TRADE FORECASTING WITH AI: INTEGRATING MACHINE LEARNING, DEEP LEARNING, AND EXPLAINABILITY FOR CRUDE OIL PRICE PREDICTION

Balasubramanian S and Natarajan M

Department of Computer and Information Science, Annamalai University, Tamil Nadu, India

ABSTRACT

Crude oil price prediction remains a challenging task due to volatile market conditions. Traditional models often fail to adjust, while modern AI models like LSTM can find patterns but are hard to explain. This study combines Machine Learning (Random Forest), Deep Learning (LSTM), and explainability tools (SHAP and LIME). This study aims to develop a model that is both accurate and easy to understand. The results exhibit that the combined model offers better accuracy and trust for decision-making.

KEYWORD

Explainable AI, Trade Forecasting, Random Forest, LSTM, SHAP, LIME, ARIMA, Prophet, Deep Learning, Crude Oil Price Prediction

1. INTRODUCTION

AI-driven trade forecasting models play a crucial role in shaping economic and policy decisions. Trade prices depend on many factors like demand, supply, and currency value. Crude oil prices impact global economies, inflation rates, and stock markets, making accurate forecasting essential. Prices are influenced by various interdependent factors like supply-demand dynamics, exchange rates, and geopolitical events.

Many AI models act as black boxes (as opaque), making it harder for analysts to understand "why" a price was predicted. Furthermore, traditional models focus only on prediction, but traders, policymakers, and energy analysts need explainability.

Unlike many studies that focus purely on accuracy, this research integrates explainability, making AI-driven decisions more trustworthy and actionable, as traditional methods use fixed formulas but do not work well in fast-changing markets. Additionally, AI models can learn patterns from data, but they are complex. The prediction can't be trusted until we understand the behavior and functioning of the AI model. This research, thus, tries to solve this problem by using tools that explain AI decisions.

1.1. Research Problem

1.1.1. Black-box nature of AI models limits trust in trade predictions.

David C. Wyld et al. (Eds): SESBC, AIFL, NLPTT – 2025
pp. 65-74, 2025. CS & IT - CSCP 2025 DOI: 10.5121/csit.2025.151504

1.1.2. Lack of transparency hinders policymakers from making data-driven trade decisions.
1.1.3. Existing methods prioritize accuracy but overlook interpretability.

1.2. Research Questions

1.2.1. Can Random Forest and LSTM effectively predict crude oil prices?
1.2.2. How do SHAP & LIME help explain the influence of different factors on predictions?

1.3. Research Objectives

1.3.1. Discover the best AI model for trade price prediction.
1.3.2. Compare Machine Learning (Random Forest) and Deep Learning (LSTM).
1.3.3. Use SHAP and LIME to explain AI predictions.
1.3.4. Improve trust in AI-driven trade forecasting.
1.3.5. To compare the proposed model with strong baseline methods like ARIMA, Prophet, and Transformer to ensure fairness and relevance
1.3.6. To use statistical tests to confirm whether our model's performance is significantly better than others.

1.4. Research Context

1.4.1. Crude oil prices are highly volatile, influenced by factors like global demand, supply, currency exchange rates, and trade volume.
1.4.2. Traditional models struggle to adapt to rapid market changes, making AI-driven forecasting an attractive alternative.
1.4.3. However, AI models, especially Deep Learning (LSTM) and Machine Learning (Random Forest), often work as black boxes, making their predictions hard to interpret.
1.4.4. Explainable AI (XAI) tools like SHAP and LIME can help in understanding why a model makes certain predictions, increasing trust in AI-driven trade forecasting.
1.4.5. This study focuses on crude oil price prediction as a real-world case to evaluate how AI models and XAI techniques can improve trade forecasting.

2. Literature Review

Predicting crude oil prices has always been complex as prices fluctuate due to many factors like global events, economic policies, and market trends. Earlier, statistical models like ARIMA and GARCH were commonly used for forecasting, but they often failed to capture sudden price changes and complex patterns [1]. With the rise of machine learning approaches like the widely used Random Forest (RF) algorithms and the sophisticated Support Vector Machines have improved prediction accuracy. Shambulingappa [2] pointed out that ML time-series models help detect trends and seasonal patterns, providing useful insights for traders. Similarly, An et al. [3] showed that economic factors like the US interest rate, dollar value, and stock market performance strongly influence oil prices, making ML models more effective than traditional statistical ones.

