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FORCASTING NATURAL GAS PRICE PREDICTION USING MACHINE LEARNING

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Abstract : In this paper, we will use statistical modeling techniques to forecast natural gas prices in US markets. We will investigate the application and contrast of the decision-tree and random forest linear regression models. Using a total of 5800 records, we used a dataset of natural gas prices in the US expressed as US dollars per Btu from 1998 to 2020. Random forest conducts regression using ensemble learning techniques since it is a supervised learning algorithm. Random forest will forecast the price by utilizing the current prices and comparing them, which will be useful for the user to determine the risk in bidding prices. The results are indicated with up to 97% accuracy. The stage has been prepared for the potential new opportunities that these technologies may present.

Keywords **:** Random Forest, Decision Tree, Prediction, Natural Gas.

1.Introduction Predictions of natural gas prices can aid in making judgments on economic changes as well as resource management and reserve optimization. Global economies are significantly impacted by fluctuations in its price. Natural gas price forecasting is essential for commercial enterprises to manage the amount of gas they order and benefit from the projected price trend. Numerous forecasting methods, including conventional econometrics, have been developed to forecast natural gas prices. Machine learning models would perform prediction more successfully than econometrics. Natural gas price predictions could be made using regression classification methods like Random Forest and Decision-tree models.

4. METHODOLOGY

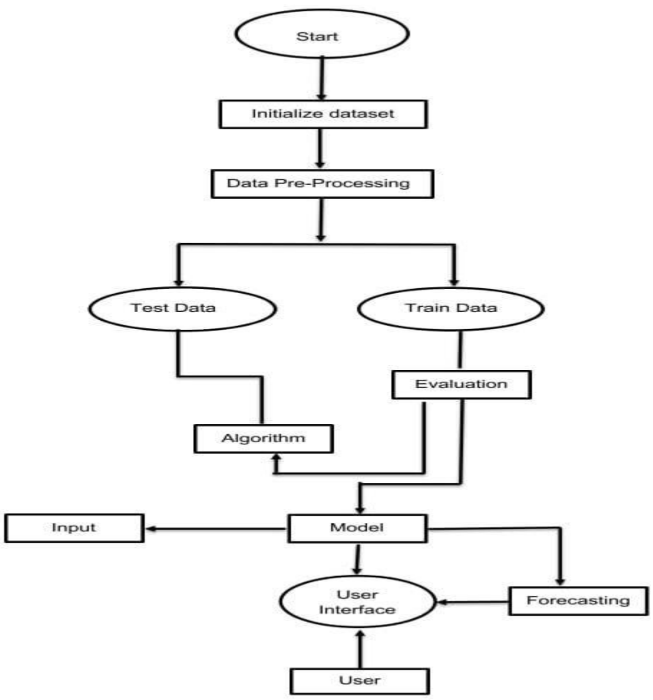

Figure 1: Flow diagram

Forecasting the price of natural gas might aid businesses in boosting their economies. This study investigates the use of machine learning to natural gas price prediction. Based on historical data on natural gas price changes, the prediction model was created. The linear regression produced the best accuracy. In order to train and test the dataset utilized by the system, we employed the Scikit-learn module. A predictive model is used to estimate natural gas prices in the US.

Using the various graphing options, the data are thoroughly examined and significant pricing tendencies are identified. After pre-processing, which entails cleaning and handling outliers, the dataset is split into two portions for training and testing. Training data is used to create the machine learning models.

This work required the following effort to produce: Multiple linear regression aims to ascertain the relationship between the variables by fitting the equation to the determined data. In order to create a large number of low correlated decision trees, the random forest model splits the data into many individual decision trees during training. When the model's output has been fitted, the predictions will be made based on the trees with the majority of votes. As a result, predictions made using the random forest will be more accurate than those made using a few other techniques.
The decision tree technique is also used for prediction to compare its accuracy with that of the random forest approach. ID3 is the name of the decision tree regression method. We will attempt to lower the standard deviation of the dataset's values by segmenting the data into several subtrees. The testing data is used to assess the trained model.

