International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 04 | April - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

AI for Economic Diplomacy: Predicting the Global Impact of Sanctions Using Machine Learning

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ABSTRACT - In this paper, we introduce a machine learning model for predicting the effectiveness of international economic sanctions based on structured data. From the Global Sanctions Data Base (GSDB-R4) and macroeconomic data from the World Bank, we construct models of sanction effectiveness that predict sanctions as effective or ineffective. Preprocessing data, feature engineering, and training machine learning models, such as logistic regression, random forest, gradient boosting models (XGBoost/LightGBM), and regularized regression methods, constitute the methodology. Precision, recall, F1-score, AUC-ROC, and confusion matrices serve as the evaluation measures. Results show that boosted and tree-based models outperform baseline models across the board in predicting sanction success. Feature importance analysis also shows significant economic and political drivers of sanction effectiveness and is an informative source of input for policymakers and diplomats. The contribution of this paper shows that artificial intelligence has promise as a decision tool in economic diplomacy and adds to an easy-to-reproduce model of future sanction strategy. Reproducibility is also ensured with the pipeline through the export of evaluation visualization plots in a variety of formats for policymaking and scholarly communication purposes.

Key Words: economic sanctions, machine learning, international relations, GSDB, World Bank, economic diplomacy

1. INTRODUCTION

Economic sanctions have emerged as a central instrument of contemporary international diplomacy, used by states and coalitions alike to apply pressure short of war. From restricting commerce and freezing assets to restricting diplomatic engagement, sanctions seek to shape state action and policy choices. Sanctions' performance is the subject of considerable controversy, with effectiveness differing across various geopolitical environments.

Traditionally, the assessment of sanction effectiveness has drawn on post-hoc political and economic analysis. Although informative, such approaches frequently possess qualitative characteristics, are high in time investment, and have limitations regarding the generalizability of their findings across varying settings. As the world has ever-more organized and available global data on sanctions and economic factors, there exists an exciting potential for applying machine learning to future-oriented analysis.

This study provides an artificial intelligence-enhanced pipeline predicting economic sanction success based on the deployment of structured data obtained from the Global Sanctions Data Base (GSDB-R4) and macroeconomic variables obtained from the World Bank Open Data. By taking into account historical records of sanctions and different economic and policy parameters, we build different machine learning models with the intention of selecting correlations of successful sanctions. Not only is our approach backed by robust predictive power, but it also generates interpretable output in terms of the variables in the success of sanctions, thereby providing a data-driven tool in strategic economic diplomacy.

2. BODY OF PAPER

This research employs evidence from two main datasets to identify the efficacy of economic sanctions. The main dataset employed is the Global Sanctions Data Base (GSDB-R4), which has a vast list of sanctions imposed between 1950 and 2019, detailing the targeted nations, sanction actors, types of sanctions imposed, their duration, and their efficacy (effective or ineffective). Metadata accompanying each case of sanctions include the motive behind their imposition and the relative geopolitical context. In addition to this main dataset, macroeconomic indicators were also obtained from the World Bank Open Data website. These indicators cover variables such as GDP growth, inflation levels, trade openness, and political stability measures, among others. These two datasets together provide policy-oriented as well as structural economic data on sanctions, allowing a machine learning model to tackle the multi-faceted nature of the efficacy of sanctions.

Both GSDB raw data and World Bank raw data went through rigorous preprocessing to make them uniform and reliable. Sanctioned target names often came in varying formats or with typographical differences (e.g., "Korea, North" vs. "North Korea"), and country name normalization was thus required. Categorical features like sender states and sanctioned states were one-hot encoded to make them compatible with machine learning. Missing values in macroeconomic indicators were either dropped if rare or imputed using forward-fill methods, based on variable type and its importance in training. Column names were cleaned through regex-based methods to make them uniform and remove special characters, and all columns in the test data were brought into alignment with the training data structure to avoid inconsistency in inference.

