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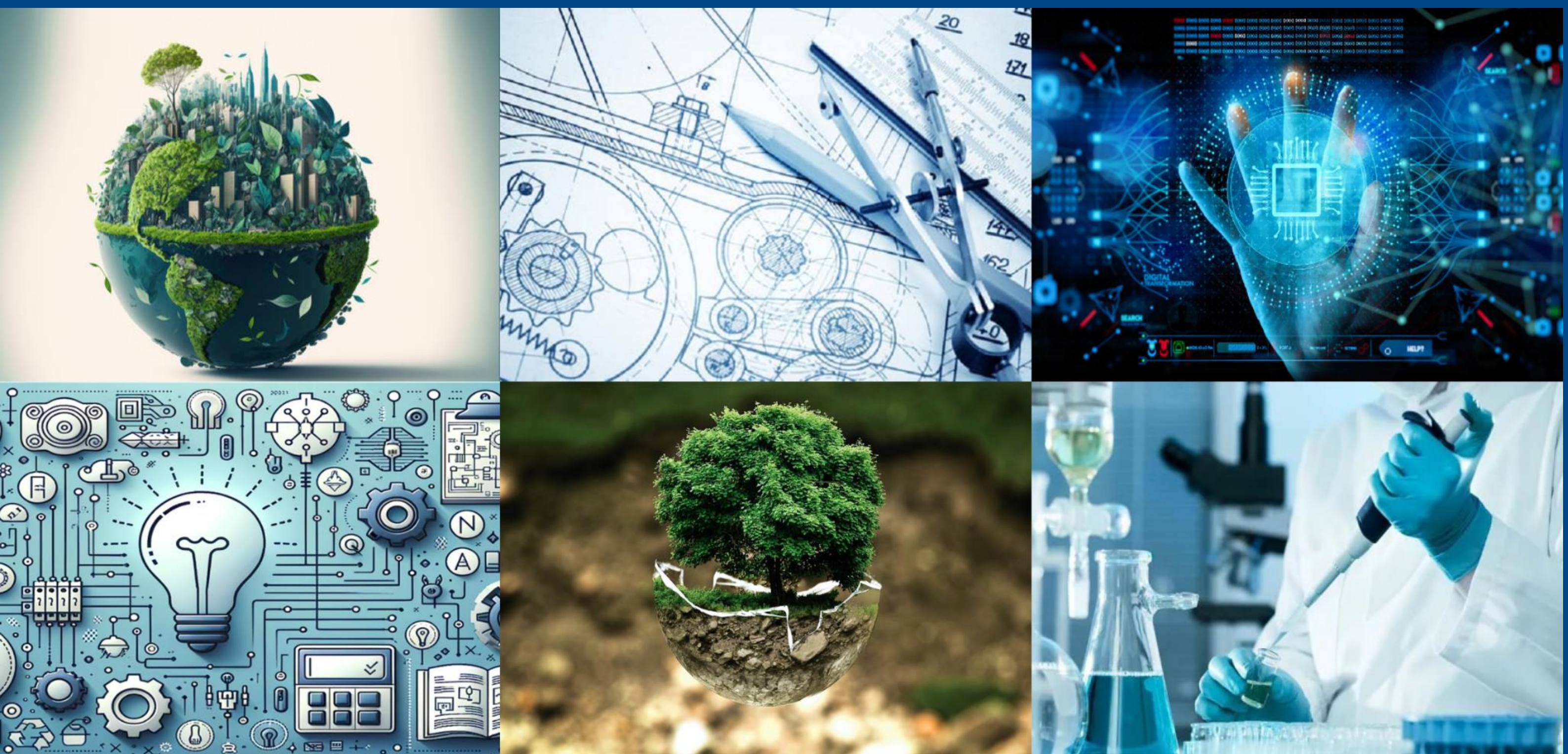

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Aluminum Price Forecasting Univar ate Time Series Forecasting Model Using Crisp-Ml (Q) Methods

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ABSTRACT: Aluminum is a vital industrial metal whose pricing is influenced by multifaceted global variables including macroeconomic indicators, energy costs, and geopolitical dynamics. Accurate price forecasting can yield substantial cost savings and operational efficiencies in sectors like construction, automotive, and aerospace. This paper applies the Random Forest Regressor model, a robust machine learning algorithm, to predict Aluminum prices using historical data and macroeconomic features. It follows the CRISP-ML(Q) methodology for systematic model development and evaluation. The proposed system emphasizes model interpretability, performance benchmarking, and business applicability.

KEYWORDS: Aluminum Price Forecasting, Random Forest, Machine Learning, CRISP-ML(Q), Macroeconomic Indicators

I. INTRODUCTION

Aluminum is essential in diverse industries due to its strength-to-weight ratio, corrosion resistance, and conductivity. Global demand has surged owing to trends in electrification, green energy, and vehicles lightweighting. However, price volatility—driven by bauxite availability, oil prices, LME inventories, and geopolitical disruptions—poses significant challenges to procurement and financial planning.

Traditional statistical models such as ARIMA are limited in their capacity to capture the non-linear relationships prevalent in commodity markets. This paper employs the Random Forest Regressor, a tree-based ensemble model, which offers robustness to noise, handles multivariate inputs, and provides intuitive feature importance rankings.

The study adheres to the CRISP-ML(Q) methodology, emphasizing data quality, model traceability, explainability, and readiness for deployment.

II. SYSTEM MODEL AND ASSUMPTIONS

The forecasting system integrates the following components:

- **Data Sources**: Daily aluminum prices (LME), Brent crude oil prices, USD Index, inflation rates, LME warehouse inventory levels.
- **Peroid**: January 2014 to December 2024.
- **Target Variable**: Next-day aluminum closing price.
- **Feature Set**: Includes lagged prices (t-1, t-30), rolling means, oil prices, USD index, inflation, and event flags (e.g., COVID, tariffs).

