A Graph Neural Network Approach to Country-Level GDP Forecasting

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FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements for the **Degree of Bachelor of Science in Computer Science and Engineering**

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APPROVAL

This Project titled **"A Graph Neural Network Approach to Country-Level GDP Forecasting"**, submitted by Parthib Saha, ID No: 213-15-4253 to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on **16 September, 2025**.

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DECLARATION

I hereby declare that this project has been done by me under the supervision of **Md. Ferdouse Ahmed Foysal**, **Lecturer**, Department of Computer Science and Engineering, Daffodil International University. I also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

GDP forecasting is a major issue that requires accurate estimates on economic planning, policy formulation, trade policies and development objectives. Conventional statistical and machine learning models have delivered encouraging outcomes but have focused more on country level measures and have ignored the fact that countries are intricately linked through international trade. To overcome this shortcoming, this study introduces a GDP prediction method based on Graph Neural Network (GNN) which combines node-level economic signals and edge-level trade characteristics.

The analysis makes use of the World Bank data (GDP, population, consumer price index, unemployment rate) and the BACI international trade database in order to create annual graphs, with the country being the node and the key trade relations the edges. Node features are based on economic indicators and edge features based on trade volumes of the ten most traded products worldwide. The Graph Attention Network v2 (GATv2) model incorporates multi-head attention, batch normalization and residual connections to learn country-level log-GDP representations and predictors.

Through experimental analysis, the GATv2 model with edge features is shown to significantly outperform baseline machine learning models (linear regression, random forest) and previous graph-based models (GCN, GAT) across various evaluation metrics, including Mean Squared Error (MSE) and Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and R2 score. The findings underscore the need to integrate trade-based relational information in order to provide accurate macroeconomic forecasts.

The paper will be relevant to the existing literature on graph-based economic modeling as it will illustrate the usefulness of attention-based GNNs in modeling dependencies in global trade. The given framework can be applied to other macroeconomic indicators and provide substantial information to policymakers, economists, and researchers in order to create data-driven economic policies.

Keywords: Graph neural networks, GATv2, GDP forecasting, international trade, world bank indicators, BACI trade data, node and edge features, economic forecasting, machine learning, deep learning, attention mechanisms, graph representation learning.

Table of Contents

List of Figures

List of Tables

Chapter 1

Introduction

This chapter gives the background and motivation for the research, talks about the problem statement, sets the goals and scope, and explains why the study is important. It lays the groundwork for comprehending the necessity of GDP forecasting through advanced machine learning methodologies, especially Graph Neural Networks (GNNs).

1.1 Introduction

The most significant measure of economic state within a state and its eventual contribution to policy-making, investing plans, and a general outlook on the global economy is the Gross Domestic Product (GDP). This highlights another reason why proper forecasting of GDP is vital to governments, corporate entities in addition to banks and other financial institutions. In the conventional methods of forecasting, which include a variety of statistical methodologies like ARIMA, Box-Jenkins models and others, past time series information is consumed. This leads to a simpler method of identifying long-term trends whilst disregarding the enormous qualitative impacts of between-country interactions through trade due to economic integration.

The new solution to this limitation is the recent advances in machine learning pioneered by deep learning and Graph Neural Networks (GNNs). The international economic relationships can now be explicitly modeled using GNNs as countries are nodes and trade flows are edges. The present project, in turn, applies a Graph Attention Network (GAT) architecture to the prediction of country-level GDP in one of the extended variants, GATv2, which adds edge features based on international-trade data to more effectively predict the country-level GDP.

1.2 Motivation

There is a rationale behind this research: the classic approaches to forecasting do have certain evident shortcomings in the context of addressing the interdependence of the global economy. The GDP of a country can no longer be determined with internal factors only in a connected world. It includes trade relations, resource flows and external shocks, which most forecasts neglect and, therefore, leave them incomplete.

This is a deep learning application. It tries to capture both the country specific indicators (population, inflation, unemployment, lagged GDP) and the dependency among countries (trade volumes across top products). The combination of node and edge features can provide a more realistic impression regarding the modeling of the global economy.

1.3 Objectives

The major goals of this project are:

1. **Graph Construction:** Transform World Bank and BACI data is converted into a graph, with countries representing nodes, and trade flows representing the edges.

2. **Model Development:** Apply a Graph Attention Network (GAT) on node feature alone, and upgrade into a GATv2 model to include edge feature to learn inter-country work interdependencies.

3. **Performance Evaluation:** Evaluate both models using regression measures (MAE, RMSE, R2) to show the effectiveness of edge-sensitive methods for increasing the accuracy of GDP prediction.

1.4 Methodology

The methodology involves multiple steps:

- **Data Collection & Preprocessing:** GDP, population, CPI and unemployment data are collected from the World Bank while the trade flow is sourced from the BACI dataset. The data is cleaned, imputed and transformed into graph structures.

- **Graph Construction:** The nodes represent countries described by a set of features that correspond to socio economic indicators. The edges denote international trade relationships, where top 10 product trade volumes are stored as edge attributes.

- **Model Design:** The Baseline GAT does not use edge features while the Advanced GATv2 uses edge features as part of its attention mechanism.

- **Training & Evaluation:** The training set runs from 1996–2010, and validation covers 2010–2013 with testing from 2013–2019. Models are trained using mean squared error (MSE) loss and evaluated with R^2, MAE, RMSE.

- **Comparison & Analysis**: Performance differences between the baseline and proposed models are analyzed to assess the impact of edge features.

1.5 Project Outcome

The project led to a successful implementation of a Graph Neural Network (GATv2)-based model that would predict country-level GDP. This is in contrast to the more traditional approaches where both edge-level (International trade flows, based on BACI data) and node-level features obtained based on World Bank indicators including population, employment, and inflation are incorporated. The framework emphasizes the need to model cross country dependencies that are usually ignored by more traditional statistical and sequential models through its representation of the global economy as a graph of interconnected countries.

Besides the fact that the project offers a new approach towards GDP forecasting, it also offers the basis on which future economic forecasting work can be established on a basis that is scalable. Graph-based design can be easily extended with additions of new indicators or may capture temporal dynamics over several years. This flexibility provides the avenue to further study the relationship between international trade and local signals and economic growth, and this preconditions the more sophisticated research in computational economics and in policy analysis. Moreover, the project result indicates the increasing opportunities of machine learning to fill in the data science-economics gap, and provide the way to more data-driven and globally informed decisions.

1.6 Organization of the Report

This report is structured as follows:

- **Chapter 1: Introduction** - Introduction to the problem, motivation, objectives, methodology and outcomes.

- **Chapter 2: Background** - overviews the literature that exists on GDP forecasting, machine learning methods and graph neural networks, and a gap analysis.

- **Chapter 3: Research Methodology** - Provides a description of the preprocessing pipeline, dataset representation and model design.

- **Chapter 4: Implementation and Results** - This chapter outlines the experimental design, the evaluation of the performance and comments on the results.

- **Chapter 5: Engineering Standards and Design Challenges** - Addresses software and data standard compliance, impact and challenges to society.

- **Chapter 6: Conclusion** - summarizes, notes limitations and suggests future research.

Chapter 2

Background

In chapter one, the author examines some of the previous theories and literature on GDP forecasting. It contains previous descriptions of the econometric and machine learning techniques, applications by other authors of somewhat similar graph-based techniques, gaps in the current literature can be established in the work and an overview of how they have been applied to the establishment of the rationale of the proposed work.

1.1 Introduction

Gross Domestic Product (GDP) is regarded as one of the most important problems in economics and data science because it can offer helpful information to policy makers, investors, or even to international organizations. However, it is extremely hard to obtain a good GDP forecast because in addition to the local forces like inflation, unemployment, and population, there are also international market forces and international trade forces that have significant influence on the GDP forecast. Over time, classical methods of economics have been modified to use machine learning (ML), more recently deep learning and much more advanced hybrid models. Graph Neural Networks or GNNs enable a researcher to model the connection between countries in a far more efficient manner. The chapter thus draws literature review within the identified gaps in order to motivate GNNs application in GDP forecasting.

