Using machine learning to predict clean energy stock prices: How important are market volatility and economic policy uncertainty?

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INTRODUCTION

The disruptive impacts of climate change have created an urgent need to transition to a low carbon economy and an important part of this transition is an increase in the usage of clean energy. The greater adoption of clean energy is creating new opportunities for clean energy equity investing. The existing literature mostly focuses on the dynamic relationship between clean energy equities, oil prices, technology stock prices, and other important macroeconomic variables like market volatility and economic policy uncertainty. However, there is a shortage of literature on forecasting clean energy stock prices. Forecasting clean energy equity prices is important for making investment decisions. This paper uses machine learning methods to predict the clean energy stock prices. Initially the main motive of the project was just to predict the direction of the clean energy stock prices , but I used a regressor model thinking that even if it has some loss, it will still tell us direction with high precision.

Objective

The primary goal of this project is to evaluate the impact of market volatility and economic uncertainty on clean energy stocks. To capture market volatility, we are considering the following non-technical indicators:

- Oil Price Volatility (OVX)
- Volatility Index (VIX)
- Hindustan Zinc Ltd. stock (HZNC)
- Economic Policy Uncertainty Index (EPU)

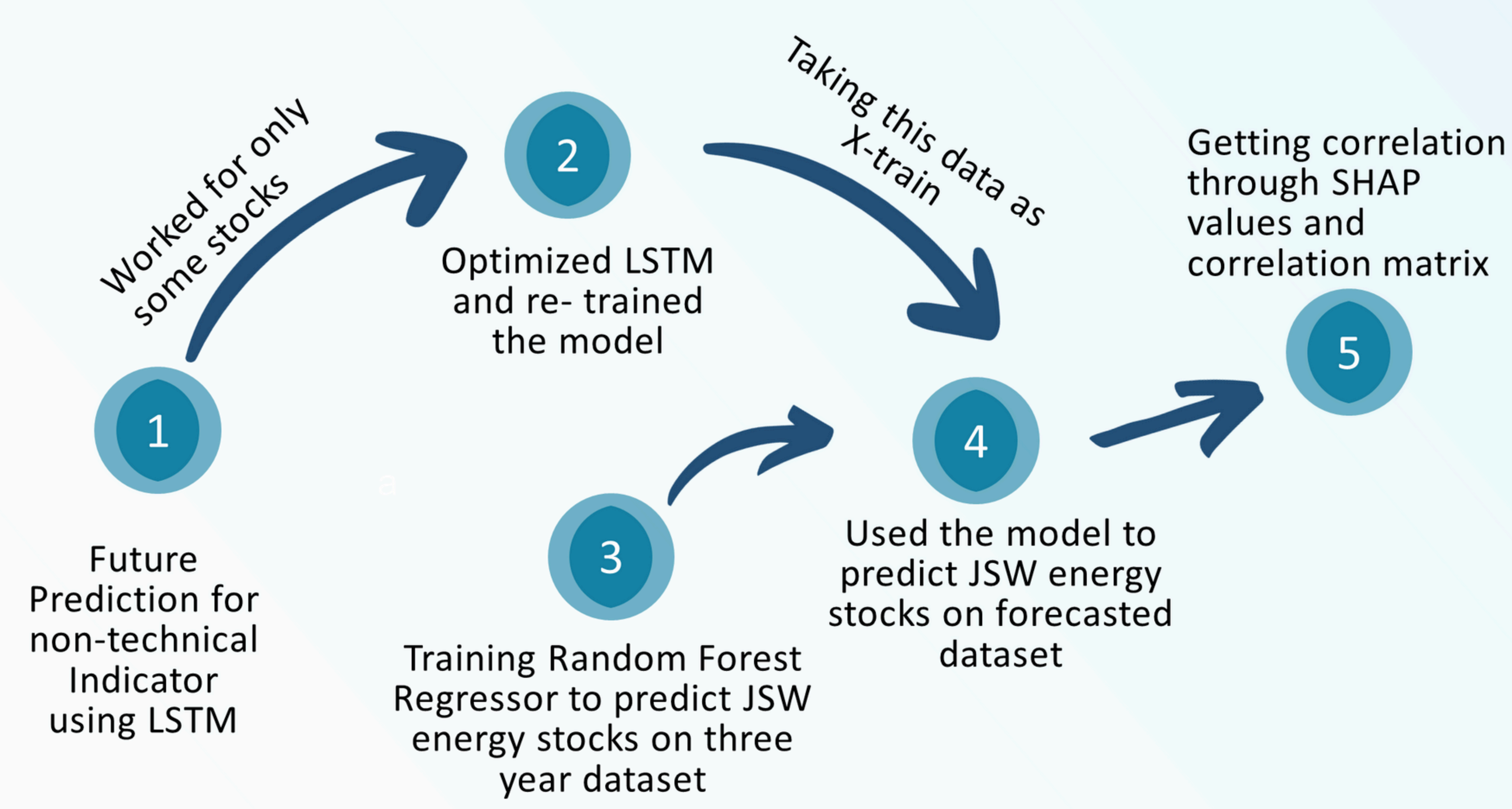
Additionally, we are incorporating the following technical indicators:

