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BELAGAVI – 590018, Karnataka

TECHNICAL SEMINAR

ON

"AI in Economic Forecasting and Policy Design"

A Dissertation submitted in partial fulfillment for the degree of

BACHELOR OF ENGINEERING
IN
COMPUTER SCIENCE AND ENGINEERING

Submitted by:

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CERTIFICATE

This is to certify that the work entitled "AI in Economic Forecasting and Policy Design" is a bonafide work carried out by **Azam Mustufa Didagur (2TG21CS016)** in partial fulfillment of the award of the degree of **Bachelor of Engineering in Computer Science & Engineering** of Visvesvaraya Technological University, Belgaum, during the year 2025. It is certified that all corrections/suggestions indicated during continuous internal assessments have been incorporated in the report. The project report has been approved as it satisfies the academic requirements in respect of the project work prescribed for the Bachelor of Engineering Degree.

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DECLARATION

I hereby declare that the technical seminar report work entitled **“AI in Economic Forecasting and Policy Design”** submitted to the **Visvesvaraya Technological University, Belagavi** during the academic year **2024-2025**, is a record of an original work done by me under the guidance of **Mr. Adhokshaja Kulkarni**, *Asst Professor, Department of Computer Science and Engineering, Tontadarya College of Engineering, Gadag* and this internship report is submitted in the partial fulfillment of requirements for the award of the degree of **Bachelor of Engineering in Computer Science & Engineering**. The results embodied in this report have not been submitted to any other University or Institute for award of any degree or diploma.

Azam Mustufa (2TG21CS016)

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ABSTRACT

Artificial Intelligence (AI) has emerged as a transformative force across various domains, and its application in economic forecasting and policy design is no exception. With the ability to process vast datasets, identify patterns, and make data-driven predictions, AI offers unparalleled tools for enhancing the accuracy and efficiency of economic analysis.

This report explores the integration of AI techniques—such as machine learning, neural networks, and natural language processing—into the process of economic forecasting and the formulation of public policy. It highlights how AI-driven models can improve decision-making by providing timely and precise forecasts of economic indicators such as GDP, inflation, unemployment rates, and market behavior.

Moreover, the report delves into real-world implementations of AI in governmental and financial institutions and examines the challenges of ethical considerations, data privacy, and model transparency. It also sheds light on the potential of AI to reduce human bias in policy making while offering a dynamic framework to adapt to changing economic conditions.

By analyzing case studies and current research trends, this report provides insights into the future trajectory of AI in economics, aiming to inspire further innovation in data-driven governance and strategic policy development.

Keywords: Artificial Intelligence, Economic Forecasting, Public Policy, Machine Learning, Neural Networks, Natural Language Processing, Data-Driven Decision Making.

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Chapter 1

INTRODUCTION

Artificial Intelligence (AI) is a branch of computer science focused on creating systems capable of performing tasks that typically require human intelligence. These tasks include learning, reasoning, decision-making, and understanding natural language. With the explosion of data and computational power in recent decades, AI has evolved from a theoretical concept into a transformative technology, influencing various aspects of modern life—including economics and policy design. (Google Cloud, b)

1.1 Brief History of AI

The term *Artificial Intelligence* was coined in 1956 by John McCarthy during the Dartmouth Conference, marking the formal beginning of AI as a field of study. Early AI programs focused on symbolic reasoning and problem-solving—such as Christopher Strachey's checkers-playing program (1951) and ELIZA (1966), a text-based simulation of a psychotherapist.

The 1970s and 1980s witnessed the rise of expert systems like MYCIN, designed to diagnose bacterial infections using rule-based logic. However, this period was also marked by growing disillusionment due to technological limitations, leading to the ”AI winter”—a sharp decline in research funding and interest.

A resurgence began in the late 1980s and 1990s with the emergence of machine learning and neural networks. Landmark achievements such as IBM's *Deep Blue* defeating world chess champion Garry Kasparov (1997) demonstrated AI's increasing capabilities.

