Title : Prediction of oil and natural gas prices using Long Short Term Memory(LSTM).

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- ABSTRACT :

Oil and natural gas prices play an important role in various international aspects including economics, politics, international relations and many more. Ability to precisely predict its future prices helps in confidently making the economic decisions for any nation. Not only that, it is also a great boon for the people who invest into those commodities. In this research paper, we are conducting a thorough analysis on the LSTM model that we trained on the oil and natural gas dataset. As a part of the research, we surveyed the recent papers and articles available on the topic published after the year 2020. This particular study highlights the use of the LSTM model for capturing temporal dependencies.

This research paper delves into the realm of predicting oil and natural gas prices by employing Long Short-Term Memory (LSTM) neural networks, a powerful subset of recurrent neural networks (RNNs). The study revolves around the development and utilization of an extensive dataset which encompass various factors influencing the volatile energy markets. Our primary objective is to enhance the accuracy of price predictions thus contributing to a better understanding of the dynamics in price prediction of these commodities.

The results of our LSTM-based predictions are analyzed and compared with traditional forecasting methods, revealing the superior performance and adaptability of the proposed approach. Furthermore, insights gleaned from the study provide valuable implications for risk management, investment strategies, and policy formulation in the volatile oil and natural gas sectors. This research serves as a stepping stone towards more robust predictive models, contributing to the ongoing discourse on efficient energy market analysis and decision-making.

- INTRODUCTION:

The global energy sector is quite unambiguous due to its fluctuating nature. Certain geopolitical events and tensions contribute to a lot of chaos in the field.

At the heart of this intricate ecosystem lie the prices of two pivotal commodities: oil and natural gas. The volatile nature of these markets poses significant challenges for investors, policymakers, and industry stakeholders seeking accurate forecasting mechanisms. In response to this imperative, our research focuses on harnessing the power of Long Short-Term Memory (LSTM) neural networks to predict oil and natural gas prices with unprecedented precision.

Historically, traditional forecasting models have struggled to capture the nuanced dynamics of energy markets, often falling short in the face of rapidly changing variables. In contrast, LSTM neural networks have emerged as a promising solution, capable of comprehending long-term dependencies in sequential data – a characteristic essential for modeling the evolving patterns of oil and natural gas prices. This study undertakes an ambitious exploration by leveraging a meticulously curated dataset that encompasses a diverse array of influential factors, including economic indicators, geopolitical events, and technological breakthroughs.

As we delve into the methodology, our approach not only introduces the LSTM model but also emphasizes the significance of a holistic dataset for comprehensive training. By amalgamating historical price trends with a rich set of contextual variables, our research seeks to enhance the predictive capabilities of the LSTM model, offering a nuanced understanding of the intricate forces governing energy markets. Through this exploration, we aim to contribute to the refinement of forecasting tools, empowering stakeholders with actionable insights in navigating the uncertainties inherent in the oil and natural gas sectors.

- Keywords:

Oil and Natural Gas Prices, Long Short-Term Memory (LSTM), Energy Markets, Forecasting, Geopolitical Events, LSTM Neural Networks, Data Preprocessing, Dataset, Sequential Data, Temporal Dependencies, Financial Market Data, Min-Max Scaling, LSTM Architecture, Attention Layers, L2 Regularization, Batch Normalization, Dropout Layers, Stochastic Gradient Descent (SGD), Mean Squared Error (MSE), Early Stopping, Risk Management, Investment Strategies, Policy Formulation, Machine Learning Techniques, Economic Forecasting, Global Commodity Markets.

- Literature Survey:

In the investigation conducted by Y. J. Nagendra Kumar, P. Preetham, P. Kiran Varma, P. Rohith, and P. Dilip Kumar in their 2020 paper on crude oil price prediction using deep learning, the study adopts a third-person perspective to assess the effectiveness of LSTM models in forecasting crude oil prices and understanding their consequential impact on the global economy. Utilizing data sourced from the Federal Reserve Bank of St. Louis, the research scrutinizes the intricate relationship between crude oil prices and three primary external factors: Supply, Demand, and Shale Oil Production. Employing a sequential LSTM model, the researchers systematically explore various combinations of step sizes and epochs, striving to achieve optimal accuracy in predicting crude oil price movements. This analytical approach underscores the commitment to leveraging advanced deep learning techniques for a nuanced comprehension of the dynamic interplay between crude oil markets and global economic forces.