- Williams Accumulation/Distribution (WAD)
- 20-day Moving Average (MA20)
- 10-day Moving Average (MA10)

By analyzing the correlations between clean energy stocks and these parameters, we aim to gain insights into how fluctuations in market conditions and economic policies influence the performance of clean energy investments

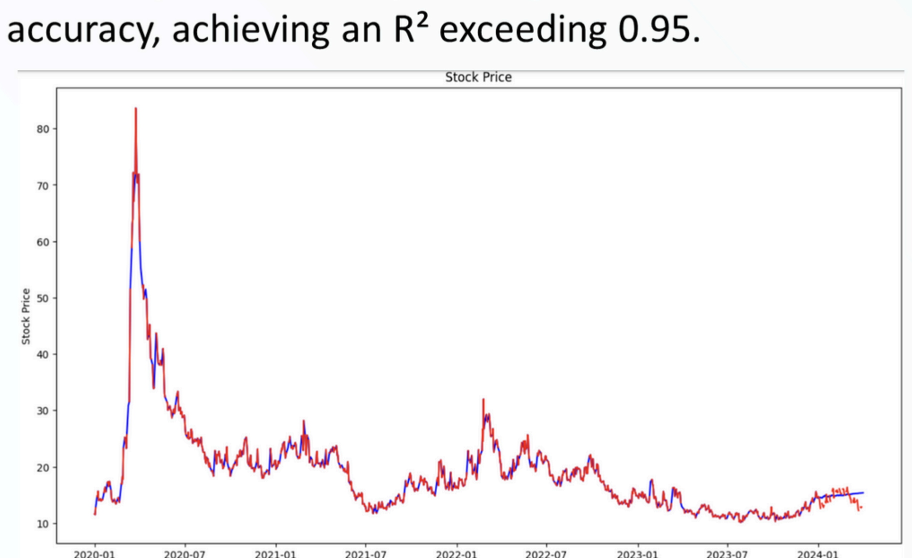
METHODOLOGY & RESULT

Following the given flow let us now understand the methodology :



1. **Feature Prediction:**

- Independent Features: The chosen independent features included the Oil Volatility Index (OVX), the Volatility Index (VIX), metal prices such as zinc (HZNC), and the Economic Policy Uncertainty (EPU) index as non-technical indicators. Additionally, technical indicators included the Williams Accumulation/Distribution (WAD), and moving averages (MA20, MA10).
- Model Selection: Initially, a basic Long Short-Term Memory (LSTM) model was employed to predict the future prices of these independent features. Although this model achieved an R^2 of up to 0.85 for some stocks, it required optimization for improved accuracy.
- Model Optimization: By refining the LSTM model, I enhanced the prediction accuracy, achieving an R^2 exceeding 0.95.