1.2 Literature Review

This review focuses on different approaches to the use of statistical models, deep learning, and machine learning to forecast GDP. It discusses the positive and the negative aspects of each approach. Yoon [1] used the Random Forest and Gradient Boosting models to predict the real GDP growth, and Baffigi et al. [2] used bridge models to predict the Euro Area with the same accuracy. Richardson et al. [3] proved that machine learning algorithms are better than conventional autoregressive and factor models in nowcasting. Lehmann and Wohlrabe [4] investigated ways of predicting the GDP of a region based on different predictors. Abonazel and Abd-Elftah [5], on the other hand, have used ARIMA to predict the GDP of Egypt reasonably accurately. Kouziokas [6] used the optimized SVM kernels along with neural networks, and NARX neural networks were used by Sanusi et al. [7] to analyze the GDP of Malaysia. Shams et al. [8] used urban profiling using hybrid PC-LSTM-RNN models, and their accuracy was almost perfect. To develop a correlation between CO2 emissions and GDP growth, Marjanovic et al. [9] used ELM. Zhao et al. [10] used nocturnal light and demographic imagery to make pixel level predictions about the GDP of China. In a recent study, Soybilgen and Yazgan [11] showed that tree-based ensembles are favored over linear algorithms. Wu et al. [12] proposed a more advanced nonlinear grey Bernoulli model and Alaminos et al. [13] studied how quantum computing and deep learning can be combined to forecast

GDP. In a comparative study of ARIMA, LSTM, as well as hybrid models, Hamiane et al. [14] determined that hybrid models had better performance. Aastveit et al. [15] applied the concept of real-time density combination to predict the future.

Table 2.1: Summary of Literature Reviewed.

Author(s)	Year	Title	Methodology	Key Findings
Jaehyun Yoon	2020	Forecasting of Real GDP Growth Using Machine Learning Models: Gradient Boosting and Random Forest Approach	Supervised ML (Gradient Boosting, Random Forest) via Scikit-Learn; 10-fold CV with grid search; expanding window to reduce overfitting	Gradient Boosting: MAPE 19.86%, RMSE 0.35; Random Forest: MAPE 67.23%, RMSE 0.79
Alberto Baffigi, Roberto Golinelli, Giuseppe Parigi	2004	Bridge Models to Forecast the Euro Area GDP	Bridge Models compared to ARIMA, VAR, VEqCM; aggregation techniques	RMSE 0.15, effective forecasting
Adam Richardson, Thomas van Florenstein Mulder, Tuğrul Vehbi	2019	Nowcasting GDP Using Machine Learning Algorithms: A Real-Time Assessment	ML models (LSBoost, SVM, Neural Nets, Lasso, etc.); expanding windows; benchmarked vs AR and dynamic factor models	20–30% accuracy improvement over benchmarks
Robert Lehmann, Klaus Wohlrabe	2015	Forecasting GDP at the Regional Level with Many Predictors	Pseudo-real-time recursive forecasting; ADL models, pooling, factor models (PC, PCKF, QML)	RMFSE: Saxony 0.582, Baden-Württemberg 0.589, Eastern Germany 0.815
Mohamed Reda Abonazel, Ahmed Ibrahim Abd-Elftah	2019	Forecasting Egyptian GDP Using ARIMA Models	Box-Jenkins: stationarity checks, MLE estimation, residual diagnostics	R^2 0.9953, highly accurate for Egyptian GDP

			(AIC/BIC/MSE) ; ARIMA forecasting	
Georgios N. Kouziokas	2020	A New W-SVM Kernel Combining PSO-Neural Network Transformed Vector and Bayesian Optimized SVM in GDP Forecasting	Data normalization; FFNN with PSO optimization; Bayesian-optimized SVM kernels; 10-fold CV	W-SVM achieves best MSE 0.59
Nur Azura Sanusi, Adzie Faraha Moosin, Suhal Kusairi	2020	Neural Network Analysis in Forecasting the Malaysian GDP	NARX ANN; min-max normalization; 70/15/15 split; hyperparamete r tuning by MSE	Best MSE: train 0.1110, validation 0.1073, test 0.1303
Mahmoud Y. Shams, Zahraa Tarek, El-Sayed M. El-kenawy, Marwa M. Eid, Ahmed M. Elshewey	2024	Predicting GDP Using a PC-LSTM-RNN Model in Urban Profiling Areas	Hybrid: Pearson correlation + LSTM-RNN; median imputation; min-max normalization	R^2: Dataset A 99.99%, Dataset B 99.18%, near-perfect prediction
Vladislav Marjanović, Miloš Milovančević, Igor Mladenović	2016	Prediction of GDP Growth Rate Based on Carbon Dioxide (CO_2) Emissions	ELM vs GP and ANN; evaluated via R^2 and RMSE on CO_2 inputs	ELM best: Train RMSE 0.8833, R^2 0.9531; Test RMSE 1.1198, R^2 0.9271
Naizhuo Zhao, Ying Liu, Guofeng Cao, Eric L. Samson, Jingqi Zhang	2017	Forecasting China's GDP at the Pixel Level Using Nighttime Lights Time Series and Population Images	GDP disaggregation via nighttime lights + population; Holt-Winters smoothing for pixel-level forecasts	Improved accuracy using lit population; validated against official data

Barış Soybilgen, Ege Yazgan	2021	Nowcasting US GDP Using Tree-Based Ensemble Models and Dynamic Factors	Dynamic factors with Kalman filter + tree ensembles (Bagged Trees, RF, Boosting)	Tree-based ensembles outperform linear models
Wen-Ze Wu, Tao Zhang, Chengli Zheng	2019	A Novel Optimized Nonlinear Grey Bernoulli Model for Forecasting China's GDP	Optimized NGBM(1,1): new-info priority, background reconstruction, power index optimization, rolling window	MAPE 0.65%, highly accurate
David Alaminos, M. Belén Salas, Manuel A. Fernández-Gámez	2021	Quantum Computing and Deep Learning Methods for GDP Growth Forecasting	Quantum (SVRQBA, QBM, QNN) + DL (DRCNN, DBN, DNDT, DLSVM); 70/10/20 split; 10-fold CV; Sobol sensitivity	DNDT best: Testing accuracy 98.29% (developed), 97.63% (global), 96.83% (emerging)
Sana Hamiane, Youssef Ghanou, Hamid Khalifi, Meryam Telmem	2024	Comparative Analysis of LSTM, ARIMA, and Hybrid Models for Forecasting Future GDP	Univariate comparison: ARIMA, LSTM, hybrid ARIMA-LSTM with seasonal decomposition	Hybrid ARIMA-LSTM excels: MSE 0.0018, R^2 0.99

1.2.1 Similar Applications

Some programs have considered the use of deep learning and sophisticated machine learning to predict GDP. To build Gradient Boosting and Random Forest models, Yoon [1] made use of World Bank indicators. These models outperformed general regression models, although by a small margin. Richardson et al. [2] created a nowcasting model based on machine learning such as LSBoost, SVM, and neural networks. These models performed 20-30% more efficiently than the autoregressive standards in terms of prediction. Holt-Winters smoothing of nocturnal light images derived by satellite has been used by Zhao et al. [3] to break down the GDP of China at the pixel level. This was closer than the figures that the government provided. Shams et al. [4] constructed a hybrid PC-LSTM-RNN model to profile urban GDP with an almost perfect prediction accuracy ($R2 > 0.99$). A study performed by Hamiane et al. [5] compared ARIMA and LSTM models as well as hybrid ARIMA-LSTM. They found that the hybrid model was the most accurate in general.

These examples demonstrate that machine learning can be applied to the prediction of the economy, however, we do not see much of the GDP prediction as a time series or regression problem. This project is not like the rest since it is based on a graph method. Under this method, countries are turned into nodes of socio-economic characteristics while the trade flows turn into edge characteristics. This means the model can capture global interdependencies which would not be captured by other models.

1.3 Gap Analysis

The analysis demonstrates that big progress has been achieved in predicting GDP using statistical, machine learning, and deep learning techniques. But there are still problems. A lot of research examines data on a small scale of one country or region. This does not reveal the relations of trade networks existing in various locations throughout the world that are reliant on one another. They only use a few or one predictor, and some get very good results. This does not necessarily work in all economies. Few studies examine trade flows and other associated data that matters in determining how GDP in various regions of the globe vary.

The following table summarizes the gaps identified from the literature and positions the proposed GNN-based methodology as a solution.

