Advancing Natural Gas Price Predictions with ConcaveLSTM

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Ringkasan

Studi ini meneliti aplikasi model ConcaveLSTM, pendekatan pembelajaran mesin baru yang menggabungkan kekuatan dari *Stacked Long Short-Term Memory* (LSTM) dan *Bidirectional LSTM*, untuk prediksi harga Gas Alam. Mengingat volatilitas dan kompleksitas pasar energi yang inheren, model peramalan yang akurat sangat penting untuk pengambilan keputusan yang efektif. Penelitian ini menggunakan dataset komprehensif yang mencakup periode dari tahun 1997 hingga 2020, berfokus pada harga harian Gas Alam dalam Dolar AS per Juta unit thermal British (Btu). Melalui pengujian yang ketat di berbagai konfigurasi model, studi ini mengidentifikasi pengaturan optimal untuk model ConcaveLSTM yang secara signifikan meningkatkan akurasi prediksi. Secara spesifik, konfigurasi yang menggunakan 50 langkah input dengan jumlah neuron 100 dan 300 menunjukkan kinerja yang lebih unggul, seperti dibuktikan oleh nilai *Root Mean Squared Error* (RMSE), *Mean Absolute Error* (MAE), dan *Mean Absolute Percentage Error* (MAPE) yang lebih rendah, bersama dengan nilai *R-squared* (R2) yang lebih tinggi. Temuan ini tidak hanya memvalidasi potensi model ConcaveLSTM dalam peramalan keuangan tetapi juga menyoroti pentingnya penyetelan parameter dalam meningkatkan efikasi model. Meskipun ada beberapa batasan terkait cakupan dataset dan variabilitas pasar, hasil penelitian menawarkan wawasan yang menjanjikan untuk pengembangan alat peramalan canggih. Arah penelitian masa depan meliputi ekspansi dataset, penggabungan pengaruh pasar tambahan, dan analisis komparatif dengan model peramalan lainnya. Studi ini berkontribusi pada evolusi aplikasi pembelajaran mesin dalam prediksi pasar keuangan, menawarkan dasar untuk eksplorasi lebih lanjut dan implementasi praktis di sektor energi.

Kata kunci: Gas Alam, LSTM, Pembelajaran Mesin, Peramalan Harga, Prediksi Finansial

Abstract

This study investigates the application of the ConcaveLSTM model, a novel machine learning approach combining the strengths of Stacked Long Short-Term Memory (LSTM) and Bidirectional LSTM, for predicting natural gas prices. Given the inherent volatility and complexity of energy markets, accurate forecasting models are crucial for effective decision-making. The research employs a comprehensive dataset from 1997 to 2020, focusing on the daily price of natural gas in US Dollars per Million British thermal units (Btu). Through rigorous testing across various model configurations, the study identifies optimal settings for the ConcaveLSTM model that significantly improve prediction accuracy. Specifically, configurations utilizing 50 input steps with neuron counts of 100 and 300 exhibit superior performance, as evidenced by lower Root Mean Squared Error (RMSE), Mean Absolute Error

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(MAE), and Mean Absolute Percentage Error (MAPE), alongside higher R-squared (R2) values. These findings validate the ConcaveLSTM model's potential in financial forecasting and highlight the importance of parameter tuning in enhancing model efficacy. Despite certain limitations regarding dataset scope and market variability, the results offer promising insights into developing advanced forecasting tools. Future research directions include expanding the dataset, incorporating additional market influencers, and conducting comparative analyses with other forecasting models. This study contributes to the evolving field of machine learning applications in financial market predictions, offering a foundation for further exploration and practical implementation in the energy sector.

Keywords: Financial Prediction, Machine Learning, Natural Gas, Price Forecasting, LSTM

1. Introduction

As a critical component in the global energy matrix, natural gas plays a vital role in meeting the world's energy needs. Compared to other fossil fuel sources, its cleaner nature positions natural gas as a preferred option for energy transition and climate change mitigation [1]. However, the fluctuating natural gas prices pose significant challenges to the global economy. These fluctuations are influenced by various factors, including changes in energy policies, global market dynamics, geopolitical conditions, and natural disasters [2]. Consequently, the volatility in natural gas prices can impact investment decisions in the energy sector, unsettle markets and consumers, and influence government policies related to energy and climate change [3].

