International Journal of Engineering Technology Research & Management (IJETRM)
Journal Article
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AI MODELS FOR PREDICTING ECONOMIC RECESSION USING MULTI SOURCE DATA

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ABSTRACT
The prediction of economic recessions has taken on an even greater importance in a time where we have volatile financial systems, globally connected markets and an ever-growing digital data landscape. Conventional ways of forecasting recession have been traditionally based on a limited base of macroeconomic indicators and use linear econometric assumptions and methods that usually do not capture the complexity, the nonlinearity, and the temporal instability associated with current economies. In contrast, the very flexible paradigm based on artificial intelligence (AI) models for detecting recessionary patterns across multi-source data such as macroeconomic variables, financial market indicators, government bond yields, gross domestic product trends, crisis signals, as well as structured and unstructured economic information, can be more data-driven. Recent advancements in multi-source data fusion, machine learning, hybrid modelling and deep forecasting architecture prove that the fusion of heterogeneous datasets can improve the predictive accuracy, robustness and horizon specific forecasting performance (Li et al., 2021; Seth & Chaudhary 2021; Laborda et al., 2023). Empirical studies on recession prediction and more generally on financial risk prediction further suggest the utility of AI-based models in the analysis of uncertainty, nonlinear dependencies and large-scale economic data sets (Molepo, 2022; Cicceri et al., 2020; Cao, 2022). Moreover, insights learned from other related fields such as healthcare, disaster resilience, epidemiological forecasting and remote sensing-based hybrid modelling suggested that multi-source intelligent systems are especially beneficial in predictive tasks that involve fragmented, incomplete or rapidly evolving data environments (Ahmed et al., 2020; Cao, 2023; Yang et al., 2020; Ren et al., 2023). This article discusses the role of AI models in predicting economic recessions with multi hypothesis source data, with focus on conceptual foundation, relevant families of models, the role of data integration, benefits of the model in terms of prediction, challenges of methodologies and practical implications for developing more reliable recession early warning systems.

Keywords:
Artificial intelligence, economic recession prediction, multi-source data, machine learning, data fusion, macroeconomic forecasting, early warning systems, financial crisis forecasting, deep learning

1.0 INTRODUCTION

One of the most important shocks in the economic systems of the countries and the whole world is economic recessions. They are normally defined by a falling economic productivity, low rate of employment, consumer demand and unsteadiness in financial markets. Prior knowledge of economic recessions makes it thus indispensable among governments, policy makers, financial institutions, and businesses that aim at reducing economic risks and employ preventive measures. Conventional methods of recession forecasting have been based on econometric techniques that involve the use of the macroeconomic variables namely gross domestic product (GDP), unemployment rates, inflation rates and government bond yields. Though these models have been helpful, they are not always able to reflect the complex, nonlinear, and dynamic nature of contemporary economic systems (Cao, 2022).

The recent developments in artificial intelligence (AI) and machine learning have inspired the new possibilities of enhancing economic forecasts. The AI-based models have shown to be able to handle large amounts of structured

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and unstructured data, identify patterns that are obscure and model nonlinear relationships in the complicated systems. Consequently, scientists have paid more attention to the potential of AI methods in economic forecasting, such as detecting recession and early warning (Molepo, 2022; Cicceri et al., 2020). These models have demonstrated a high potential in enhancing better forecasting and better informed economic decision-making.

Meanwhile, the digital economy of the present day produces vast amounts of data of various sources, such as financial markets, government databases, social media networks, and international trade systems. The combination of these heterogeneous sources of data gives a more profound basis of prediction modeling in relation to the use of the traditional macroeconomic data. Multi-source data fusion methods enable the researcher to merge data of various economic indicators, and upon this, AI models can identify recession trends that would otherwise be concealed in single datasets (Li et al., 2021).

1.1 Background of the Study

1.1.1 Economic Recession Forecasting Development.

Economic recessions have been a major focus of the macroeconomic research. In the past economists used statistical and econometric methods to explain and predict declines. Early models concentrated on links among two macroeconomic variables including the GDP growth, interest rates, inflation and unemployment rates. These models could be characterized by the linear assumption of correlation between variables and relied heavily on past historical economic data.

Despite the fact that such traditional forecasting methods were useful in certain situations, they could not in many cases measure the complex dynamics and non-linear relations that occur in the contemporary economic systems. Economic dynamics have become more dynamic and unpredictable through the financial globalization, technological transformation and increasingly connected markets, which could not be predicted using traditional statistical models (Cao, 2022). Consequently, scientists have started to investigate more sophisticated computational techniques that could capture nonlinear relations and adjust to the changing economical settings at a very fast pace.