Table 2.2: Gap Analysis

Features	**Yoon (2020)**	**Richardson et al. (2019)**	**Shams et al. (2024)**	**Zhao et al. (2017)**	**Hamiane et al. (2024)**	**Proposed GNN System**
Captures temporal trends	Yes	Yes	Yes	Yes	Yes	Yes
Handles nonlinear patterns	No	Yes	Yes	No	Yes	Yes
Uses multiple socioeconomic indicators	Yes	Yes	Yes	No	No	Yes

Graph representation of countries	No	No	No	No	No	Yes
Incorporates trade/edge features	No	No	No	No	No	Yes
Works at global scale	No	No	No	No	No	Yes
Dynamic modeling (yearly evolution)	No	No	Yes	No	Yes	Yes
Interpretability (explainable results)	No	No	Yes	Yes	No	Yes

1.4 Summary

The chapter has discussed the available literature on forecasting GDP with conventional statistical models, machine learning, as well as more recent work on using deep learning. Classical models (autoreclive integrated moving average model, ARIMA) and bridge models have shown reasonable prediction skills but are generally constrained in modeling nonlinearities and dependencies from country to country. ML models have demonstrated better accuracy, especially with larger datasets and non linear relationships such as Random Forests, Gradient Boosting and neural networks. The recent research also discussed working with hybrid and improved models like LSTM, PC-LSTM, and Grey Bernoulli models and they demonstrated good results in particular scenarios.

However, most of the previous studies have relied on country-level indicators without including inter-country dependencies like trade flows, which play an important role in economic growth. While GNNs have been recently used in several applications, their use for macroeconomic forecasting is still largely unexplored and few works have investigated the inclusion of edge-level trade features for GDP forecasting.

In summary, the gap this research aims to address is highlighted by the literature, that is, to develop a GNN-based framework with trade-aware edge features (GATv2) to simultaneously capture the global interdependencies and improve the accuracy of GDP forecasting.

Chapter 3

Research Methodology

This chapter comments on the approach which was adopted to do the research. It provides a summary of the methodology used, details system design and specifies both data collection and preprocessing procedures, in addition to identifying the proposed model and evaluation measures used to measure performance.

1.1 Methodology

1.1.1 Overview

This study employs graph neural networks, or GNNs with node-level and edge-level features to forecast the country's GDP. The countries are represented by the nodes and the international trade relations between the countries are represented by the edges with product-based properties. The node features are informed by socioeconomic indicators including GDP, population, consumer price index and unemployment rates and the edge features by bilateral trade data. Graph Attention Networks (GAT and GATv2) are included in the proposed model to learn detailed dependencies among countries.

1.1.2 Proposed Methodology

The methodology of this research is presented in the form of a pipeline where it begins with the gathering of data from the World Bank indicators (GDP, Population, CPI, Employment) and the BACI international trade database. These complementary sources include both country-level socioeconomic indicators as well as bilateral trade flow information. Additionally, the data collected is preprocessed, meaning it is cleaned, the missing values are handled, and the data is formatted uniformly. The data sets are processed and then converted into a graph format with the countries being represented by nodes and the trade flows represented by weighted edges. The node features used in this graph are population, CPI, and unemployment whereas the edge features used are the 10 most traded products by volume.

Two variants of the GNN-based models are trained to process this data, a baseline Graph Attention Network (GAT) without edge features that uses only node features, and an extended GATv2 model with both node and edge features to more accurately model inter-country dependencies. Both models are trained and validated on historical yearly snapshots, and are evaluated by regression measures such as MAE, RMSE, and R2. Finally, the results are compared in order to show the advantages of using edge-sensitive features to enhance the GDP prediction accuracy. Figure 3.1 sums up the entire process.

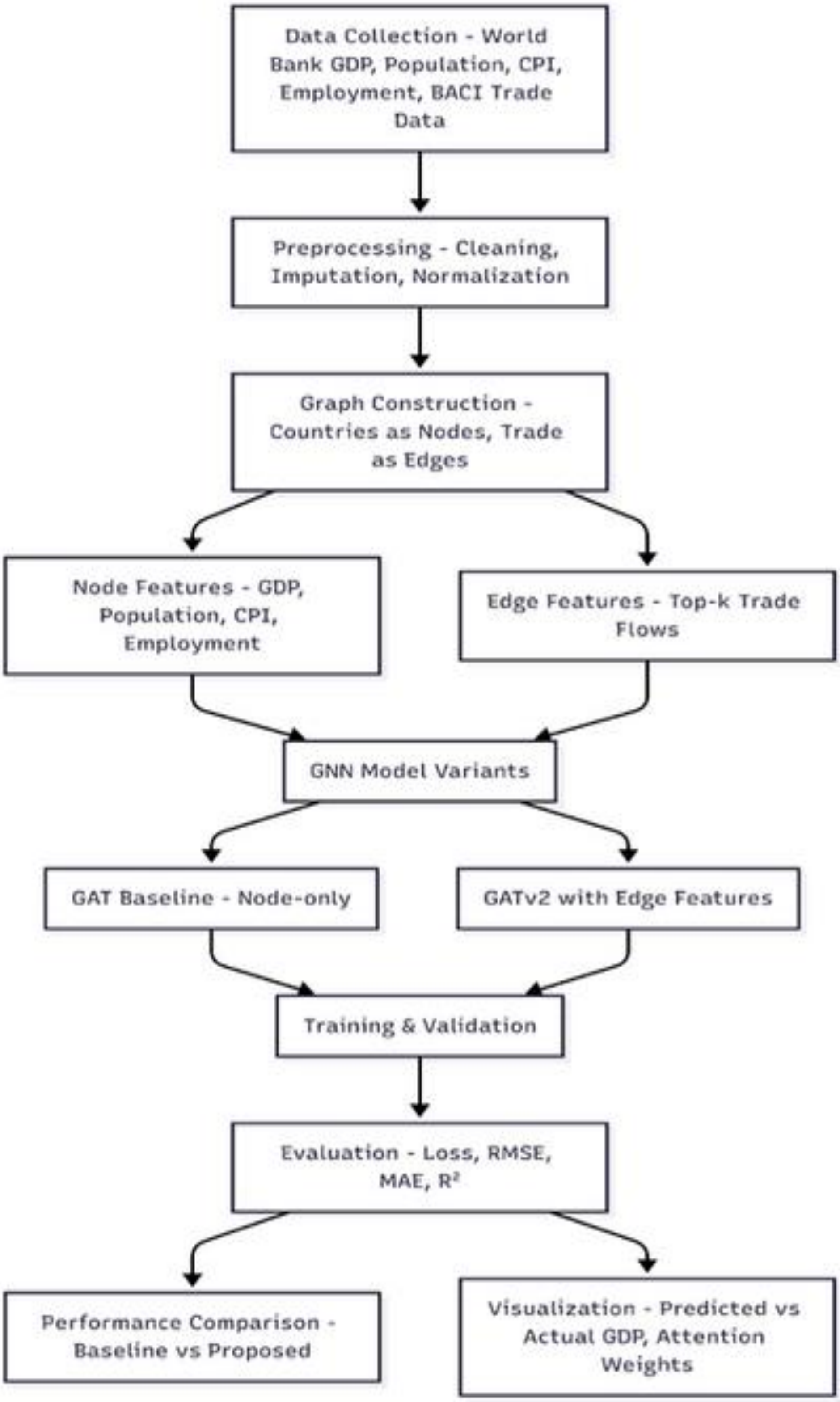

Figure 3.1: Methodology

1.1.3 Functional and Nonfunctional Requirements

Functional Requirements:

The first functional aspect of this project is the possibility to work with several sources of economic information and to unite them in one logical framework to be used in modeling. In particular, the system needs to preprocess and combine the BACI trade data containing the detailed trade flows between countries with the World Bank data containing the economic indicators of the GDP, population, consumer price index (CPI), and employment rates. The system must be able to process missing values using suitable imputation procedures, to remove invalid or irrelevant records, and to derive meaningful features out of the raw data, during preprocessing. After cleaning and structuring the data, the system will also have to visualize it as a graph, where each country will be represented as a node and trade relations as edges with edge-level attributes attached to them. The other fundamental requirement will be to train the proposed GATv2 model on this graph representation such that node and edge features are appropriately exploited during the learning process. The system must then be capable of making reasonable predictions on the GDP of each of the target countries. In order to verify that the model is functioning like it is supposed to, the model should be able to give strict evaluation measurements (Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the Coefficient of Determination (R2) which will not only be used to establish the accuracy of the predictors, but also the potential of the model to express the economic relations.

