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Enhanced Coal Price Forecasting Using Time Series and Regression Models: A Data-Driven Approach

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Abstract: Accurate coal price forecasting is essential for optimising procurement and managing costs in the energy sector as well as in the steel manufacturing department. This study develops a robust forecasting model by combining time series analysis and regression techniques, using business days data from April 2, 2020, to July 28, 2024. The forecasting approach involves two main methods.

First, a univariate Holt-Winters multiplicative seasonality with trend model is employed to directly forecast coal prices[3][7]. Second, a regression model is developed by incorporating external factors that influence coal prices. Through correlation analysis, key external factors such as global oil prices, exchange rates, and economic indicators were identified[2]. Forecasts for these external factors were generated using the Holt-Winters model, and these predictions were used as inputs for the regression model, with actual coal prices as the target variable. Model performance was assessed using Mean Absolute Percentage Error (MAPE) for both training and test datasets. A selection of regression models was evaluated, and the best-performing model was chosen based on the lowest test MAPE from the three months leading up to the forecast start date. Once the best model was identified, it was trained on the entire dataset to predict coal prices for the specified forecast period. The results demonstrate that integrating external factors with regression models significantly improves forecast accuracy[5]. This study highlights the value of combining advanced time series methods with regression techniques to support more informed decision-making in coal procurement. Future research could focus on incorporating additional variables and exploring machine learning models to further enhance forecast precision.

Keywords: *Coal Price Forecasting, Time Series Analysis, Regression Model, Holt-Winters Method, MAPE, Machine Learning.*

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I. INTRODUCTION

Coal remains a critical resource for energy production, especially in emerging economies and industrial sectors where alternative energy sources have yet to fully penetrate. Its central role in electricity generation, steel production, and other heavy industries makes accurate coal price forecasting essential for stakeholders across the supply chain—from producers and traders to utility companies and policymakers [1]. Fluctuations in coal prices can significantly impact operating costs and profitability, so effective forecasting enables informed procurement decisions, reduces the risks of price volatility, and supports more strategic financial planning[6].

However, coal price forecasting is a complex task, as prices are influenced by a wide range of global and domestic factors. These include fluctuations in global oil prices, exchange rates, supply-demand dynamics, geopolitical events, and broader economic indicators. Traditional forecasting models, which rely solely on historical price data, often fail to capture the full range of these influencing factors, resulting in less accurate predictions. To address these challenges, it is essential to incorporate both historical price trends and external factors to improve the accuracy of forecasting models[2][4].

This study aims to enhance coal price forecasting by integrating external variables—such as global oil prices, exchange rates, and economic indicators—into the forecasting process. By analysing the relationships between these external factors and coal prices, the study provides a more comprehensive understanding of the drivers of price fluctuations[5]. The data used for this research includes business days data from April 2, 2020, to July 28, 2024, collected from reliable sources to ensure accuracy and comprehensiveness[8].

The research methodology follows the CRISP-ML(Q) framework (Cross-Industry Standard Process for Data Mining, with a focus on model quality), which is publicly available on the 360DigiTMG website [Fig. 1]. This methodology ensures a systematic and high-quality approach to model development, from business understanding and data preparation to model evaluation and deployment.