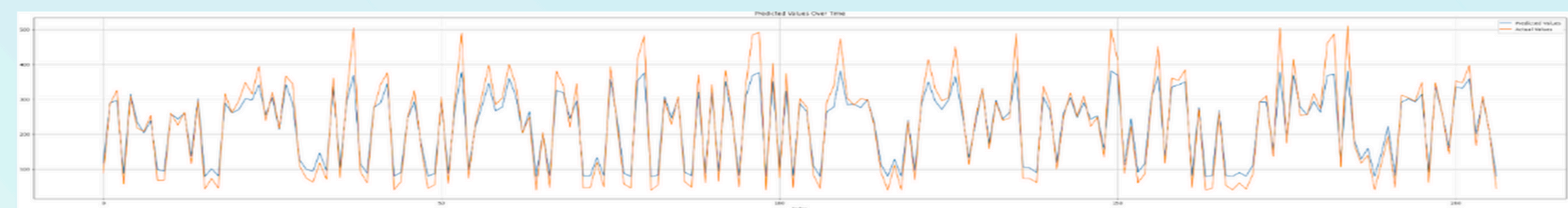


VIX price prediction

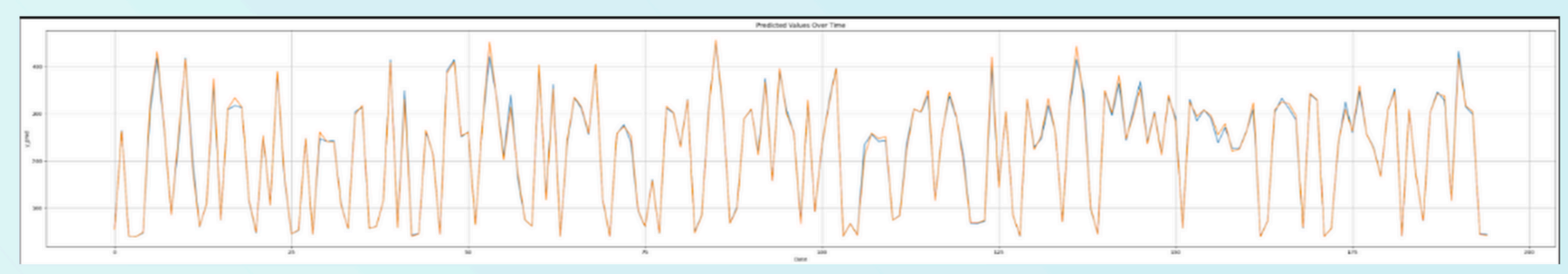
---- Prediction
---- Actual

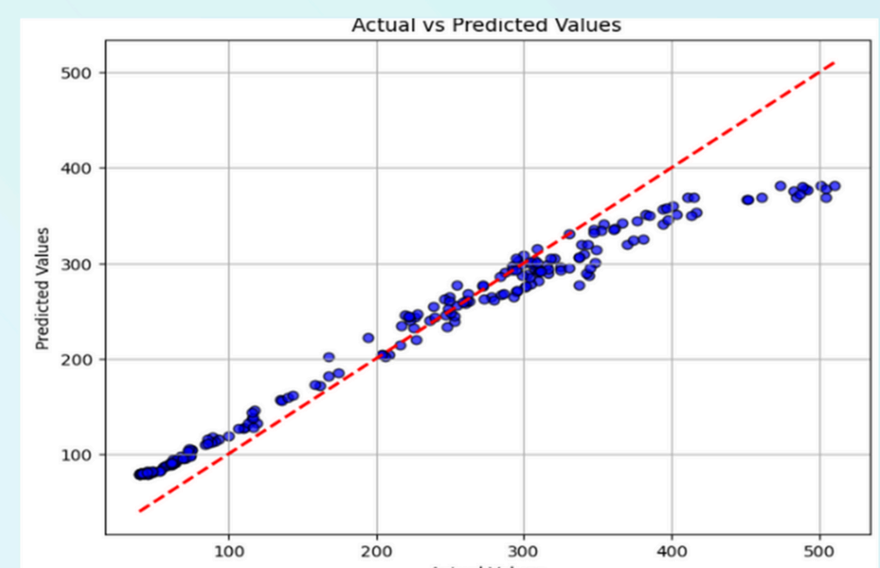
2. **Price Prediction of JSW Energy Stocks:**

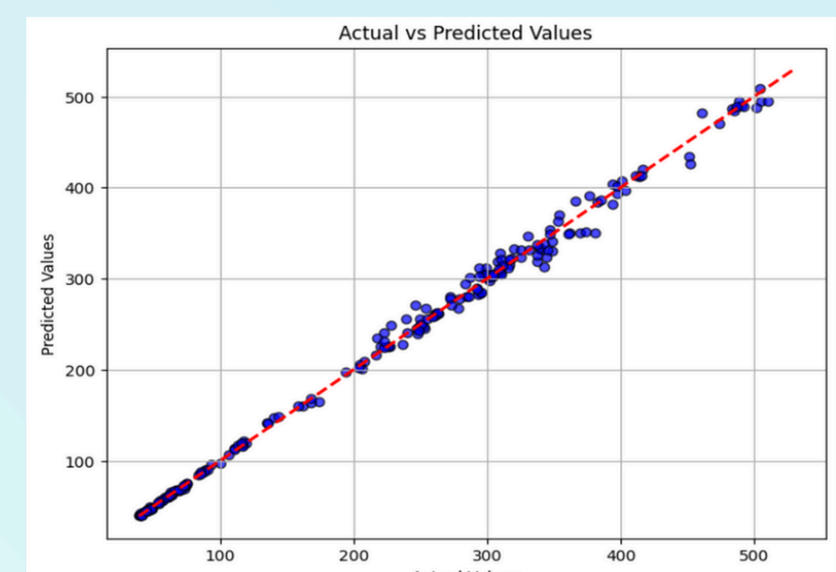
- After predicting the independent features, I employed a Support Vector Machine (SVM) to train a model for predicting the price of JSW Energy stocks. This approach resulted in an R^2 of 0.91.