Nonfunctional Requirements:

Besides being able to perform various functions, the system should meet various non-functional requirements which guarantee quality, robustness and usability. One such non-functional metric is that of data consistency, whereby preprocessing procedures, including imputation and feature extraction, must be systematically applied to all the datasets, in order to prevent bias or differences in the training data. Another need is scalability since the system must handle a large number of countries and years of data without negatively affecting its functionality. This means that the model and data pipeline must be structured to scale to large-scale inputs effectively and scale to the addition of new features and datasets in future projects. It must also be reproducible, the system must be able to produce the same results in identical experimental conditions, so that the results can be relied upon in research. Another feature of interest is computational efficiency because the process of training graph neural networks is resource-consuming; therefore, the framework must take advantage of the acceleration capabilities of a graphical processing unit (GPU) and specialized libraries like PyTorch Geometric to help minimize the time spent on computation. Finally, the system must be able to be accurate and consistent in the predictions. This implies that the model must not only give good results, but it must show strength in repetitions of the results and no significant variation in results. Together, these non-functional requirements help to guarantee that the system is both efficient in predicting GDP and practical, scalable, and consistent in research and policy analysis in the future.

1.1.4 Data Flow Diagram

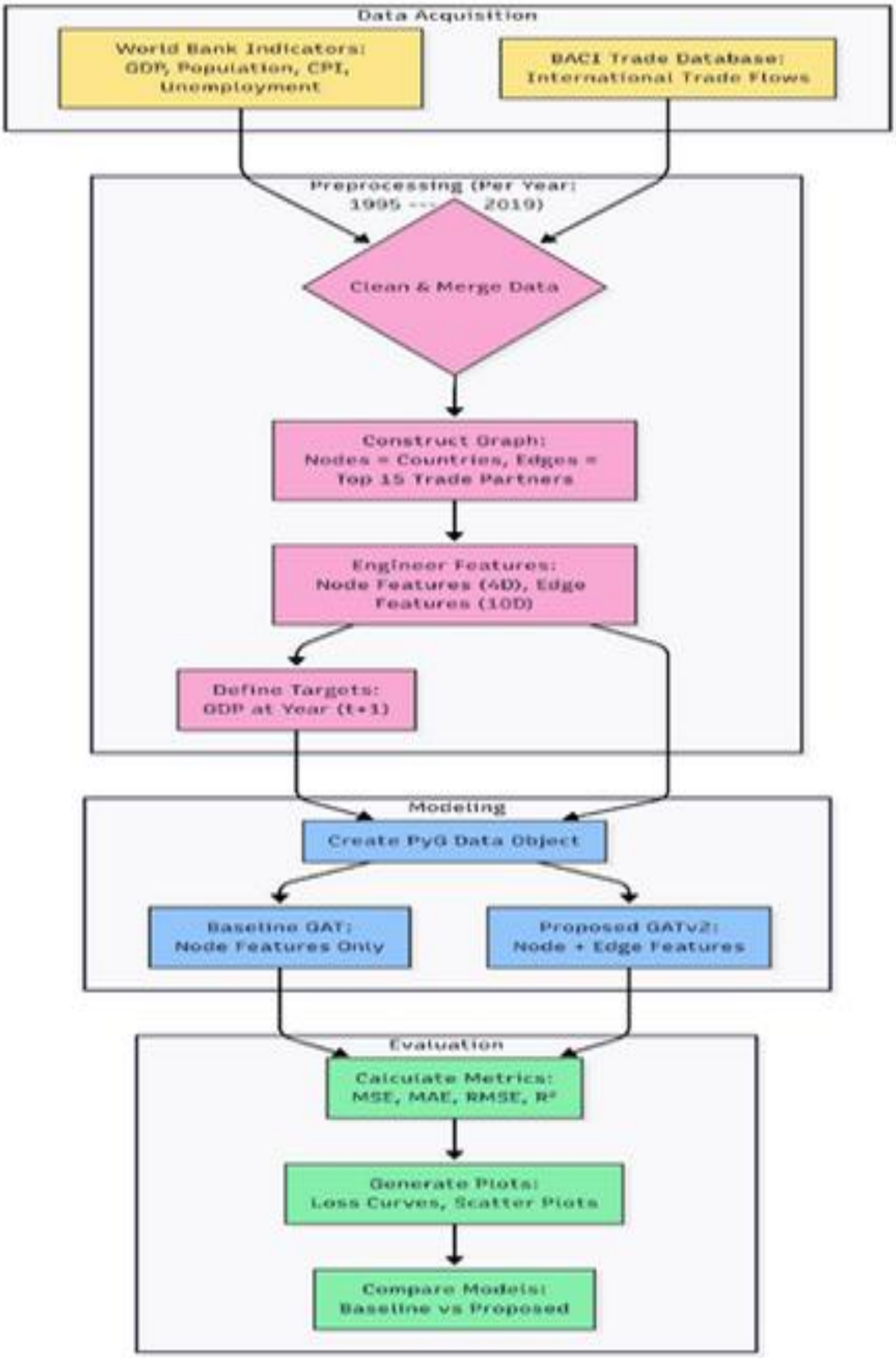

Figure 3.2: Data Flow

1.1 Detailed Methodology and Design

Alternate Solutions Considered

- **ARIMA Models**: It works well with simple time series of a single variable but cannot identify complex non-linear trade relationships or cross-national trade relationships.
- **Bridge Models (ARIMA, VAR, VEqCM hybrids)**: Work well for short-term forecasts but are based on high levels of linearity.
- **Random Forest and Gradient Boosting**: Apply high dimensional analysis without considering the graph of international trade.
- **LSTM and Hybrid Models**: Well, represent (but not explicitly model) the temporal dynamics but not trade networks or country interdependencies.
- **GCN (Graph Convolutional Networks)**: Includes network structure but is inflexible in weighting various neighbors.

Reasons for Selecting GATv2

- Captures node features (population, CPI, employment, lagged GDP) and edge features (trade flows of top products).
- Uses attention mechanism to assign different importance to trading partners.
- GATv2 improves on GAT by making the attention mechanism more expressive.
- Batch Normalization after each layer improves training stability.
- Residual connections prevent vanishing gradient and allow deeper architecture.
- A two-layer MLP regression head provides robust mapping from embeddings to log-GDP values.

Proposed Model Design

1. Input graph: countries as nodes, trade flows as edges.
2. Node features: population, CPI, employment, lagged GDP.
3. Edge features: top 10 traded products.
4. GATv2 Layers (with BatchNorm + ELU).
5. Residual connections from Layer 1 → Layer 2 and Layer 2 → Layer 3.
6. Regression head: two-layer MLP.

7. Output: Predicted log-GDP.

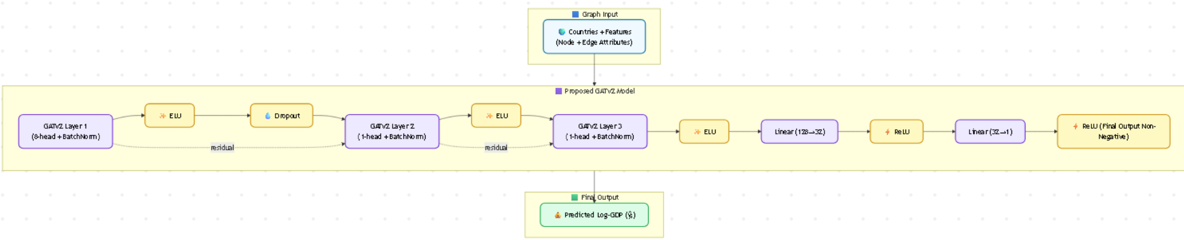

Figure 3.3: Model Architecture

1.3 Project Plan

The project was executed in a structured manner to ensure timely completion and proper allocation of resources. The plan was divided into four major phases:

Phase 1: Literature Review and Problem Definition (Weeks 1–3)

- Undertook an extensive survey of the already available GDP prediction approaches.
- Classical machine learning methods that were analyzed, time-series forecasting methods, and graph-based (GCN, GAT).
- Framed the research gap: failure to exploit edge characteristics of GDP prediction models.
- Finalized the problem statement, objectives, and scope of the study.

