Analyzing the Impact of West Asian Economic Indicators on India's GDP Growth

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***Abstract*— This research aims to analyze the impact and influence of economic indicators from West Asian countries on India's GDP growth. By employing linear regression and more advanced LSTM and BiLSTM models, along with machine learning models such as Random Forest and Gradient Boosting, we seek to assess predictive performance and explore potential improvements in modeling India's GDP growth. The data used in this research is sourced from the World Development Indicators (WDI) database compiled by the World Bank.**

Keywords—component, formatting, style, styling, insert (*key words*)

I. Introduction

The economic relationship between West Asian countries and India is of critical importance, given the strategic significance of the region and the deep-rooted economic ties between the two. West Asia, also known as the Middle East, is home to a diverse group of countries with rich natural resources, including oil and gas, which play a crucial role in the global economy. India, on the other hand, is one of the fastest-growing major economies and has a significant stake in the stability and growth of the West Asian region.

The recent economic challenges faced by West Asian countries, often referred to as the "West Asian crisis," have raised concerns about the potential impact on India's economy. The region has been grappling with various issues, including political instability, conflicts, and fluctuations in oil prices, which have had far-reaching implications for its economic stability. These challenges have underscored the need for a comprehensive analysis of the economic indicators from West Asian countries and their influence on India's GDP growth.

The West Asian crisis refers to the period of economic turmoil and uncertainty faced by countries in the West Asian region. The crisis has been driven by a combination of factors, including political instability, armed conflicts, and economic challenges. One of the key drivers of the crisis has been the volatility in oil prices, which has had a significant impact on the economies of oil-exporting countries in the region. The decline in oil prices has led to a reduction in government revenues, budget deficits, and a slowdown in economic growth.

The political instability and armed conflicts in the region have also taken a toll on the economy, leading to disruptions in trade and investment, damage to infrastructure, and a loss of human capital. These challenges have been exacerbated by the influx of refugees and the humanitarian crisis in countries like Syria, further straining the resources of the affected nations.

West Asia is a region that comprises several countries, each with its own unique economic characteristics and challenges. Some of the key countries in the region include Saudi Arabia, the United Arab Emirates (UAE), Qatar, Iran, and Iraq. These countries play a significant role in the global economy, particularly in the oil and gas sector..

The economic indicators from West Asian countries might have a significant impact on India's GDP growth, this paper hypothesizes on it and by analyzing these indicators and using advanced modeling techniques, we can gain valuable insights that can help policymakers and economists navigate the challenges posed by the West Asian crisis and strengthen the economic relationship between India and West Asian countries.

II. Data

The dataset used in this research is sourced from the World Development Indicators (WDI), a collection of development indicators compiled by the World Bank from officially recognized international sources. The dataset is publicly accessible and is classified as Public under the Access to Information Classification Policy of the World Bank.

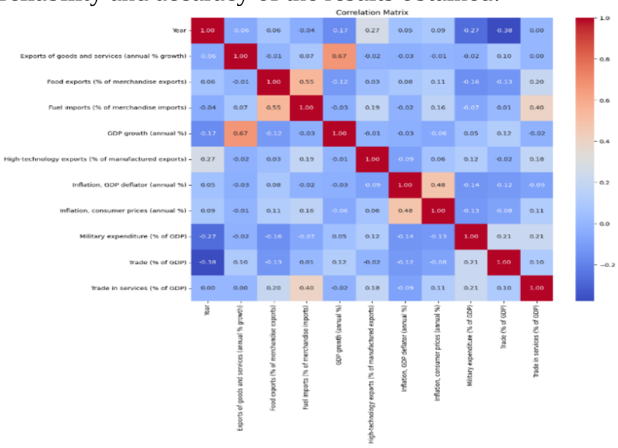
Data Description

The dataset consists of the following columns:

1. Country Name: The name of the country.
2. Year: The year for which the data is recorded.
3. Exports of goods and services (% of GDP): The percentage of GDP represented by exports of goods and services.
4. Food exports (% of merchandise exports): The percentage of merchandise exports represented by food exports.
5. Fuel imports (% of merchandise imports): The percentage of merchandise imports represented by fuel imports.
6. GDP growth (annual %): The annual percentage growth rate of the GDP.
7. High-technology exports (% of manufactured exports): The percentage of manufactured exports represented by high-technology exports.
8. Inflation, GDP deflator (annual %): The annual percentage change in the GDP deflator.
9. Inflation, consumer prices (annual %): The annual percentage change in consumer prices.
10. Military expenditure (% of GDP): The percentage of GDP represented by military expenditure.
11. Trade (% of GDP): The percentage of GDP represented by trade.
12. Trade in services (% of GDP): The percentage of GDP represented by trade in services.