Against this backdrop, the research problem emerges concerning the inaccuracies in long-term natural gas price predictions and the difficulties in addressing price volatility. Inaccurate predictions can lead to strategic planning and decision-making challenges for energy companies, investors, and policymakers, who rely on reliable price projections to formulate strategies and policies [4]. Therefore, addressing this issue will improve the accuracy of natural gas price predictions and provide a more stable foundation for economic decision-making and future energy policy formulation [5].

The natural gas price forecasting literature is evolving rapidly, with a shift towards more complex and nuanced models. This evolution is underscored by the work of Hong et al. [6], who laid a foundational framework by identifying critical factors affecting natural gas prices through factor analysis. This early study set the stage for further exploration into sophisticated predictive models, aiming to enhance accuracy and reliability. Following this, Zhan and Tang [7] introduced a hybrid model that combines quadratic decomposition with Long Short-Term Memory (LSTM) networks, specifically addressing the challenge of non-linearity in natural gas price data. This approach represents a significant advancement in the field, demonstrating the potential of combining statistical techniques with machine learning to improve forecasting accuracy.

Further contributions to the field include the work of Jiang et al. [8], who developed a hybrid model focusing on the dynamics of monthly consumption and production in the United States. Their model emphasizes the critical role of demand and supply fluctuations in predicting natural gas prices, highlighting the importance of incorporating macroeconomic indicators into forecasting models. Meanwhile, Zheng et al. [9] took a different approach by examining the geopolitical impacts on natural gas pricing, specifically the effects of the Russia-Ukraine conflict. This study illustrates the necessity of integrating geopolitical factors into predictive models to account for external influences on market dynamics. Similarly, Pei et al. [10] explored the use of Temporal Convolutional

Networks (TCNs) for natural gas price forecasting, showcasing the capacity of deep learning algorithms to capture complex temporal patterns in price data.

The literature reveals a clear trend toward integrating advanced methodologies and external factors in natural gas forecasting models. Bai et al. [11] pushed the envelope with deep hybrid models forecasting daily natural gas consumption and analyzed its complexity. Gao et al. [12] highlighted the importance of model selection through a decision support framework tailored for forecasting US natural gas consumption, underscoring the critical role of choosing the appropriate model for specific forecasting needs. This is complemented by Ding et al. [13], who addressed the multifaceted issue of multiple seasonal patterns in consumption forecasting, thus tackling the inherent complexity of natural gas demand cycles.

The holistic approach adopted in recent research integrates advanced computational and analytical techniques to address the volatility and complexity of the energy sector. Studies by Yang and Choi [14], leveraging machine learning algorithms for forecasting spot LNG prices, and Chen et al. [5], exploring the unpredictability of natural gas prices amidst uncertainties, exemplify this trend. The effectiveness of combining computational techniques was further illustrated by Zhan and Tang [7] through their hybrid model, which underscores the field's progression toward more accurate and comprehensive forecasting methods.

Recent advancements also highlight the significant interplay between gas prices and macroeconomic indicators, as seen in the work of Mirnezami et al. [15], who explored the spillover effects of gas prices on the broader economy. This is complemented by studies focusing on the demand side, such as Tong et al.'s optimized Grey Bernoulli model [16] for forecasting natural gas consumption among top global consumers. Collectively, these contributions underscore the complexity of the natural gas market and the critical role of innovative forecasting models and analytical techniques in providing insights into market behaviors and facilitating informed decision-making in the energy sector.