Phase 2: Data Acquisition and Preprocessing (Weeks 4–7)

- Collected macroeconomic indicators from the World Bank (GDP, population, CPI, unemployment).
- Extracted international trade flows from the BACI trade database.
- Cleaned, standardized, and merged the datasets for the period 1995–2019.
- Constructed yearly graphs:
    - Nodes = Countries.
    - Edges = Top 15 trade partners.
    - Node features = [Population, CPI, Unemployment, Lagged GDP].
    - Edge features = Trade volumes of top 10 products.
- Defined the prediction target as GDP at year (t+1).

Phase 3: Model Development and Training (Weeks 8–12)

- Implemented baseline models: Linear Regression, GCN, and standard GAT.
- Designed and implemented the proposed GATv2 with edge features architecture.
- Residual connections and batch normalization are combined and stable.
- Training was done on PyTorch Geometric and tested on MSE, MAE, RMSE, and R2.
- Hyperparameter searching and ablation experiments were performed.

Phase 4: Evaluation and Documentation (Weeks 13–16)

- Preferred baseline and proposed models against each other based on accuracy and strength.
- Created loss curves, scatter plots and evaluation tables.
- Results extracted in economic forecasting.
- Prepared the final thesis report and presentation slides.

1.4 Task Allocation

This table depicts the timeline of the principal activities in each period of the project, from week 12 to week 48.

Tasks	**Weeks**																		
	12	14	16	18	20	22	24	26	28	30	32	34	36	38	40	42	44	46	48
Data collection phase																			
Preprocess all the data																			
Model training																			
Evaluation																			

1.5 Summary

In this chapter, the methodology used in building the framework for this proposed GDP forecasting was elucidated. The method started with data extraction from the World Bank and BACI datasets, then preprocessing to harmonize countries, impute missing values and create graph-structured data in terms of node features, edge features and GDP targets. Each country was represented as a node, and trade relations were modeled by edges weighted by economic indicators, both for the internal indicators of countries and for the cross-country dependencies. The predictive model was selected to be the

Graph Attention Network v2 (GATv2) because it possesses the ability to learn expressive attention weights but is free from the shortcomings of typical GAT. Two architectures were developed: a baseline with node-level features only and a proposed system with node- and edge-level features. In order to avoid overfitting and promote generalization, many training strategies were used such as early stopping and dropout.

In summary, the methodology provides a fully-pipelined solution from raw data ingestion to graph-based modeling training and evaluation, and provides a foundation for evaluating the contribution of trade-aware edge features for GDP forecasting. In the next chapter the experimental implementation and results based on this framework are presented.

Chapter 4

Implementation and Results

In this chapter, the experimental setup and results and analysis of proposed GDP prediction models are provided. It begins by explaining the evaluation metrics and baseline comparisons, then we discuss the performance of the GATv2 model with edge features in detail.

1.1 Environment Setup

The entire implementation and testing of this project were done on Google Colab, a cloud-based, development environment that offers free access to high-performance computing systems. Colab was selected because it can easily integrate with popular machine learning libraries, including embedded GPU accelerators and reproducibility functionality that are required in research-intensive projects.

The code itself is written in Python version 3.10 and builds on a number of various libraries. Implementation of the Graph Attention Network v2 (GATv2) model, including node and edge embedding, was done in PyTorch and PyTorch Geometric (PyG). Pandas, NumPy, Matplotlib were used to process and clean data and assess plots and visualizations, respectively. Further, NetworkX was also used to represent graph structures and to handle edge-based properties obtained as a result of trade flows.

The experimental code was run using NVIDIA Tesla T4 graphics on Colab, which is a CUDA-capable graphics card that is capable of running deep learning models. It used CUDA 11.8 and cuDNN backends to perform fast parallel jobs and to speed up training. Figure 1 shows that, with the help of GPU acceleration, training time of graph neural network models has significantly decreased, as they are more computationally demanding than conventional machine learning algorithms.

All data, such as BACI trade dataset and World Bank economic indicators (GDP, population, CPI, unemployment) was stored in CSV and directly worked with the Colab environment. Data consolidation of several datasets involved preprocessing pipelines, written in Python, to standardize and align the data to construct the graphs.

Google Colab was selected, not only due to its access to GPUs but also because of its scaling capabilities, team-work aspects and reproducibility. The experiments are reproducible on any system with an internet connection since the Colab environment is cloud-based, and all runs will have the same result. This dependability, together with zero-cost access to GPUs, made Colab an appropriate platform to execute the end-to-end workflow of preprocessing, model training, and evaluation.

1.2 Testing and Evaluation/Performance/Comparative Analysis

The study evaluated two models:

1. **Baseline GAT (Node only features)** – uses only socio-economic indicators (Population, CPI, Employment, lagged GDP).

2. **Proposed GATv2 (Node + Edge features)** – integrates node indicators with trade-based edge features (top 10 products from BACI).

Evaluation Metrics:

- Coefficient of Determination (R^2)
- Mean Absolute Error (MAE)
- Root Mean Square Error (RMSE)

Data Split: 70% Training, 15% Validation, 15% Testing (1995–2019).

Table 4.1: Experimental Results

Model	MAE	MSE	RMSE	R^2
Baseline (Node only)	1.27	2.28	1.51	0.58
Proposed (Node+Edge)	0.68	0.69	0.83	0.87

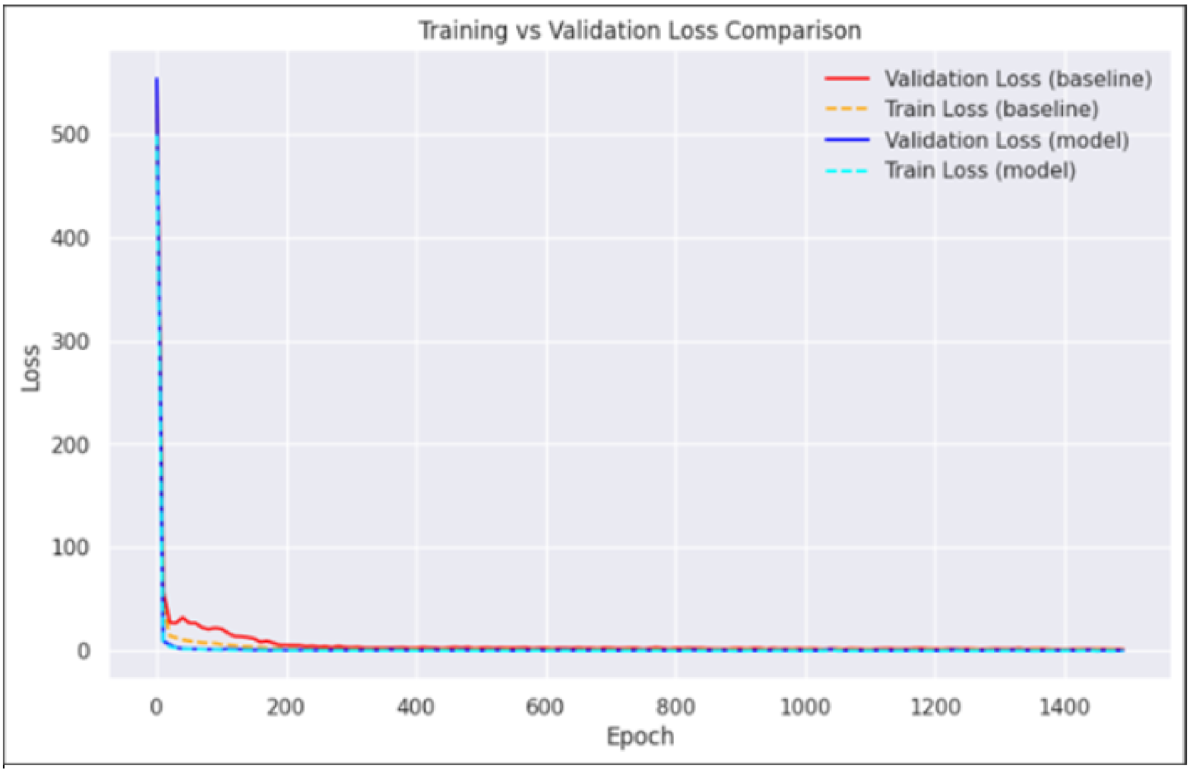

Figure 4.2: Training vs. Validation Loss

1.3 Results and Discussion

The comparative analysis of the existing GAT model and the suggested GATv2 including edge features gives clear results about the benefits of considering trade-based dependencies in the forecast of GDP. The findings demonstrate that the baseline model that only used node-level variables including population, CPI, unemployment, and lagged GDP did not explain the entire variance with an R2 of 0.58. This affirms that the use of domestic indicators on its own is not adequate to model the dynamics of GDP.

