VISVESVARAYA TECHNOLOGICAL UNIVERSITY

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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

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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.

Table of Contents

List of Figures

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.

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