Artificial intelligence and machine learning methods have become a strong substitute to economic forecasting. These methods can find the concealed patterns in large datasets, learn on the basis of the past, and make predictions without referring directly to theoretical considerations. Research has revealed that machine learning models have the potential to enhance the quality of forecasts related to recession by detecting complicated relationships between macroeconomic and financial variables (Molepo, 2022; Cicceri et al., 2020).

1.1.2 The Multi-source Data in Economic Forecasting.

Over the past few years, economical analysis has been transformed greatly due to the availability of large scale digital data. The economic forecasting is not restricted to macro economic indicators but a researcher can use various sources of information including financial market indicators, government bond yields, corporate financial reports, social media sentiment and international trade statistics.

Integration of several sources of data boosts predictive capability of forecasting models by offering a more detailed portrayal of the economic activity. Multi-source data fusion algorithms can be used to merge non-homogenous data, which results in AI models that can elicit multi-dimensional ties between economic variables (Li et al., 2021). These strategies come in very handy when it comes to providing a pre-emptive signal of a recession.

Also with the development of machine learning and deep learning architectures, hybrid forecasting models have become possible, which can combine both temporal and cross-sectional economic data. To illustrate it, recent studies have proved the success of the use of temporal fusion transformers and other deep learning models in multi-country GDP predictions in various time scales (Laborda et al., 2023). These advancements point to the increased potential of AI-based models to enhance the accuracy of economic prediction.

1.2 The Artificial Intelligence in Economic Recession Prediction.

Artificial intelligence offers effective analytical applications that can overcome most of the shortcomings that are linked to conventional econometric frameworks. Neural networks, decision trees, ensemble learning models and deep learning architectures are AI techniques that are intended to process high dimensional data and discover complex nonlinear relationships in economic systems.

As a number of studies have shown, AI models are effective in predicting financial crisis and instability. The machine learning methods have been used to forecast the likelihood of recession based on macroeconomic variables, trends of financial markets, and government bonds yields (Cicceri et al., 2020). Equally, studies in the field of

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financial risk forecasting have indicated the fact that AI models can enhance the accuracy of forecasts in highly uncertain conditions (Korol and Fotiadis, 2022).

In addition to economic forecasting, predictive systems developed using AI have been effective in other areas like healthcare, disaster resilience, and epidemiological forecasting. As an illustration, AI-based multi-source predictive systems have been deployed to predict disease outbreaks and process complex medical data, and they have proven to be able to deal with fragmented and dynamically changing data (Ahmed et al., 2020; Yang et al., 2020). The examples above demonstrate the flexibility of AI models and how they can be used to enhance predictive performance in economic studies.

1.3 Relevance of Multi-Source Data Integration.

Multi-source data integration is a very important consideration in enhancing effectiveness of AI-based recession forecasting models. The economic downturns are not triggered by one particular factor, but they manifest themselves as a result of sophisticated relationships between financial markets, macroeconomic environment, geopolitical events, and institutional policies.

Multi-source data fusion can be used to combine various data and to achieve a greater variety of economic signals. The method enhances the strength of predictive models and minimizes the weaknesses related to the use of one source of data. It has been found that the combination of heterogeneous datasets can have a significant positive impact on forecasting, especially in the context of complex predictive tasks with incomplete or fast-changing information (Li et al., 2021; Cao, 2023).

Moreover, multi-source predictive frameworks have proven effective in other data-intensive fields such as environmental monitoring, flood simulation, and crisis management, where hybrid models integrate remote sensing data with computational models to improve predictive accuracy (Ren et al., 2023). These developments provide valuable insights for the design of advanced recession prediction systems.

Table 1: Examples of Data Sources Used in AI-Based Recession Prediction

Data Source Type	Example Indicators	Contribution to Prediction
Macroeconomic Indicators	GDP growth, inflation, unemployment	Measures overall economic performance
Financial Market Data	Stock indices, bond yields, credit spreads	Detects market instability
Government Economic Data	Fiscal policy indicators, public debt	Reflects policy impacts
Alternative Data Sources	Social media sentiment, news analytics	Captures market expectations
Global Economic Signals	International trade flows, commodity prices	Identifies global economic shocks

1.4 Research Significance

Understanding the potential of AI-based models for recession prediction is increasingly important in modern economic research. The combination of artificial intelligence techniques and multi-source data integration offers a promising pathway for developing more accurate and reliable economic forecasting systems. Improved recession prediction models can support policymakers in designing proactive economic policies, enable financial institutions to manage risk more effectively, and assist businesses in making strategic investment decisions.

