# Crude Oil Price Prediction Using Machine Learning LSTM.

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## Abstract.

This research paper explores the innovative application of Long Short-Term Memory (LSTM) neural networks with minimal input features for crude oil price forecasting. The research encompasses a comprehensive examination of the model's architecture, training process, data preprocessing, and comparative analysis against actual values. The use of date as the sole input feature challenges conventional practices and highlights the model's ability to capture intricate temporal dependencies and seasonality. The research emphasizes the LSTM model's accuracy, robustness, adaptability, and data efficiency, demonstrating its potential for wider applicability across financial markets. This work advances the role of deep learning in financial forecasting, introduces a minimalist approach to modeling, and fosters the fusion of minimalism and deep learning. The overarching contribution lies in shaping the future of predictive modeling and decision-making in the complex and dynamic world of financial markets.

Keywords: Long Short-Term Memory (LSTM), Neural Networks, Crude Oil Price Forecasting.

## Introduction

Crude oil occupies a central and irreplaceable role in shaping the economic landscape of nations worldwide[1,2]. This hydrocarbon resource, extracted from deep within the Earth's crust, serves as the primary source of energy for transportation, heating, and electricity generation. Beyond fuel, crude oil is the elemental building block for an extensive array of products, including plastics, chemicals, and pharmaceuticals. As such, the significance of crude oil transcends mere commodity trade; it is deeply intertwined with the well-being and stability of economies and societies across the globe.

### 1.1. Energy Backbone of Modern Civilization

Crude oil plays an unparalleled role in powering the modern world. It serves as the lifeblood of transportation, ships, airplanes, and industrial vehicles.[3–7] Without it, global supply chains would stutter, impacting the movement of goods and people, and hampering international trade. Moreover, the aviation and maritime industries, which are pivotal for connecting distant regions, heavily rely on a consistent and cost-effective supply of crude oil-derived fuels. This interconnectivity between oil and transportation underscores the inextricable bond between crude oil prices and the functioning of the global economy.

In addition to transportation, crude oil provides a significant share of the world's electricity and heat generation. Many power plants and heating systems depend on oil to ensure the availability of electricity and warmth for households and industries.[8,9] Sudden disruptions in the oil supply chain can lead to energy shortages, driving up energy costs and affecting both domestic and industrial consumers.

Crude oil's utility is not confined solely to the energy sector. It is a foundational source of petrochemicals, which are fundamental to the production of plastics, synthetic rubber, pharmaceuticals, and a wide range of chemical products.[10–12] The plastics industry is heavily dependent on crude oil derivatives. This sector produces materials used in packaging, construction, electronics, medical devices, and countless consumer products. Consequently, the fluctuations in crude oil prices have a far-reaching impact on the cost structure of numerous industries.

## 1.2. Economic Implications and Macroeconomic Significance

The crude oil market has a profound influence on the macroeconomic stability of nations[13–15]. Fluctuations in oil prices can affect a nation's balance of payments, inflation rates, fiscal policies, and exchange rates[16–18]. It plays a role in shaping fiscal policies, as governments often rely on revenues generated from oil exports to fund public spending. Conversely, when oil prices plummet, countries that are heavily dependent on oil exports can face economic challenges.

Oil price volatility, stemming from geopolitical tensions, supply disruptions, or shifts in global demand, introduces an element of uncertainty in global financial markets. The impact is felt by investors, businesses, and policymakers, as these fluctuations can lead to market turmoil and economic uncertainty.

Considering its pivotal role in various sectors, the economic impact of crude oil prices extends beyond specific industries to influence the overall economic health of nations. Consequently, understanding and predicting crude oil price movements has profound implications for economic stability, national security, and the welfare of societies.

Given the presence of crude oil in modern civilization and its far-reaching economic ramifications, this research embarks on a journey to harness machine learning techniques, specifically Long Short-Term Memory (LSTM) neural networks[19–24], to enhance the accuracy of crude oil price predictions. In doing so, it aims to address the critical need for reliable forecasting in an increasingly dynamic and interconnected global economy.

