Artificial Intelligence and Machine Learning:

Techniques to Analyze Trade and Tariff impacts on the Economic Outcomes

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# Report

## Introduction

Over the past 25 years, international trade has undergone significant transformation driven by evolving trade agreements, shifting economic conditions, and disruptive events such as the Great Recession and the COVID-19 pandemic. In parallel, trade policies, including tariffs and trade agreements, have had cascading effects on both trade flows and broader economic performance. Recent headlines have focused on the tariff policies introduced by the Trump administration, yet public understanding of trade policy and its real-world economic impacts remains limited.

This raises a compelling question: Can Artificial Intelligence (AI) and Machine Learning (ML) be used to predict key trade statistics and macroeconomic growth using only a small number of core features/indicators? And if so, how accurate can such simplified models be?

## Objective

The objective of our research is to assess whether Gross Domestic Product (GDP) growth can be reliably predicted using a combination of population dynamics, trade patterns (imports and exports), and tariff data over time. We employed various AI/ML techniques, including supervised learning (classification and regression), Gradient Boosted Decision Trees (GBDT), and time series models such as Long Short-Term Memory (LSTM) neural networks.

Our goal is to compare the predictive performance of different algorithms using these features to determine how well they model GDP growth across different economies. The resulting insights could contribute to more informed policy-making, particularly regarding how global trade and tariff changes may shape future economic trajectories.

## Datasets

We sourced our data from a wide array of global economic databases. Trade statistics were obtained from the U.S. Census Bureau, while trade agreement insights were drawn from the U.S. International Trade Commission’s *Trade Shifts* report. GDP data was accessed through the World Bank (via Kaggle), and additional economic indicators such as tariff rates and the Consumer Price Index (CPI) were compiled using secondary Kaggle datasets. Some data were parsed directly from databases, while others came from precompiled datasets. Naturally, gaps exist in the data due to geopolitical or societal disruptions (e.g., war or revolution), and these inconsistencies were addressed as part of our data preparation.

## Models and Methodology

The models and algorithms were implemented independently, using techniques learned in the AAI501 course, with occasional use of ChatGPT for clarification and debugging support.

### 1. Supervised Classification – Predicting GDP Growth Classes

We began by predicting Compound Annual Growth Rate (CAGR) categories across approximately 146 countries using supervised classification models. Historical GDP data from 1992 onward was used to compute CAGR using the formula:

where n is the number of years.

Countries were categorized into four groups based on growth: *Very Low*, *Low*, *Moderate*, and *High*. Two classification models—Support Vector Machines (SVM) and Decision Trees—were evaluated through 1000 randomized trials.

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#### *Performance:*

While the Decision Tree classifier seems somewhat more accurate than the SVM classifier in predicting how economies grew, both seem somewhat limited, with accuracy generally falling below 80%.  This may still allow a reasonable degree of prediction with a sufficiently large dataset.

### 2. Supervised Regression – Trade Balance as a Predictor

Next, we investigated whether continuous GDP growth could be predicted using trade data. We calculated a per capita trade balance metric by subtracting total imports from total exports, and dividing the result by population.

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#### *Performance:*

We trained a Random Forest regressor to predict CAGR using this metric. However, the model produced an R² value of -0.018, indicating that per capita trade balance is not a reliable predictor of GDP growth. This suggests that trade volume alone, without deeper contextual variables, offers limited forecasting power.

### 3. Gradient Boosted Decision Trees (CatBoost)

We applied the CatBoost library, a highly optimized GBDT model, to forecast GDP using annual data from 2000 to 2023 across 130+ countries. Features included:

* Consumer Price Index (CPI)
* Imports and Exports (USD)
* Estimated Applied Weighted Average Tariff Rates
* Lag features (previous year values for each feature and GDP)

CatBoost is well-suited for tabular data, handles missing values effectively, and supports non-linear relationships, making it ideal for time series forecasting. We trained the model on data from 2000–2021 and used 2022–2023 data for validation.

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#### *Performance:*

* **Mean Absolute Error (MAE):** $79.58 billion USD
* **R² Score:** 0.9687

These results indicate strong performance overall, particularly for large economies (e.g., U.S., China). However, for smaller economies (e.g., Belize), the absolute error can exceed the country's GDP, emphasizing the need for tailored models or additional features for such contexts.

### 4. Long Short-Term Memory (LSTM) Model

LSTM is a type of Recurrent Neural Network (RNN) designed for sequential data. It effectively overcomes the vanishing gradient problem by using memory cells and gating mechanisms to retain long-term dependencies—ideal for economic time series.

We trained an LSTM model using the same dataset (excluding lag features), to compare with CatBoost.

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#### *Performance:*

* **MAE:** $168 billion
* **R² Score:** 0.9744

While this model outperformed CatBoost slightly in explaining variance, it showed higher MAE, again disproportionately affecting predictions for smaller economies.

### 5. Optimized Custom Deep Learning Model (Feedforward Neural Network)

In my individual contribution, I developed a custom deep learning model using a multilayer perceptron (MLP) architecture to predict GDP based on trade and tariff data.

#### Data Pipeline:

* Country-level trade and tariff data from 2000–2023
* Lag features for previous-year values
* Normalization using MinMaxScaler
* Train/test split: 2000–2020 (train), 2021–2023 (test)
* Inclusion of 2025 Trump tariff updates

#### Model Architecture:

* Input layer matching the number of features
* Dense layer (64 ReLU units) + 20% Dropout
* Dense layer (32 ReLU units) + Dropout
* Output layer (1 unit, linear activation)
* Loss: Huber
* Optimizer: Adam (with gradient clipping)

#### *Performance:*

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* **MAE:** $71.44 billion
* **R² Score:** 0.9731

Like the CatBoost model, this approach demonstrated an excellent variance explanation. Relative errors remained low for large countries and high for smaller ones, reaffirming prior findings.

## Visualization and Insights

Visual comparisons between predicted and actual GDPs across countries—such as the U.S., China, Mexico, and Australia—reinforced model validity. Changes in tariff regimes and trade flows had visible correlations with GDP forecasts. These visualization tools, developed using the trade\_visualization module, validated the models' ability to detect real-world economic signals.

## Conclusion

Our research demonstrates that AI models can effectively forecast GDP using a small, well-engineered feature set. While each model has strengths—LSTM for long-term dependencies, CatBoost for tabular efficiency, and MLP for fast interpretability, they all face challenges when predicting GDP for smaller or volatile economies.

To improve accuracy in such cases, future models could incorporate qualitative variables like political stability, institutional quality, and investment flows. We can also use features that are based on relative metrics (GDP growth rate, import/exports as a ratio of GDP, etc.) vs some of the absolute ones. Lastly, we can train separate models by different GDP tiers (developed vs developing) to have separate models depending on classification. Still, these results affirm that macroeconomic forecasting using machine learning is both viable and insightful for understanding global trade dynamics.

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# Appendix

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| **Team Member** | **Contributions** |
| **Atul Aneja** | **Section:**  **Model and Coding:**  **Optimized LSTM Model**  **Overall Code**  **Deliverables:**  **Github**  **Video hosting**  **Readme**  **Report and Presentation** |
| **Divya Kamath** | **Section:**  **Classification, Regression and Decision Tree Models**  **Deliverables:**  **Wrote Proposal**  **Scheduled Zoom Meetings**  **Initial Logistics coordination**  **Report and Presentation** |
| **Syed Sirajuddin** | **Section:**  **Catboost and LSTM (Initial) Model**  **Deliverables:**  **Data Scrubbing**  **Data Table Formation**  **Model Comparison**  **Report and Presentation** |