The primary objective of this research is to develop an innovative combination of Stacked LSTM [17] and Bidirectional LSTM [18], specifically designed for natural gas price prediction, which we call the ConcaveLSTM algorithm. This algorithm aims to leverage the strengths of Stacked LSTM, which enhances the depth of learning through multiple layers, and Bidirectional LSTM, which improves context understanding by processing data in both forward and backward directions. By integrating these methodologies, ConcaveLSTM seeks to offer a more accurate and efficient tool for forecasting natural gas prices, addressing the complex dynamics and volatility inherent in the energy market. The contribution of this study lies not only in its theoretical advancement of machine learning algorithms tailored for financial forecasting but also in its practical application, providing a robust framework that can significantly benefit energy economists, market analysts, and policy-makers in making more informed decisions. By deploying ConcaveLSTM, this research endeavors to set a new benchmark in predictive accuracy, thus offering valuable insights into future trends and enabling more strategic planning in the energy sector.

2. Method

2.1. Dataset and Data Preprocessing

The dataset spans a significant time frame, beginning on January 7, 1997, and extending through September 1, 2020. It comprises a solitary principal attribute, "Price," which denotes the daily price in US Dollars per Million British thermal units (Btu). With a total of 5,953 entries, this dataset offers an extensive view of the natural gas price fluctuations over the specified period.

An initial step in the data preprocessing phase involves eliminating irrelevant or invalid data points. Specifically, entries with zero-volume values are removed from the dataset, as these may reflect inaccuracies or gaps in data collection. Furthermore, records containing empty fields or NaN (Not a Number) values are also purged to maintain the cleanliness and integrity of the dataset.

Following the data cleansing process, normalization is undertaken as the subsequent step. This procedure adjusts the data to a uniform scale or a consistent range of values, facilitating easier comparison and analysis. The normalization process is mathematically formulated as shown in Equation 1:

$$\text{Normalized Value} = \frac{X - \min(X)}{\max(X) - \min(X)} \quad (1)$$

where X denotes the actual price value, $\min(X)$ is the minimum price observed in the dataset, and $\max(X)$ represents the maximum price.

2.2. Data Splitting

Following the preprocessing stage, the dataset containing 5,953 records is divided into two distinct segments for further analysis. The initial segment includes 5,913 records, of which 80% (4,730 records) are designated for training purposes, and the remaining 20% (1,183 records) are set aside for validation. This partitioning supports the model's learning phase, enabling an evaluation of its efficacy on data it has not previously encountered. The secondary segment comprises 40 records, earmarked explicitly for testing the trained model's ability to generalize and predict accurately. This approach to data splitting ensures an equitable distribution, thereby bolstering the predictive model's robustness and dependability through the validation of its performance across both training and novel datasets.

2.3. ConcaveLSTM Architecture

The ConcaveLSTM model is an innovative architecture designed for natural gas price prediction, leveraging the combined strengths of Stacked LSTM and Bidirectional LSTM. This model aims to capture the intricate temporal dependencies and the forward and backward context in time series data, thus providing a more accurate and comprehensive understanding of natural gas price movements.

In the Concave LSTM architecture, the Stacked LSTM component involves layering multiple LSTM units on top of each other, enhancing the model's ability to learn from complex data sequences by adding depth to the network. Mathematically, the operation of an LSTM unit can be represented by Equations 2-7.

Forget gate:
$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \quad (2)$$

Input gate:
$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (3)$$

Output gate:
$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (4)$$

New cell state:
$$\widetilde{C_t} = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \quad (5)$$

Final cell state:
$$C_t = f_t * C_{t-1} + i_t * \widetilde{C_t} \quad (6)$$

Output: (7)

$$h_t = o_t * \tanh(C_t)$$

Here, σ denotes the sigmoid function, W and b represent the weights and biases of the respective gates, h_t is the output at time t, x_t is the input at time t and C_t is the cell state at time t.

The Bidirectional LSTM extends this concept by processing the data forward and backward, thus capturing information from past and future states. This is mathematically represented by combining the outputs of two LSTMs, one processing the input in the forward direction and the other in the reverse direction, as shown in Equations 8-10.