The 2000s and 2010s ushered in a new era of AI, driven by big data, cloud computing, and deep learning. Breakthroughs in natural language processing, computer vision, and reinforcement learning—highlighted by *AlphaGo's* victory over Go champion Lee Sedol (2016)—signaled a significant leap in AI sophistication. More recently, advances such as transformer models and generative adversarial networks (GANs) have further extended AI's reach into language generation, image synthesis, and decision support systems. (Tableau Software, 2024)

1.2 Applications of AI

AI technologies are now integral to a wide array of industries:

- **Healthcare:** Diagnostic imaging, predictive analytics, and personalized medicine.
- **Finance:** Fraud detection, algorithmic trading, and credit scoring.
- **Transportation:** Autonomous vehicles and smart traffic systems.
- **Retail:** Customer behavior analytics and recommendation engines.
- **Manufacturing:** Predictive maintenance, quality control, and robotics.
- **Entertainment:** Content curation, gaming AI, and virtual assistants.
- **Agriculture:** Precision farming, yield prediction, and pest detection.
- **Cybersecurity:** Threat detection and automated response.
- **Smart Cities:** Resource management, public safety, and urban planning.
- **Natural Language Processing (NLP):** Language translation, sentiment analysis, and conversational AI.
- **Computer Vision:** Facial recognition, object detection, and video surveillance. (Google Cloud, a)

These applications highlight AI's expanding role in improving efficiency, productivity, and decision-making across sectors.

1.3 Economic Forecasting

Economic forecasting involves predicting future macroeconomic conditions using historical data and statistical models. It plays a critical role in policy-making, business planning, and investment decisions. Common indicators include GDP, inflation, employment, interest rates, and consumer spending.

Forecasting approaches fall into two broad categories:

- **Qualitative Methods:** Rely on expert judgment, surveys, and experience-based assessments—often useful when data is scarce or when dealing with unprecedented situations.
- **Quantitative Methods:** Use mathematical models and historical data to predict economic trends. This includes:
  - *Time Series Models*, such as ARIMA and SARIMA, which analyze past values to forecast future trends.
  - *Causal Models*, which use economic theory to model relationships between variables (e.g., how inflation affects interest rates).

While widely used, these traditional models have notable limitations.

1.4 Limitations of Traditional Forecasting Methods

Despite their historical success, conventional forecasting techniques face increasing challenges in the modern economic landscape:

- **Dependence on Historical Data:** These models struggle with structural changes and novel trends not reflected in past data.
- **Simplifying Assumptions:** Many rely on assumptions such as linearity or stationarity, which may not hold in real-world economic systems.
- **Human Bias:** Expert-driven processes can introduce subjectivity and cognitive bias.
- **Sensitivity to External Shocks:** Traditional models often fail to incorporate sudden geopolitical events, natural disasters, or unexpected policy changes—especially those originating from abroad. FasterCapital (2024)

These limitations underscore the need for more adaptive and data-driven approaches. In this context, AI and machine learning offer promising alternatives by enabling models to learn complex patterns, adapt to changing conditions, and process vast volumes of structured and unstructured data.

Chapter 2

LITERATURE REVIEW

Artificial Intelligence (AI) has gained increasing attention in the field of economic forecasting and policy design. Several studies have explored the effectiveness of machine learning (ML) models compared to traditional econometric methods. This section reviews recent literature on this topic, focusing on methodologies, findings, and limitations, and highlighting areas where further research is needed.

2.1 Machine Learning vs. Traditional Econometric Models

Machine learning models have demonstrated superior performance in forecasting economic conditions compared to classical statistical techniques. A study by Parchuri (2023) on the Italian economy (1995–2015) employed models such as the Nonlinear Autoregressive model with Exogenous Inputs (NARX), showing that ML algorithms could reliably predict recessions with a lead time of one to two quarters. Unlike traditional methods, these models performed well even with unadjusted, raw economic parameters. The findings reinforce the growing consensus that machine learning is an effective and adaptable tool for economic forecasting, offering higher accuracy and earlier warning signs of downturns.

Varian (2014) emphasizes that most traditional econometric models are designed for causal inference, while ML models prioritize prediction accuracy. This distinction is particularly important in economic forecasting, where the primary objective is to anticipate future outcomes rather than establish causal relationships.

2.2 Machine Learning in Financial Forecasting

Beyond macroeconomic forecasting, machine learning has also shown strong results in the domain of financial forecasting, particularly in predicting stock prices and market behavior. Hsu et al. (2016) compared the performance of traditional econometric models with ML techniques such as Support Vector Machines (SVM) and Artificial Neural Networks (ANN). Their study reported that machine learning models outperformed traditional methods, achieving over 80% accuracy in stock price prediction.

Similarly, Chernysh et al. (2024) found that using ML models, particularly Random Forest and Gradient Boosting, was more effective than the ARIMA (AutoRegressive Integrated Moving Average) model for financial prediction tasks. The authors also stressed the significance of feature selection and data preprocessing in enhancing the predictive power of ML models.