In the study conducted by V. Khullar, R. Chhabra, M. Angurala, M. Veeramanickam, K. Singh, and V. Lamba in 2023, exploring the dynamics of crude oil price forecasting in the context of the Indian National Stock Exchange, a third-person perspective is adopted. The research delves into the profound impact of crude oil price fluctuations on the Indian Stock Market and the broader global economy. Utilizing a dataset spanning from 2000, the authors focus on predicting the Close price of crude oil, employing target features such as Open, High, Low, and Volume. Through a meticulous comparative analysis, the study assesses the efficacy of LSTM and Bi-LSTM multivariate deep learning approaches in forecasting crude oil prices. The conclusive findings suggest that BiLSTM emerges as the superior approach, demonstrating lower Mean Squared Error (MSE), Root Mean Squared Error (RMSE), R2-Score, Normalized Mutual Information Criterion (NMIC), Mean Absolute Percentage Error (MAPE), and Mean Absolute Error (MAE) in predicting the close price of the crude oil index.

In the research conducted by F. Rabbi, S. U. Tareq, M. M. Islam, M. A. Chowdhury, and M. Abul Kashem in 2020, the focus is on the escalating electricity consumption, particularly during the Covid-19 pandemic, and its forecasting implications for decision-making and management in power systems. Adopting a third-person perspective, the authors compare five distinct approaches for electricity consumption forecasting: ARIMAX, SARIMAX, LSTM, GRU, and Bidirectional LSTM and GRU. Implementation of ARIMAX and SARIMAX models is carried out using pmdarima and statsmodels API, while RNN-based deep learning models are developed using Keras with TensorFlow computation backend. The research findings reveal that the GRU model attains the lowest Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) scores on the testing dataset. Consequently, the study concludes that RNN-based deep learning models, particularly the GRU, outperform traditional ARIMAX and SARIMAX models in providing more accurate predictions for electricity consumption forecasting.

In their 2022 study, A. Mahawan, S. Jaiteang, K. Srijiranon, and N. Eiamkanitchat present a hybrid model for predicting Hom Mali Rice and White Rice prices in Thailand. The model combines Autoregressive Integrated Moving Average with Exogenous Variable (ARIMAX) for feature transformation and Long Short-Term Memory (LSTM). The key preprocessing steps outlined in the paper involve Extract-Transform-Load (ETL), utilizing a genetic algorithm (GA) for feature selection, and tuning hyperparameters for ARIMA, ARIMAX, and LSTM models. The genetic algorithm contributes to enhancing model performance by selecting the most relevant input features. The research findings demonstrate that the hybrid ARIMAX-LSTM model outperforms other models and plays a significant role in informing government export policy formulation in Thailand. The study sheds light on data mining techniques aimed at improving the accuracy of rice price predictions, offering valuable insights for practitioners and policymakers alike.

The 2022 research by H. G. Al-Jasoor and S. Al-Janabi focuses on the critical task of predicting oil prices, a matter with profound implications for global economies, especially in oil-producing nations like Iraq. Employing multivariate analysis, the paper aims to comprehensively grasp the diverse factors influencing oil prices. The authors introduce a hybrid model that incorporates deep learning techniques, notably the Gated Recurrent Unit (GRU), with particular attention given to its effectiveness in addressing the vanishing gradient problem. The research methodology unfolds through three main steps: data preprocessing, the application of deep neural networks, and the evaluation of the model's performance using correlation metrics. Going beyond the exploration of the GRU, the paper conducts a comparative analysis with other prediction models, showcasing their respective utilities and potential to minimize errors and reduce training time, ultimately enhancing overall model effectiveness.