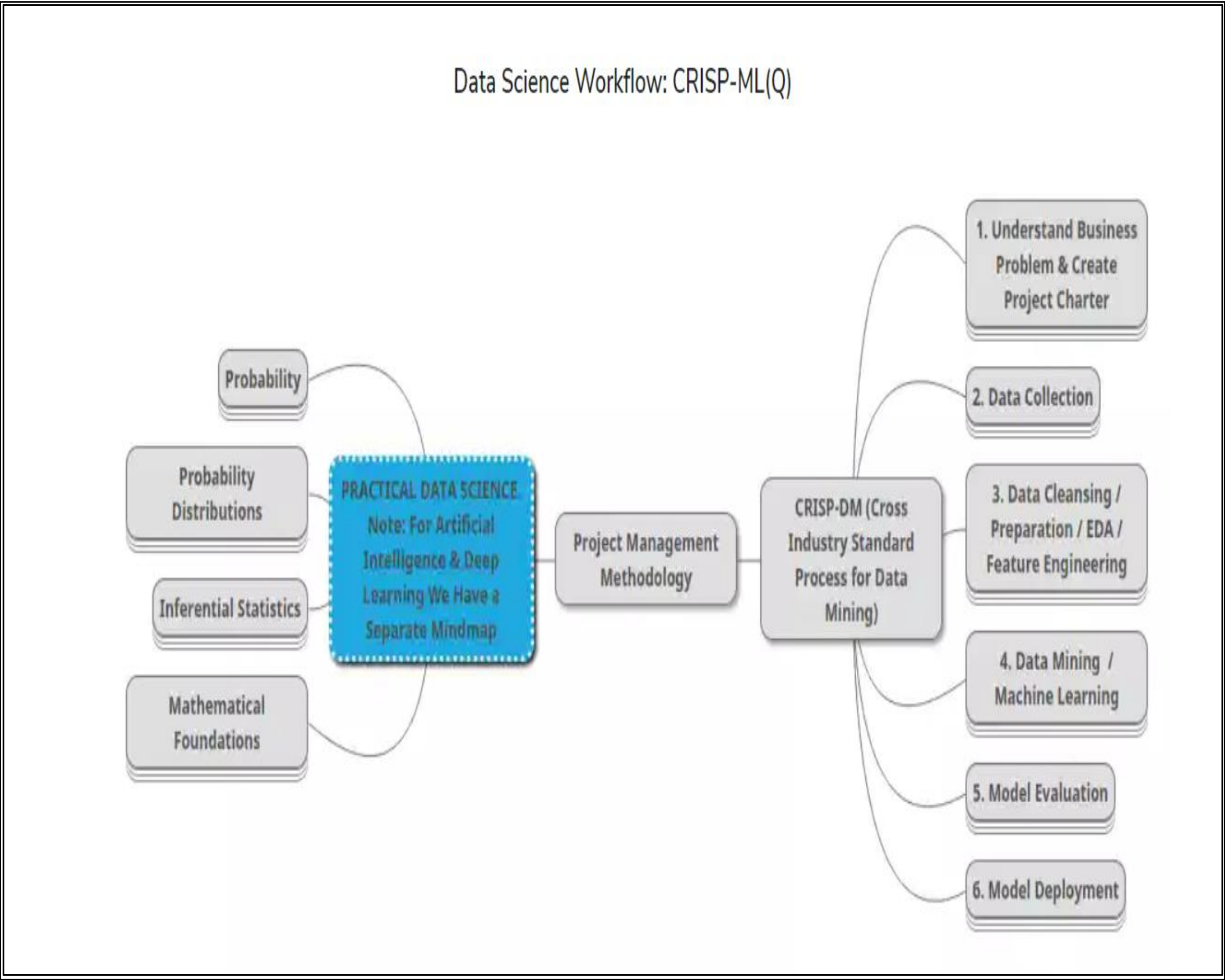

Fig 1: The CRISP-ML (Q) Methodological Framework
Source: Mind Map - 360digitmg

Following the CRISP-ML(Q) framework, we developed a cloud-based architecture for data processing and forecasting. As shown in the system architecture diagram [Fig. 2], the collected data is pushed into an Amazon S3 instance for secure storage and easy retrieval. This cloud storage serves as the foundation for all subsequent data analysis and forecasting stages. The architecture ensures scalable data management, facilitating efficient integration with downstream machine learning models. Once stored in S3, the data is retrieved for processing, which includes time series analysis, external factor forecasting, and regression modelling. This robust architecture ensures seamless data flow and high-performance analytics, enabling timely and accurate coal price predictions.