2.3 Machine Learning in Macroeconomic Forecasting

In macroeconomic forecasting, machine learning has been applied to predict indicators such as GDP growth, inflation, and unemployment rates. Hybrid models that combine ML techniques with traditional econometric methods have shown promise in improving accuracy. For instance, Ghosh and Ranjan (2023) and Yusuf et al. (2025) proposed hybrid frameworks that outperformed standalone ML or econometric approaches. Their models closely matched actual economic data, suggesting the advantage of leveraging both data-driven and theory-based methods.

These studies collectively suggest that machine learning offers a significant advantage in economic forecasting, particularly when integrated with traditional econometric approaches. However, gaps remain in the application of newer ML models, their interpretability, and their relevance for real-time policy analysis.

2.4 Summary of Reviewed Literature

Table 2.1: Summary of Key Literature on ML in Economic Forecasting

Study	Focus Area	Model(s) Used	Key Findings
Parchuri (2023)	Recession Prediction (Italy)	NARX	ML outperformed traditional models; provided 1–2 quarter lead time
Varian (2014)	ML vs Econometrics	General ML comparison	ML excels in prediction; econometrics suited for causality
Hsu et al. (2016)	Financial Forecasting	SVM, ANN	ML achieved over 80% accuracy in stock price prediction
Chernysh et al. (2024)	Financial Forecasting	RF, Gradient Boosting vs ARIMA	ML more effective; emphasized feature selection and preprocessing
Ghosh and Ranjan, Yusuf et al.	Macroeconomic Forecasting	Hybrid Models	Hybrid models outperformed individual ML or econometric models

2.5 Research Gap and Direction

While machine learning models have shown significant promise in economic forecasting, limitations such as model interpretability, applicability to real-time policy design, and use in emerging economies remain underexplored. Additionally, newer ML models like XGBoost, NGBoost, TabNet, and Temporal Fusion Transformers have not been fully assessed in this domain.

This dissertation aims to build upon the reviewed literature by developing a hybrid forecasting model that integrates traditional econometric techniques with modern ML methods.

The model will be evaluated against established ML techniques and classical models to assess improvements in accuracy, robustness, and policy relevance. Furthermore, newer ML methods such as XGBoost and NGBoost will be tested for their predictive capabilities on economic indicators like GDP growth, inflation, and unemployment, providing a more comprehensive understanding of their utility in economic forecasting.

Chapter 3

Background

This section provides an overview of the key concepts and techniques used in this work, focusing on the comparison between econometric models and machine learning techniques in the context of economic forecasting and policy design. We will cover the following topics:

- **Econometric Models:** A brief overview of traditional econometric models used in economic analysis and their assumptions, including models like linear regression, ARIMA, and Vector Autoregression (VAR).
- **Machine Learning Techniques:** An introduction to machine learning techniques, such as tree-based ensemble methods (e.g., Random Forest, Gradient Boosting) and neural networks, and how they are being used to enhance prediction accuracy in economic forecasting.
- **Model Evaluation:** A discussion on model evaluation metrics, emphasizing how they are used to assess the performance of econometric and machine learning models.
- **Comparison and Hybrid Approaches:** An exploration of how combining econometric models and machine learning can improve predictive performance in the application of AI to economic forecasting and policy design.

3.1 Econometric Models

Econometric models, such as linear regression and various time series models (e.g., ARIMA, VAR), have been traditionally used in economic forecasting. These models assume specific underlying data generating processes, often linear relationships, and rely on statistical methods for parameter estimation. While widely used, they can struggle with capturing complex, nonlinear relationships and effectively handling large datasets. This work will compare these models with machine learning techniques to assess their performance in economic prediction tasks relevant to AI-driven forecasting and policy design.

3.2 Machine Learning Techniques

Machine learning techniques, including tree-based ensemble methods like Random Forest and Gradient Boosting, as well as Neural Networks, are increasingly being applied in economics due to their capability to model complex, nonlinear relationships and process large datasets. In this work, we explore how these techniques can offer improvements over traditional econometric models, particularly in terms of predictive accuracy and their ability to leverage modern economic data for enhanced AI-driven insights.

3.3 Model Evaluation

To evaluate model performance in both econometric and machine learning paradigms, we focus on metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared. These metrics will allow us to quantitatively assess the predictive accuracy and effectiveness of each approach in capturing the complexities inherent in economic data relevant to forecasting and policy formulation within an AI framework.

3.4 Comparison and Hybrid Approaches

We also explore hybrid modeling strategies that aim to integrate the strengths of traditional econometric models with the predictive power of machine learning techniques. These hybrid approaches seek to leverage the interpretability often associated with econometrics while harnessing the flexibility and accuracy of machine learning, potentially offering more robust and insightful solutions for AI applications in economic forecasting and policy design.