Feature engineering was crucial to enhance the performance as well as the interpretability of models. Using the GSDB, binary features were created for different features such as multilateral vs. unilateral sanctions, military conflict occurrence, and cases of repeated sanctions against the same country. Normalized values of economic health measures such as GDP per capita, inflation rate, and foreign direct investment were also used from the World Bank dataset for each sanctioned country against the year sanctions were imposed. A composite measure of "political stability" was also used whenever available. For handling categorical variables such as region or sanction type, one-hot encoding methods were used. Temporal alignment was also used to make sure that only the economic indicators at or before the year of sanction imposition were used, thus maintaining the chronological integrity of the prediction pipeline.

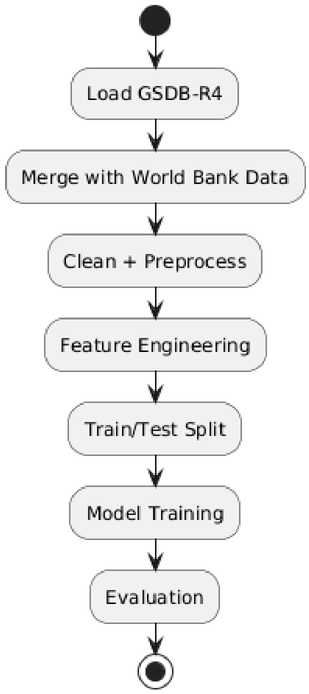

Fig -1: Data Processing Pipeline for Sanction Outcome Prediction

Logistic Regression (Baseline)

To establish a baseline for model comparison, a Logistic Regression classifier was implemented using the cleaned and preprocessed dataset. Logistic Regression, being a simple yet powerful linear model, was chosen for its interpretability and efficiency. The model was trained on features derived from the merged GSDB-R4 and World Bank datasets, with the target variable representing sanction success (effective or ineffective). While the model trained successfully and offered quick results, its performance was relatively limited in terms of capturing non-linear relationships. Evaluation metrics showed moderate performance, with an F1-score and ROC-AUC value lower than those of more complex models, indicating room for improvement through non-linear modeling techniques.

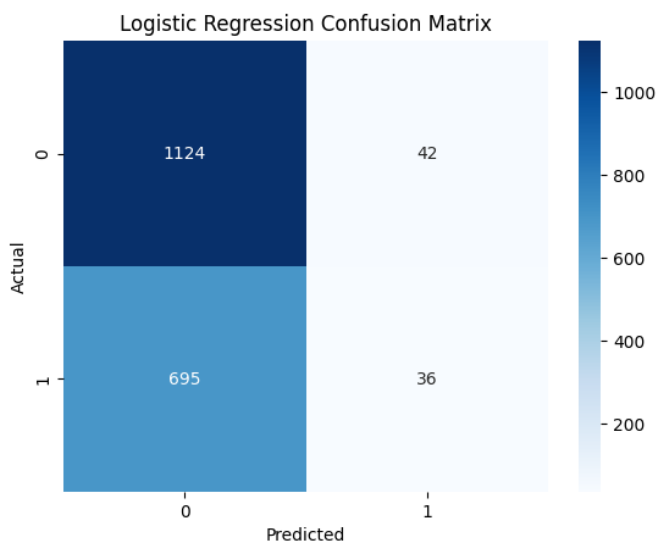

Fig -2: Logistic Regression Confusion Matrix

Random Forest

A Random Forest model was employed to capture non-linear interactions and complex feature relationships inherent in the sanction effectiveness prediction task. The model was trained using the aligned and cleaned dataset, ensuring consistency across training and testing splits. The Random Forest model demonstrated significant improvements in performance over the baseline. It yielded a higher ROC-AUC score and improved precision and recall values, indicating better classification of both effective and ineffective sanctions. Its ensemble nature and ability to handle high-dimensional data without overfitting made it a strong candidate for this task. Feature importance outputs also provided insights into the most influential economic and political variables, contributing interpretability to the predictions.