ALGORITHM STEPS

Step 1: Dataset initialization.

Step 2: Cleaning the dataset as part of pre-processing

Step 3: Training

Step 4: Developing Machine Learning Algorithm

Step 5: modelling

Step 6: Forecasting

RESULTS

We'll discuss the results of the aforementioned process in this session, as well as how machine learning models were employed. When the user enters a valid date through the interface, the trained model will forecast the anticipated price for that particular day. The decision tree and random forest models are also available to the user.

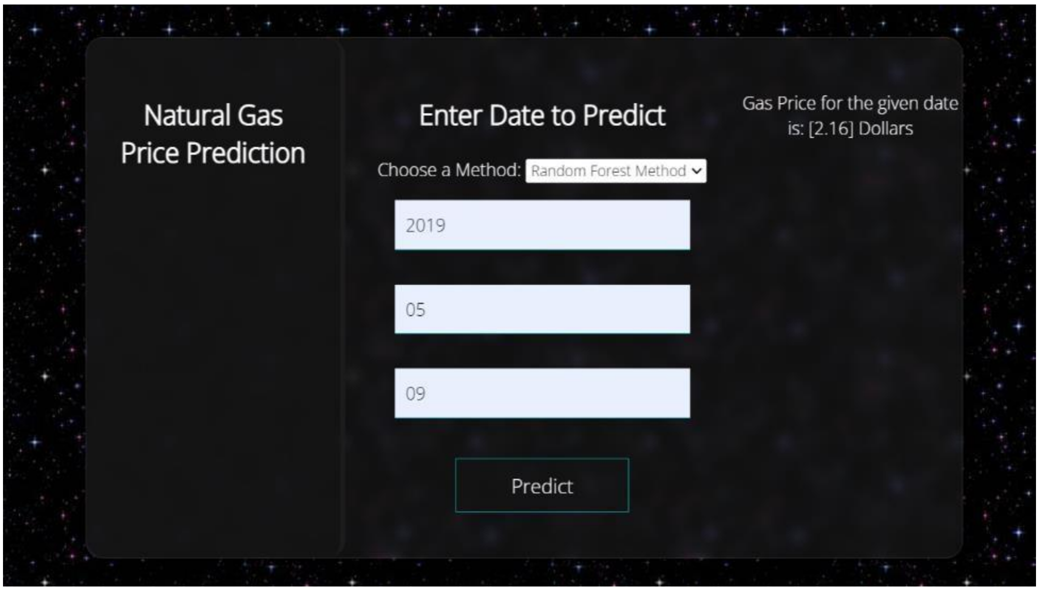

Figure 2: the above figure shows that The natural gas price for May 9, 2019, Using the Random Forest model, the prediction is made. The forecast's outcome is shown as US dollars for every million British thermal units.

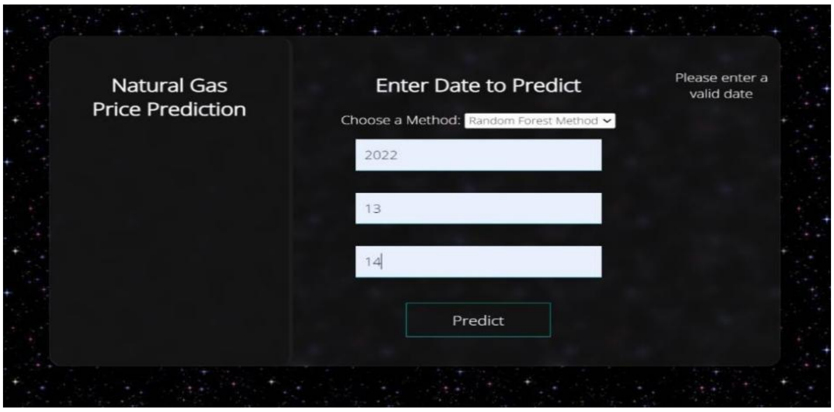

Figure 3: The above figure shows that when incorrect data is used as input, the consequence is. The illustration above demonstrates that the number 13 is entered for a month that does not exist. In this situation, the user interface will prompt them to provide valid data.