The motivation behind this research stems from the dire need for more accurate and reliable crude oil price forecasts. Efforts have been made in the development of models for oil production rates[25–28]. Accurate predictions of crude oil prices can facilitate prudent decision-making, benefiting industries, governments, and individuals alike. Moreover, the unprecedented volatility experienced in the oil market in recent years, often driven by a confluence of geopolitical, economic, and environmental factors, has amplified the demand for advanced forecasting methods. Traditional time series analysis, while valuable, may not adequately capture the nuances of the modern crude oil market. Machine Learning (ML), particularly LSTM neural networks, offers a promising avenue for improving predictive accuracy. Additionally, the innovative approach of using only the date as an input feature is intriguing, as it challenges conventional wisdom and may present a novel path to enhanced prediction. Gaussian process regression models have also been useful in ML studies[29–32] but are better used for data with more than one input feature.

# Methodology

## 2.1. Data Collection and Preprocessing

The foundation of our research lies in the acquisition of high-quality historical crude oil price data as collected from https://www.cbn.gov.ng/rates/dailycrude.asp. The historical price data comprises a period that enables us to capture a wide range of market conditions, spanning several years. This diverse dataset is instrumental in training our LSTM neural network for accurate price predictions. The dataset consists of two primary variables: date and crude oil price. Each data point is associated with a specific date and its corresponding crude oil price.

The date variable is formatted in the month/day/year (MM/DD/YYYY) style. It was extracted directly from the historical data source and remained in this format throughout the preprocessing steps. The price variable represents the closing price of crude oil on the given date. This variable is recorded in the dataset as a continuous numerical value. No further preprocessing was required for this variable, as it was already in a suitable format for training the LSTM model.

## 2.2. Data Transformation and Preprocessing

To prepare the data for training the LSTM neural network, several preprocessing steps were undertaken:

i. Conversion of Date Variables: The date variables were transformed into datetime objects, utilizing Python's datetime library. This conversion allowed for the utilization of date data as a numerical feature, crucial for the LSTM model's comprehension of the chronological aspect of the data.

ii. Transformation to Ordinal Numbers: Following the conversion to DateTime objects, the dates were further transformed into ordinal numbers. This numerical representation of dates was crucial in facilitating the LSTM model's ability to process the temporal aspect of the data.

iii. Data Splitting: The dataset was divided into training and testing subsets. In this research, 80% of the data was allocated for training, while the remaining 20% was reserved for testing. This partitioning of the data allowed for an objective evaluation of the model's predictive performance on unseen data.

iv. Scaling with MinMaxScaler: To ensure that the date and price variables were within a consistent and uniform numerical range, the data was scaled using the MinMaxScaler from the sklearn library [33,34]. This scaling process transformed the variables into a range between 0 and 1, ensuring that they did not dominate the model's training process due to differing numerical magnitudes.

v. Data Reshaping: Given the LSTM model's requirement of a 3D input shape, the date and price variables were reshaped to match this format. Specifically, the NumPy arrays representing these variables were transformed to be 2D, and then an additional dimension was added to achieve a 3D shape, suitable for LSTM processing.

The culmination of these data transformation and preprocessing steps set the stage for training the LSTM neural network to forecast crude oil prices accurately. The chronological aspect of the date data, in combination with the scaled and reshaped input features, is pivotal in enabling the LSTM model to capture complex temporal patterns in the crude oil price dataset.

Certainly, here's content for the section on the architecture of the LSTM neural network, including the number of units, layers, and the use of dropout:

## 2.3. Architecture of the LSTM Neural Network

The heart of this research lies in the design and configuration of an LSTM neural network, a specialized deep learning model renowned for its ability to effectively capture temporal dependencies within sequential data. The architecture of the LSTM model plays a pivotal role in shaping the model's predictive capabilities. In this section, we provide a comprehensive overview of the architecture, including the number of units, layers, and the incorporation of dropout for regularization.

### 2.3.1. Number of Units

The LSTM model consists of multiple units within each layer. These units, often referred to as cells, are the fundamental building blocks responsible for capturing and storing information from previous time steps. In our model, each LSTM layer is equipped with 50 units. This selection is guided by a balance between model complexity and the capacity to capture intricate temporal patterns. A higher number of units in each layer can lead to greater model expressiveness, but it may also increase the risk of overfitting if not appropriately regularized.