The data is sourced from the World Bank's World Development Indicators (WDI) database. The WDI database is considered to be the primary source of global development data, providing national, regional, and global estimates. Although the Global Development Finance (GDF) publication is no longer listed in the WDI database name, all external debt and financial flows data from GDF are included in WDI. The GDF publication has been renamed International Debt Statistics (IDS) and has its own separate database.

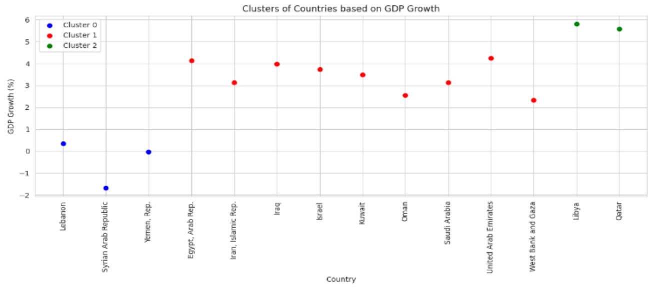
The initial dataset was structured with years as columns and economic indicator variables as rows, requiring a significant reshaping effort for analysis. The data was loaded and pre-processed to address missing values and convert data types as necessary. Subsequently, exploratory data analysis (EDA) was conducted to gain insights into the distribution and relationships between variables. This process was crucial in preparing the dataset for further analysis, ensuring the reliability and accuracy of the results obtained.

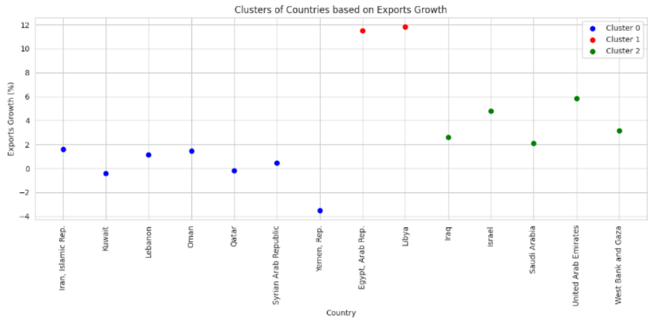


III. Clustering Analysis

The clustering analysis on GDP growth percentage revealed distinct groupings among Middle Eastern countries based on similar economic or social characteristics. Cluster 0 includes countries facing more significant challenges such as Lebanon, the Syrian Arab Republic, and Yemen. Cluster 1 comprises a mix of developing and developed nations, including Egypt, the Islamic Republic of Iran, Iraq, Israel, Kuwait, Oman, Saudi Arabia, the United Arab Emirates, and the West Bank and Gaza. Cluster 2 consists of Libya and Qatar, suggesting potentially higher economic performance in these countries.

Similarly, clustering based on exports growth highlighted different groupings. Cluster 0 includes countries like Iran, Kuwait, Lebanon, Oman, Qatar, the Syrian Arab Republic, and Yemen, exhibiting a certain range of export growth characteristics. Cluster 1 comprises Egypt and the Arab Republic of Libya, representing another set of countries with distinct export growth patterns. Cluster 2 consists of Iraq, Israel, Saudi Arabia, the United Arab Emirates, and the West Bank and Gaza, indicating yet another grouping with potentially different export growth characteristics.





IV. Modelling

The approach taken involved several steps to analyze the influence of the West Asian crisis on the Indian economy using advanced techniques. First, two datasets containing economic indicators for India and West Asian countries were merged based on the year column. Then, regression analysis was performed using a linear regression model to understand the relationship between West Asian country indicators and Indian indicators. The independent variables considered for the regression analysis included various economic indicators for West Asian countries, while the dependent variable was an indicator for India.

Additionally, a weighted score was calculated using custom weights for each feature. This allowed for a more nuanced analysis of the Indian economy's performance based on specific indicators.

A. Linear Regression:

We employed linear regression to understand the relationship between West Asian country indicators and Indian indicators. The independent variables included various economic indicators for West Asian countries, while the dependent variable was an indicator for India. This analysis provided a foundational understanding of the influence of West Asian economic indicators on India's economy.