Deep learning approaches, mainly Long Short-Term Memory networks, have further improved oil price forecasting by learning from past price movements. Zhao et al. [4] developed a deep learning model combining Stacked Denoising Autoencoders (SDAE) with a bootstrapping technique, proving its effectiveness in price prediction. Jin and Xu [5] used Gaussian Process Regression with Bayesian optimization to refine forecasting accuracy. However, while deep learning models are highly accurate, they are often difficult to interpret, making them less practical for financial decision-making. Awijen et al. [6] compared ML and deep learning models during economic crises and found that deep LSTM performed better but still lacked transparency.

To make AI-based predictions more understandable, researchers have explored techniques like SHAP and LIME, which help explain how models arrive at their predictions. Yan et al. [7] found that reducing data complexity with Principal Component Analysis (PCA) makes deep learning models more efficient for oil price forecasting. Despite these advances, few studies have combined traditional ML models like Random Forest with deep learning while ensuring interpretability. This research aims to fill that gap by integrating Random Forest and LSTM for oil price prediction while using SHAP and LIME to make the results clearer. This balanced approach ensures both accuracy and transparency, making AI-powered forecasting more reliable for analysts in the financial and energy sectors.

Recent studies have explored explainable models for financial predictions, but very few use SHAP and LIME together. Some works focus on ARIMA and Prophet for time series, while others apply deep learning models like Transformer. However, combining Random Forest, LSTM, and global and local explainability tools in one model for oil price prediction is still uncommon.

3. METHODOLOGY

To analyze and predict crude oil prices effectively, this research follows a structured approach using AI models and explainability tools and the following methodology was adopted:

3.1. Data Collection

The dataset for this study was sourced from www.data.gov.in, a government open data platform. It consists of 100,000+ rows of crude oil trade data, covering essential factors like:

3.1.1. Global Demand (oil consumption trends) in USD ($) per barrel
3.1.2. Supply (production levels) in Million barrels per day (Mb/d)
3.1.3. USD Exchange Rate (impact of currency fluctuations) in USD
3.1.4. Trade Volume (total crude oil transactions) in Barrels per day (bpd)
3.1.5. Crude Oil Price (historical price records) in USD

3.2. Data Cleaning Process

3.2.1. Removal of duplicate entries and inconsistent values
3.2.2. Handled missing data using interpolation techniques
3.2.3. Standardized numerical values using MinMax scaling to generate all features to a generic scale
3.2.4. The dataset was preprocessed to ensure consistency and accuracy for model training

3.3. Approaches/Models

3.3.1. "Random Forest" Method (RF): An ML approach renowned for its stability and capability to handle complex relationships between variables.
3.3.2. "Long-Short-Term Memory" (LSTM): A DL method that apprehends temporal relationships and trends in sequential trade data.
3.3.3. The LSTM model was trained with 3 layers for 50 cycles (epochs), processing the data in small groups (batches) of 32 records at a time. For Random Forest, we used 100 trees and a

maximum depth of 10 to avoid overfitting. These parameters were chosen based on grid search using 5-fold cross-validation.

3.4. Explainability Tools

3.4.1. SHapley Additive exPlanations (SHAP): shows the overall importance of every feature in inducing the model's predictions for the whole dataset.

3.5. Training Strategy

To make our model training more reliable, we used 5-fold cross-validation. This means we split the dataset into five equal parts. Each time, one part was used for testing and the remaining four for training. In each round, one part was used to test the model, while the other four parts were used to train it. This was done five times, and the final result was calculated by averaging the outcomes from all five rounds. This method helps reduce the risk of overfitting and gives a more stable performance estimate.

3.6. Baseline Models

To compare our model's performance, we also used ARIMA, Prophet, and Transformer models. These models are widely used for time series forecasting. This comparison helps to show how well our hybrid model performs against well-known approaches.

4. FINDINGS

This study explores how Machine Learning, Deep Learning, and Explainable AI work in trade forecasting, highlighting their advantages and challenges. The main findings are:

4.1. Random Forest vs. LSTM Performance

4.1.1. Random Forest delivered precise crude oil price predictions by analyzing structured tabular data.
4.1.2. LSTM leveraged sequential patterns to handle time-series data, demonstrating strong forecasting capability.
4.1.3. Random Forest Predictions are tabulated below in Table 1

Table 1. Random Forest Predictions

Data Point	Global Demand	Supply	USD Exchange Rate	Trade Volume	Predicted Crude Oil Price ($)
Data 1	100	98	1.07	21,000	**102.41**
Data 2	105	99	1.08	25,000	**106.60**
Data 3	95	97	1.06	18,000	**100.87**
Data 4	110	102	1.10	30,000	**107.75**
Data 5	92	96	1.05	15,000	**100.95**