### 2.3.2. Layer Configuration

The LSTM model employed in this research is designed with a total of four LSTM layers. These layers are stacked on top of each other, creating a deep neural network architecture. The choice of having multiple LSTM layers allows the model to capture hierarchical and increasingly complex temporal relationships in the data.

i. The first three LSTM layers are configured to return sequences, ensuring that the output of each time step is used as input for the subsequent layer. This configuration is essential for preserving the sequential nature of the data and facilitates the model's ability to capture intricate temporal patterns.
ii. The fourth and final LSTM layer, which does not return sequences, serves as the output layer of the model. It receives the processed information from the preceding layers and produces the final output, which is the predicted crude oil price.

### 2.3.3. Use of Dropout network

To mitigate overfitting, a common challenge in deep learning[35,36], we use dropout for the LSTM model[37,38]. Dropout is a regularization technique that randomly deactivates a fraction of the neurons during training. In our model, a dropout rate of 0.2 is employed. This means that, during each training iteration, 20% of the neurons are deactivated, preventing any single neuron from becoming overly reliant on specific features and patterns in the training data.

The use of dropout introduces an element of randomness and diversity into the training process, encouraging the model to generalize effectively to unseen data. This regularization technique is instrumental in improving the model's robustness and preventing it from memorizing the training data, ensuring that it captures meaningful temporal patterns without overfitting.

The LSTM neural network architecture outlined in this section is specifically tailored to leverage the chronological aspect of the date data and facilitate accurate predictions of crude oil prices. The combination of LSTM layers, units, and dropout is designed to enable the model to capture intricate temporal dependencies and enhance its ability to forecast price trends effectively.

Certainly, here's the content for the section on the model configuration, including the choice of the Adam optimizer and mean squared error (MSE) as the loss function:

## 2.4. Model Configuration and Optimization

The configuration of the LSTM neural network is a crucial step in the development of a predictive model for crude oil prices. In this section, we detail the specific choices made regarding the model's configuration, including the selection of the Adam optimizer[39] and the use of mean squared error (MSE) as the loss function.

### 2.4.1. Choice of the Adam Optimizer

The optimizer is a fundamental component of the model's configuration, as it determines how the model updates its internal parameters during training to minimize the chosen loss function. In this research, the Adam optimizer was selected for its effectiveness in handling complex, high-dimensional data and dynamic learning rates. Adam combines the advantages of both the AdaGrad[40] and RMSprop[41] optimizers, offering efficient and adaptive learning.

The choice of the Adam optimizer was motivated by its ability to effectively handle the temporal dynamics of the crude oil price dataset. Its adaptive learning rate mechanisms make it particularly well-suited for financial time series data, where patterns and trends can evolve. The use of the Adam optimizer facilitates faster convergence during training and, in many cases, better overall performance.

### 2.4.2. Mean Squared Error (MSE) as the Loss Function

The selection of an appropriate loss function is critical in training a regression model. For this research, the mean squared error (MSE) was chosen as the primary loss function. MSE calculates the average squared difference between the model's predictions and the actual crude oil prices. This loss function is particularly well-suited for regression tasks, where the goal is to minimize the error between predicted and actual continuous values.

The choice of MSE aligns to create a model that accurately forecasts crude oil prices. By minimizing the squared differences between predicted and actual prices, the model is trained to reduce the overall prediction error, resulting in predictions that closely match the real-world data. This metric offers a straightforward and interpretable measure of the model's performance, quantifying the accuracy of its predictions.

The configuration of the LSTM neural network, coupled with the choice of the Adam optimizer and the MSE loss function, represents a deliberate and informed approach to creating a predictive model for crude oil prices. These choices collectively contribute to the model's capacity to learn from the data, adapt to temporal dependencies, and generate accurate forecasts, which will be further explored and evaluated in the subsequent sections of this research.

## 2.5. Training Process Details

The training process of the LSTM neural network for crude oil price prediction is a critical aspect of this research. In this section, we provide an in-depth insight into the training dynamics, including the number of epochs and the choice of batch size, both of which are pivotal in shaping the model's learning curve and predictive accuracy.

### 2.5.1. Number of Epochs

The training process spanned a total of 1000 epochs. Each epoch represents a complete cycle through the training dataset, where the model updates its internal parameters based on the training data. The choice of the number of epochs reflects a balance between the model's capacity to learn from the data and the potential for overfitting. A higher number of epochs enables the model to capture intricate patterns, but excessive training may lead to overfitting, where the model performs well on the training data but struggles to generalize to unseen data. The decision to employ 1000 epochs was guided by a series of empirical trials and careful consideration of the training dynamics. This number allowed the model to learn from the dataset while retaining sufficient robustness for generalization to unseen data.