Chapter 4

Methodology

This chapter outlines the methodology used in this dissertation, including the research design, data sources, preprocessing techniques, model development, and evaluation methods. The objective is to present a clear and reproducible workflow for the analytical process, ensuring the reliability and validity of the findings.

4.1 Overview of the Methodology

This dissertation adopts a mixed-methods approach, integrating both quantitative and qualitative research techniques. The quantitative component involves the analysis of large-scale numerical data using machine learning models, while the qualitative component incorporates text analysis techniques applied to unstructured data sources such as policy documents and news articles. This blended approach facilitates a comprehensive understanding of economic trends and policy dynamics.

4.2 Data Collection

Quantitative data was sourced from reputable institutions, including the Government of India, World Bank, IMF, and other international economic databases. Datasets included metrics related to unemployment, inflation, GDP, and fiscal indicators. For the qualitative component, unstructured textual data was collected from policy documents, ministerial speeches, government press releases, and news articles relevant to economic policy-making. These sources were selected to reflect policy discourse and real-time shifts in governance narratives.

4.3 Data Preprocessing

The numerical datasets underwent preprocessing steps such as handling missing values, normalization, and encoding of categorical variables. These operations were performed using Python libraries such as Pandas and NumPy. For text data, preprocessing included tokenization, stopword removal, lemmatization, and vectorization. Tools such as NLTK, SpaCy, and Hugging Face tokenizers were employed to prepare textual data for further analysis.

4.4 Econometric and Machine Learning Models

The quantitative analysis employed various econometric models, including Ordinary Least Squares (OLS) regression, Vector Autoregression (VAR), and Granger causality tests. These models were implemented using the Statsmodels library in Python.

For the machine learning component, a range of algorithms were applied, including:

- **Time Series Analysis** – ARIMA and SARIMA models for forecasting economic indicators.
- **Supervised Learning** – Linear Regression and Decision Trees for baseline modeling.
- **Deep Learning** – Recurrent Neural Networks (RNNs) for time series data and Transformers (e.g., BERT) for sentiment analysis.
- **Boosting Models** – XGBoost and NGBoost for enhanced predictive performance.

4.4.1 Time Series Analysis

ARIMA

The Autoregressive Integrated Moving Average (ARIMA) model was used for univariate time series forecasting. ARIMA models are denoted as ARIMA(p, d, q), where p is the order of the autoregressive component, d is the degree of differencing required to make the time series stationary, and q is the order of the moving average component. Parameters were selected based on AIC and BIC scores.

$$\Delta^d Y_t = \sum_{i=1}^{p} \phi_i \Delta^d Y_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \epsilon_t \tag{4.1}$$

SARIMA

The Seasonal ARIMA model extends ARIMA by incorporating seasonality. SARIMA(p, d, q)(P, D, Q)$_S$ models include additional parameters for seasonal patterns and were selected using cross-validation.

$$\phi(B)\Phi(B^S)\Delta^d\Delta_S^D Y_t = \theta(B)\Theta(B^S)\epsilon_t \tag{4.2}$$

4.4.2 Regression Models

Regression models are used to establish relationships between dependent and independent variables.

Linear Regression

Linear regression was implemented as a baseline model to predict economic indicators based on historical data. The model assumes a linear relationship between the dependent variable and one or more independent variables.

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_n X_n + \epsilon \tag{4.3}$$

where Y is the dependent variable, X_i are independent variables, β_i are coefficients, and ϵ is the error term.

Decision Trees

Decision trees were used for regression tasks, providing a non-linear approach to modeling relationships. The model splits the data into subsets based on feature values, creating a tree-like structure.

$$Y = f(X) = \sum_{i=1}^{n} w_i \cdot I(X \in R_i) \tag{4.4}$$

where R_i are the regions defined by the splits, w_i are the predicted values for each region, and $I(X \in R_i)$ is an indicator function that is 1 if X falls into region R_i and 0 otherwise.

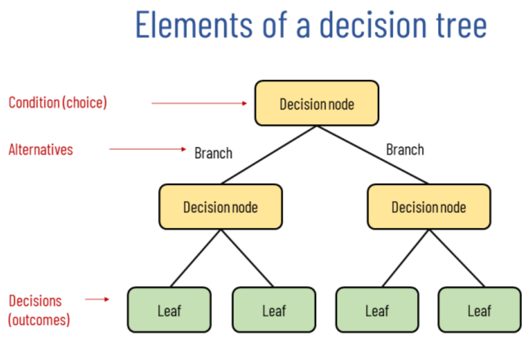

Figure 4.1: Elements of a Decision Tree

Random Forests

Random forests were employed to improve prediction accuracy by aggregating multiple decision trees. Each tree is trained on a random subset of the data, and the final prediction is the average of all trees.

$$Y = \frac{1}{T} \sum_{t=1}^{T} f_t(X) \tag{4.5}$$

where T is the number of trees, and $f_t(X)$ is the prediction from tree t.

