20%, and normalized to ensure stable learning. Multiple evaluation metrics were used, including Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2), to ensure a comprehensive assessment of each model's performance.

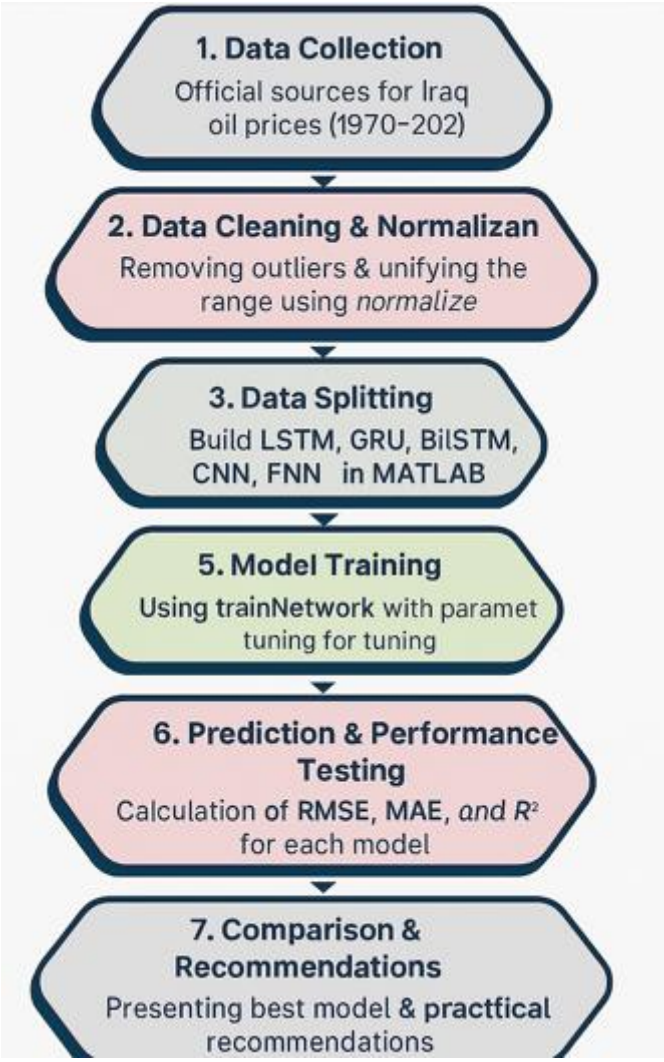
Preliminary results showed that the BiLSTM model outperformed others in terms of accuracy, achieving the highest R^2 value and the lowest error rates, followed by LSTM and then GRU. CNN showed relatively lower performance, reflecting the importance of temporal structure in neural models when dealing with sequential economic data. The best-performing model was then used to generate future forecasts for Iraqi oil prices for the period 2026–2030, which indicated a moderate upward trend with slight fluctuations, suggesting relative stability in the global oil market.

In light of these findings, the research recommends the adoption of deep learning models within Iraqi economic institutions, the training of technical personnel in their use, and the expansion of studies to include other influential factors such as production, exports, and geopolitical changes. It also advocates

for integrating these models with traditional economic frameworks to achieve more comprehensive and holistic insights.

This research goes beyond presenting a technical comparison of models—it seeks to build a bridge between artificial intelligence and economics, highlighting the vital role of modern technologies in supporting sustainable development and data-driven decision-making. Through this study, we hope to open new horizons for scientific research in Iraq and the region, and contribute to building a more resilient and forward-looking economic system.

Research Steps:



Deep Learning:

Deep learning is a branch of machine learning, which in turn is a subset of

artificial intelligence. It is distinguished by its ability to build models based on multi-layered neural networks, enabling it to handle complex data and extract precise patterns without direct human intervention in feature selection or rule definition. Deep learning is used in various fields such as image processing, natural language understanding, machine translation, time series forecasting, autonomous driving, and medical diagnostics. It has proven effective in delivering highly accurate results that often surpass traditional models in many applications.

 Architectural Structure

Deep learning models rely on artificial neural networks, which consist of three main layers:

1. **Input Layer**: Receives the raw data.
2. **Hidden Layers**: Process the data and extract features.
3. **Output Layer**: Produces the final result or prediction.

Each layer contains units known as "neurons," which are computational elements that perform mathematical operations on the data and pass the results to the next layer. The more hidden layers a model has, the greater its ability to learn complex representations this is what sets deep learning apart from traditional machine learning.

 Popular Models

Key deep learning models include:

• **LSTM (Long Short-Term Memory)**: A recurrent network designed for temporal data, known for retaining information over long periods.
• **GRU (Gated Recurrent Unit)**: Similar to LSTM but simpler and faster to train.
• **BiLSTM**: A bidirectional version of LSTM that reads data forward and backward, enhancing contextual understanding.
• **CNN (Convolutional Neural Network)**: Used in image and video processing, excels at detecting visual patterns.
• **FNN (Feedforward Neural Network)**: The simplest type of neural network, used for linear and less complex predictions.