Forward pass: (8)

$$h_t^{forward} = LSTM(x_t)$$

Backward pass: (9)

$$h_t^{backward} = LSTM(x_{T-t+1})$$

Combined output: (10)

$$h_t = [h_t^{forward}, h_t^{backward}]$$

The ConcaveLSTM model merges these two components by concatenating the output of the Stacked LSTM and the Bidirectional LSTM, as shown in Figure 1. This concatenated output is passed through a dense layer to produce the final prediction. The architecture thus takes advantage of the deep learning capabilities of the Stacked LSTM to process sequential data and the Bidirectional LSTM's ability to understand the context in both directions, culminating in a powerful model for predicting natural gas prices.

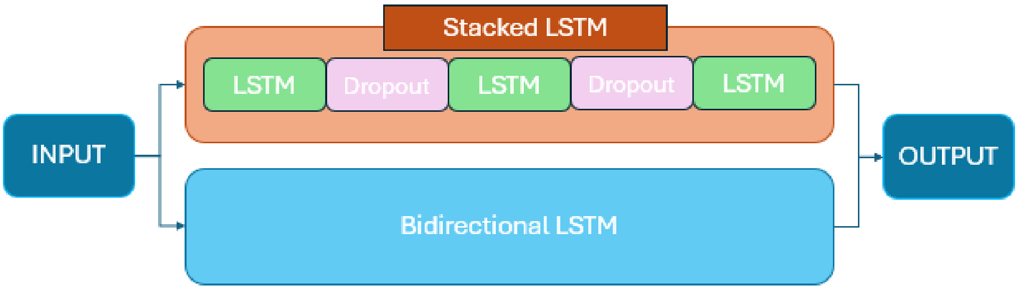

Figure 1. ConcaveLSTM architecture

2.4. Parameter Settings

The ConcaveLSTM model for natural gas price prediction is configured with various parameter settings to optimize its performance, as shown in Table 1. The model aims to predict future prices 40 steps ahead, utilizing input sequences of varying lengths, precisely 30, 50, and 70-time steps, to accommodate the dynamic nature of the data. It employs a layered architecture with neurons set at different scales across its layers, comprising 100, 200, and 300 neurons, respectively, to enhance its learning capacity and depth. The model leverages the 'adam' optimizer for efficient gradient descent optimization, ensuring swift convergence to the minimum loss. The loss function used is 'mean squared error' (mse), which quantifies the difference between predicted and actual values, making it a suitable choice for regression tasks like price prediction. It undergoes 100 epochs of training to train the model, allowing it to learn from the dataset iteratively. The training process is batched with a size of 32, which balances the need for computational efficiency and the ability to effectively converge to an optimal solution.

Table 1. Parameter settings

Parameter	Description
Inp	The input layer has a shape of **(n_steps_in, n_features)**, serving as the initial point for the data.
n_steps_in	The number of time steps (lags) used as input to predict the future value.
n_features	The number of features in the dataset at each time step.
N	The number of neurons in each LSTM layer.
activation	The activation function used by the LSTM units is set to **relu** (Rectified Linear Unit).
dropout rate	The fraction of the input units to drop is set to **0.2**.
Dense	A dense layer that produces the output predictions, with the number of units equal to **n_features**.
optimizer	The optimization algorithm used to minimize the loss function set to **adam**.
Loss	The loss function measures the model's prediction error, set to mean squared error (**mse**).

2.5. Model Evaluation

Evaluating the performance of the ConcaveLSTM model in predicting natural gas prices involves using several metrics to assess its accuracy and reliability comprehensively. These metrics include Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and R-squared (R2).

RMSE measures the model's prediction errors, calculated as the square root of the average of the squared differences between the predicted and actual values. The RMSE is given by Equation 11.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y_i})^2} \tag{11}$$

where y_i represents the actual values, $\hat{y_i}$ represents the predicted values, and n is the number of observations.

