AutoML for Crude Oil Price Forecasting: A Comparative Study

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***Abstract*—Crude oil price forecasting is a critical task for industrial decision-making in volatile economic environments. This study proposes an automated forecasting system based on historical crude oil price data and investigates the problem using both time-series and tabular data representations. An Automated Machine Learning (AutoML) framework is employed to automate model selection and hyperparameter optimization, reducing reliance on domain-specific expertise. A unified AutoML pipeline is developed to evaluate multiple forecasting models across different temporal granularities and prediction horizons, using time-aware validation to preserve data chronology. Historical prices are collected via an application programming interface, ensuring reproducibility and enabling continuous data updates. Experimental results demonstrate that AutoML-based approaches deliver robust, scalable forecasting performance, supporting their use as effective decision-support tools in industrial contexts. Comparisons with traditional methods, including autoregressive models and recurrent neural networks, are conducted to assess the empirical benefits of adopting AutoML.**

***Index Terms*—Crude Oil Forecasting, AutoML, Time Series, Industrial Decision Support**

I. Introduction

Crude oil is one of the most strategic commodities in the global economy, directly influencing transportation systems, industrial production, and energy markets worldwide [1]. Its price dynamics are characterized by high volatility driven by geopolitical events, supply–demand imbalances, macroeconomic cycles, and financial speculation, which makes reliable forecasting a persistent challenge for both academia and industry [2]. Accurate oil price forecasts are therefore not merely an academic concern but a practical requirement for organizations whose operational planning, procurement strategies, and cost structures are directly exposed to energy price fluctuations.

A wide range of forecasting techniques has been applied to crude oil prices, including classical econometric models such as ARIMA and machine learning and deep learning approaches such as LSTM networks [3]. Although these methods have demonstrated competitive performance under specific conditions, they typically require substantial domain expertise, careful feature engineering, and extensive manual tuning of hyperparameters. Moreover, their effectiveness is often sensitive to the statistical properties of the dataset, such as stationarity, seasonality, or regime stability. As market conditions evolve, models that were previously well calibrated may rapidly lose predictive accuracy, demanding continuous redesign and revalidation. This dependency on manual intervention limits scalability, reproducibility, and long-term robustness.

In this context, Automated Machine Learning (AutoML) [4] has emerged as a promising alternative. AutoML frameworks aim to automate the end-to-end modeling pipeline, including data handling, model selection, hyperparameter optimization, and evaluation, thereby reducing reliance on expert-driven trial-and-error processes. By systematically exploring diverse model families under standardized validation protocols, AutoML enables reproducible benchmarking while adapting dynamically to changing data characteristics.

Motivated by these considerations, this work investigates crude oil price forecasting through two complementary data paradigms under an AutoML framework. The same historical price series is analyzed both as a *time series*, where temporal dependencies are modeled explicitly, and as *tabular data*, where forecasting is formulated as a supervised learning task using lag-based representations. Importantly, this distinction concerns the structure of the data rather than the nature of the learning problem itself, which remains regression in both cases. Treating the task under these two paradigms allows a systematic assessment of how different inductive biases and modeling abstractions impact forecasting performance.

The proposed pipeline relies exclusively on AutoML solutions: AutoTS for time-series modeling and H2O AutoML and AutoGluon for tabular data. The experimental design spans multiple temporal granularities (daily, pentadal, and biweekly), forecast horizons (5, 10, and 15 steps ahead), and historical window sizes (5, 10, and 15 years), enabling a comprehensive evaluation across realistic decision-making scenarios. In addition, traditional models such as ARIMA, LSTM, and NeuralForecast are evaluated separately as external baselines to assess whether adopting AutoML is empirically justified compared with established forecasting pipelines.

The main contributions of this work are threefold. First, it presents a unified AutoML-based forecasting framework that supports both time-series and tabular data representations under a consistent experimental protocol. Second, it provides an empirical assessment of AutoML performance across multiple granularities and horizons, highlighting conditions under which automated approaches are particularly advantageous. Third, it offers a practical validation of AutoML against traditional forecasting methods, supporting informed methodological choices for industrial and financial applications.

The remainder of this paper is organized as follows. Section II introduces the theoretical foundations of time series forecasting and AutoML. Section III reviews related work. Section IV describes the proposed methodology. Section V presents the experimental evaluation, and Section VI concludes the paper and outlines future research directions.