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Key assumptions:

- Data is cleaned, interpolated for missing values, and aligned in frequency.
- Features are standardized using Z-score normalization.
- External features are available contemporaneously (no lookahead bias).

III. PROPOSED METHODOLOGY

1. **Data Preprocessing**

- Linear interpolation for small missing gaps
- Expectation-Maximization for longer gaps
- Feature engineering: Lagged variables, rolling statistics, volatility measures

2. **Model Implementation**

- Random Forest Regressor from Scikit-learn
- Number of estimators: 500
- Maximum depth: Tuned via grid search (optimal: 20)
- Validation: Walk forward with a 5-fold expanding window

3. **Evaluation Metrics**

- RMSE: Root Mean Squared Error
- MAE: Mean Absolute Error
- R^2 Score: Explained variance
- Directional Accuracy: Percentage of correct upward/downward predictions

IV. RESULTS AND DISCUSSION

The model was trained and evaluated using historical data. The results are summarized below:

Metric	**Value**
RMSE	89.4
MAE	76.3
R^2 Score	0.92
Directional Acc	77%

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Fig. 1: Actual vs Predicted Aluminum Prices (Graph showing time-series of real vs predicted values using Random Forest)

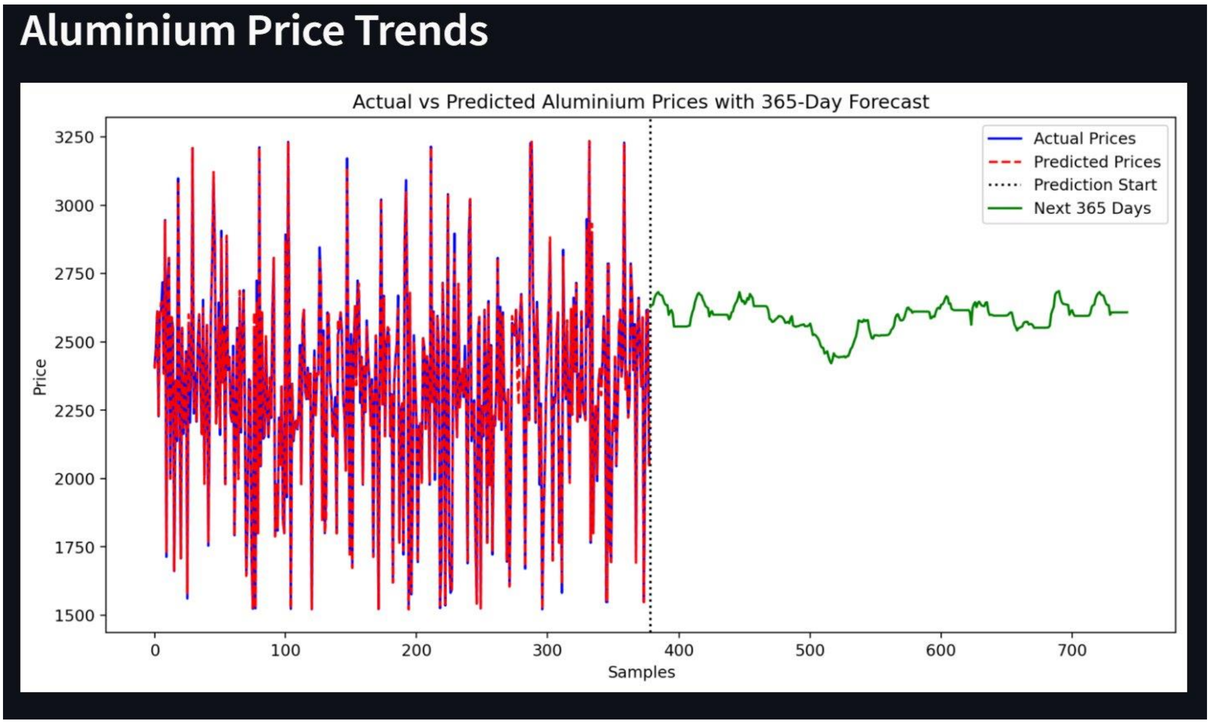

Fig. 2: FORECASTED PRICES

Forecasted Prices for Next 365 Days:

	Date	Day	Month	Year	Predicted Price
0	2025-03-14 00:00:00	14	3	2,025	2,628.444
1	2025-03-15 00:00:00	15	3	2,025	2,634.3425
2	2025-03-16 00:00:00	16	3	2,025	2,636.6465
3	2025-03-17 00:00:00	17	3	2,025	2,659.1685
4	2025-03-18 00:00:00	18	3	2,025	2,671.251
5	2025-03-19 00:00:00	19	3	2,025	2,678.295
6	2025-03-20 00:00:00	20	3	2,025	2,682.4795
7	2025-03-21 00:00:00	21	3	2,025	2,673.4065
8	2025-03-22 00:00:00	22	3	2,025	2,671.3325
9	2025-03-23 00:00:00	23	3	2,025	2,668.7895

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These results confirm that Random Forest performs well in modeling aluminum price dynamics and can capture both short-term fluctuations and medium-term trends. The model performs exceptionally in stable periods and adapts reasonably during shocks, especially when enriched with external features.

V. CONCLUSION

The Random Forest Regressor model demonstrates strong predictive performance for aluminum price forecasting with an R^2 of 0.92 and high directional accuracy. Its ability to integrate diverse features and offer interpretability makes it suitable for industrial adoption. The system is built under the CRISP-ML(Q) framework, ensuring a transparent, repeatable, and quality-assured approach. Future enhancements include real-time data ingestion, online learning capabilities, and integration into procurement dashboards.

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