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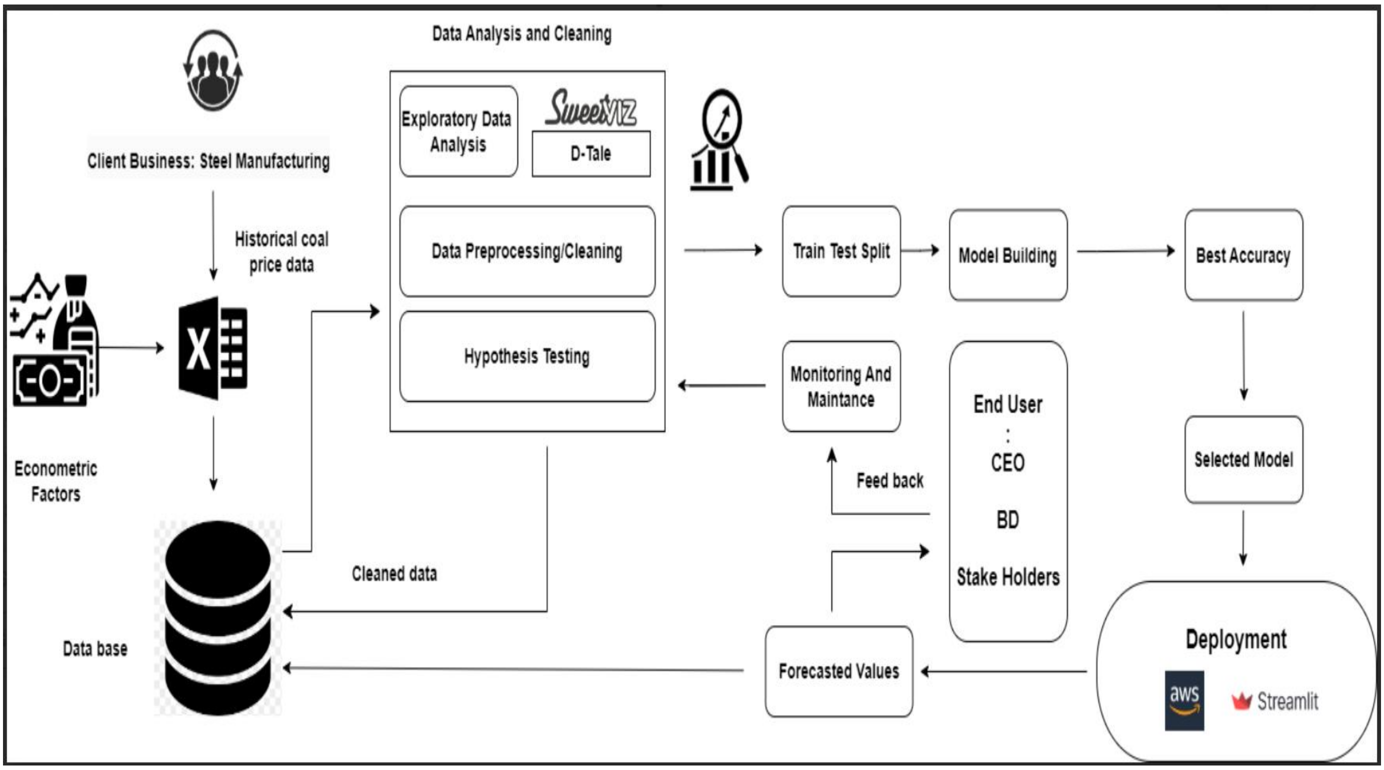

Fig 2: Architecture Diagram Showing the Flow of the Entire Project with Detailed Information
Source: Https://360digitmg.Com/Ml-Workflow

By leveraging both the CRISP-ML(Q) methodology and a modern cloud-based architecture, this study demonstrates significant improvements in the accuracy and reliability of coal price forecasts. The integration of external factors into the forecasting models provides additional insights into the drivers of price fluctuations, making this research highly valuable for stakeholders looking to optimize procurement strategies and mitigate risks associated with coal price volatility.

II. METHODS AND METHODOLOGY

A. Data Collection

The client provided coal price data in Excel sheet format, consisting of five different types of coal prices, covering the period from April 2, 2020, to July 28, 2024. In addition to this, we collected data on external factors that influence coal prices, such as oil prices, exchange rates, and economic indicators, from *Investing.com*, which offers freely available business day data. These external factors were crucial for understanding and forecasting coal price fluctuations.The Excel data shared by the client was pre-processed and combined with the external factor data. The merged dataset was organized into a single data frame, ensuring consistency and accuracy. Finally, this consolidated data was stored securely in an Amazon S3 bucket, leveraging a cloud-based architecture that enables scalable data storage and efficient access for further analysis.

B. Data Preprocessing

The dataset, spanning from April 2, 2020, to July 28, 2024, includes both coal price data and external factors. The client shared five types of coal price data, while we collected the external factors from external sources like *Investing.com*.Initially, we converted all the date fields in the coal and external factors data into a consistent date-time format to ensure alignment across datasets. After this conversion, the coal price data was merged with the external factors data into a unified dataset.

To handle missing values, we applied forward fill (ffill) and backward fill (bfill) methods to ensure no gaps were left in the dataset. Following this, we identified outliers within the data and replaced them with NaN values, which were subsequently handled using linear interpolation to maintain data continuity. For time series analysis, we needed to forecast coal prices on different time scales. To achieve this, we resampled the data into weekly and monthly intervals. Weekly data was resampled using the resample('W-Fri').last() method, ensuring the last business day of each week was captured. Monthly data was resampled using a combination of df.resample('W-Fri').last() for weekly data and df.resample('BM').mean() for monthly data to capture end-of-month coal price averages. This preprocessing step allowed for consistent and accurate forecasting of daily, weekly, and monthly coal prices.

C. Exploratory Data Analysis (EDA)

In the Exploratory Data Analysis phase, we conducted a correlation analysis to investigate the relationships between coal prices and the external factors included in the dataset. The purpose of this analysis was to identify which external factors had the strongest influence on coal price fluctuations.