II. Theoretical Foundations

A. Time Series Forecasting

Time series consist of sequences of observations indexed in chronological order, where temporal dependence plays a fundamental role in the data-generating process [5]. Let y_t denote the observed value of a stochastic process at time t, with $t \in \mathbb{Z}$. A univariate time series can be represented as $\{y_1, y_2, \dots, y_T\}$, where each observation is potentially correlated with past values. This temporal dependency differentiates time series data from independent and identically distributed samples and requires specialized modeling strategies.

Time series forecasting aims to predict future observations based on historical patterns, capturing components such as trend, seasonality, and autocorrelation. Classical statistical models, including ARIMA and SARIMA, explicitly model linear dependencies and have long served as standard tools for this task. More recently, machine learning and deep learning approaches have been employed to address nonlinear dynamics and complex temporal interactions [6]. Recurrent architectures, such as LSTM networks, are designed to retain information over extended sequences, making them particularly suitable for volatile financial data.

In the context of crude oil markets, time series forecasting is especially challenging due to abrupt regime changes, structural breaks, and external shocks. These characteristics motivate the use of adaptive modeling frameworks that reconfigure themselves as data properties evolve, a requirement that aligns naturally with AutoML-based approaches.

B. Automated Machine Learning

The increasing complexity of modern machine learning pipelines has amplified the need for expertise in data preparation, feature engineering, algorithm selection, and hyperparameter tuning [7]. Automated Machine Learning (AutoML) [4] addresses these challenges by automating the end-to-end modeling process. Instead of relying on manually specified pipelines, AutoML systems systematically explore combinations of preprocessing steps, model families, and hyperparameters under a unified evaluation protocol.

General-purpose AutoML frameworks such as H2O AutoML [8] and AutoGluon are designed for tabular data and regression tasks, leveraging ensembles, stacking, and efficient search strategies to achieve competitive performance with minimal user intervention. In parallel, specialized frameworks such as AutoTS [9] focus on time series forecasting, incorporating domain-specific validation schemes and a diverse set of candidate models tailored to sequential data.

A key advantage of AutoML lies in its ability to balance predictive performance and computational cost through configurable search budgets and execution profiles. This flexibility makes AutoML particularly attractive for industrial and financial applications, where data evolves continuously, and rapid model adaptation is often required.

C. From Traditional Forecasting to AutoML

Traditional crude oil forecasting pipelines, including ARIMA- and LSTM-based models, have provided valuable insights into temporal dynamics and nonlinear behavior. However, their reliance on manual design choices and dataset-specific tuning limits scalability and reproducibility, especially under volatile market conditions. As data distributions shift and new patterns emerge, maintaining optimal performance often requires repeated expert intervention.

AutoML offers a principled alternative by automating pipeline construction and evaluation. Within this paradigm, crude oil price forecasting can be naturally framed in terms of two complementary data representations. When treated as a time series, the focus lies on preserving temporal order and exploiting sequential inductive biases through time-aware validation. When treated as tabular data, forecasting is reformulated as supervised regression using lagged values and derived features, enabling access to a broader class of learners and ensemble strategies.

Evaluating these two representations within a unified AutoML protocol allows a systematic assessment of their relative strengths and limitations. Rather than advocating a single modeling abstraction, this study investigates how different data representations interact with automated model selection, providing insights into robustness, adaptability, and operational suitability for real-world decision-making.

III. Related Work

Crude oil price forecasting is a challenging task due to market volatility, nonlinear dynamics, and sensitivity to geopolitical and macroeconomic factors [10]. Early approaches relied on econometric models such as ARIMA and GARCH, which provide interpretability but struggle to capture complex temporal patterns [11].

With increased data availability and computational power, machine learning methods—including support vector machines, Random Forests, and gradient boosting—became prominent by modeling nonlinear relationships and incorporating additional explanatory variables [12], [13]. However, these approaches typically require extensive feature engineering and manual hyperparameter tuning, limiting scalability and reproducibility.

Deep learning models, particularly LSTM-based architectures, further improved performance by capturing long-range temporal dependencies [6]. Despite their expressiveness, they introduce higher complexity and sensitivity to architectural and training configurations [3].