In comparison, the GATv2 model proposed had an R2 almost twice as high with 0.87. A high decrease in the error values (MAE decreased to 0.68, RMSE decreased to 0.83) shows that the model was able to use the inter-country trade relations to further increase precision. This proves the importance of edge sensitive graph learning where the trade flows are modeled as edges between countries.

The results are in agreement with the hunch that GDP growth is not a one-dimensional process since it is largely affected by global trading systems. The proposed method overcomes a structural advantage compared to traditional time-series models, like ARIMA, or purely sequential deep learning methods, such as LSTM: the former combines household characteristics with international dynamics, the latter ignores the former.

In addition, the model is more stable as indicated by reduced error variance, which implies strong generalization. This indicates that GNN-based forecasting can be relevant in practice in policy and economic planning, where it is necessary to consider global trade interdependencies.

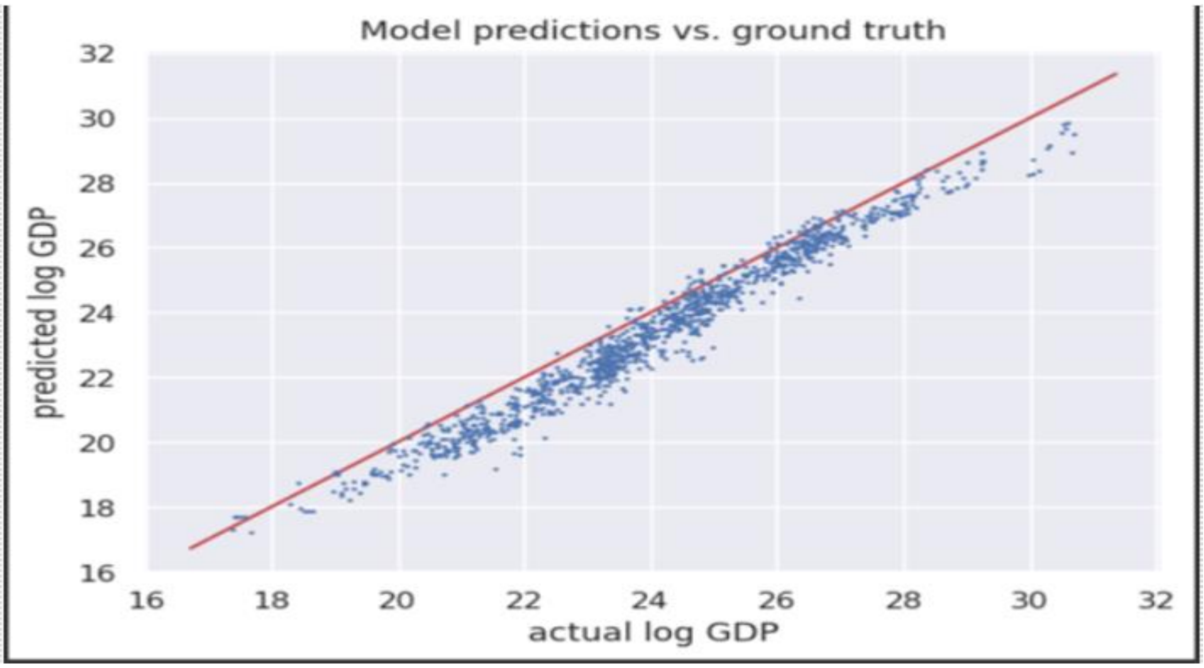

Figure 4.3: Prediction vs. Truth

Figure 4.4: GNN Attention Between Major Economies

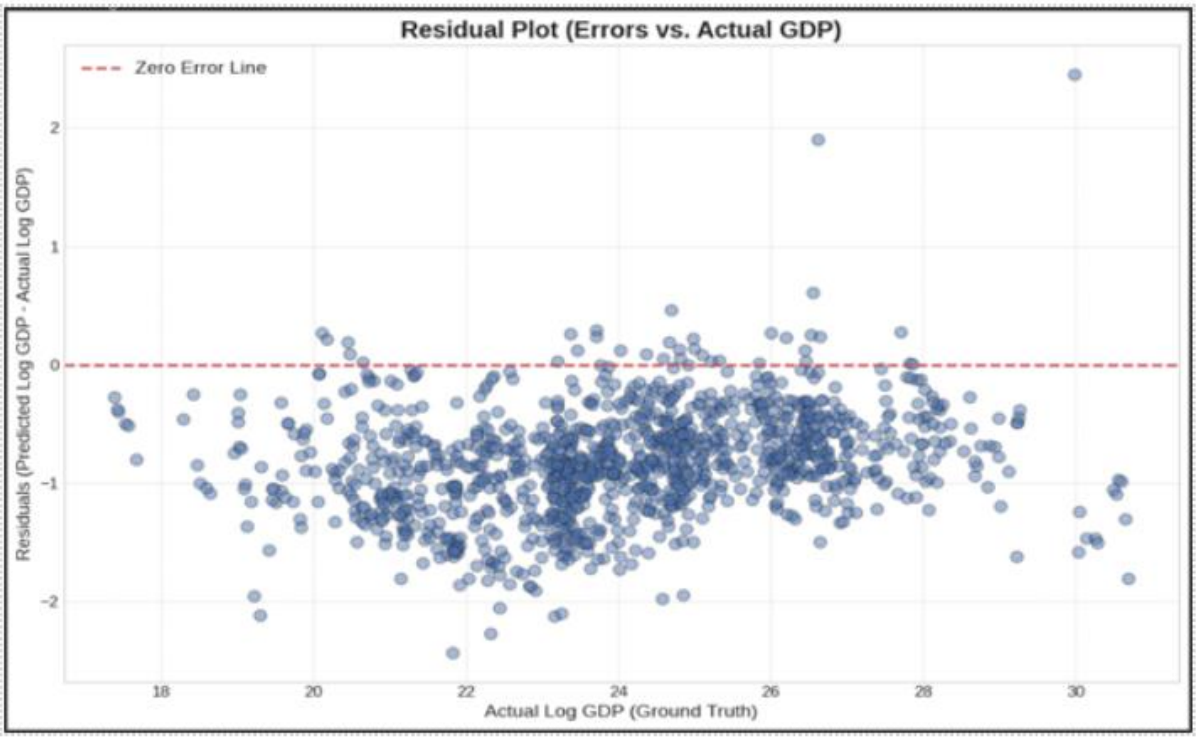

Figure 4.5: Errors vs. Actual GDP

1.4 Summary

The chapter introduced the implementation procedure and experimental analysis of the suggested GATv2-based GDP forecasting model. World Bank indicators and BACI trade data were converted into graphs in which countries were represented as nodes and trade flows as edges. Two models were contrasted, a control Graph Attention Network where only node-level features were used, and the proposed GATv2 model using both node and edge features.

These findings revealed that the original model had a weak predictive power and R2 of 0.58 on the test data. Conversely, the GATv2 model suggested demonstrated a significantly better performance, with the R2 of 0.87 and significantly lower errors (MAE and RMSE). The results indicate that it is important to model international trade relationship in addition to country-specific indicators to forecast the GDP successfully.

On the whole, the experiments proved the possibility and efficiency of graph based techniques in economy prediction. Combining edge features helped the proposed framework to enhance accuracy and robustness as well as provide a new outlook to macroeconomic modeling. This development makes GNNs a promising substitute to the conventional statistical and sequential machine learning methods. The following chapter is about the larger contribution to the research, limitations, and future research.

Chapter 5

Engineering Standards and Design Challenges

In this chapter, this will be the architecture and practical engineering decisions about the project and established in the broad context. Next, we'll discuss the standards and the practical implications of such research in the real world and how we did the project as a complex engineering project. It is a look into history on which the research was based.