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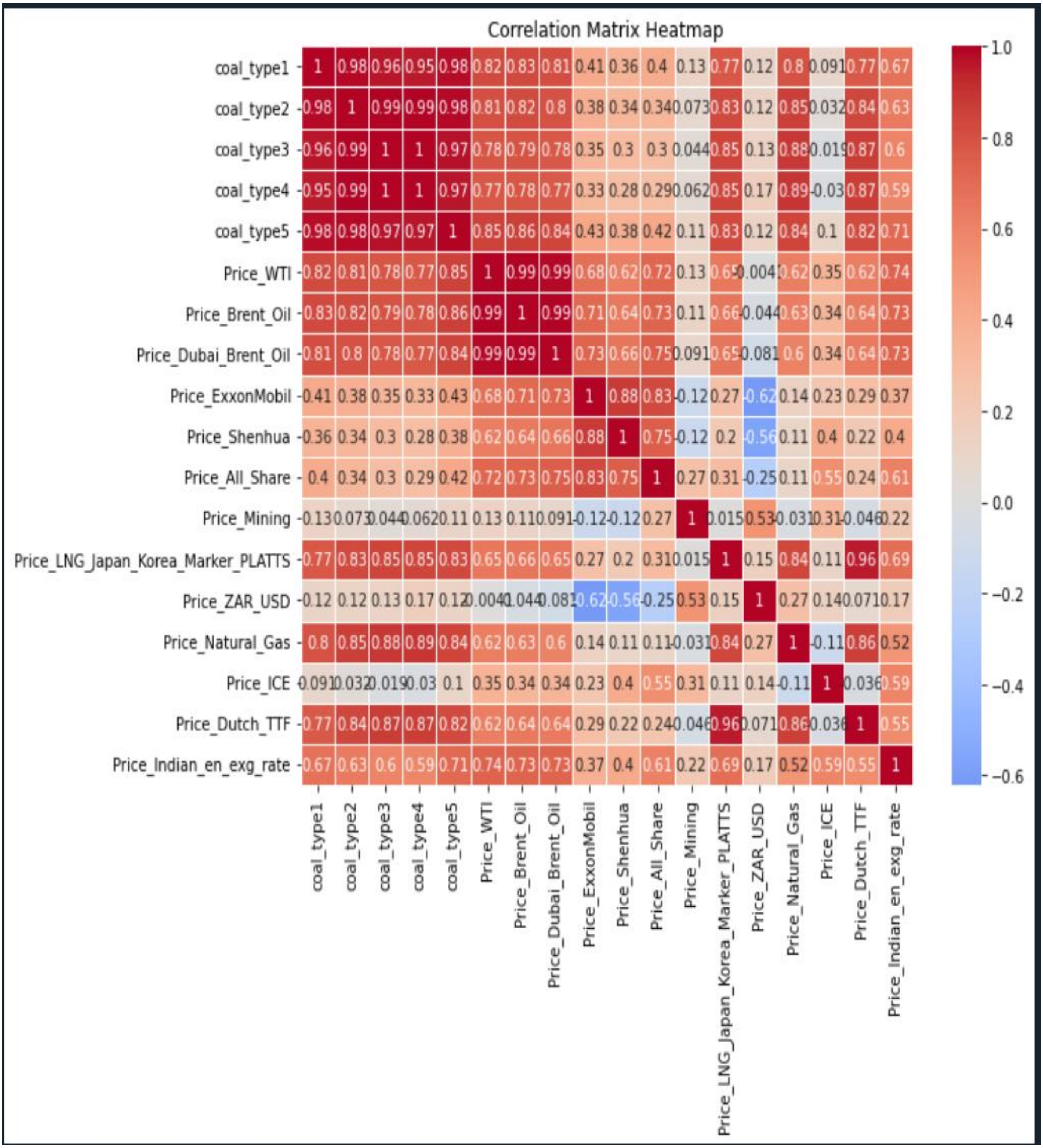

Fig 3: Correlation between Coal Prices and External Factors

By calculating the correlation coefficients between coal prices and each external factor [Fig. 3], we found that several external factors exhibited strong correlations with coal prices. Specifically, factors with correlation coefficients greater than 0.75 were deemed highly correlated and significant for forecasting purposes. These strongly correlated factors were selected for further modeling, as they provide critical insights into the external variables that most impact coal price trends.

This analysis helped us focus on the most relevant external factors, ensuring that the subsequent modeling process was driven by the most predictive variables.