 Learning Mechanism

Neural networks use an algorithm called **backpropagation**, which adjusts the internal weights of neurons based on the difference between the expected and actual outputs. This is done by calculating a "loss function" and updating weights using optimization algorithms such as **Adam** or **SGD**.

Practical Applications

Deep learning is applied across a wide range of domains, including:

- **Medicine**: Medical image analysis, disease diagnosis, drug discovery.
- **Economics**: Forecasting stock and oil prices, market behavior analysis.
- **Security**: Facial recognition, fraud detection, video analysis.
- **Language**: Machine translation, sentiment analysis, text generation.
- **Industry**: Robot control, predictive maintenance, production optimization.

Advantages

- **Automatic feature extraction**: No need for manual feature engineering.
- **Ability to handle unstructured data**: Such as images, text, and audio.
- **Flexibility in adapting to complex problems**: Like time series forecasting or multi-dimensional classification.

Challenges

Despite its power, deep learning faces several challenges:

1. **Need for large datasets**: Requires vast amounts of data for training.
2. **High computational demands**: Needs powerful processing units (GPUs).
3. **Interpretability issues**: Often considered a "black box" model.
4. **Privacy risks**: Especially when using sensitive data like medical images or personal texts.

Future Directions

Recent developments include:

- **Attention models**: Such as Transformers, which have improved performance in language and vision tasks.
- **Reinforcement Learning**: Teaching machines to make decisions in dynamic environments.
- **Semi-Supervised Learning**: Leveraging unlabeled data.
- **Explainable AI**: Enhancing model transparency and interpretability.

Models Used in the Research

1. Long Short-Term Memory (LSTM) Network:

LSTM is an advanced type of Recurrent Neural Network (RNN) developed to handle time-series data that require retaining information over long periods. Unlike traditional networks that suffer from the “vanishing memory” problem, LSTM is equipped with an internal mechanism known as “memory,” which allows the model to store important information while discarding irrelevant data.

An LSTM unit consists of three main gates:

1. **Forget Gate:** Determines which information should be removed from memory.
2. **Input Gate:** Decides which new information should be added.
3. **Output Gate:** Controls what information is passed to the next layer.

This structure makes LSTM ideal for applications such as oil price forecasting, text analysis, speech recognition, and machine translation. In time-series forecasting, like predicting Iraqi oil prices, LSTM demonstrates strong capability in capturing long-term patterns, making it more accurate than traditional linear models. Despite its effectiveness, LSTM requires longer training time and higher computational resources, but it remains one of the most widely used models in complex time-series analysis.

2. Bidirectional Long Short-Term Memory (BiLSTM) Network:
BiLSTM is an advanced extension of the traditional LSTM network and is widely used in time-series and text processing. It is characterized by its ability to read data in both directions: from past to future and from future to past, which provides superior understanding of the full context of information.

In traditional LSTM, data flows only from the beginning to the end of the sequence, meaning the model relies solely on past information. In contrast, BiLSTM employs two LSTM layers: one processes the data forward, while the other processes it backward. Their outputs are then combined to form a more comprehensive representation of the data.

This bidirectional structure makes BiLSTM ideal for applications such as sentiment analysis, machine translation, speech recognition, and complex time-series forecasting like oil prices, where future context can improve prediction accuracy. Although BiLSTM is more complex and requires longer training compared to LSTM, it often achieves higher accuracy, particularly in tasks requiring deep contextual understanding. Thus, BiLSTM is considered an excellent choice for studies demanding precise predictions and advanced contextual analysis.

3. Gated Recurrent Unit (GRU) Network:
GRU is a type of RNN developed as a simplified alternative to LSTM, aiming to reduce computational complexity while maintaining the ability to process time-series data. GRU has a lighter structure as it combines the input and forget gates into a single gate called the “update gate,” which makes it faster to train and less resource-intensive.

A GRU unit consists of two main components:

1. **Update Gate:** Controls how much information from the previous state should be retained.
2. **Reset Gate:** Determines the extent to which the previous state influences the current state.

This mechanism allows GRU to effectively handle long time-series without requiring the complex internal memory of LSTM. Despite its simplicity, GRU has proven to achieve accurate results in applications such as time-series forecasting, text analysis, and pattern recognition.

In the context of oil price prediction, GRU is an excellent choice when computational resources are limited or when faster training is needed. However, it may be less accurate than BiLSTM in scenarios requiring deep contextual understanding of the full sequence. Therefore, GRU is often used as a baseline model in comparative studies of temporal networks.