The growing complexity of ML pipelines motivated the development of Automated Machine Learning (AutoML), which automates model selection, hyperparameter tuning, and evaluation [4]. Frameworks such as Auto-sklearn, TPOT, and H2O AutoML demonstrated strong performance with minimal manual intervention, including scalable ensemble-based solutions [14], [8].

More recently, AutoML has been extended to time series forecasting. Surveys highlight challenges such as temporal validation and dependency handling [15], while empirical studies show that performance depends heavily on dataset characteristics and experimental design [16]. Additional limitations include sensitivity to data drift, regime changes, and insufficient temporal inductive bias [17], [18].

Dedicated time series AutoML frameworks such as AutoTS and AutoGluon-TimeSeries have been proposed, combining statistical and machine learning models with automated validation and ensemble strategies to achieve competitive forecasting performance [9], [19].

Despite these advances, AutoML for tabular regression and time series forecasting are often treated separately, and comparative studies with traditional methods remain limited, especially for crude oil prediction [20]. Many works also rely on exogenous variables, which may not be available in practical scenarios [13].

To address these gaps, this study performs a structured evaluation of AutoML frameworks (AutoTS, H2O AutoML, and AutoGluon) for crude oil price forecasting using both time series and tabular representations, benchmarking them against classical and deep learning approaches (ARIMA, LSTM, NeuralForecast) to assess their practical effectiveness in real-world decision-support contexts.

IV. Methodology

This work proposes a unified AutoML-based framework for crude oil price forecasting that evaluates two complementary data representations under a consistent experimental protocol: *time series* and *tabular data*. Importantly, both formulations address the same regression task, differing only in how temporal information is structured and presented to the learning algorithms. The methodology is designed to ensure comparability, reproducibility, and practical relevance, while minimizing manual intervention.

A. Problem Definition

Let $\{y_t\}_{t=1}^{T}$ denote a univariate time series representing crude oil prices sampled at a given temporal granularity. The forecasting objective is to predict future values $\hat{y}_{T+h}$ for horizons $h \in \{5, 10, 15\}$, corresponding to short- and medium-term decision horizons.

The task is evaluated under two complementary data representations:

- **Time series representation:** the original sequential structure of the data is preserved, and models explicitly account for temporal dependencies, trends, and seasonality.
- **Tabular representation:** the forecasting problem is reformulated as a supervised regression task, where future values are predicted from feature vectors constructed from past observations (e.g., lagged values and rolling statistics).

This distinction reflects differences in data organization rather than differences in the learning objective, which remains regression in both cases.

B. Data Source and Temporal Granularity

The dataset consists of historical crude oil prices obtained from a publicly available financial data source. To capture different temporal dynamics and operational use cases, the original series is resampled into three granularities: daily, pentadal (five trading days), and biweekly.

For each granularity, experiments are conducted using historical windows of 5, 10, and 15 years, allowing analysis of how data availability affects predictive performance. Apart from basic consistency checks (duplicate removal and enforcement of monotonic time indexing), no statistical transformations or scaling procedures are applied. All experiments are performed using *raw, unprocessed data*, in accordance with the post-benchmark methodological refinement.

C. Experimental Splitting Strategy

To ensure realistic evaluation and avoid information leakage, the dataset is partitioned chronologically into four segments:

- **Subtrain:** used by AutoML frameworks for model training and internal optimization;
- **Validation (val):** used exclusively for model selection;
- **Train:** formed by merging subtrain and validation after model selection;
- **Test:** a strictly held-out set used only for final performance assessment.

The size of the validation and test partitions is determined by the selected forecast horizon. For instance, when forecasting $h = 10$ steps ahead, the last 10 observations are reserved for validation during model selection, and an additional disjoint segment is held out for final testing. This protocol preserves temporal causality and reflects real-world deployment conditions.

D. AutoML Frameworks

The proposed pipeline relies exclusively on AutoML solutions, which constitute the core contribution of this study. Three frameworks are considered: AutoTS, H2O, and AutoGluon. All frameworks operate under predefined execution modes that constrain runtime and search depth, ensuring fair comparison across methods and scenarios.

E. Model Selection Criterion

Model selection is performed exclusively on the validation set using the **Root Mean Squared Error (RMSE)** as the primary evaluation metric. RMSE is chosen for its widespread adoption in the forecasting literature and its sensitivity to large prediction errors, which are particularly relevant in financial contexts.