In their study "Natural Gas Price Forecasting using Statistical Models and Deep Learning Models," D. Murugan, R. Sivaramakrishnan, B. P. C, and Y. D, in 2023, investigate the forecasting of natural gas prices, underlining natural gas's role in fostering a sustainable environment through its lower carbon emissions. The authors explore the efficacy of a hybrid approach that merges statistical and deep learning models to enhance the accuracy of natural gas price predictions, crucial for informed energy planning and sustainable living. Their research evaluates a mix of models, including ARIMA, LSTM, Bidirectional LSTM, and Neural Prophet, aiming to determine the most effective combination for price forecasting. The findings reveal that integrating ARIMA with LSTM outperforms other model combinations, achieving the highest efficiency and accuracy with a score of 0.308851. This conclusion advocates for the superiority of hybrid models in forecasting natural gas prices, emphasizing their enhanced predictive accuracy and efficiency.

- METHODOLOGY:

Model's wIn this research endeavor, the dataset under scrutiny encapsulated a wealth of historical financial market data, honing in specifically on the opening prices of the designated target variable. To render the data amenable to the LSTM (Long Short-Term Memory) architecture, a meticulous data preprocessing phase was conducted. This encompassed the strategic application of the Min-Max scaling technique, an operation designed to normalize the target variable and constrict its range within a standardized interval of [0, 1]. This normalization procedure holds paramount significance in enabling the LSTM model to effectively capture intricate patterns across disparate scales.

The subsequent step in the methodology was the generation of sequences, a pivotal task for training the LSTM model adeptly. This was achieved through the implementation of a sliding window approach, where a judicious sequence length of 10 time steps was chosen. This choice allowed for the creation of sequential segments or windows, each comprising consecutive data points. The adoption of this sliding window strategy inherently facilitated the model's capacity to glean insights into temporal dependencies ingrained within the data.

The architectural framework of the model was carefully crafted, showcasing an integration of the LSTM neural network renowned for its prowess in assimilating and comprehending long-term dependencies within sequential data. The model's architecture featured three LSTM layers, each characterized by a reduction in hidden units (128, 64, and 32). The inclusion of attention layers further enriched the model's capabilities by dynamically weighting the importance of different elements within the input sequence during the training process. In tandem with this, L2 regularization with a coefficient of 0.001 was judiciously applied to the LSTM layers to forestall overfitting tendencies.

To fortify the model against overfitting, Batch Normalization layers were interspersed following each LSTM layer. This procedural step facilitated the normalization of activations, augmenting convergence speed. Complementary to this, Dropout layers with a rate of 0.5 were strategically introduced, acting as a safeguard mechanism to impede the co-adaptation of neurons and enhance the model's generalization capabilities. The output layer of the model assumed the form of a dense layer harboring a solitary neuron, serving as the conduit for the representation of the predicted opening price.

The compilation and training of the model ensued with the employment of Stochastic Gradient Descent (SGD) as the optimizer. This optimizer was meticulously configured with a learning rate of 0.0005 and a momentum parameter of 0.9. The chosen loss function for this study was the Mean Squared Error (MSE), adept at quantifying the dissonance between the model's predicted values and the actual observations. Notably, an early stopping mechanism was implemented with a patience threshold set at 15 epochs, thus precluding overfitting. This mechanism was devised to monitor the validation loss, automatically restoring the model weights corresponding to the epoch with the lowest validation loss.

The training process unfolded in batches, with each batch comprising 64 samples. This procedural choice was motivated by a desire to efficiently update the moeights and biases. The

training extended over a span of 80 epochs, allowing the model to iteratively learn from the dataset. Concurrently, validation was performed on a distinct subset of the data, a practice aimed at assessing the model's generalization prowess.

The historical trajectory of the training process, encapsulating metrics such as training and validation loss, was meticulously tracked. This archival of metrics bestowed valuable insights into the model's convergence dynamics and susceptibility to overfitting.