1.1 Compliance with the Standards

We wanted our work to be strong and repeatable, and therefore we constructed it on top of familiar, industry-standard tools. Each of these was a decision that was weighed in comparison to others, and a decision was taken concerning a given project based on the requirements of that project.

1.1.1 Software Standards

The software stack in this project was chosen with great care to ensure compatibility, efficiency and scalability in the implementation and experimentation stages. This was developed with Python 3.10, a popular machine learning and data science programming language because of its simplicity, high readability, and rich library ecosystem.

The main deep learning model used was PyTorch as its dynamically compiled computation graph, support on GPUs, and high-level community. To support graph-based learning, PyTorch Geometric (PyG) was incorporated, which offers a collection of optimized graph-based data processing functions to configure GATv2 architecture, graph data structure management, and large-scale graph neural network training.

Panda and NumPy were used to process data and perform feature engineering to support useful cold data manipulation and arithmetic operations on values in tabular form. Visualisation of results was done by plotting training loss curves, performance metrics and a comparison of GDP prediction using Matplotlib. In addition, NetworkX was used in specific examples to construct and manipulate the graphs, in particular to represent trade-based edge properties.

Google Colab was used to conduct the experiments and most of these libraries are included by default. In order to make the library versions reproducible, the library versions were pinned, and the Colab notebooks were arranged to run preprocessing, training, and evaluation in a workflow.

These tools in tandem enabled the project to follow the best practices in the machine learning and deep learning research field, thereby, ensuring the credibility of the results, their repeatability, and adherence to the accepted software engineering principles.

1.1.2 Hardware Standards

The entire implementation and experimentation was conducted within a cloud based platform with Google Colab that offers access to high-end computing infrastructure. The main hardware to carry out training and evaluation was an NVIDIA Tesla T4 graphics processing unit, which is a CUDA-enabled deep learning workload-optimized GPU. The environment also used a 16 GB GDDR6 memory, which means that it can easily process large graph structures and can train graph neural networks more easily than when using only a CPU.

A two-core Intel Xeon processor and 12 GB of system RAM were also available in the Colab runtime environment and could be used to perform data preprocessing, such as loading datasets, combining features, and building intermediate graphs. As the CPU was busy processing files and doing other tasks, the computationally heavy forward and backward passes necessary to train the GATv2 model were done on the GPU.

Optimization of tension operations, parallelism and shorter training time in the CUDA 11.8 libraries and cuDNN support the GPU environment. This combination of GPU acceleration and optimized backend libraries was critical to scaling the experiments to years of economic data and converging the experiments in reasonable runtimes.

The project was scalable, reproducible, and accessible by using the cloud-based hardware provided by Google Colab. This architecture was cheaper than the special purpose hardware required to implement it, but offered a high standard of reliable operation, and can be successfully used to facilitate research in graph neural network and economic forecasting.

1.1.3 Communication Standards

The project communication standards were set to provide comfortable data flow between various elements of the system and compatibility between tools. Because the project ran in a cloud-based Google Colab environment, data processing and communication were performed using standard formats and protocols that are most often used in machine learning research.

All the data sets of the World Bank economic indicators (GDP, population, CPI, unemployment), and BACI international trade dataset were saved and manipulated in the CSV (Comma-Separated Values) format. The format has been selected because it is highly compatible, lightweight in structure and can be integrated with data analysis libraries, including Pandas and NumPy.

In order to simplify the communication between the preprocessing, training, and evaluation steps, the project used a structured workflow in which the input files (node features, edge features, and target labels) were read and written in the CSV and NumPy arrays format, respectively, every time. PyTorch Geometric (PyG) was used to work with graph structures with or without NetworkX to guarantee standard in-memory graph representations.

CUDA 11.8 and cuDNN themselves handled the communication between the runtime environment and the GPU resources, based on their optimized protocols related to memory allocation, and to the operations on tensors. This guaranteed effective communication between the CPU and the GPU when training the model and making inferences.

In addition, files uploading and downloading and saving it on Google drive integration provided a satisfactory file flow using Google Colab cloud architecture that ensured that final results are acquired and reproducible. The project was consistent, portable, and interoperable across the entire experimental workflow by following the generally accepted standards of communication, including CSV to communicate datasets, NumPy arrays to perform in-memory computations, and CUDA/cuDNN to execute code on hardware.

1.2 Impact on Society, Environment and Sustainability

1.2.1 Impact on Life

The direct effect of accurate GDP forecasting on the lives of people is that it helps governments and policy-makers predict future changes in the economy and create more effective fiscal and monetary policies. Good projections can result in better employment and job creation policies, superior resource distribution in education and health, and superior poverty reduction strategies. The said model can represent the global trade relationship and, consequently, enhance the description of the external shock, in turn, adding to the quality of economic planning, thus, adding to the improvement of life quality of the citizens.

1.2.2 Impact on Society & Environment

At the government level, better predictability of the GDP contributes to better transparency and leads to data-oriented government. The economy is not so unpredictable as the governments can work out how to build the infrastructure, welfare program and investments. In the environmental case, the policy can be extended to include sustainability indicators (use of renewable energy, CO_2 emissions), which would allow the policy makers to trade-off the economy and the environment. By doing so, the project will lead to sustainable development as it allows taking evidence-based decisions.

1.2.3 Ethical Aspects

To be transparent and follow the ethics of data, the project is founded on publicly available records of the World Bank or BACI. No personal or sensitive data is involved, and it removes the privacy and data protection risks. The ethical responsibility is to make sure that the results of the forecasting are not used badly to promote a certain political or corporate agenda. The objectives of the studies are to support inclusive and equitable policy-making with sound information on economic performance.

1.2.4 Sustainability Plan

This work is subject to sustainability based on whether the model is reproducible and scalable. As all implementation is conducted on open platforms like the Google Colab, and datasets are openly available, subsequent researchers and policymakers can duplicate and expand the study at the lowest possible cost. With new economic and trade statistics, the model can be updated every year to remain relevant. In addition, the model may facilitate planning that balances economic development with environmental and social well-being through the inclusion of additional indicators of sustainability in further applications.

1.3 Project Management and Financial Analysis

Project Management

There were four main phases to the project, each with its own goals and deadlines:
Phase 1: Reading the literature and defining the problem (Weeks 1–3)

- Developed an extensive review of the literature that uses machine learning and graph neural networks in predicting GDP.
- Identified research gaps: edge features were not used in prior models.
- Achieved the objectives of the project and a road map to the destination.

Phase 2 – Data Acquisition and Preprocessing (Weeks 4–7)

- Gathered World bank macroeconomic data and BACI international trade data (1995-2019).
- Washed and combined datasets in the form of graphs (nodes = countries, edges = top trade partners).
- Defined GDP(t+1) as target of prediction, constructed node and edge features.

Phase 3 – Model Development and Training (Weeks 8–12)

- Applied baseline models (Random Forest, GCN, GAT, Linear Regression).
- Developed proposed GATv2 with edge features architecture.
- Did hyperparameter tuning and ablation studies.

Phase 4 – Evaluation, Analysis, and Report Writing (Weeks 13–16)

- Comparison with proposed model versus baselines based on MSE, RMSE, MAE and R2.
- Produced plots, tables, and graphics of results.
- Recorded results and thesis report and presentation slides.

Project Timeline (Gantt Overview):

- Weeks 1–3: Literature Review.
- Weeks 4–7: Data Preprocessing.
- Weeks 8–12: Model Development & Training.
- Weeks 13–16: Evaluation, Report & Presentation.

Financial Analysis

Although the project was constructed mainly using open source datasets and open source software, a cost evaluation was undertaken to determine the viability of this work in an academic and industrial setting.

Resources Used

Hardware: It was implemented on a personal laptop with the support of the graphics card. The models were also trained and tested in Google Colab (free tier), as an alternative.

Software: The project was conducted by purely utilizing open and free tools. Python was used as the programming language and some of the libraries called PyTorch Geometric, NumPy, Pandas, Matplotlib and Scikit-learn were applied in the development and analysis of models.

Tools: Jupyter Notebook was used for experimentation and GitHub was used for version control and project hosting.

Data Sources: In the research, World Bank indicators (GDP, Population, CPI, Employment) and the BACI trade dataset, available free for research purposes, have been used.