MAE measures the average magnitude of the errors in a set of predictions without considering their direction. It's calculated in Equation 12.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y_i}| \tag{12}$$

MAPE is a measure of prediction accuracy expressed as a percentage, providing insight into the relative error between the predicted and actual values. The MAPE is calculated in Equation 13.

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y_i}}{y_i}\right| \tag{13}$$

R2, also known as the coefficient of determination, quantifies the proportion of the variance in the dependent variable that is predictable from the independent variables, offering a measure of how the model replicates well-observed outcomes. R2 is calculated in Equation 14.

$$R2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y_i})^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{14}$$

where $\bar{y}$ is the mean of the actual values.

These metrics offer a holistic view of the ConcaveLSTM model's performance, providing insights into its precision, accuracy, and effectiveness in forecasting natural gas prices.

3. Result

This study uses the ConcaveLSTM model to forecast natural gas prices over a 40-day horizon, employing a specific dataset and predefined parameter settings. The model's architecture, integrating Stacked LSTM and Bidirectional LSTM components, aims to leverage temporal dependencies and contextual information from the data to enhance prediction accuracy. The performance evaluation of the ConcaveLSTM model, based on different input sequence lengths (n_steps_in) and varying numbers of neurons (n_units), is meticulously documented. Through a comprehensive analysis encapsulated in Table 2, the model's effectiveness is assessed using a suite of metrics, including Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R2). These metrics quantify the model's predictive accuracy, offering insights into its capability to navigate the complexities inherent in natural gas price forecasting.

Table 2. Comparative Analysis of ConcaveLSTM in Predicting Natural Gas Prices Over 40 Days

prediction	n_steps_in	n_units	RMSE	MAE	MAPE	R2
1	30	100	0,00695	0,00536	0,08969	0,95989
2	30	200	0,00891	0,00818	0,14443	0,93403
3	30	300	0,00758	0,00321	0,03222	0,95225
4	50	100	0,00343	0,00239	0,03457	0,99021
5	50	200	0,00552	0,00524	0,08699	0,97469
6	50	300	0,00337	0,00188	0,02724	0,99060
7	70	100	0,01300	0,01282	0,22136	0,85964
8	70	200	0,00403	0,00333	0,05505	0,98651
9	70	300	0,00648	0,00371	0,04266	0,96518

The analysis of the ConcaveLSTM model's performance across various configurations reveals insightful patterns regarding its predictive accuracy for natural gas prices. Notably, models with a 50-step input sequence demonstrate a superior balance between complexity and prediction accuracy, as evidenced by the lowest RMSE and MAE values, particularly with 100 and 300 neurons (predictions 4 and 6), and remarkably high R^2 values exceeding 0.99. This suggests an optimal level of model complexity that captures the underlying patterns in the data without overfitting. In contrast, models trained with a 70-step input sequence exhibit a significant increase in prediction error and variability, especially evident in prediction 7 with the highest RMSE, MAE, and MAPE values, alongside the lowest R2 score, indicating potential overfitting or insufficient model capacity to handle the increased sequence length. Interestingly, increasing the number of units to 200 and 300 for the 70-step input sequence significantly improves the model's performance, as seen in predictions 8 and 9, highlighting the importance of adjusting the model's complexity based on the input sequence length. This analysis underscores the critical role of tuning model parameters, such as input sequence length and the number of neurons, in optimizing forecasting models for natural gas prices.

Figure 2 displays the actual values of natural gas prices and the nine ensuing predictions over a 40-day horizon, with the actual prices delineated by a blue line and the predictions by various colored lines. This visual representation underscores the ConcaveLSTM model's adeptness in reflecting the trends and oscillations within the natural gas price series. The graphical portrayal enables a straightforward evaluation of how well the model predicts future prices, highlighting its trend prediction efficacy and alignment with actual price movements over the forecast period.