Subsequent to the training phase, the model's performance evaluation transpired on an independent test set, carefully segregated to avoid any overlap with the training dataset. Predictions generated by the model underwent an inverse transformation to restore them to the original scale using the Min-Max scaler. This restorative measure was crucial for meaningful interpretation and facilitated a robust assessment of the model's predictive accuracy. The Mean Squared Error (MSE) was computed as a quantitative metric, providing a numerical gauge of the disparity between the predicted and actual opening prices.

A visual appraisal of the model's performance materialized through the construction of a plot, wherein predicted opening prices were juxtaposed against their actual counterparts on the test set. This graphical representation served as an intuitive means to discern the model's proficiency in capturing intricate market patterns.

In ensuring the longevity and usability of the trained model, a model persistence strategy was instituted. The model, in its entirety, was saved in the Hierarchical Data Format 5 (HDF5), fostering ease of retrieval for future applications. Additionally, the parameters of the Min-Max scaler were safeguarded in order to preserve a consistent scaling framework during model inference.

This exhaustive and granular methodology elucidates the step-by-step journey undertaken in the experimental setup, ranging from the nuanced intricacies of data preprocessing and architectural choices to the rigors of training, evaluation, and the establishment of model persistence.

- Results:

The analysis concentrated on predicting commodity prices, emphasizing key attributes such as opening, closing, high, and low prices, along with volume. Initial data preprocessing addressed outliers in the volume column, standardized numeric values, and applied power transformations for skewness correction. Feature engineering included extracting date-related features and label encoding the 'commodity' column, while a heatmap visually highlighted potential feature relationships.

The core of the analysis implemented Long Short-Term Memory (LSTM) neural networks designed to capture temporal dependencies in time series data, incorporating layers like LSTM, dropout, and attention layers. Evaluation utilized the RMSprop optimizer and mean squared error loss, providing MSE values for 'open,' 'high,' 'low,' and 'close' variables. Visual representations facilitated a comprehensive assessment of model performance.

Results exhibited varying prediction accuracy levels. The 'high' variable demonstrated relatively accurate predictions (MSE: 0.39196), and the 'open' variable showed reasonably accurate predictions with slight underestimation (MSE: 0.3964). Conversely, the 'close' variable displayed moderate accuracy with consistent underestimation (MSE: 0.4115). In contrast, the 'low' variable exhibited commendable performance, closely aligning predictions with actual prices (MSE: 0.28299). Overall, the analysis presented a systematic approach to predicting commodity prices, showcasing LSTM models' effectiveness in capturing historical patterns. While results indicated reasonable performance, further exploration and refinement could enhance predictive capabilities and model robustness.