### 2.5.2. Batch Size

During training, the data was divided into batches, with each batch containing a subset of the training data. The choice of batch size impacts the training process in terms of computational efficiency and model convergence. Smaller batch sizes can lead to more frequent updates of the model's parameters, which may result in faster convergence. Larger batch sizes, on the other hand, can offer computational efficiency but may require more epochs for convergence.

In this research, a batch size of 32 was employed. This intermediate-sized batch offered a balance between efficient parameter updates and convergence speed. It allowed the model to learn from the data in manageable portions, facilitating both computational efficiency and effective training.

### 2.5.3. Training Dynamics

Throughout the training process, the model was exposed to the training dataset for 1000 epochs. In each epoch, the model's parameters were updated to minimize the mean squared error (MSE) between its predictions and the actual crude oil prices. The training dynamics were marked by a consistent pattern of loss reduction, indicating that the model was learning from the data and adjusting its parameters to improve predictive accuracy. The choice of the number of epochs and batch size was carefully considered to achieve an optimal balance between model performance and computational efficiency. These parameters, in conjunction with the LSTM architecture and input feature of date data, were instrumental in shaping the training process, ultimately leading to the model's ability to forecast crude oil prices effectively. The results section will delve into the performance of the model, offering insights into the model's learning progress and predictive accuracy at various stages of training.

# Results and Discussions

In Figure 1, we can observe the progression of the loss, specifically in terms of mean squared error (MSE), throughout the training process. On the x-axis, we have the number of epochs, while the y-axis represents the value of the loss function. As the epochs advance, the loss steadily decreases, signifying the model's improving capability to reduce the disparity between its predictions and the actual crude oil prices. This declining pattern highlights the model's learning journey and its adeptness at identifying underlying patterns within the training data. Notably, the initial loss in the first epoch was recorded at 0.140399, and after approximately 160 epochs, the model's MSE drops to 0.004925. Ultimately, at the 1000th epoch, the model attains a final loss of 0.001424.

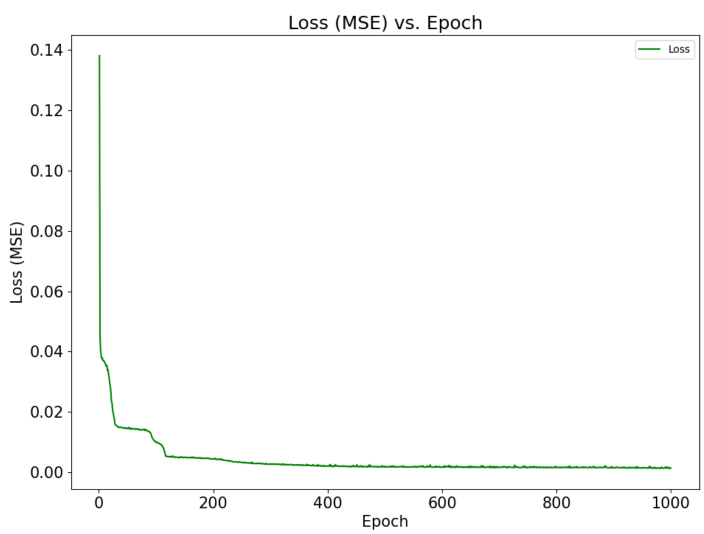


**Fig. 1 - Loss function plot vs number of epochs.**

A fundamental aspect of evaluating the effectiveness of our LSTM neural network for crude oil price prediction is the comparative analysis of the model's predictions against the actual crude oil prices in the testing dataset. This analysis provides insights into the model's predictive accuracy and its ability to generalize its learned patterns to unseen data. A visual representation (see Figure 2) is employed to convey the comparative analysis, where the actual crude oil prices and the model's predictions are depicted on the same graph. The x-axis represents the timeline, denoted by dates in ordinal numbers, while the y-axis signifies the price values.