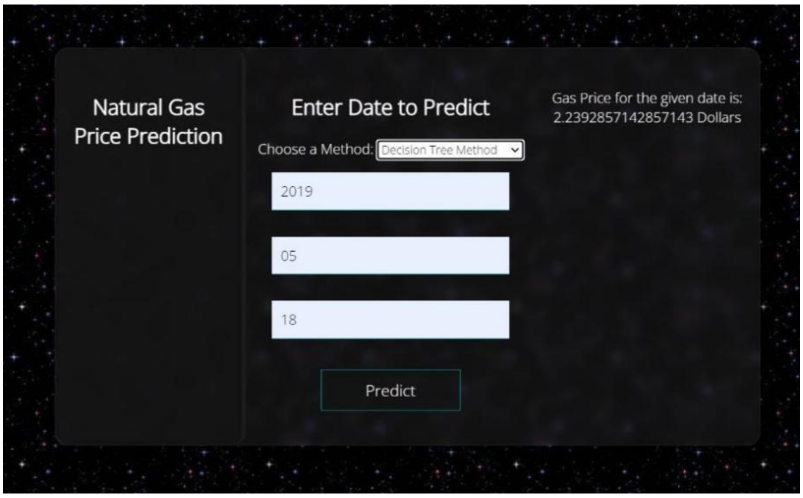

Figure 4: The above figure shows the Natural gas price forecast for May 18, 2019. Using a decision tree model, the prediction is made. The forecast's outcome is shown as US dollars for every million British thermal units.

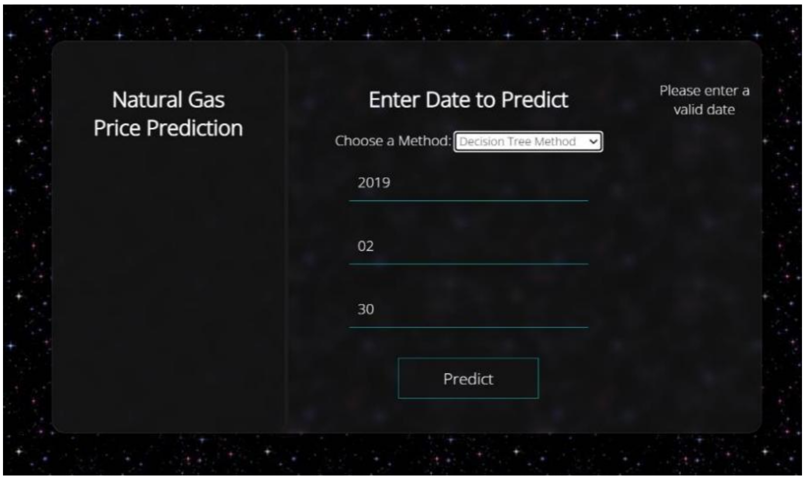

Figure 5: The above figure shows that when incorrect data is used as input, the consequence is. The illustration above demonstrates that a date of 30th is entered for the hypothetical month of February. In this situation, the user interface will prompt them to provide valid data.

CONCLUSION

In this study, Natural gas price forecasts are based on artificial intelligence (AI) algorithms. 97% of the time, these models are accurate. It has been shown that decision trees and random forests both predict outcomes rather accurately. Numerous elements, such as political shifts, broader economic conditions, and trading expectations, will affect the spot price index.

FUTURE ENHANCEMENT

The framework might be developed with a specific goal in mind—forecasting natural gas prices for the entire day. The ability to predict the price of natural gas at various times of the day may be improved in the future. The price of the other gases that are required may also be predicted using this model, which can be expanded.

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