Table 1. Performance Evaluation :-

Target Variable	MSE Score
Open	0.39638
High	0.3551
Low	0.2829
Close	0.3747

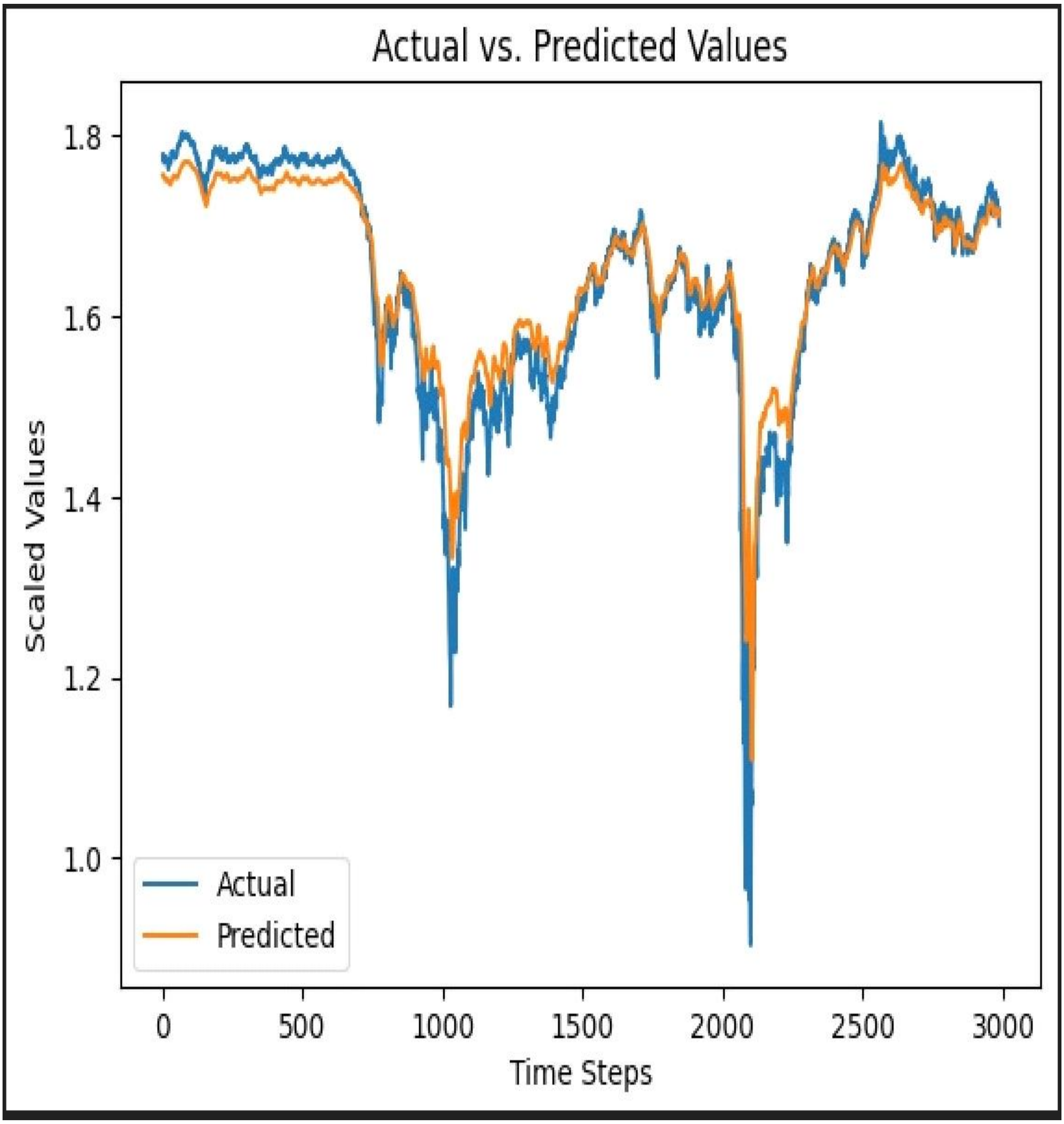

Figure 6.1 “Actual Values vs Predicted Values” for “High Price”