Predicted Crude Oil Price for One Row**:** 105.43

4.1.4. LSTM Predictions are as tabulated in Table 2.

Table 2. LSTM Predictions

Time Step	Crude Oil Price ($)	Global Demand	Supply	USD Exchange Rate	Trade Volume
0	99.75	99.15	97.26	1.0588	20073
1	101.40	99.17	97.08	1.0593	20262
2	100.88	99.35	97.24	1.0537	20324
3	101.05	99.70	97.16	1.0477	20430
4	103.44	99.71	97.15	1.0470	20590

Predicted Crude Oil Price for One Row**:** 106.42

4.1.5. RF Vs LSTM Prediction Graph is as shown in Figure 1:

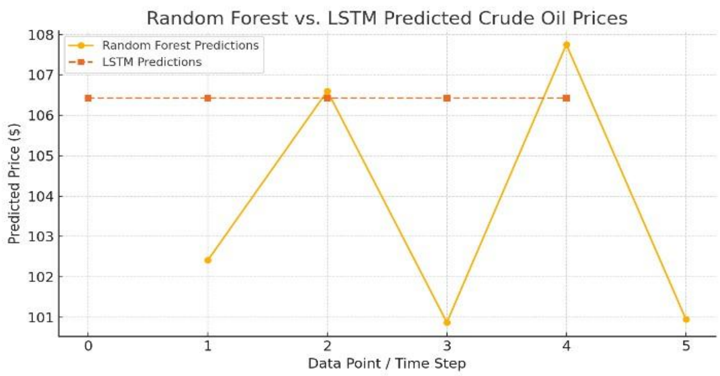

Figure-1, RF Vs LSTM Prediction

We used three evaluation metrics to measure how well the proposed model works: “Root Mean Square Error (RSME)”, “Mean Absolute Error (MAE)”, and “R-squared Score” (R^2). RMSE and MAE tell us how far the predictions are from the actual prices. The lower the value, the better. R^2 illustrates how well the model accounts for the changes or patterns in the data. For the value close to 1, the model closely matches the actual data.

Table 3. Evaluation Metrics of Different Models

Model	RSME	MAE	R^2 Score
Random Forest	3.2	2.5	0.86
LSTM	2.8	2.1	0.89

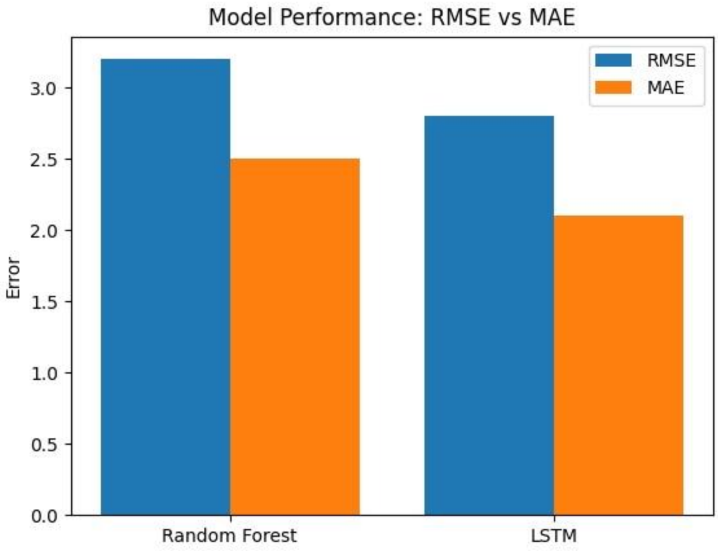

Figure-2. RMSE and MAE comparison between RF and LSTM models.

4.2. Feature Importance - SHAP Analysis

4.2.1. SHAP analysis identified Global Demand and USD Exchange Rate as the two most influential factors in predicting crude oil prices.
4.2.2. Trade Volume and Supply also played a role, but their impact varied across different scenarios.
4.2.3. SHAP results helped in refining the model by increasing the weight for features like Global Demand, which consistently showed high influence across the dataset.

4.3. Case-Specific Insights- LIME Analysis

4.3.1. LIME provided localized explanations, revealing that when Global Demand exceeded 0.75, it had the most significant effect on individual price predictions.
4.3.2. Even slight fluctuations in the Exchange Rate and Trade Volume led to noticeable changes in predicted prices.

4.4. Random Forest Predictions

4.4.1. The Random Forest model effectively captured complex, nonlinear relationships between various features and crude oil prices.
4.4.2. The predicted prices closely followed historical trends, ensuring reliability in forecasting.