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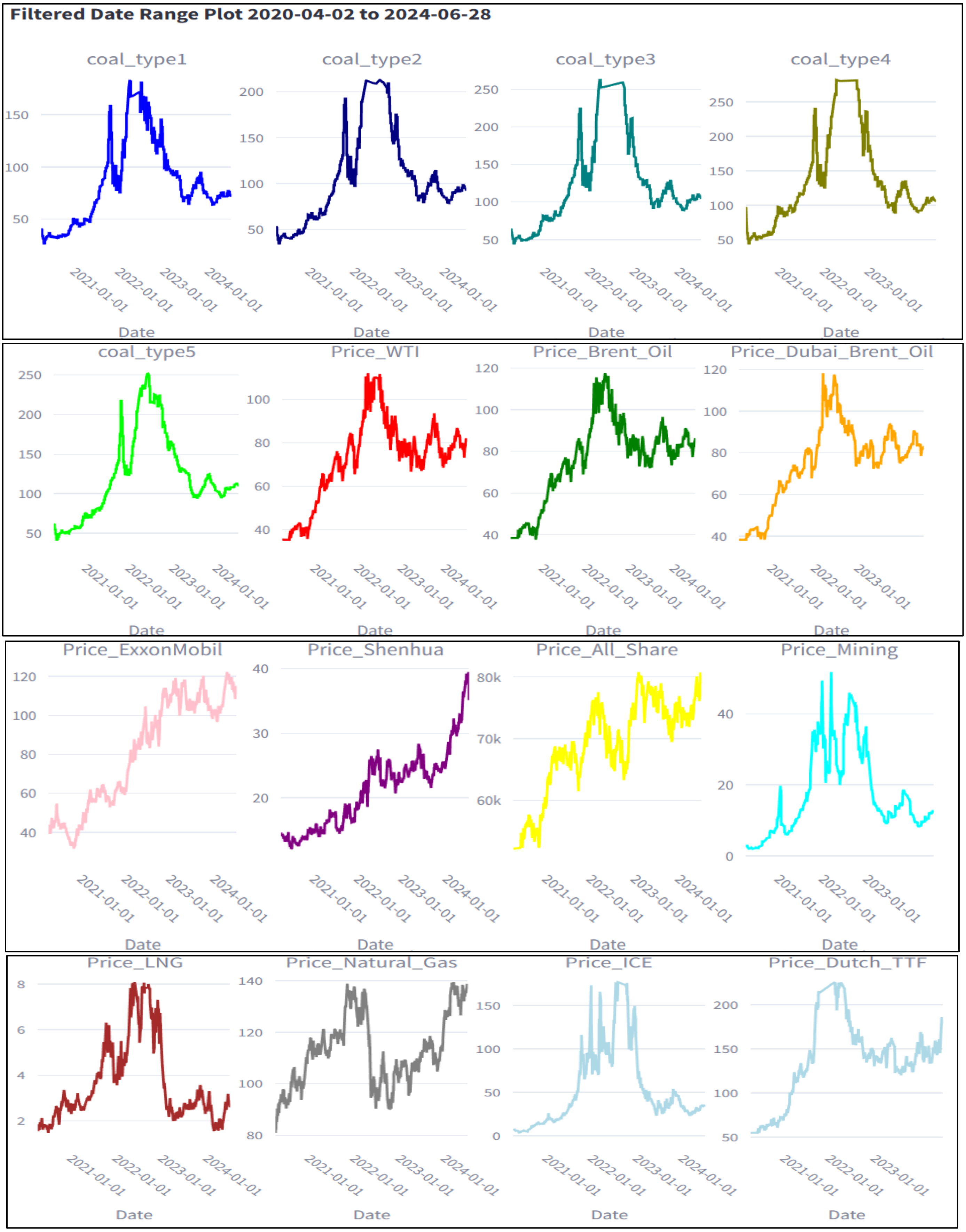

Fig 4: Data Distribution of Coal Prices and External Factors

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D. Model Building

In this study, we employed two distinct forecasting approaches to predict coal prices: a univariate time series model and a regression model that incorporates external factors. We split the dataset into training and testing sets, with data up to **December 29, 2023** used for training and data from **January 1, 2024, to June 28, 2024**, used for testing.

E. Univariate (Time Series) Approach

For the univariate model, we applied several time series forecasting techniques() to coal price data[4]. Among the models explored, the **Holt-Winters Multiplicative Seasonality with Trend model** provided the most accurate forecasts, as it was able to effectively capture the seasonal patterns and trends in the coal price data[7]. This model resulted in lower **Mean Absolute Percentage Error (MAPE)** values for each of the five coal types[6]. The MAPE values for the five coal types are presented in the table below[Fig 5].