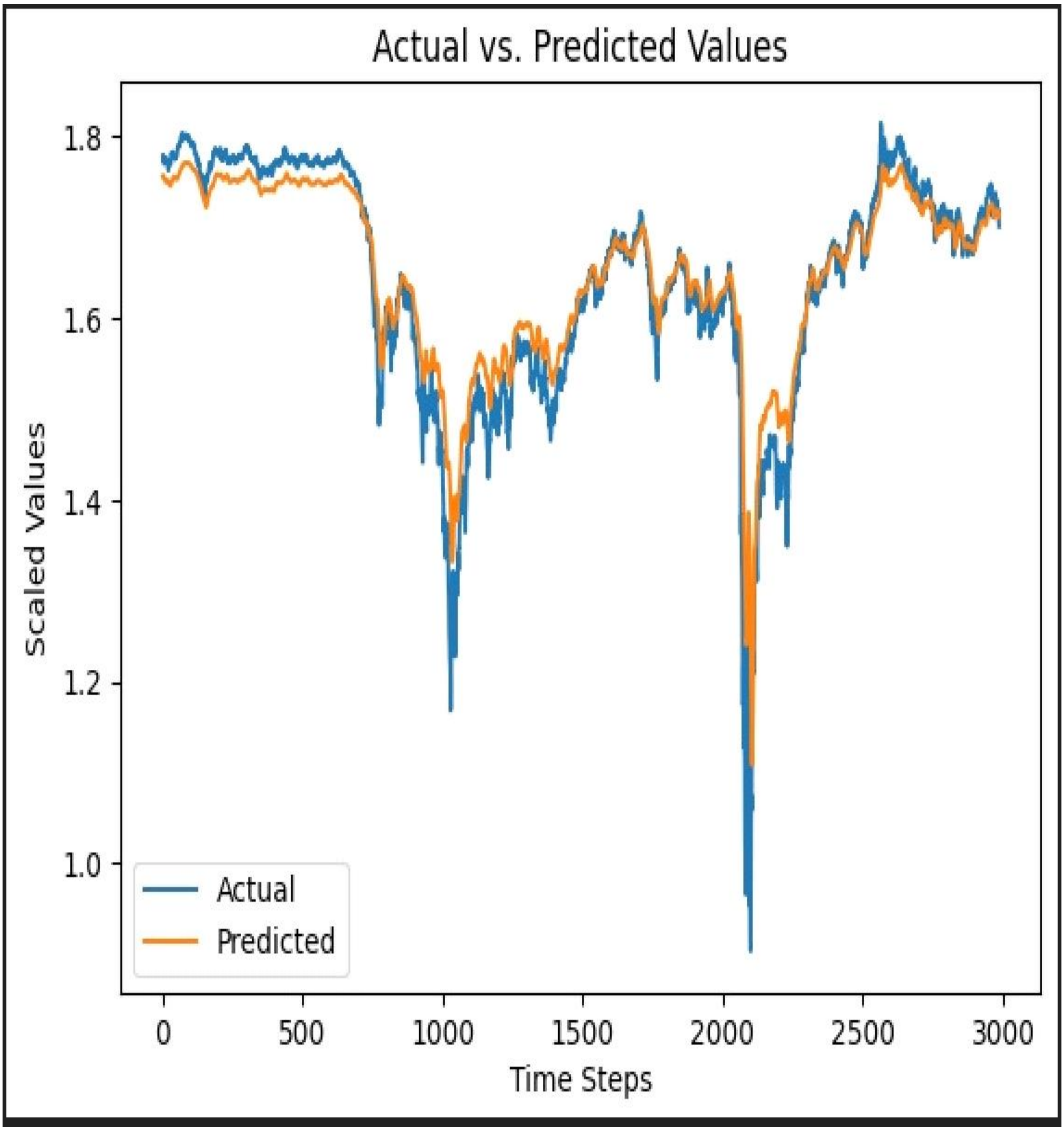

Figure 6.2 “Actual Values vs Predicted Values” for “Open Price”