By examining the conceptual foundations and methodological challenges associated with AI-based recession prediction, this study contributes to the growing body of research exploring the intersection of artificial intelligence, economic forecasting, and data-driven decision-making.

2.0 LITERATURE REVIEW

The prediction of economic recessions has been widely studied in economic and financial research due to its importance for policymakers, financial institutions, and investors. Traditional forecasting models have relied mainly on econometric approaches using macroeconomic indicators such as gross domestic product (GDP), inflation rates, unemployment levels, and interest rates. Although these models have contributed significantly to economic analysis,

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they often assume linear relationships among variables and therefore struggle to capture the complex dynamics of modern financial systems (Cao, 2022).

2.1 Traditional Approaches to Recession Prediction

Early research on recession forecasting relied on statistical and econometric models such as autoregressive models, probit models, and vector autoregression (VAR). These approaches typically analyzed historical economic data to identify cyclical patterns in economic activity. For instance, forecasting models using macroeconomic indicators and bond yield spreads have been used to detect early warning signals of economic downturns (Castellani & Santos, 2006). However, these models often perform poorly when dealing with nonlinear relationships, structural breaks, and rapidly changing economic conditions.

Economic systems have become increasingly complex due to globalization, financial integration, and technological development. As a result, researchers have argued that traditional econometric models may not adequately capture the nonlinear dependencies and hidden interactions among economic variables (Cao, 2022). These limitations have encouraged the exploration of more advanced computational methods for economic forecasting.

2.2 Artificial Intelligence in Economic Forecasting

Artificial intelligence (AI) and machine learning techniques have recently gained attention as powerful tools for predicting economic recessions. AI models can analyze large volumes of data, identify complex patterns, and adapt to changing economic environments. Machine learning algorithms such as neural networks, decision trees, and ensemble models have been applied to recession forecasting with promising results.

Research conducted by Molepo (2022) demonstrated that machine learning models can improve the accuracy of recession predictions by analyzing multiple economic indicators simultaneously. Similarly, Cicceri et al. (2020) applied machine learning methods to forecast economic recessions and found that AI-based models outperformed traditional econometric approaches in detecting recession signals.

Furthermore, AI applications in finance have expanded rapidly due to their ability to process high-dimensional datasets and detect nonlinear relationships within financial markets (Korol & Fotiadis, 2022). These capabilities make AI models particularly suitable for predicting economic crises and financial instability.

2.3 Multi-Source Data Integration in Predictive Models

One of the most significant developments in AI-based forecasting is the use of multi-source data integration. Traditional economic models rely primarily on macroeconomic data; however, modern predictive systems incorporate multiple types of information such as financial market data, government policy indicators, global economic signals, and alternative data sources.

Li et al. (2021) highlighted the importance of multi-source data fusion techniques in improving economic analysis and forecasting accuracy. By combining heterogeneous datasets, AI models can capture complex interactions between economic variables that would otherwise remain hidden.

Recent studies have also explored advanced deep learning architectures capable of integrating multiple data streams. For example, Laborda et al. (2023) demonstrated the effectiveness of temporal fusion transformers in multi-country GDP forecasting across different time horizons. These models enable the integration of time-series data with cross-sectional economic information, improving predictive performance.

Similar multi-source predictive systems have been successfully applied in other domains such as healthcare, disaster management, and epidemiological forecasting. For instance, AI-driven systems have been used to analyze medical data and predict disease outbreaks by combining multiple datasets (Ahmed et al., 2020; Yang et al., 2020). Hybrid modeling techniques have also been applied in environmental prediction using remote sensing and simulation data (Ren et al., 2023).

These developments suggest that integrating artificial intelligence with multi-source data can significantly enhance the predictive capabilities of economic forecasting systems.