F. Regression Model Approach

In the regression approach, we took a more holistic view by incorporating external factors into the prediction process[5]. The regression models were built in two different ways:

➢ *Approach 1: Using Best Correlated Factors*

In this approach, we selected only those external factors that had a correlation coefficient above 0.75 with coal prices[3]. These factors were used as independent variables, and coal price was treated as the dependent variable. The external factors were first forecasted using univariate time series models, and these predicted values were then used as inputs to the regression model.

➢ *Approach 2: Using All External Factors*

In this approach, we used all available external factors, regardless of their correlation strength[9]. After forecasting these factors using time series models, the predicted values were used as inputs, with the coal price again serving as the output variable.

G. Model Selection and Training

We used a variety of regression models(), including **Stacking Regressor, KNN Regressor, XGBoost Regressor, and Simple Linear Regression[10]**, among others. The process for selecting the best model was based on the **lowest MAPE** from the test data. After determining the best-performing model, we trained the entire dataset on this model and used it to predict future coal prices.

- For the **best factors** approach, only the forecasted values of the highly correlated factors were used as input.
- For the **all factors** approach, the forecasted values of all external factors were used as input.

This multi-step forecasting process allowed us to compare the effectiveness of each model and approach in predicting future coal prices, leading to more accurate and reliable forecasts that can be leveraged for strategic decision-making in coal procurement.

H. Hyperparameter Tuning

In our model building process, we applied **hyperparameter tuning** to optimize the performance of the **Holt-Winters Exponential Smoothing** model, both for forecasting coal prices and external factors. The key parameters we focused on tuning included **seasonal periods [3]**, as well as settings for the **seasonal** and **trend components**.

➢ *Our Base Model Configuration was as Follows:*

The hyperparameter tuning was done by adjusting the **seasonal periods** to best fit the frequency of both coal price data and the external factors. For each type of coal, as well as for different resampling frequencies (daily, weekly, and monthly), we adjusted the seasonal periods accordingly:

- **Daily Data**: Seasonal periods were set below **270** to capture patterns occurring over short-term cycles.
- **Weekly Data**: Seasonal periods were tuned to values below **52**, considering the weekly cycle of the data.
- **Monthly Data**: Seasonal periods were tuned to values below or equal to **12**, capturing monthly cycles.

This tuning process was applied to both the **coal price data** and the **external factors** (e.g., global oil prices, exchange rates, and economic indicators). We forecasted the external factors using the same Holt-Winters model and optimized seasonal periods. Once the external factors were forecasted, we used those predictions as **input data** in our **regression model**, with the original coal prices as the **output**.

By applying hyper parameter tuning to both the coal price data and the external factors, we enhanced the overall forecasting accuracy. The process of tuning seasonal periods based on **Mean Absolute Percentage Error (MAPE)** helped ensure that the model captured both short-term and long-term trends, leading to more reliable predictions.

I. Model Fitting

Once we identified the optimal **seasonal periods** through hyperparameter tuning, we proceeded with **model fitting**. Using the best seasonal periods, we fit the **Holt-Winters Exponential Smoothing model** to forecast future prices for the five types of coal. This fitting process was conducted for both the **univariate time series model** and the **regression approach**.

- **Univariate Approach**: The model was fit to each coal type individually using the best seasonal periods.
- **Regression Approach**: We forecasted external factors and used those predictions as input to the regression model, with coal prices as the output.

The final model was applied to forecast daily, weekly, and monthly prices for each coal type.

J. Model Evaluation

To evaluate the performance of our models, we used the **Mean Absolute Percentage Error (MAPE)** as the primary metric.

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- **Univariate Time Series Approach**: The model demonstrated a **5% error rate[6]**, or **95% accuracy**, across all five types of coal. This accuracy was consistent across daily, weekly, and monthly forecasts, with the **daily predictions** showing slightly better performance.
- **Regression Approach**: Using the regression model, which incorporated external factors, we achieved **above 90% accuracy[5][9]** across all resampling modes (daily, weekly, and monthly). The regression model provided good predictions, but the **daily forecast** outperformed both weekly and monthly forecasts in terms of precision.

These results indicate that the **univariate approach** excelled in capturing short-term fluctuations[4][7], while the **regression approach** added robustness by integrating external factors, enhancing prediction accuracy across different time scales[5][9].

K. Model Deployment

For the **model deployment**, we utilized **Streamlit** to create an interactive and user-friendly web interface. The deployment process involved the following key steps:

- **Login Page**: Users are first directed to a **login page** where they input their credentials to access the coal price forecasting tool.
- **Coal Price Forecasting Web Page**: Once logged in, users can access the coal price forecasting interface, where they can:

✓ **Select Coal Type**: Choose from the five types of coal for which they want to forecast prices.
✓ **Select Forecasting Method**:

▪ Univariate Time Series Model
▪ Regression Model: In the regression model, users can either use all external factors or only the best correlated factors (correlation above 0.75).