- To further improve accuracy, I used a Random Forest Regressor with 500 trees, which significantly enhanced the R^2 to 0.99, outperforming the SVM regressor model.

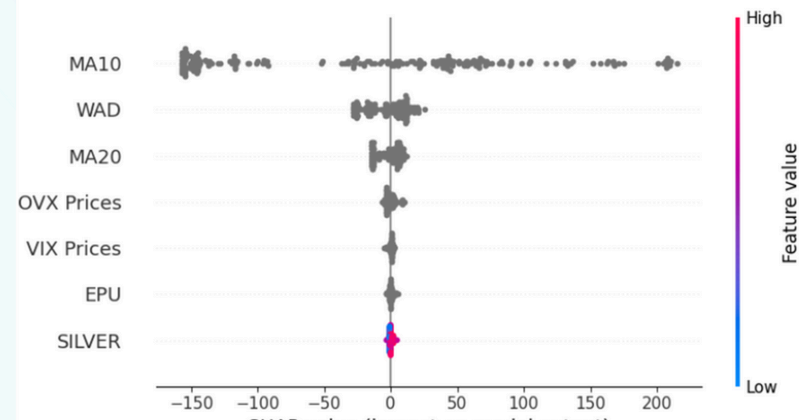






3. SHAP values and Correlation Matrix:

Using SHAP values and a correlation matrix, we analyzed the importance and relationships of various features affecting clean energy stocks. The SHAP analysis revealed that MA10, MA20, and WAD have the highest impact on the model's output, with OVX Prices also showing significant influence. In contrast, VIX Prices, EPU, and SILVER have lesser impacts. The color-coded SHAP plot helps visualize feature value distributions, with blue indicating low values and red indicating high values, showing how these feature values are distributed for different SHAP values.
The correlation matrix provides Pearson correlation coefficients between the SHAP values of the features, indicating how the features' influences on the model are related. High positive correlations were observed between MA10 and MA20 (0.737506), suggesting that these moving averages are closely related measures of market trends over different periods. Similarly, WAD showed strong correlations with both MA10 (0.863001) and MA20 (0.909812), indicating that it captures similar market dynamics as the moving averages. OVX Prices also exhibited high correlations with MA10 (0.757224) and MA20 (0.661610), reflecting the influence of oil price volatility on market trends.
Moderate correlations were found between OVX Prices and WAD (0.676427), and OVX Prices and SILVER (0.574782), indicating some degree of shared influence on the model output. Additionally, EPU showed moderate correlations with SILVER (0.173426) and OVX Prices (0.156394), suggesting that economic policy uncertainty affects these features to some extent.
Low or negative correlations were observed between VIX Prices and other features, highlighting a more independent influence on the model's predictions. Specifically, EPU and VIX Prices showed a negative correlation (-0.055818), indicating that higher economic policy uncertainty may slightly reduce the impact of VIX Prices on the model output. Overall, this analysis provides valuable insights into how various market volatility and economic uncertainty indicators, along with technical indicators, influence the performance of clean energy stocks.



	OVX Prices	VIX Prices	EPU	WAD	MA20	MA10	SILVER
OVX Prices	1.000000	0.023090	0.156394	0.676427	0.661610	0.757224	0.574782
VIX Prices	0.023090	1.000000	-0.055818	-0.072571	-0.089994	-0.042741	0.099445
EPU	0.156394	-0.055818	1.000000	0.231490	0.203237	0.140339	0.173426
WAD	0.676427	-0.072571	0.231490	1.000000	0.909812	0.863001	0.556020
MA20	0.661610	-0.089994	0.203237	0.909812	1.000000	0.737506	0.546506
MA10	0.757224	-0.042741	0.140339	0.863001	0.737506	1.000000	0.488985
SILVER	0.574782	0.099445	0.173426	0.556020	0.546506	0.488985	1.000000

Future Course Of Action

Advanced machine learning techniques, such as neural networks and ensemble methods, can be explored to improve model performance and capture complex relationships between features.

References

Reference Paper : Using machine learning to predict clean energy stock prices: How important are market volatility and economic policy uncertainty? – ScienceDirect
Data Collection Site : Investing.com - Stock Market Quotes & Financial News & Economic Policy Uncertainty | FRED | St. Louis Fed (stlouisfed.org)