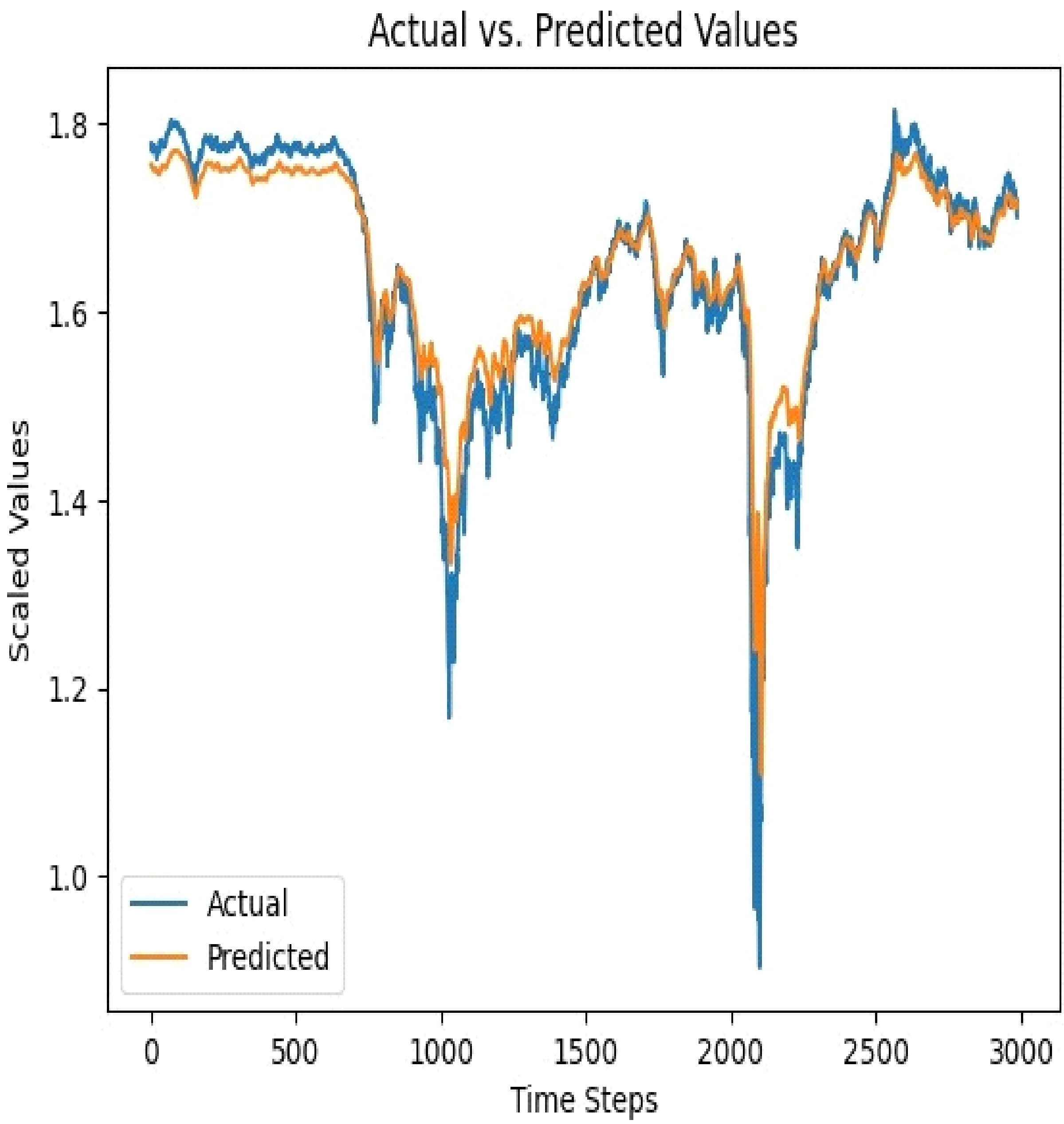

Figure 6.3 “Actual Values vs Predicted Values” for “Low Price”