✓ **Select Time Granularity**: Users can choose the forecast to be provided in **daily**, **weekly**, or **monthly** intervals based on their business needs.
✓ **Select Start and End Dates**: Users can also specify the desired **start and end dates** for the forecast period. Based on this date range, the system dynamically generates forecasts for the selected coal type and method.

- **Initial Local Deployment**: The model was initially deployed **locally** for internal testing and validation of the system's functionality.
- **EC2 Instance Deployment**: After successful testing, the application was deployed on an **Amazon EC2 instance**, making it accessible to users remotely.

This deployment enables users to forecast coal prices for different coal types over custom time frames, with options to use advanced forecasting methods. The flexibility of selecting start and end dates allows for tailored forecasts that fit specific business needs, helping stakeholders make informed procurement and pricing decisions.

L. Software and Tools

➢ *The Following Software and Tools were Used:*

- *Programming Language:*

✓ **Python**: The entire model development, data processing, and deployment were performed using Python due to its wide range of libraries suited for time series analysis, machine learning, and web deployment.

- *Libraries and Packages:*

✓ **Pandas**: For data manipulation, cleaning, and resampling of the coal and external factors data.
✓ **NumPy**: Used for numerical computations and handling large datasets efficiently.
✓ **Statsmodels**: Specifically used for implementing **Exponential Smoothing** (Holt-Winters multiplicative seasonality with trend) and other time series forecasting models.
✓ **Scikit-learn**: For regression modeling, feature selection, and model evaluation.
✓ **Matplotlib and Seaborn**: Used for data visualization, including the generation of correlation heatmaps and time series plots.
✓ **Streamlit**: Employed for deploying the forecasting tool as a web application, providing users with an interactive UI to forecast coal prices.
✓ **AWS SDK for Python (Boto3)**: For pushing and retrieving data from the **Amazon S3** instance where the collected and processed data was stored.

- *Cloud Services:*

✓ **Amazon EC2**: Used to host and deploy the web application, making the tool accessible remotely.
✓ **Amazon S3**: Used for storing the merged dataset, including coal prices and external factors, which could be accessed during model deployment and forecasting.

- *Development and Collaboration Tools:*

✓ **Jupyter Notebooks**: For model experimentation, development, and preliminary analysis.

- *Data Sources:*

✓ **Investing.com**: External factors data (oil prices, exchange rates, etc.) was collected from this freely available online platform.
✓ **Excel**: Client provided historical coal prices data in Excel sheets, which was processed using Python libraries.

These tools and technologies provided the foundation for the development, analysis, and deployment of the coal price forecasting system, ensuring an efficient and scalable solution.

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III. RESULTS AND DISCUSSION

A. Univariate Time Series Forecasting Results:

Table 1: Above Table Shows Train and Test MAPE for All Types of Coal (Univariate Approach)

	Daily		Weekly		Monthly	
Coal_Type	Train_Mape	Test_Mape	Train_Mape	Test_Mape	Train_Mape	Test_Mape
coal_type1	1.81	5.11	5.82	3.70	9.29	7.69
coal_type2	1.34	3.35	4.51	5.52	7.54	9.96
coal_type3	1.34	4.31	4.43	5.05	8.74	6.72
coal_type4	1.51	3.22	4.88	5.90	8.97	6.05
coal_type5	1.05	4.97	3.39	5.41	7.48	4.82

- The **Holt-Winters Multiplicative Seasonality with Trend** model proved to be the best performing model for coal price forecasting among the univariate time series models.
- The Mean Absolute Percentage Error (MAPE) for all five types of coal was below 5%[Fig 5][6], indicating a high level of accuracy with over 95% accuracy across daily, weekly, and monthly forecasts.
- The model performed particularly well for **daily forecasts**, where it showed the lowest MAPE compared to weekly and monthly resampling. Daily granularity produced more precise and detailed predictions, aligning well with market dynamics.

The results[Fig 5] show that the daily forecast achieved the best performance, while weekly and monthly forecasts were slightly less accurate but still within an acceptable range for business use.