For each combination of granularity, forecast horizon, historical window, and AutoML framework, the configuration achieving the lowest validation RMSE is selected as the best-performing model.

F. Final Training and Testing

Once the optimal configuration is identified, the corresponding AutoML framework is retrained using the full training set (subtrain + validation). This final model is then applied to the test set, which remains completely unseen during both model selection and retraining phases.

This two-stage process—selection on validation data followed by retraining on expanded data—maximizes data utilization while preserving an unbiased assessment of generalization performance.

V. Experimental Results and Discussion

This section presents an extended analysis of the experimental results obtained under different temporal granularities, forecasting horizons, historical window sizes, and execution profiles. Beyond aggregate performance trends, particular attention is given to comparative behavior among AutoML frameworks, their relationship with traditional pipelines, and the trade-off between predictive accuracy and computational cost.

All experiments were conducted using a strictly temporal evaluation protocol, with a fixed cutoff date (December 31, 2023) and a holdout test set comprising future observations. Model performance was primarily assessed using RMSE to ensure direct comparability across all scenarios.

A. Cross-scale comparison

Across all experimental configurations, forecasting performance was strongly influenced by the interaction between temporal granularity, forecasting horizon, and historical window size. In high-resolution scenarios, particularly daily and pentadal granularities, AutoML approaches based on tabular data consistently achieved lower RMSE values for short forecasting horizons. This behavior indicates that lag-based tabular representations are effective at capturing short-term nonlinear dynamics present in crude oil price movements.

As temporal aggregation increases toward quinzenal granularity, performance differences between approaches become less pronounced. At higher aggregation levels, the series exhibits smoother dynamics, reducing the marginal benefit of complex nonlinear feature interactions and enabling time-series-oriented models, as well as classical statistical baselines, to perform competitively.

The length of the forecasting horizon also plays a decisive role. Increasing the horizon generally leads to higher prediction error due to uncertainty accumulation. However, tabular AutoML pipelines were more robust for short to intermediate horizons, whereas time-series-oriented approaches were more sensitive as the prediction horizon increased, particularly when trained on shorter historical windows.

The size of the historical dataset had a systematic and positive effect on model stability. Expanding the training window from 5 to 10 and 15 years resulted in consistent reductions in RMSE across all approaches. This effect was especially pronounced for tabular AutoML frameworks, which directly benefit from larger sample sizes, but it also improved generalization for time-series-oriented models in longer-horizon scenarios.

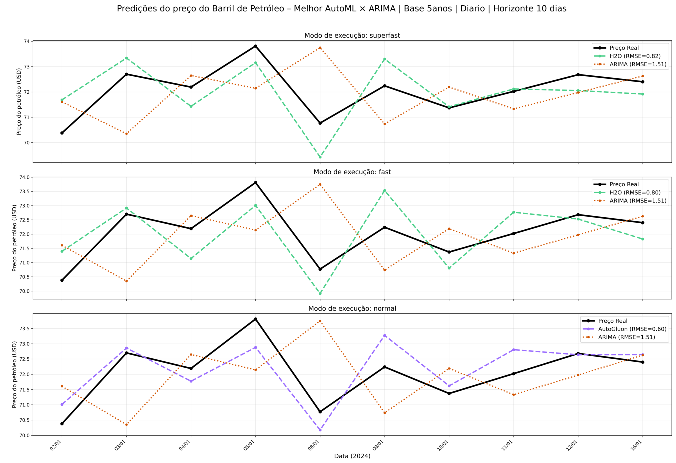

Fig. 1: Best AutoML model vs ARIMA for daily granularity, 5-year window, and a 10-step forecasting horizon.

B. Interpretation of trends

The experimental results indicate that no single AutoML framework dominates across all forecasting scenarios. Instead, performance depends strongly on the alignment between data representation, temporal resolution, and prediction horizon.

Tabular AutoML pipelines consistently demonstrated superior performance in short-term forecasting tasks and high-resolution granularities, where local temporal patterns and nonlinear interactions between lagged variables are most informative. In contrast, time-series-oriented AutoML approaches performed better as temporal aggregation increased or when longer historical windows were available, benefiting from more stable long-term structures.