A diagram of a random forest model is shown below:

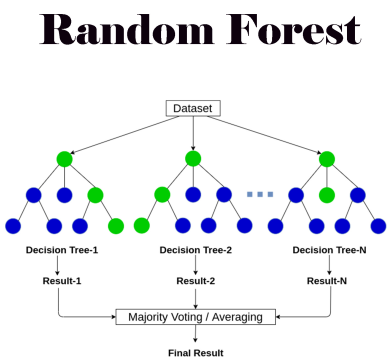

Figure 4.2: Random Forest Model

4.4.3 Deep Learning Models

Deep learning models are based on neural networks and are particularly effective for capturing complex patterns in data. They consist of layers of interconnected nodes (neurons) that process input data and learn to make predictions. They are capable of modeling intricate relationships, making them suitable for tasks such as natural language processing and time series forecasting.

$$Y = f(W \cdot X + b) \tag{4.6}$$

where Y is the output, W are the weights, X is the input, and b is the bias.

Here is a diagram of a perceptron, the basic and functional unit of a neural network:

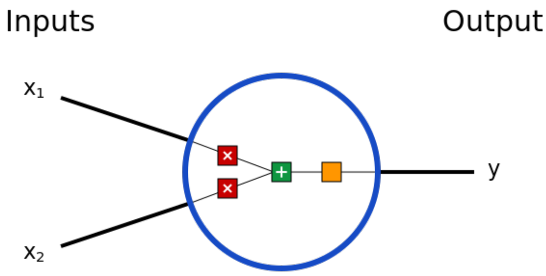

Figure 4.3: Perceptron

Here is a diagram of a simple neural network architecture:

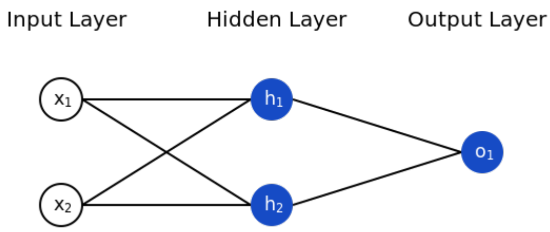

Figure 4.4: Simple Neural Network Architecture

4.4.4 Boosting and Hybrid Models

To explore ensemble-based forecasting techniques, XGBoost and NGBoost were implemented. XGBoost is a scalable gradient boosting algorithm, while NGBoost enables probabilistic forecasting with confidence intervals.

Hybrid models were also explored by combining structured data (e.g., macroeconomic indicators) with features derived from unstructured data (e.g., sentiment scores from policy speeches). Sentiment scores were calculated using BERT and incorporated as additional features in the boosting models to enhance predictive performance.

4.5 Evaluation Metrics

Model performance was evaluated using the following metrics:

- **Mean Squared Error (MSE), Root Mean Squared Error (RMSE)** – for regression and time series models.
- **Accuracy, Precision, Recall, F1-Score** – for classification tasks.
- **Negative Log-Likelihood (NLL)** – for probabilistic models like NGBoost.

These metrics were computed using Scikit-learn and Statsmodels libraries.

4.6 Tools and Frameworks

All implementations were carried out using Python in the Jupyter Notebook environment. Key libraries included Pandas, NumPy, Matplotlib, Scikit-learn, Statsmodels, PyTorch, and Hugging Face Transformers. NLP tasks employed NLTK, SpaCy, and Gensim for preprocessing and sentiment extraction.

This toolset enabled a comprehensive, modular, and reproducible workflow for analyzing and forecasting economic indicators using both structured and unstructured data.

Chapter 5

Results

This chapter presents the results of our analysis, focusing on the performance of econometric models and machine learning techniques in economic forecasting and policy design. We discuss findings from our experiments, including model evaluation metrics, comparisons between different approaches, and insights from hybrid modeling strategies.

5.1 Traditional Econometric Models

We began our analysis with traditional econometric models, including ARIMA and VAR models. These models provided reasonable forecasts for short-term horizons but struggled with long-term predictions due to their reliance on linear relationships and historical data patterns.