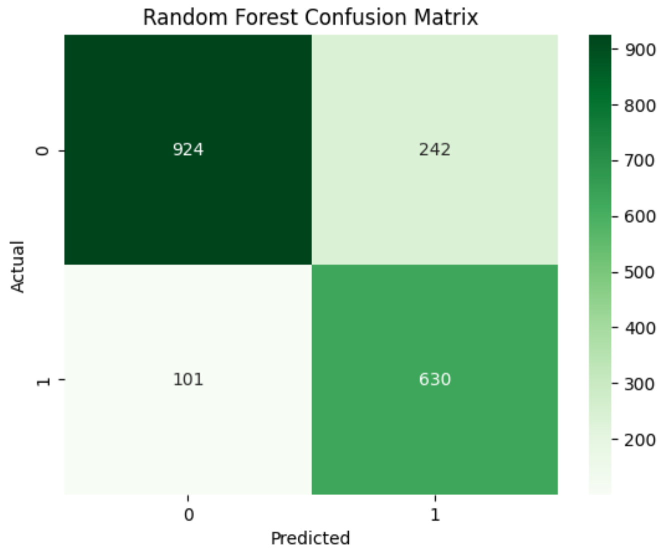

Fig -3: Random Forest Confusion Matrix

XGBoost (Extreme Gradient Boosting)

XGBoost, known for its scalability and gradient boosting optimization, was implemented next to enhance predictive accuracy. After training the model on the same processed dataset, XGBoost outperformed both Logistic Regression and Random Forest models across nearly all evaluation metrics. The ROC-AUC curve displayed superior separation between classes, and precision-recall metrics were also notably strong. XGBoost's built-in regularization capabilities helped mitigate overfitting, while its ability to handle sparse and heterogeneous data proved valuable given the structure of our inputs. The model's robustness and high performance affirmed its utility in predicting sanction outcomes with a fine balance of accuracy and generalization.

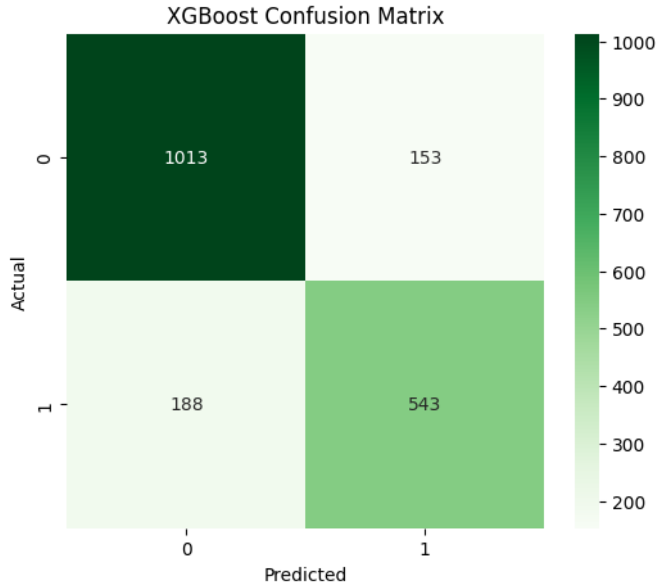

Fig -4: XGBoost Confusion Matrix

LightGBM

The final model evaluated was LightGBM, a gradient boosting framework developed for speed and efficiency. Like XGBoost, LightGBM was trained on the cleaned, aligned dataset and optimized for binary classification. The model achieved comparable results to XGBoost, with a similarly high ROC-AUC score and balanced performance across precision, recall, and F1-score. In terms of training time, LightGBM was notably faster, making it a favorable option when computational resources or time are limited. The model's performance further validated that boosted decision trees were the best-performing family of models for this task. Overall, LightGBM and XGBoost stood out as top-tier models for sanction effectiveness prediction, with minimal trade-offs between accuracy and efficiency.