These trends are illustrated in Figure 1, which presents a representative daily forecasting scenario with a 5-year historical window and a 10-step horizon. In this setting, the best AutoML model clearly outperforms the ARIMA baseline, demonstrating lower error propagation and closer adherence to observed values.

A complementary scenario is shown in Figure 2, where quinzenal aggregation reduces the performance gap between AutoML and ARIMA, indicating that under strong temporal smoothing, traditional linear models become more competitive.

C. Comparison among AutoML frameworks

A direct comparison among AutoML frameworks reveals complementary strengths rather than a single dominant approach. Although the experimental pipeline does not generate joint visualizations comparing AutoTS, H2O AutoML, and AutoGluon in a single plot, their relative performance can be consistently assessed by comparing the best RMSE for each scenario.

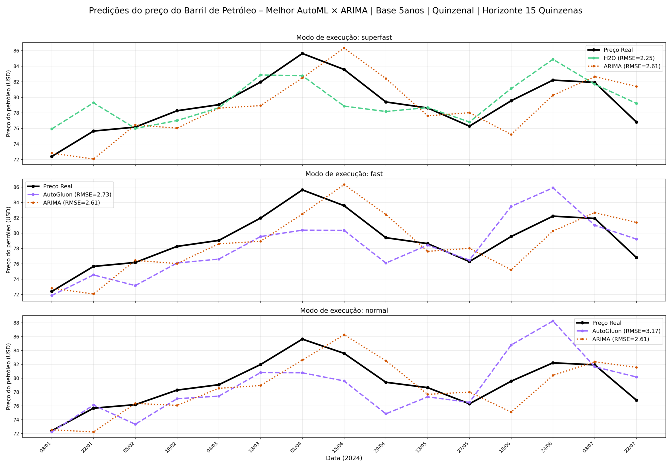

Fig. 2: Best AutoML model vs ARIMA for biweekly granularity, 5-year window, and a 15-step forecasting horizon.

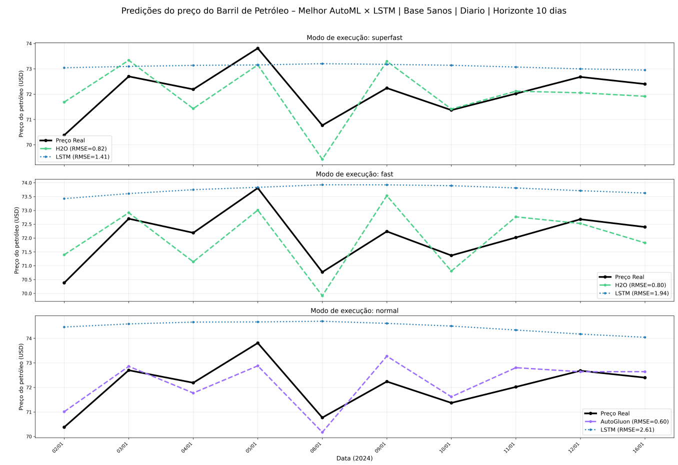

Fig. 3: Best AutoML model vs LSTM for daily granularity, 5-year window, and a 10-step forecasting horizon.

Across experiments, AutoTS performed better in scenarios with stronger temporal aggregation and longer forecasting horizons. This behavior can be attributed to its explicit time-series inductive bias and validation strategy, which preserve temporal ordering. Conversely, tabular AutoML frameworks such as H2O AutoML and AutoGluon tended to achieve lower errors in high-resolution scenarios (daily and pentadal granularities), where nonlinear interactions among lagged variables are more informative.

These results indicate that the choice between time-series-oriented and tabular AutoML approaches should be driven primarily by the temporal resolution and horizon of interest. Rather than competing directly, the frameworks provide complementary modeling capabilities that are advantageous under different data conditions.

Overall, the absence of a universally superior AutoML framework reinforces the importance of scenario-dependent evaluation and justifies the dual modeling perspective adopted in this study.

D. *AutoML versus neural baselines*

Comparisons against manually configured neural pipelines further reinforce the robustness of AutoML-based approaches. Figures 3 and 4 illustrate representative scenarios comparing the best AutoML configuration against LSTM and NeuralForecast baselines, respectively.

While neural models can capture complex temporal dynamics, their performance is more sensitive to architectural choices, training configurations, and data availability. In contrast, AutoML pipelines consistently delivered competitive or superior accuracy across a wide range of scenarios while requiring substantially less manual intervention. This robustness highlights AutoML as a practical alternative to handcrafted neural pipelines in applied forecasting contexts.