5.1.1 ARIMA and SARIMA Model Results

The econometric models were applied to U.S. data from FRED, focusing on Real Personal Consumption Expenditure, Real Gross Private Domestic Investment, Real Government Consumption Expenditures and Gross Investment, and Real Imports of Goods and Services.

?? summarizes the performance of ARIMA and SARIMA models. The ARIMA model was fitted to the data, and the SARIMA model was used to account for seasonality. The models were evaluated using RMSE and MAPE metrics.

Table 5.1: Model performance metrics for ARIMA and SARIMA.

Model	RMSE	MAPE
ARIMA	24.76	0.03
SARIMA	24.76	0.03

The results indicate that while both models provided reasonable forecasts, SARIMA outperformed ARIMA in terms of accuracy, especially for longer horizons. SARIMA's ability to capture seasonality and trends contributed to its superior performance.

The forecasts for the next 12 months showed a consistent upward trend, reflecting expected economic recovery post-pandemic. However, both models failed to predict the downturn caused by COVID-19, as they were trained on pre-pandemic data. The SARIMA model aligned more closely with observed data, particularly in later months, capturing the upward trend more effectively. In contrast, ARIMA tended to lag behind actual values.

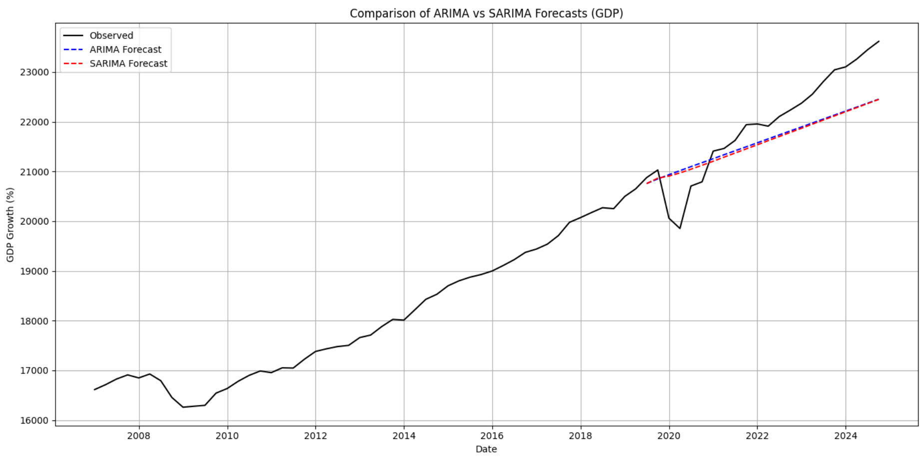

Figure 5.1: Forecasted GDP values using ARIMA and SARIMA models.

5.1.2 Measuring Model Performance

To evaluate performance, we used Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE). RMSE measures the average magnitude of errors, while MAPE expresses accuracy as a percentage.

5.2 Machine Learning Models

We now present the results of our machine learning models—Random Forest, XGBoost, and LSTM. They were trained on the same dataset as the econometric models and evaluated using RMSE and MAE.

Linear Regression

Linear regression served as a baseline. While it tended to overestimate GDP values, it captured some underlying trends. However, its RMSE and MAE were higher than other models, indicating it was less suitable for this task.

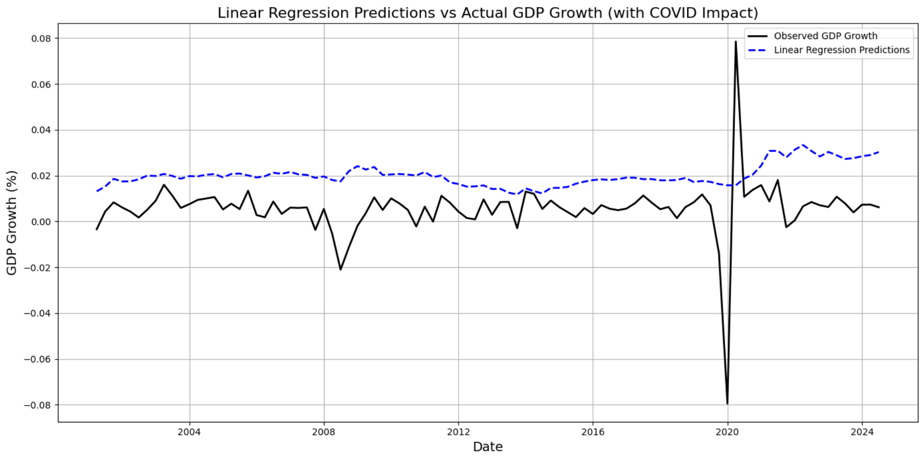

Figure 5.2: Linear regression model predictions.