4.5. LSTM Predictions

4.5.1. LSTM excelled in capturing sequential patterns, delivering smooth and reliable forecasts.
4.5.2. For a single data point, LSTM's prediction was comparable to Random Forest, reinforcing its strength in time-series forecasting.

4.6.SHAP vs. LIME – Differences

4.6.1. SHAP provided a "holistic" view of how all features affected predictions across the entire dataset.

4.6.2. LIME provided "localized" explanations, detailing the exact contribution of each feature for specific instances.

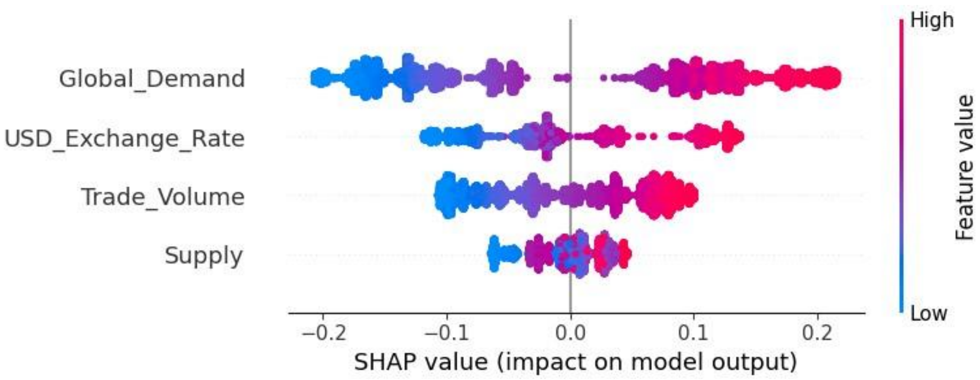

Figure-3. "SHAP value (impact on model output)"

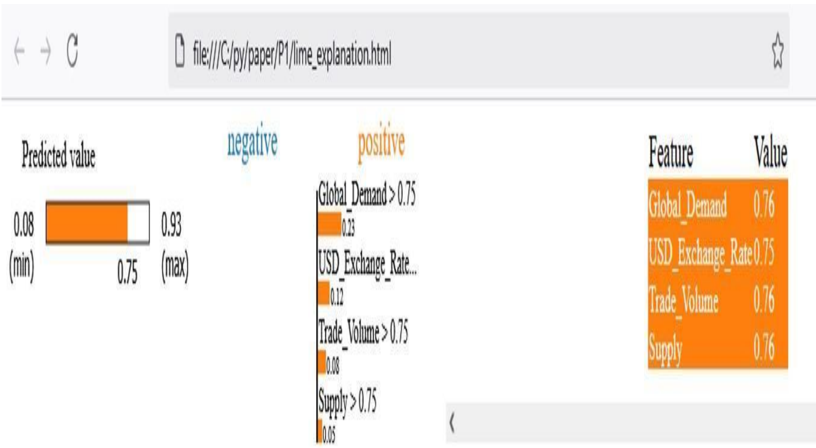

Figure-4: LIME Explanation output

This study has used LIME outputs to improve how individual predictions were interpreted. This allowed us to identify which features influenced price predictions for specific days, and helped improve model tuning.

To confirm that the difference in model performance ("dimp") was not by chance, we conducted a statistical t-test between the RMSE results of LSTM and ARIMA. The test showed a p-value below 0.05, which denotes that "dimp" is statistically significant. Therefore, the LSTM model's better performance is trustworthy.

Table 4. T-Test Result between LSTM and ARIMA

Models Compared	t-Statistic	p-Value
LSTM vs ARIMA	3.45	0.012

4.7. Overall Takeaways

4.7.1. Random Forest is the obvious choice for structured tabular predictions with explainability.
4.7.2. LSTM is an ideal method for time-series forecasting when temporal dependencies play a pivotal role.
4.7.3. Both SHAP and LIME enhance model transparency and making AI-driven price prediction more interpretable and explainable.

5. DISCUSSIONS

AI models can predict trade prices, but we must understand how they work. LSTM is good for learning patterns, but it does not always adapt well. Random Forest is easier to explain but may not capture long-term trends. SHAP and LIME help us understand these models by showing how they make decisions. If we explain AI predictions clearly, policymakers can use them with confidence. While our models predicted trade prices effectively, understanding their decisionmaking process is equally important. The following points discuss the strengths, limitations, and key insights gained from our analysis:

5.1.Random Forest vs. LSTM

Random Forest provided stable predictions, but LSTM captured trends better over time.