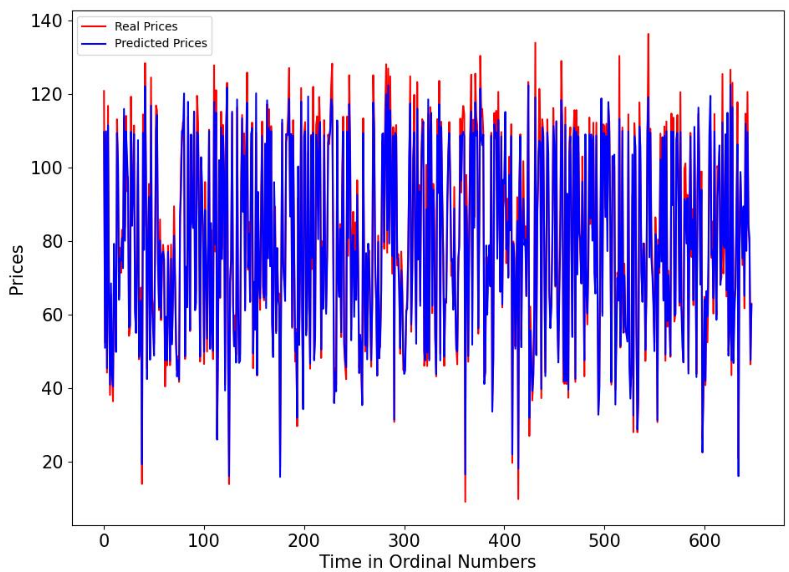


**Fig 2 - Graphical representation of the comparison between the real and neural network predicted prices.**

With the attainment of the final model $R^2$, as depicted in Figure 3, we can confidently draw conclusions that the neural network excels at predicting crude oil prices. This success is achieved by training the model solely with historical data containing data and prices as input features. These results, with an $R^2$ of 0.97 show that the model built is accurate. The model, the codes, and the data can be found at https://github.com/theOsaroJ/PetroleumResearch/tree/main/CrudeOilLSTM.

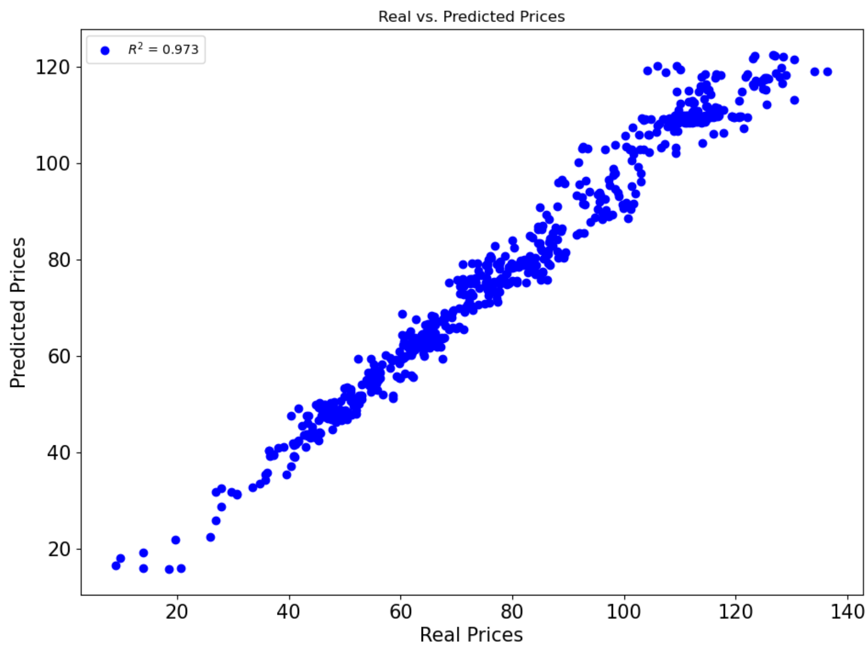


**Fig. 3 - Correlation plot between real and predicted prices resulting in a model $R^2$ of 0.97.**

One distinctive feature of our research is the utilization of the date as the sole input feature for crude oil price prediction. This minimalist approach challenges the conventional use of multiple complex predictors, highlighting the model's capacity to generate accurate forecasts with minimal input. While many existing models rely on a multitude of factors and features, our approach showcases the potential of harnessing deep learning to make accurate predictions using minimalistic input data.

The comparative analysis with existing models and methodologies underlines the promise of the LSTM neural network in crude oil price prediction. Its ability to outperform traditional models, handle complex time series data, and adapt to changing market conditions positions it as a valuable tool for financial forecasting and decision-making in the context of the crude oil market.