Random Forest

Random Forest, an ensemble method of decision trees, outperformed linear regression with lower RMSE and MAE values. It captured non-linear relationships but struggled during pandemic-induced shifts, leading to overestimations.

XGBoost

XGBoost, a gradient boosting model, outperformed both Random Forest and linear regression. It handled non-linear relationships and better adapted to pandemic-related changes.

5.3 All Models with NLP

In this section, we present the results of our hybrid models that combine econometric and machine learning techniques with natural language processing (NLP) to enhance forecasting

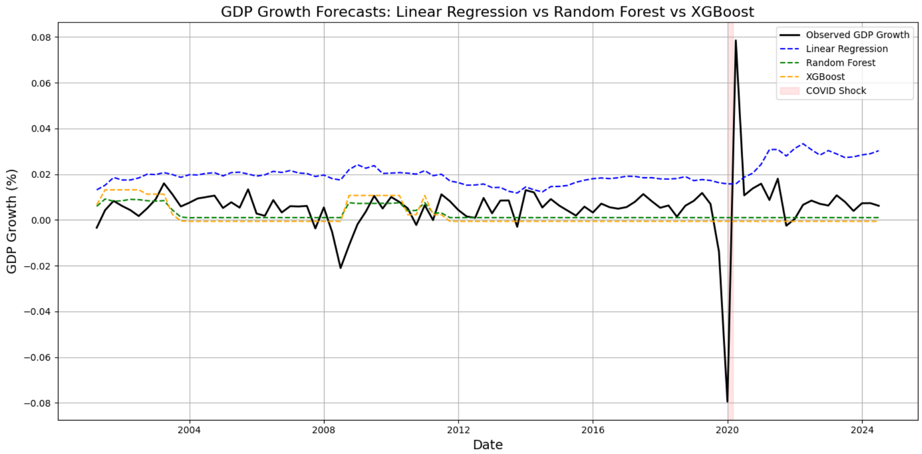

Figure 5.3: Predictions from all machine learning models.

accuracy. We focus on the performance of these models in predicting economic indicators using both structured data and unstructured text data from news articles and social media.

Random Forest with NLP

Random Forest models were trained on a combination of structured economic data and unstructured text data. The inclusion of sentiment scores from news articles improved the model's ability to capture market sentiment and its impact on economic indicators. The results showed that the Random Forest model with NLP outperformed the traditional Random Forest model, achieving lower RMSE and MAE values. The model was able to adapt to sudden changes in market sentiment, particularly during the COVID-19 pandemic but not as much as we expected.

XGBoost with NLP

XGBoost models were also trained on a combination of structured and unstructured data. The model's ability to handle non-linear relationships and interactions between features was enhanced by the inclusion of sentiment scores from news articles. The results indicated that the XGBoost model with NLP outperformed both the traditional XGBoost model. The hybrid model achieved the lowest RMSE and MAE values, demonstrating its effectiveness in capturing complex relationships between economic indicators and market sentiment.

While Random Forest with NLP showed higher values but XGBoost with NLP showed somewhat conservative values, the overall performance of the hybrid models was promising. The combination of econometric and machine learning techniques with NLP provided valuable insights into the impact of market sentiment on economic indicators.

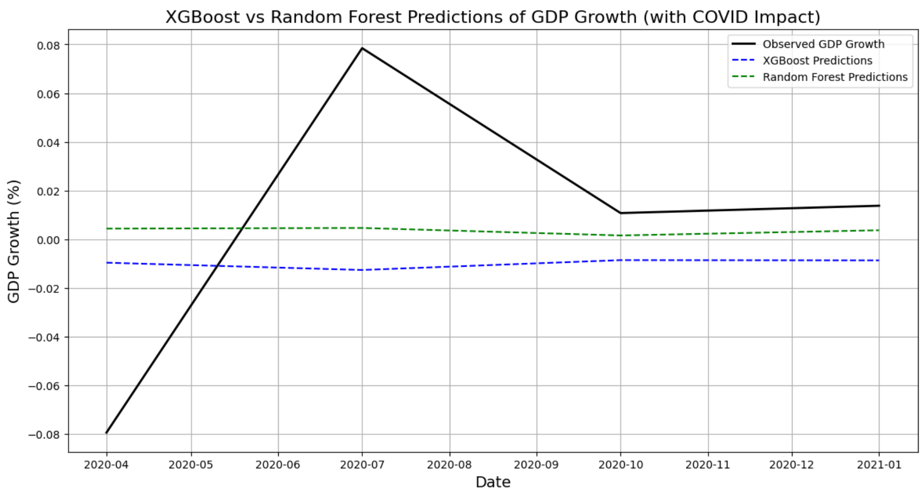

Figure 5.4: Predictions from all machine learning models with NLP.