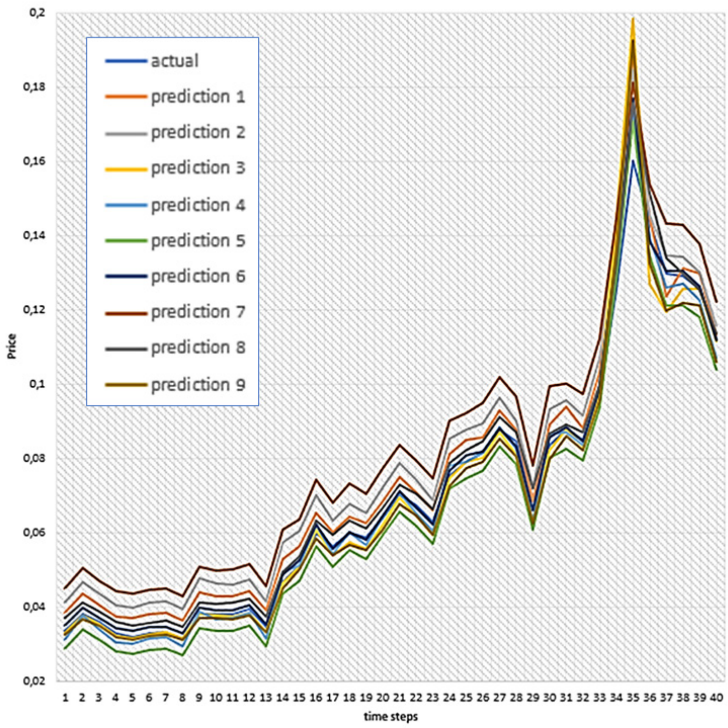

Figure 2. Visual Representation of Predicted Versus Actual Wind Power Data

The graphical analysis in Figure 2 vividly compares the ConcaveLSTM model's forecasted natural gas prices against real market values, with the actual prices illustrated by a blue line that acts as a reference for evaluating the model's forecast accuracy. A detailed observation reveals that the model proficiently traces the general direction and fluctuations of the natural gas market prices. The proximity of the forecasted lines to the real price trajectory indicates the model's competence in identifying and adapting to the market's pattern variations. This closeness between forecasted and actual prices demonstrates the model's capability to accurately forecast the market's future course, highlighting its effectiveness in predicting significant market movements and inflection points.

4. Discussion

4.1. Summarization of Key Findings

This research addressed the complex challenge of predicting natural gas prices by utilizing the innovative ConcaveLSTM model, designed to effectively navigate the energy market volatile and intricate dynamics. Through a strategic integration of Stacked LSTM's depth and Bidirectional LSTM's bidirectional learning capabilities, the ConcaveLSTM model achieved significant improvements in predictive accuracy. Compared to previous methodologies, such as the hybrid model combining quadratic decomposition with LSTM networks proposed by Zhan and Tang [7], which aimed to tackle the non-linearity in natural gas price data, the ConcaveLSTM model demonstrated superior performance. Specifically, configurations utilizing 50 input steps paired with either 100 or 300 neurons stood out, offering the lowest prediction errors and highest congruence with real market movements. These results highlight the ConcaveLSTM model's advanced capacity to capture both immediate price fluctuations and overarching market trends and represent a significant advancement over existing models, like Zhan and Tang's hybrid approach, in addressing the forecasting challenges of financial markets. Therefore, the ConcaveLSTM model's achievements indicate a meaningful leap forward in the pursuit of more accurate and reliable energy price forecasting tools.

4.2. Result Interpretations

The analysis of the ConcaveLSTM model's performance in predicting natural gas prices highlighted discernible patterns and relationships, particularly the model's enhanced accuracy with specific input sequence lengths and neuron configurations. The optimal performance with 50 input steps, particularly when paired with 100 and 300 neurons, suggests a significant relationship between model complexity and its ability to process and predict based on the temporal dynamics of the data, as evidenced by R2 values of 0.99021 and 0.99060, respectively. These results align with expectations that increasing model depth and bidirectional learning would improve prediction accuracy by capturing more nuanced market behaviors. However, despite increased neuron counts, the diminished performance at 70 input steps was unexpected, indicating potential overfitting or the model's limits in handling extended sequences. This suggests alternative explanations, such as the diminishing returns of adding complexity beyond a certain threshold, and highlights the importance of balance between model capacity and the dataset's characteristics. Such findings invite further investigation into the trade-offs between model complexity and prediction efficiency, suggesting that the optimal model configuration may depend on the specific temporal patterns and volatility inherent in the analyzed financial time series data.