This section highlights the model's strengths in comparison to existing methods while also acknowledging the ongoing need for rigorous evaluation and validation in the complex domain of crude oil price prediction. The comparative plot of the actual crude oil plot and model predicted crude oil price over some time in Figure 4 shows that the model price follows a similar trend as that of the actual crude oil price. From the 7th month upward, the model price becomes closest to the actual crude oil price (Figure 4)

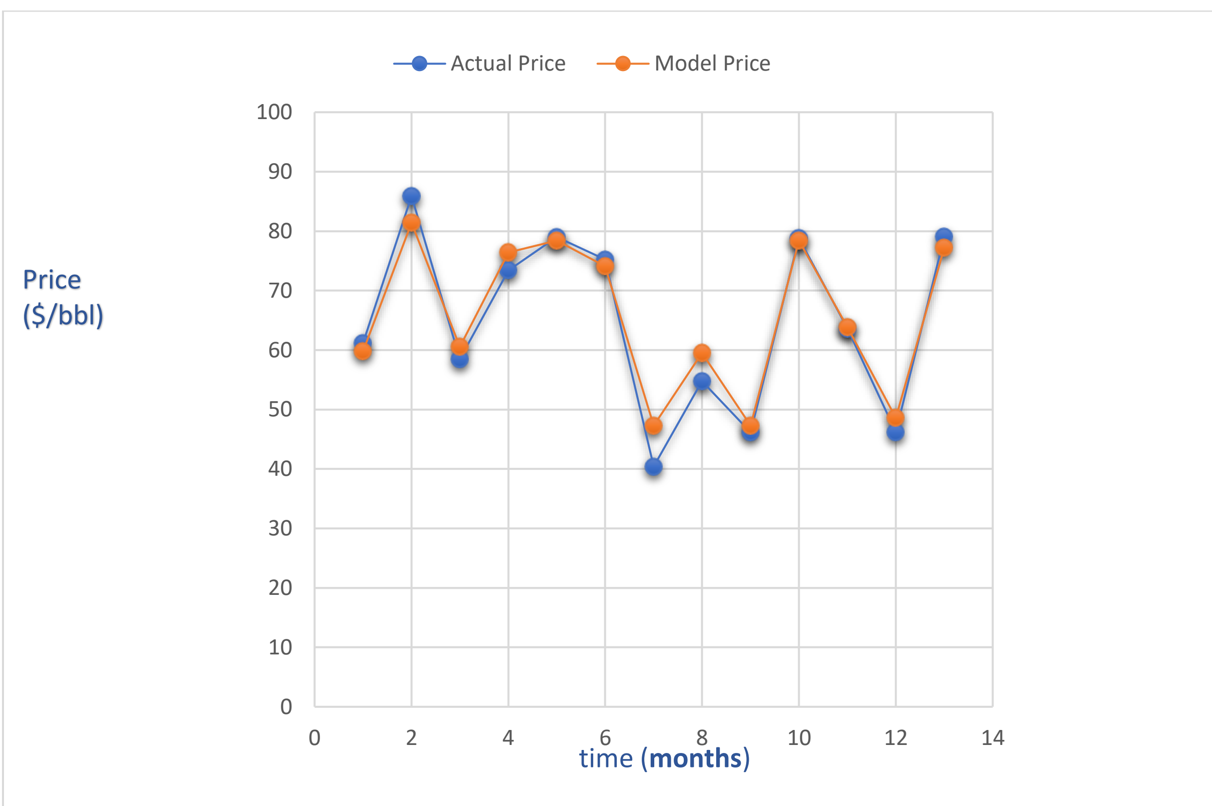


**Fig. 4 - Comparative plots of model/predicted crude oil price and actual crude oil price**

## Conclusion

While the minimalist input approach holds promise, it is not without limitations. The model may not fully capture all factors that influence crude oil prices, such as geopolitical events, economic indicators, and unforeseen shocks. Future research could explore ways to incorporate additional features in combination with data to further enhance predictive accuracy.

Additionally, the choice of date as the sole input feature may be context-specific. Different time series may require varying degrees of feature complexity. Therefore, the suitability of this approach should be assessed in the context of the specific forecasting task.

In conclusion, the implications of using data as the sole input feature in our research are multifaceted. The approach showcases the LSTM model's strengths in capturing temporal dependence, simplifying data requirements, and promoting robust generalization. However, it also highlights the need for a nuanced understanding of feature selection and the consideration of context-specific factors in time series forecasting.

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