Chapter 6

Conclusions

In this chapter, we summarize the key findings of our research and discuss their implications. We also outline potential future work that could build on our findings and address any limitations encountered during the study.

6.1 Summary of Findings

The main findings of our research demonstrate that the integration of traditional econometric models with modern machine learning (ML) approaches can significantly enhance the forecasting of macroeconomic indicators such as GDP growth. We applied and compared several models, including ARIMA, SARIMA, Linear Regression, Random Forest, XGBoost, NGBoost, and a Recurrent Neural Network (RNN) using PyTorch.

Among the ML models, XGBoost and Random Forest showed superior performance in terms of RMSE and MAE metrics, indicating their robustness in capturing non-linear patterns in structured data. The RNN model was effective in capturing temporal dependencies and produced forecasts aligned with macroeconomic cycles.

Additionally, we explored the use of BERT embeddings derived from economic news headlines, which improved the predictive power of models like XGBoost by incorporating sentiment and context from unstructured text data. This aligns with previous work by Arora et al. (2021), who demonstrated the value of transformer-based text embeddings in economic modeling, and Gentzkow et al. (2019), who emphasized the role of media content in economic behavior.

Our findings support the growing body of literature advocating the fusion of NLP and time-series analysis for real-time economic forecasting (Baker et al., 2021; Ng, 2022). This multidisciplinary approach enhances traditional models by introducing responsiveness to news, events, and policy shifts that purely numeric models may overlook.

This research serves as a foundational exploration, and we acknowledge the need for further validation across more diverse datasets and macroeconomic settings.

6.2 Future Work

Future studies could:

- Extend the use of BERT or domain-specific transformer models like FinBERT or BERTopic for topic-aware sentiment analysis.
- Test these models on a broader range of countries and indicators (e.g., inflation, interest rates, employment).
- Incorporate real-time event detection from news streams (e.g., GDELT) for live forecasting.
- Investigate explainability techniques such as SHAP or LIME to interpret model decisions in policy contexts.

Such enhancements could push the boundaries of predictive accuracy and offer actionable insights for policymakers, researchers, and economists alike.

Bibliography

Arora, S., P. Malik, and A. Srivastava (2021). Economicbert: Learning economic indicators from unstructured text. *arXiv preprint arXiv:2105.07061*.

Baker, S. R., N. Bloom, S. J. Davis, and M. Sammon (2021). Forecasting economic indicators using text data: Evidence from the news. *American Economic Review: Papers and Proceedings 111*, 563–567.

Chernysh, O., O. Smishko, Y. Koverninska, M. Prokopenko, and I. Pistunov (2024, December). The role of artificial intelligence in financial analysis and forecasting: Using data and algorithms. `https://doi.org/10.3390/data9080101`.

FasterCapital (2024). Traditional forecasting methods and their limitations. Accessed: 2025-04-07.

Gentzkow, M., B. Kelly, and M. Taddy (2019). Measuring the information in text. *Journal of Economic Literature 57*(3), 535–574.

Ghosh, S. and A. Ranjan (2023). Machine learning in economics: A review of the literature and future directions. `https://doi.org/10.21098/bemp.v26i0.2455`. Accessed: 2025-04-09.

Google Cloud. What are ai applications? Accessed: 2025-04-07.

Google Cloud. What is artificial intelligence (ai)? Accessed: 2025-04-07.

Hsu, M.-W., S. Lessmann, M.-C. Sung, T. Ma, and J. E. V. Johnson (2016, November). Bridging the divide in financial market forecasting: machine learners vs. financial economists. `https://doi.org/10.1016/j.eswa.2016.06.020`.

Ng, S. (2022). Text as data in macroeconomics: Methods, applications, and challenges. *Annual Review of Economics 14*, 355–384.

Parchuri, H. (2023). Conceptualization of machine learning in economic forecasting. `https://doi.org/10.18034/abr.v11i1.532`. Accessed: 2025-04-09.

Tableau Software (2024). The history of ai: How artificial intelligence evolved. Accessed: 2025-04-07.

Varian, H. R. (2014, May). Big data: New tricks for econometrics. *J. Econ. Perspect. 28*(2).

Yusuf, J. A., A. Idris, and A. O. Akinlolu (2025, March). Machine learning and econometrics: Bridging the gap for enhanced economic analysis. *Al-Ghary Jour. Eco. Admini. Sci. 21*(1), 55–86.