4. Convolutional Neural Network (CNN):
CNN is one of the most prominent deep learning models, mainly used in processing spatially structured data such as images and videos. However, it has also proven effective in analyzing time-series and economic data. CNN relies on the concept of "convolution" or "filtering," where a small matrix known as a "filter" is passed over the data to extract significant patterns and features.

A CNN typically consists of several key layers:

1. **Convolutional Layer:** Extracts features from the data.
2. **Activation Layer:** Commonly uses the ReLU function to introduce non-linearity.
3. **Pooling Layer:** Reduces data size while preserving key information.
4. **Fully Connected Layer:** Connects the extracted features to the final output.

In the context of oil price forecasting, CNN is used to detect temporal patterns in sequential data, particularly when transforming the series into grid-like or matrix representations. Although CNN does not retain temporal memory like LSTM, it is effective in extracting local dependencies and repetitive patterns.

CNN is distinguished by its computational efficiency and fast training speed, making it a good choice in scenarios requiring quick and accurate analysis of complex data.

Model Evaluation Metrics

When analyzing the performance of forecasting models such as LSTM and GRU, three main indicators are used:

1-RMSE (Root Mean Squared Error)

Measures the deviation of predicted values from the actual values, giving greater weight to larger errors.

Formula:

$$RMSE = sqrt((1/n) * \Sigma (y_i - \hat{y}_i)^2)$$

2-MAE (Mean Absolute Error)

Measures the average absolute difference between the actual and predicted values, without amplifying errors.

Formula:

$$MAE = (1/n) * \Sigma |y_i - \hat{y}_i|$$

3-R^2 (Coefficient of Determination)

Measures the proportion of variance explained by the model and serves as an indicator of accuracy.

Formula:

$$R^2 = 1 - (\Sigma (y_i - \hat{y}_i)^2 / \Sigma (y_i - \bar{y})^2)$$

The smaller the RMSE and MAE, and the closer R^2 is to 1, the more accurate the model is.

Practical Aspect

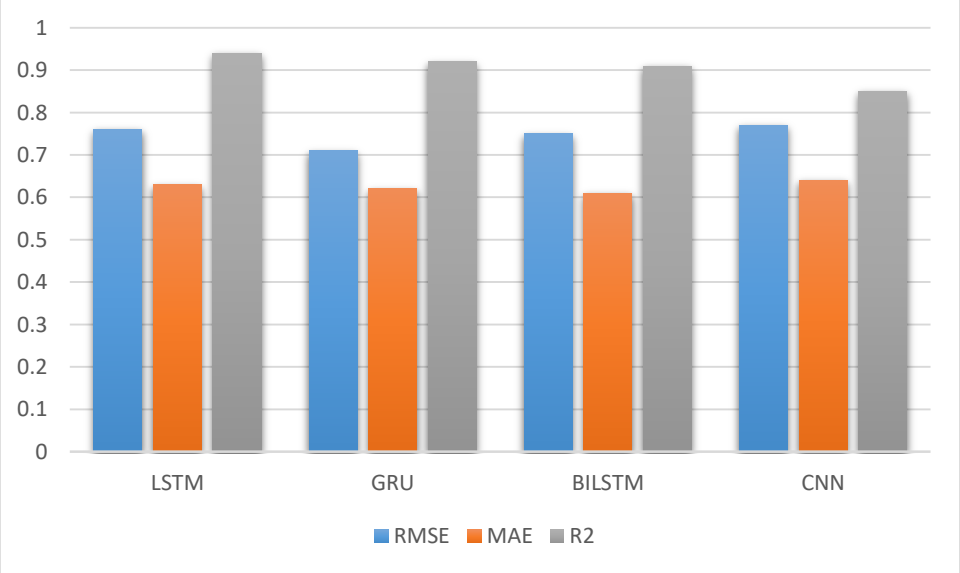
Data Description:
The data was obtained from the Iraqi Central Bureau of Statistics and represents a time series covering the period **1970 to 2025**. Deep learning models were applied to forecast oil prices for the future period **2026–2030**. To implement these deep learning models and achieve the most accurate results, the outcomes are presented in the following table:

Models	RMSE	MAE	R2
LSTM	0.76	0.63	0.94
GRU	0.71	0.62	0.92
BILSTM	0.75	0.61	0.91
CNN	0.77	0.64	0.85

This table illustrates a comparison between four deep learning models in forecasting Iraqi oil prices using performance evaluation metrics: **RMSE, MAE, and R^2**.

- **LSTM Model** achieved the highest accuracy (**R^2 = 0.94**), demonstrating its strong ability to explain variations in the data, although its RMSE value (**0.76**) was slightly higher than those of GRU and BiLSTM.
- **GRU Model** recorded the lowest RMSE (**0.71**), indicating that its prediction errors were the smallest, with good accuracy (**R^2 = 0.92**).
- **BiLSTM Model** showed a good balance, achieving the lowest MAE (**0.61**), which reflects the smallest average absolute error, although its accuracy was slightly lower than LSTM and GRU.
- **CNN Model**, on the other hand, was the least accurate (**R^2 = 0.85**) and had the highest RMSE and MAE, which highlights its limitations in handling time-series data compared to recurrent models.