The Linear Regression model demonstrates a modest fit with an R-squared of 0.0446 and a RMSE of 0.598, indicating room for improvement in predictive accuracy. The R^2 Score of 0.1221 on the entire dataset suggests that the model explains a small portion of the variance in the data.

B. Advanced Machine Learning Models

To further enhance our analysis, we implemented more advanced machine learning models, including Long Short-Term Memory (LSTM) and Bidirectional LSTM (BiLSTM). These models are well-suited for sequential data and can capture complex patterns over time. By using these models, we aimed to improve the predictive performance and gain deeper insights into the influence of West Asian economic indicators on India's GDP growth.

- LSTM Model:
  - MSE: 0.4562 - Indicates a moderate level of average squared errors.
  - RMSE: 0.6754 - Suggests the standard deviation of residuals is moderate.
  - MAE: 0.5366 - Reflects a moderate median absolute error.
  - R-squared: -0.2189 - A negative value, implying the model fails to capture the data's trend and performs worse than a simple average.
- BiLSTM Model:
  - MSE: 0.4645 - Slightly higher than LSTM, indicating more average squared errors.
  - RMSE: 0.6815 - A bit higher than LSTM, suggesting a slightly worse fit.
  - MAE: 0.5579 - Higher than LSTM, indicating less accuracy in predictions.
  - R-squared: -0.2410 - More negative than LSTM, showing a further decline in model performance.
- GRU Model:
  - MSE: 0.4153 - Lower than both LSTM and BiLSTM, indicating fewer average squared errors.
  - RMSE: 0.6444 - Lower than LSTM and BiLSTM, suggesting a better fit.
  - MAE: 0.4737 - Also lower, reflecting better accuracy in predictions.
  - R-squared: -0.1096 - Less negative, indicating a better performance than LSTM and BiLSTM but still below a simple average.
- BiGRU Model:
  - MSE: 0.5617 - The highest among the models, indicating the most average squared errors.
  - RMSE: 0.7495 - Also the highest, suggesting the poorest fit.
  - MAE: 0.5798 - The highest, indicating the least accuracy in predictions.
  - R-squared: -0.5007 - Significantly negative, showing that the model performs substantially worse than a simple average.

The GRU model outperforms the LSTM, BiLSTM, and BiGRU models in terms of lower error metrics and less negative R-squared value, suggesting it is better at capturing the underlying pattern in the data. The BiGRU model, despite its bidirectional architecture, shows the poorest performance, indicating that the additional complexity may not be beneficial for the dataset in question. The negative R-squared values across all models suggest that none of the models are particularly well-suited to the data, and further refinement or alternative approaches might be necessary.

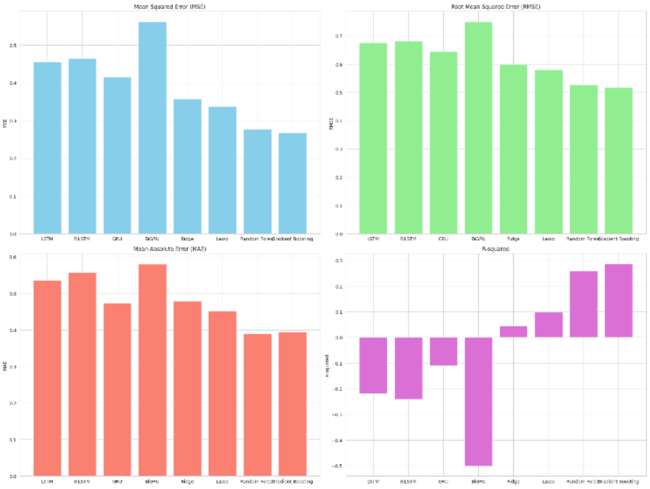
C. *Machine Learning Models*

Additionally, we utilized machine learning models such as Random Forest and Gradient Boosting to assess their predictive performance in modelling India's GDP growth. These models were trained and evaluated using metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-squared to determine their effectiveness in predicting India's economic performance based on the selected features.