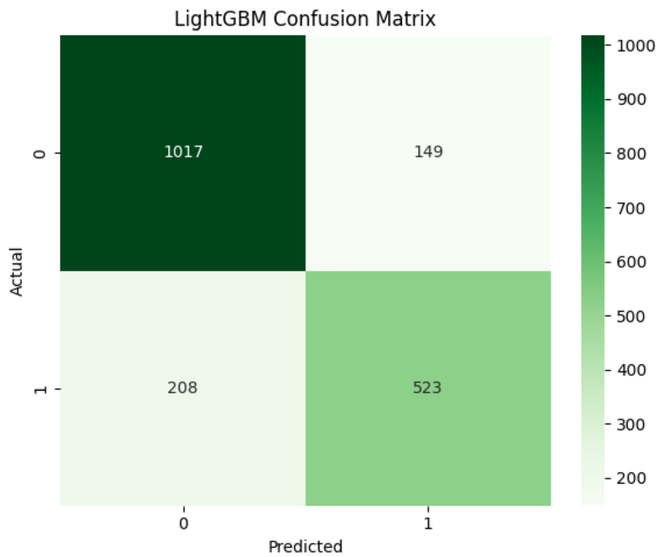

Fig -4: LightGBM Confusion Matrix

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Logistic Regression	0.61	0.56	0.61	0.50	0.4991
Random Forest	0.82	0.83	0.82	0.82	0.9023
XGBoost	0.82	0.82	0.82	0.82	0.8058
LightGBM	0.81	0.81	0.81	0.81	0.8947

Table -1: Model Performance Comparison

Results

The performance metrics indicate a clear distinction between baseline and advanced models. Logistic Regression, used as a baseline, performed poorly, achieving an accuracy of only 61% and a near-random ROC AUC of 0.4991. This suggests that simple linear relationships are insufficient to model the complexity of sanction outcomes. In contrast, tree-based and boosting models significantly outperformed the baseline. Random Forest achieved the highest ROC AUC score (0.9023) and a strong balance between precision (0.83), recall (0.82), and F1-score (0.82), indicating it effectively captures nonlinear and hierarchical feature interactions. XGBoost and LightGBM closely followed, each maintaining an accuracy of over 80% with competitive ROC AUC scores (0.8058 and 0.8947, respectively). These models demonstrated superior generalization and robustness across both classes of sanction outcomes. Such results affirm that boosted and ensemble methods are better suited for predicting sanction effectiveness due to their ability to model complex feature interactions and manage imbalanced class distributions. This not only validates the use of AI in economic diplomacy but also provides a reproducible, data-driven tool that can aid policymakers in assessing the likely success of future sanctions.

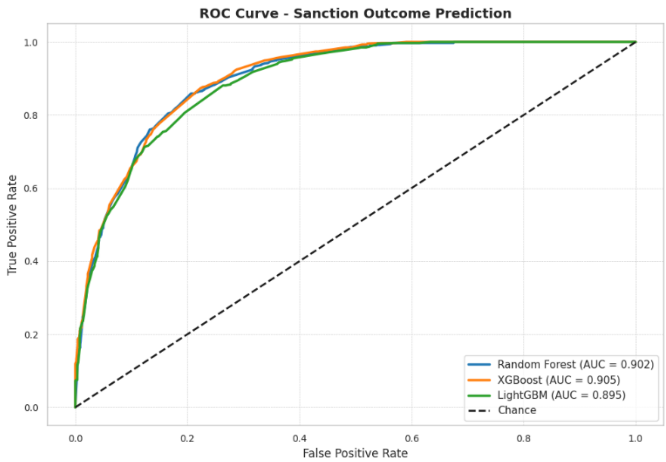

Fig -5: ROC Curve of All Models

3. CONCLUSIONS

This study illustrates the capabilities of machine learning to improve predictive analysis of global economic sanctions. Using structured data from the Global Sanctions Data Base (GSDB-R4) and macroeconomic data from the World Bank, we trained and tested a number of classification models for sanction success detection. Results indicate that state-of-the-art models such as Random Forest, XGBoost, and LightGBM significantly outperform baseline models in terms of robustness and accuracy, with Random Forest performing better than the rest. Besides predictive outcomes, the models provide interpretability, allowing one to understand the key economic and geopolitical factors driving successful sanctions. The findings put into prominence the potential of artificial intelligence as an economic diplomacy tool, facilitating informed policy-making. Our reproducible pipeline and explainable results pave the way toward incorporating AI in international relations where timely and correct decisions can alter global stability and state action.

ACKNOWLEDGEMENT

I would like to express my deepest gratitude to my fellow researchers and mentors for their constant guidance and support throughout the period of this research work. I am especially grateful to the creators and custodians of Global Sanctions Data Base (GSDB-R4) and the World Bank Open Data initiative for providing high-quality public domain data sets, through which this research became possible. I am also grateful to the open-source community for providing the crucial tools and the documentation, which simplified model development and evaluation processes to a large extent. Finally, I am grateful to the academic environment and infrastructure that allowed me to research the intersection of data science and international relations.

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