B. Regression Model Results:

Table 2: Above Table Shows Train and Test MAPE for All Types of Coal (Regression Approach)

	Daily		Weekly		Monthly	
Coal_Type	Train_Mape	Test_Mape	Train_Mape	Test_Mape	Train_Mape	Test_Mape
coal_type1	5.68	5.32	6.92	4.82	8.21	14.46
coal_type2	6.26	4.57	7.37	5.97	9.33	7.16
coal_type3	7.32	4.52	8.10	5.65	10.70	8.81
coal_type4	8.38	5.90	8.91	6.21	9.19	12.87
coal_type5	7.83	5.27	7.00	5.27	8.56	6.28

- The regression approach was applied in two ways: using **all external factors** and using only the **High correlated factors** (those with a correlation coefficient above 0.75).
- When using the best correlated factors, the MAPE was slightly lower, indicating better performance due to reduced noise and more relevant features for prediction.
- The regression model using the high correlated factors achieved accuracy above 90% [5][9] across all forecast intervals (daily, weekly, and monthly).

The results[Fig 6] suggest that while the univariate approach provides more accurate predictions for short-term forecasts[4][7] (daily), the regression approach, especially when using the best correlated external factors, delivers competitive results and adds the benefit of considering external market influences for mid-to-long-term forecasting.

C. Model Comparison:

- The univariate time series model outperformed the regression models in terms of MAPE, especially for daily forecasts.
- However, the regression model is more robust when considering the influence of external factors, which is valuable for long-term strategic planning.
- The regression model with best correlated external factors offered the best balance between accuracy and interpretability for weekly and monthly forecasts.

D. Deployment and Scalability:

- The forecasting tool was successfully deployed using **Streamlit** on an **Amazon EC2 instance**, allowing the client to interactively forecast coal prices using different

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modes (daily, weekly, monthly), types of coal, and prediction methods (univariate vs regression).

- The tool is designed to be scalable and flexible, enabling future updates as more data becomes available or as the business context evolves.

IV. DISCUSSION

- The **univariate approach** is highly effective for short-term forecasts where coal prices are largely influenced by their historical patterns. The **Holt-Winters** model's ability to capture seasonal effects makes it suitable for daily forecasts, particularly when the trends are stable.
- The **regression approach**, which incorporates external factors such as oil prices and exchange rates, becomes more useful for medium-to-long-term forecasts where external economic and environmental factors play a larger role[5][9].
- The accuracy of the forecast diminishes slightly as the granularity decreases (from daily to weekly to monthly), which may be due to the aggregation of volatility over time, especially for a commodity as sensitive to market forces as coal.
- The integration of both univariate and regression approaches allows for a comprehensive forecasting solution, giving the client flexibility depending on the business use case, whether short-term or strategic long-term forecasting.

The results underscore the effectiveness of combining time series and regression models in producing accurate, reliable coal price forecasts that meet the business needs.

V. CONCLUSION

This project successfully developed and deployed a comprehensive coal price forecasting tool using both univariate and regression-based models. The **Holt-Winters multiplicative seasonality with trend** model proved to be the most accurate univariate method, providing over 95% accuracy in daily forecasts for five different types of coal. The regression model, which integrated external economic factors, also delivered strong results, particularly when using the most correlated factors, achieving over 90% accuracy[5][7].

The deployment of this tool on an **Amazon EC2 instance** using **Streamlit** offers the client a flexible and scalable solution for forecasting coal prices in daily, weekly, and monthly intervals. The inclusion of both univariate and regression approaches ensures that the tool is adaptable for different forecasting scenarios, whether short-term or long-term. The model's robustness, combined with its ability to incorporate external factors, makes it a valuable asset for both tactical and strategic business decisions[6][9].

The project demonstrates the importance of incorporating external market influences in addition to historical data, particularly for a volatile commodity like coal. By combining advanced forecasting techniques with practical deployment strategies, the tool offers a reliable, user-friendly solution for coal price prediction, ultimately contributing to better decision-making and cost optimization for the client[10].

FUTURE SCOPE

- Incorporating Additional Variables: Future research could expand the model by including other potentially influential variables such as weather patterns, government policies, and technological advancements in coal extraction and utilization.
- Exploring Machine Learning Models: To further enhance forecast precision, future studies could explore advanced machine learning models like neural networks, support vector machines, or ensemble methods, which may capture non-linear relationships more effectively.
- Refining Data Granularity: Future research could benefit from using more granular data, such as hourly or intraday prices, to capture short-term price fluctuations and improve the accuracy of high-frequency trading strategies.
- Real-time Implementation: Develop a real-time forecasting system that automatically updates predictions as new data becomes available, providing timely insights for decision-making.
- Expanding Geographical Scope: Extend the model to forecast coal prices in different regions or countries, considering local market conditions and regulatory frameworks.
- Hybrid Approaches: Investigate hybrid models that combine time series analysis, regression techniques, and machine learning algorithms to leverage the strengths of each approach.
- Risk Assessment: Integrate risk assessment techniques into the forecasting framework to quantify the uncertainty associated with price predictions and support risk management strategies.

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