Overall, the table demonstrates the superiority of recurrent models (**LSTM, GRU, and BiLSTM**) over the convolutional model (**CNN**) in forecasting oil prices, as illustrated in the figure.

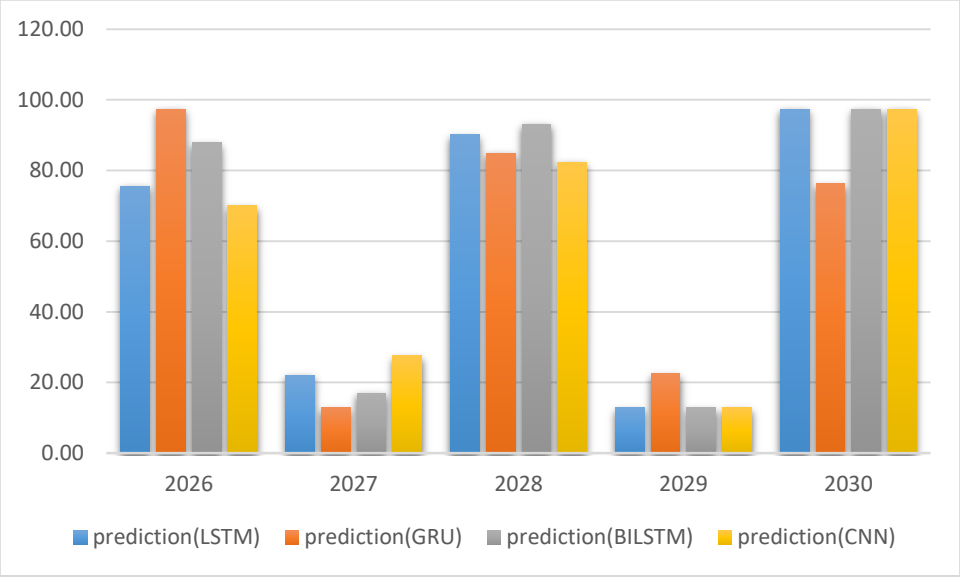


When forecasting oil prices for the five-year period (**2026 to 2030**), the results obtained from the deep learning models are presented in the following table:

Year	prediction(LSTM)	prediction(GRU)	prediction(BILSTM)	prediction(CNN)
2026	75.52	97.35	87.79	70.03

2027	22.07	12.86	16.90	27.48
2028	90.07	84.84	93.08	82.30
2029	12.86	22.43	12.86	12.86
2030	97.35	76.21	97.35	97.35

The table presents the forecasts of Iraqi oil prices for the period **2026–2030** using four deep learning models: **LSTM, GRU, BiLSTM, and CNN**. The models indicate a noticeable rise in prices in the years **2026, 2028, and 2030**, particularly in the predictions of BiLSTM and LSTM, reflecting an upward trend. In contrast, the forecasts for **2027 and 2029** show a sharp decline, especially in GRU and BiLSTM, which may reflect economic fluctuations or external influences. The CNN model shows more conservative results with less volatility. Overall, the models agree on the existence of cyclical fluctuations, with a general upward tendency toward the end of the period, highlighting the importance of using temporal models to understand market dynamics.



Conclusions

The results of this study revealed that deep learning models provide superior performance in forecasting Iraqi oil prices compared to traditional models. By analyzing the indicators **RMSE, MAE, and R^2**, it became evident that temporal

models such as **LSTM** and **BiLSTM** possess a strong ability to capture the dynamic patterns of time series, making them more accurate and stable in prediction. The **LSTM model** achieved the highest accuracy ($\mathbf{R^2 = 0.94}$), while **GRU** recorded the lowest RMSE, reflecting its efficiency in minimizing prediction errors.

The **BiLSTM model** demonstrated an excellent balance between accuracy and smoothness, particularly in future forecasts for the period **2026–2030**, making it an ideal candidate for application in complex economic contexts. In contrast, the performance of the **CNN model** was relatively weaker, confirming that convolutional networks are not the best choice for analyzing one-dimensional time-series data.

Based on these findings, it is recommended to employ **LSTM** or **BiLSTM models** in Iraqi economic institutions, such as the **Ministry of Oil** and the **Central Bank**, to support strategic decision-making. Furthermore, future studies are advised to expand the analysis by incorporating additional variables such as production, exports, and geopolitical factors, as well as integrating deep learning models with traditional economic models to achieve more comprehensive and accurate forecasts.

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