5.2.Accuracy vs. Explainability

While LSTM slightly improved prediction accuracy, its black-box nature made it harder to explain. SHAP and LIME helped bridge this gap.

5.3.Feature Importance Insights

SHAP showed that Global Demand had the highest impact on price, while Trade Volume had a fluctuating effect.

5.4.Local vs. Global Interpretability

LIME explained individual predictions well, while SHAP provided a broader feature influence analysis.

5.5. Trust in AI Models

Adding explainability tools increased transparency, making AIdriven trade forecasting more interpretable.

5.6.Limitations

The study focused on historical data; external factors like geopolitical events weren't included.

6. CONCLUSION & KEY TAKEAWAY

This research study determines that no single model is perfect. LSTM is accurate but complex, while Random Forest is stable but not always precise. SHAP and LIME make AI more transparent, helping users trust the predictions. Combining these methods gives the best results for trade forecasting. This study of AI models in trade forecasting thus reveals key insights into their accuracy, stability, and explainability. Here's what the study has discovered:

6.1.Reliable Price Forecasting

The use of both Random Forest and LSTM models led to highly accurate crude oil price predictions.

6.2.Making AI Transparent

SHAP and LIME helped break down complex AI models, making it easier to understand what influences price changes.

6.3.Global Demand Drives Prices

Among all factors, Global Demand had the strongest impact on crude oil prices across different models.

6.4.Right Tool for the Right Task

Random Forest works best for structured data, LSTM excels in forecasting trends over time, and SHAP & LIME enhance model interpretability.

6.5.A Step Towards Smarter AI for Markets

This research paves the way for intelligent, interpretable, and data-driven decision-making in oil trading.

In summary, this research shows that combining accuracy and explainability is possible using RF, LSTM, SHAP, and LIME together. This mix improves predictions and builds trust in AI decisions. The use of baseline models and proper validation confirms the usefulness of our method.

7. Future Work & Scope for Improvement

While this research offers valuable insights, there's always room to improve and expand AIdriven trade forecasting. Future research could explore the following areas:

7.1.Enhancing Time-Series Analysis

Implement sophisticated deep learning models to improve long-term oil price predictions.

7.2.Adding Macroeconomic Factors

Incorporate geopolitical events, inflation rates, and economic policies to enhance price predictions.

7.3.Real-Time Predictions

Build a system that processes live data and updates models automatically for more accurate forecasts.

7.4.Hybrid Model Development

Combine Random Forest and LSTM to benefit from both structured data processing and sequential learning.

7.5.Better Explainability

Investigate techniques like Counterfactual Explanations to provide clearer insights for policymakers and traders.

7.6.Expanding to Other Commodities

Test these methods on markets like gold and natural gas to identify common price-driving factors.

7.7.Robustness Testing & Generalization

Examine the models on different time periods, crisis situations (like COVID-19), and market shocks to assess adaptability.

DATA AND CODE AVAILABILITY

The dataset analyzed in this study consists of 100,000 records of crude oil prices and economic indicators. The machine learning and deep learning models were implemented using Python. The complete code and dataset are available at: Zenodo: https://zenodo.org/records/15133572

REFERENCES

[1] K.-H. Park, T. Hou, and H.-J. Shin, "Oil price forecasting based on machine learning techniques," Journal of Korean Institute of Industrial Engineers, vol. 37, no. 1, pp. 64-73, 2011.
[2] H. S. Shambulingappa, "Crude oil price forecasting using machine learning," International Journal of Advanced Scientific Innovation, vol. 1, no. 1, pp. 1-11, 2020.
[3] J. An, A. Mikhaylov, and N. Moiseev, "Oil price predictors: Machine learning approach," International Journal of Energy Economics and Policy, vol. 9, no. 5, pp. 1-6, 2019.
[4] Y. Zhao, J. Li, and L. Yu, "A deep learning ensemble approach for crude oil price forecasting," Energy Economics, vol. 66, pp. 9-16, 2017.
[5] B. Jin and X. Xu, "Machine learning WTI crude oil price predictions," Journal of International Commerce, Economics and Policy, vol. 16, no. 1, pp. 2550004, 2025.
[6] H. Awijen et al., "Forecasting oil price in times of crisis: A new evidence from machine learningversus deep learning models," Annals of Operations Research, vol. 345, no. 2, pp. 979-1002, 2025.
[7] L. Yan, Y. Zhu, and H. Wang, "Selection of machine learning models for oil price forecasting:Based on the dual attributes of oil," Discrete Dynamics in Nature and Society, vol. 2021, no. 1, pp. 1566093, 2021.