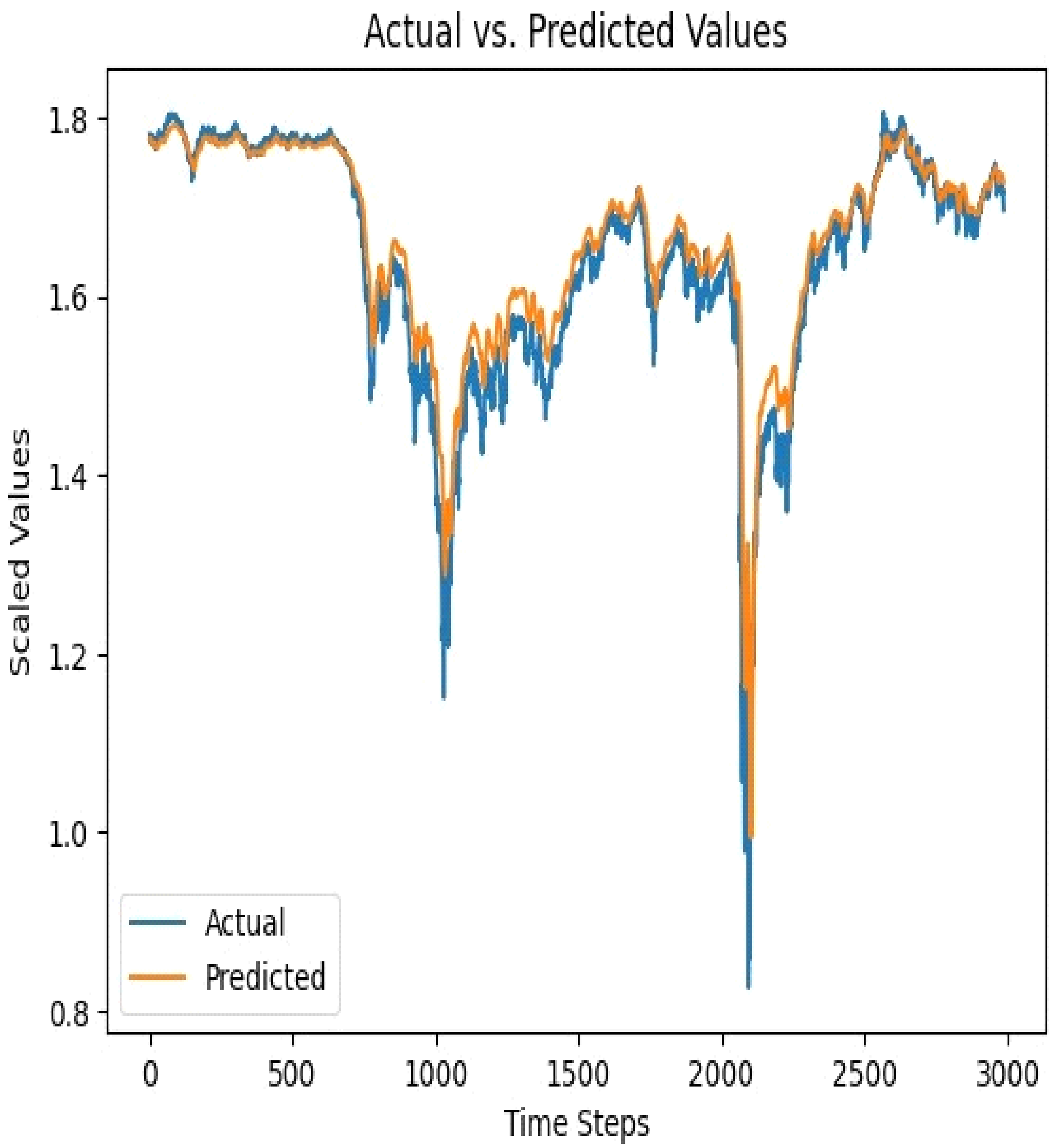

Figure 6.4 “Actual Values vs Predicted Values” for “Close Price”

- Conclusion:

The conclusion of this study underscores the profound influence of Long Short-Term Memory (LSTM) neural networks in refining the accuracy of oil and natural gas price forecasts. Utilizing a comprehensive dataset that encapsulates the various factors impacting these commodities, the research delineates the superior predictive capabilities of the LSTM model over conventional forecasting methodologies. This leap in forecasting precision transcends mere technical accomplishment, unveiling significant implications for risk management, investment strategy, and policy formulation within the volatile energy market landscape.

The investigation compellingly demonstrates the LSTM model's adeptness in modeling complex temporal dependencies, a feat that traditional models often struggle with due to the inherent volatility and non-linear nature of the energy markets. This advancement in predictive modeling is crucial for stakeholders dependent on reliable forecasts to adeptly navigate the uncertainties prevalent in the energy sector.

Moreover, the study calls for a broader exploration and adoption of machine learning techniques in the realm of economic forecasting, particularly within vital sectors such as energy. It proposes a methodological shift away from traditional statistical approaches towards more sophisticated, data-driven methodologies that are better equipped to capture the intricacies of global commodity markets.

By advocating for this paradigm shift in analytical methodologies, the research not only enriches academic and scientific discourse on predictive modeling but also offers tangible advantages for practitioners in the energy field. The implications for improved decision-making and strategic planning are profound, heralding a future where energy market analyses are imbued with greater nuance, insight, and alignment with the realities of global market dynamics. This fosters an environment where the complexities of the energy markets are more accurately represented, facilitating more informed and strategic responses to the challenges and opportunities they present.

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