- Ridge Regression:
  - MSE: 0.3575 - Indicates average squared error from true values.
  - RMSE: 0.5979 - Represents standard deviation of residuals.
  - MAE: 0.4787 - Shows median absolute error from true values.
  - R-squared: 0.0447 - Suggests that only 4.47% of the variance in the dependent variable is predictable from the independent variable.
- Lasso Regression:
  - MSE: 0.3374 - Slightly lower than Ridge, indicating better performance.
  - RMSE: 0.5808 - Lower than Ridge, suggesting better fit to the data.
  - MAE: 0.4514 - Also lower than Ridge, indicating better central tendency.
  - R-squared: 0.0986 - Higher than Ridge, with 9.86% of variance explained.
- Random Forest:
  - MSE: 0.2772 - Significantly lower than both Ridge and Lasso.
  - RMSE: 0.5265 - Indicates a good fit to the data.
  - MAE: 0.3896 - The lowest among the models, suggesting good accuracy.
  - R-squared: 0.2593 - A substantial improvement, with 25.93% of variance explained.
- Gradient Boosting:
  - MSE: 0.2669 - The lowest MSE, indicating the smallest average squared error.
  - RMSE: 0.5166 - The lowest RMSE, suggesting the best fit among the models.

- MAE: 0.3946 - Comparable to Random Forest, indicating similar accuracy.
- R-squared: 0.2869 - The highest value, with 28.69% of variance explained, making it the best predictor among the four models.

Gradient Boosting emerges as the most effective model, with the highest R-squared and lowest error metrics, indicating it is the best predictor of the dependent variable. Random Forest also shows strong performance, particularly in terms of MAE. Both Lasso and Ridge have room for improvement, especially in terms of the proportion of variance they explain in the dependent variable.



Overall, the approach involved merging and analysing datasets, performing regression analysis, implementing machine learning models, and evaluating their performance to understand the influence of the West Asian crisis on the Indian economy.

V. Feature Importance

- Random Forest Feature Importance:
  - The model places the highest importance on Inflation, GDP deflator (annual %)_WestAsia, suggesting that inflation rates are a critical predictor for the model's outcomes.
  - Trade (% of GDP)_WestAsia and GDP growth (annual %)_WestAsia also emerge as significant features, indicating the model's sensitivity to trade volumes and economic growth rates in the region.
- Gradient Boosting Feature Importance:
  - Similar to Random Forest, Inflation, GDP deflator (annual %)_WestAsia is deemed most important, reinforcing the feature's predictive strength across different models.
  - The importance of Trade (% of GDP)_WestAsia is even more pronounced in this model, followed closely by GDP growth (annual %)_WestAsia, which aligns with the Random Forest's findings but with slightly different importance weights.

These importance calculations reveal that both models consistently identify inflation and trade-related features as top predictors for the economic modeling of West Asia. This consistency across models enhances the credibility of these features as key indicators in economic forecasting for the region. The slight variations in importance weights between the two models may reflect their unique algorithmic interpretations of the data.

Feature	**Random Forest Importance**	**Gradient Boosting Importance**
Inflation, GDP deflator (annual %)_WestAsia	0.263810	0.282827
Trade (% of GDP)_WestAsia	0.140702	0.166055
GDP growth (annual %)_WestAsia	0.130898	0.160629
High-technology exports (% of manufactured exports)	0.124515	0.143541
Inflation, consumer prices (annual %)_WestAsia	0.086614	0.058728
Exports of goods and services (annual % growth)	0.067723	0.034823
Military expenditure (% of GDP)_WestAsia	0.054579	0.068283
Fuel imports (% of merchandise imports)_WestAsia	0.050327	0.025860
Food exports (% of merchandise exports)_WestAsia	0.047328	0.030417
Trade in services (% of GDP)_WestAsia	0.033505	0.028838

VI. CONCLUSION

In this research, we set out to analyse the impact and influence of economic indicators from West Asian countries on India's GDP growth. By employing various modelling techniques, including linear regression, LSTM, BiLSTM, Random Forest, and Gradient Boosting, we aimed to assess predictive performance and explore potential improvements in modelling India's GDP growth.

Our analysis revealed several key findings. First, the clustering analysis on GDP growth and exports growth highlighted distinct groupings among Middle Eastern countries, providing insights into their economic characteristics and performance. Second, our modelling efforts showed that while linear regression provided a foundational understanding, more advanced machine learning models such as LSTM and Gradient Boosting offered better predictive performance, with Gradient Boosting emerging as the most effective model for predicting India's GDP growth.

Furthermore, feature importance analysis indicated that inflation, trade, and GDP growth were significant predictors of India's economic performance in the context of West Asian economic indicators. The consistency of these findings across different models enhances their credibility and underscores their importance in economic forecasting.

Overall, our research contributes to the understanding of how economic indicators from West Asian countries can influence India's GDP growth. By leveraging advanced modelling techniques, we have provided insights that can help policymakers and economists make more informed decisions in managing economic relationships between India and West Asian countries.

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