The total financial cost of this project was low since all data sources, tools, and frameworks utilized within this project are open-source and free of charge. In a business context, however, there are other expenses that cloud computing can bring about such as high-performance hardware or access to high-quality datasets.

Estimated Costs:

Resource	Estimated Cost	Notes
Cloud Compute (GPU instances)	$300–500	Equivalent to Colab Pro+
Data Storage & Management	$50	Storing historical trade
Software Licenses	$0	All tools used were open-source
Report, Presentation prep	$20–50	Printing, formatting, etc.

Total Estimated Project Cost: ≈ $400–600.
In our case, actual costs were minimal due to reliance on open-source software and free academic datasets.

1.4 Complex Engineering Problem

1.4.1 Complex Problem Solving

This section provides a mapping of the proposed GDP forecasting system with the Complex Engineering Problem (CEP) categories. Each mapping is followed by a brief rationale to justify why the problem fits into the respective category. Table 5.1 summarizes the mapping.

Table 5.1: Mapping with Complex Engineering Problem.

EP1 Dept of Knowledge	EP2 Range Of Conflicting Requirements	EP3 Depth of Analysis	EP4 Familiarity of Issues	EP5 Extent of Applicable Codes	EP6 Extent Of Stake-holder Involvement	EP7 Interdependence
✓	✓	✓	✓	✓	✓	✓

Justification:

- **EP1:** The work demands more than standard ML models and has to be equipped with sophisticated understanding of Graph Neural Networks and economic prediction.
- **EP2:** It is a tradeoff among several requirements, including accuracy, interpretability, and computational efficiency, which can be conflicting.
- **EP3:** The analysis will deal with multi-variable and interdependent databases (the GDP, CPI, unemployment, and trade flows) and demand complex and deep

modeling.

- **EP4:** Another relatively novel and unfamiliar field of study is GDP prediction with GNNs in comparison to conventional econometric approaches.

- **EP5:** Although the datasets (World Bank, BACI) are based on the international standards, such forecasting has no formal engineering codes or guidelines.

- **EP6:** The project is meaningful to stakeholders of the globe, especially governments and policy makers that depend on proper forecasting of GDP.

- **EP7:** Inter-country trade relations are highly relied upon in the model and interdependence is thus a key aspect of the problem.

Mapping with Knowledge Profile

In this section, the identified Complex Engineering Problem (EP1) is mapped to the Knowledge Profile representing the relevant areas of knowledge that include mathematics, engineering fundamentals, specialist knowledge, design, practice, and research literature that shapes the solution of the problem.

Table 5.2: Mapping with knowledge Profile.

K1 Natural Science	K2 Mathematics	K3 Engineering Fundamentals	K4 Specialist Knowledge	K5 Engineering Design	K6 Engineering Practice	K7 Comprehension	K8 Research Literature
	✓	✓	✓	✓	✓	✓	✓

Justification:

- **K1:** The concepts of natural science are not directly used in this project.

- **K2:** Model training and evaluation is based on mathematics (statistics, probability, linear algebra, optimization).

- **K3:** The basic principles in engineering of data representation, algorithms and computation are used in data handling and model implementation.

- **K4:** The design and the implementation of the GATv2 model require specialist knowledge in the area of deep learning and GNN architectures.

- **K5:** In the project, design engineering concepts are applied in the modification of the architecture to incorporate edge features to make GDP forecasting.

- **K6:** The practical implementation of engineering practice is in Google Colab working with PyTorch Geometric.

- **K7:** The project requires comprehension of economic interdependencies between countries and how they influence GDP.
- **K8:** The design decisions were based on a substantial utilization of research literature and identified gaps that were filled by this work.

1.4.2 Engineering Activities

Mapping with Complex Engineering Activities

This section will map the project to the attributes of Complex Engineering Activities (EAs) demonstrating how the work fits within the range of resources, the level of interaction, the level of innovativeness, the consequences of the work on society and familiarity as required.

Table 5.3: Mapping with Complex Engineering Activities.

EA1 Range of re-sources	EA2 Level of Interaction	EA3 Innovation	EA4 Consequences for society and environment	EA5 Familiarity
✓	✓	✓	✓	✓

Justification:

- **EA1:** The project is based on a significant variety of business resources, such as datasets provided by the World Bank, BACI trade flows, and computational software, like PyTorch.
- **EA2:** It involves connection in various fields of work and education: economics, data science, and engineering.
- **EA3:** It is also novel in incorporating edge-level trade characteristics into GATv2 to predict GDP, which has not been studied extensively.
- **EA4:** The project is beneficial to society as it will be able to forecast GDP more accurately that can enhance policy and development planning.
- **EA5:** The space problem is not very familiar, with the use of GNNs in macroeconomic forecasting being in its infancy.

1.5 Summary

This chapter applied the problem of GDP forecasting to the structural model of complex engineering problems, engineering activities, and knowledge profiles. The problem was found to have several dimensions of complexity, involving the range of conflicting requirements, depth of analysis, stakeholder consultation and interdependence among economic systems. Using the knowledge profile, the integration of mathematics, engineering fundamentals, specialist knowledge and research literature needed to develop the GATv2 model was clearly illustrated.

Furthermore, the analysis showed that the project fits into the category of complex engineering activities because of the variety of data sources, intensity of cross-country interactions, need for innovation in modelling methods and high societal importance. By relating the work to these formal structures, this research simultaneously points to its technical rigor and its real-world relevance.

In conclusion, this chapter shows that the proposed system is a valid complex engineering problem with multidisciplinary knowledge needs and novel methods. The second chapter covers the general impact, limitations, and future directions of this work.

Chapter 6
Conclusion

This chapter contains the conclusion of the study and some recommendations on how to conduct further research.It summarizes the main findings, comments on the benefits of the proposed plan, and offers suggestions on how the plan could be clarified and refined and what research should be conducted further.

1.1 Summary

This study aimed at forecasting the GDP at the country level using graph neural networks (GNNs) using both domestic economic variables and international trade variables. The study uses the World Bank datasets including statistics on GDP, population, CPI and employment as well as the BACI dataset capturing global trade flows. These data sets were converted to annual graph format, where countries were the nodes and trade relationships with product-level features were used as the edges. A baseline GAT model with just node features was implemented, and an extended GATv2 model with edge features was suggested for better capturing the inter-country dependencies.

Training and validation of the models were done based on historical data, and their performances were measured and quantified using regression measures like MAE, RMSE, and R2. Findings showed that edge features in the GATv2 model led to better prediction accuracy than the base. The methodology was able to bring out the advantage of modelling domestic indicators and trade relations in economic forecasting. Overall, the research paves a path for the advancement of GNN-based methods in GDP forecasting beyond conventional statistical and machine learning models.

1.2 Limitation

Despite the good performance of the proposed GATv2 model with edges features in GDP forecasting, a number of limitations exist. First, the data employed (World Bank indicators and BACI trade flows) is only through 2019, thus omitting recent world events (COVID-19 pandemic and geopolitical trade disruption) that could influence robustness. Second, the model includes only a small number of node-level characteristics (population, CPI, unemployment, and lagged GDP) whereas other important macroeconomic variables including investment levels, government spending, or energy consumption were omitted because of the lack of data. Third, the experiments ran in a cloud based Colab platform which, despite its effectiveness, had memory and computing bandwidth limits that could restrict scaling to large graph structures or increased time resolutions. Lastly, interpretation is also not easy because GATv2 gives us attention weights but to have an economic understanding of the weights further analysis is necessary.

1.3 Future Work

These limitations may be overcome in future studies by expanding the set of economic indicators and shocks on GDP after 2020, allowing the model to rely on pandemic-specific and geopolitical impacts on GDP. It would be beneficial to add additional macroeconomic characteristics like variables of fiscal policy, balance of trade, energy use and environmental factors to the model to increase its ability to explain the phenomenon. Methodologically speaking, year-to-year evolution of economies could be more effectively modeled by using dynamic temporal graph neural networks (TGAT, T-GCN). Furthermore, the opportunity to plot the attentional weightings, the feature attribution and weightings along with interaction with the policy simulations, can be provided, which, possibly, can make the model complete and, possibly, may attract the interest of the economists and policy-makers. Finally, making the system an interactive dashboard, a decision-supporting tool, would improve its access and realistic applicability to actual economic planning in the real world.

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