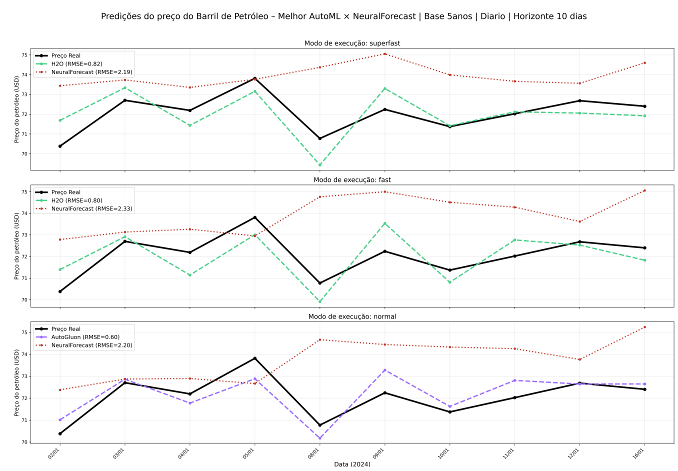

Fig. 4: Best AutoML model vs NeuralForecast for daily granularity, 5-year window, and a 10-step forecasting horizon.

E. *Effect of execution mode and cost–benefit analysis*

An important practical aspect concerns the execution profile adopted by the AutoML frameworks. Although the experimental setup does not produce visual artifacts explicitly comparing execution modes, their impact can be assessed through comparative RMSE values and observed computational effort.

Across experiments, the *superfast* mode provided rapid baseline results but frequently underperformed in scenarios involving longer horizons or lower temporal aggregation, due to its restricted search space. The *normal* mode generally achieved the lowest RMSE values by exploring a more exhaustive set of model configurations, but at a significantly higher computational cost.

Notably, the *fast* mode emerged as the most favorable compromise. In most scenarios, its predictive performance was close to that of the *normal* mode, while requiring substantially less execution time. From an operational perspective, this behavior suggests that the *fast* configuration offers the best cost–

TABLE I: Extended RMSE comparison across modeling strategies (5-year historical window).

Granularity	Horizon	AutoML	ARIMA	Neural
Daily	5	0.58	1.42	0.91
Daily	10	0.60	1.51	1.08
Daily	15	0.66	1.26	1.22
Pentadal	10	1.42	1.45	1.61
Biweekly	15	2.73	2.61	2.89

benefit balance, particularly in industrial environments where computational resources and execution time are constrained.

These findings reinforce that AutoML performance should be evaluated not only in terms of predictive accuracy but also in terms of computational efficiency and deployment feasibility.

F. Quantitative summary

Table I provides a consolidated overview of representative RMSE values across granularities, horizons, and modeling strategies. The results confirm that AutoML pipelines consistently achieve lower or comparable error rates, with the largest gains observed in high-resolution and intermediate-horizon scenarios.

Overall, the expanded experimental analysis demonstrates that AutoML pipelines not only achieve competitive predictive accuracy but also provide superior robustness and scalability across heterogeneous forecasting conditions. These characteristics are particularly relevant in applied settings, where forecasting requirements vary across temporal scales, horizons, and computational constraints.

VI. Conclusion

This work evaluated AutoML techniques for crude oil price forecasting using a unified and temporally consistent framework, considering both time series and tabular data representations under a supervised learning paradigm. Results show that AutoML pipelines consistently outperform traditional approaches, including statistical models and manually designed neural networks, achieving lower prediction errors, greater robustness to changes in granularity and forecasting horizon, and reduced sensitivity to historical window size. In addition to improved accuracy, AutoML reduces methodological risk by automating model selection and hyperparameter tuning, minimizing dependence on manual design decisions—an important advantage in volatile markets such as crude oil. The systematic evaluation across multiple experimental conditions highlights the context-dependent nature of forecasting performance, where AutoML demonstrates greater adaptability without requiring extensive expert intervention.

Future work includes incorporating exogenous variables, extending the approach to other financial assets, and integrating the framework into real-world industrial systems. Overall, the findings support AutoML as a robust, scalable, and practical alternative for crude oil price forecasting in uncertain and dynamic environments.

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