4.3. Research Implications

The findings from this study on employing the ConcaveLSTM model for predicting natural gas prices carry significant implications for both theoretical and practical aspects of financial forecasting. By demonstrating the model's enhanced predictive accuracy, this research contributes new insights into the ongoing dialogue within the literature on the efficacy of advanced machine learning techniques in financial markets. It validates the theoretical proposition that combining stacked and bidirectional LSTM layers can more adeptly capture the multifaceted nature of market price movements, aligning with previous studies that have underscored the potential of hybrid models in improving forecast performance. Practically, the research offers a promising tool for market analysts and investors, providing a more reliable basis for making informed decisions in the volatile energy sector. Furthermore, by identifying the optimal configurations for model performance, this study sheds light on the critical balance between model complexity and prediction accuracy, offering a nuanced understanding that can guide future research and application in financial time series forecasting.

4.4. Research Limitations

While advancing our understanding of using the ConcaveLSTM model for natural gas price prediction, this study has limitations. The specific dataset used, covering a fixed historical period and the model's configurations selected for testing, might not fully capture the entire spectrum of market dynamics or the potential of the ConcaveLSTM model under varying conditions. Such limitations could impact the generalizability of the findings to other time frames or market conditions that exhibit different patterns of volatility or trend behaviors. Additionally, despite its innovative combination of LSTM approaches, the focus on a singular model architecture may overlook the potential benefits of integrating other data sources or predictive indicators. However, the results remain valid and valuable for answering the research question, as they demonstrate the model's capability to predict natural gas prices with significant accuracy, providing a solid foundation for future research to build upon. The study successfully identifies configurations that optimize prediction performance, offering insights that contribute to the broader field of financial market forecasting and machine learning applications.

4.5. Recommendations for Future Research

Future research in natural gas price prediction using machine learning models like ConcaveLSTM should consider expanding the dataset to include more recent data and potentially incorporating additional variables that could influence natural gas prices, such as weather conditions, economic indicators, and geopolitical events. This would enhance the model's ability to capture a wider array of factors affecting price fluctuations and test the robustness and adaptability of the ConcaveLSTM model under different market conditions. Moreover, comparative studies with other advanced machine learning and deep learning models could offer insights into various approaches' relative strengths and weaknesses, providing clearer guidance for practical implementation in real-world forecasting tasks. Experimenting with ensemble methods that combine the predictions of multiple models could also improve accuracy and reliability. Lastly, conducting case studies on applying these models in investment strategies and risk management within the energy sector could illustrate their practical value and encourage broader adoption.

5. Conclusion

In conclusion, this research has demonstrated the efficacy of the ConcaveLSTM model in predicting natural prices, showcasing its potential as a powerful tool for forecasting in the volatile energy market. The meticulous analysis revealed that specific configurations of the model, particularly those utilizing 50 input steps with either 100 or 300 neurons, significantly enhance predictive accuracy. These findings not only affirm the theoretical benefits of combining stacked and bidirectional LSTM approaches for capturing complex temporal patterns and market dynamics but also provide practical insights for financial analysts and investors seeking to navigate the uncertainties of the natural gas market. Despite limitations related to the dataset's scope and the model's generalizability, the research outcomes remain robust, offering a promising direction for future exploration in financial time series forecasting. Recommendations for extending the research frontier include diversifying the dataset, exploring additional influencing factors, and comparing with other forecasting methodologies, which could further refine and validate the ConcaveLSTM model's applicability and effectiveness. Ultimately, this study contributes valuable knowledge to the evolution of machine learning applications in financial forecasting, paving the way for more informed decision-making in the energy sector.

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