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Figure 1: Conceptual Framework for AI-Based Recession Prediction

Multi-Source Data

| Macroeconomic Indicators |
| Financial Market Data |
| Government Policy Indicators |
| Global Economic Signals |
| Alternative Data (News, Sentiment) |

|
▼

Data Integration / Data Fusion

|
▼

Artificial Intelligence Models
(Machine Learning / Deep Learning)

|
▼

Recession Prediction Output
(Early Warning Economic Signals)

3.0 METHODOLOGY

This study adopts a conceptual and analytical research approach to examine the role of artificial intelligence (AI) models in predicting economic recessions using multi-source data. The methodology focuses on identifying relevant data sources, exploring AI-based predictive techniques, and analyzing how data integration methods improve recession forecasting. The section describes the research design, data sources, AI modeling approaches, and analytical procedures used to investigate the predictive capabilities of AI models in economic forecasting.

3.1 Research Design

The research employs a qualitative and conceptual research design supported by a structured review of existing empirical studies. The purpose of this approach is to analyze previous research on AI-based economic forecasting and identify methodological trends in recession prediction using multi-source datasets. A qualitative design is suitable for this study because it allows the integration and interpretation of findings from multiple academic sources, enabling a comprehensive understanding of how artificial intelligence models are applied in economic prediction (Cao, 2022).

The study synthesizes findings from prior research that applied machine learning, deep learning, and hybrid modeling approaches to economic forecasting. This approach enables the identification of key predictive variables, modeling techniques, and data integration strategies used in AI-driven recession prediction systems. By examining previous studies, the research highlights the methodological strengths and limitations of existing forecasting frameworks and provides insights into the potential improvements offered by multi-source data integration.

3.2 Data Sources and Multi-Source Data Integration

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Economic recession prediction requires the analysis of diverse economic signals that reflect changes in financial markets and macroeconomic conditions. In this study, the methodological framework emphasizes the use of multi-source data to improve predictive performance. Multi-source data refers to datasets collected from different economic, financial, and informational domains.

Examples of relevant data sources include macroeconomic indicators such as gross domestic product (GDP), inflation rates, unemployment levels, and industrial production. Financial market indicators such as stock market indices, credit spreads, and government bond yields also provide valuable information about investor expectations and financial stability. In addition, alternative data sources such as economic news sentiment, policy announcements, and global trade indicators may contribute to the detection of early recession signals.

The integration of multiple datasets improves the ability of predictive models to capture complex economic relationships. Data fusion techniques combine heterogeneous datasets into a unified analytical framework, enabling AI models to analyze interactions between economic variables more effectively (Li et al., 2021). Such integrated datasets provide richer information for training predictive models and can enhance forecasting accuracy.

3.3 Artificial Intelligence Models for Recession Prediction

Artificial intelligence techniques provide advanced computational tools for analyzing complex economic data. Unlike traditional econometric models, AI-based models can process large datasets, identify nonlinear relationships, and adapt to changing economic conditions.

Machine learning algorithms such as neural networks, decision trees, and ensemble models are commonly used for economic forecasting. Neural networks are particularly effective for modeling nonlinear relationships in economic data, while ensemble learning methods combine multiple models to improve prediction accuracy. These techniques allow researchers to analyze large volumes of economic indicators simultaneously and detect hidden patterns associated with recessionary trends (Molepo, 2022).

Deep learning models represent a further advancement in predictive analytics. Recent studies have applied deep learning architectures such as recurrent neural networks (RNNs) and temporal fusion transformers for forecasting economic variables across multiple time horizons (Laborda et al., 2023). These models are capable of learning temporal dependencies in economic time-series data, which is essential for detecting early warning signals of economic downturns.

In addition, hybrid AI models that combine machine learning techniques with traditional econometric approaches have shown promising results in financial forecasting. Such models integrate statistical analysis with computational learning algorithms, allowing researchers to leverage the strengths of both approaches in recession prediction.

3.4 Analytical Procedure

The analytical procedure used in this study involves several key stages. First, relevant literature on AI-based recession prediction and multi-source data integration is reviewed and analyzed to identify commonly used datasets and predictive modeling techniques. This stage establishes the conceptual framework for understanding how artificial intelligence contributes to economic forecasting.

Second, the methodological characteristics of different AI models are examined to evaluate their suitability for recession prediction tasks. Particular attention is given to machine learning algorithms, deep learning architectures, and hybrid models that combine multiple predictive techniques.

Third, the study analyzes the role of multi-source data fusion in improving predictive accuracy. By comparing findings from various studies, the research evaluates how integrating diverse economic datasets influences the performance of AI-based forecasting models.

Finally, the study synthesizes insights from the reviewed literature to highlight methodological challenges and opportunities associated with the implementation of AI models in recession prediction. These insights provide a foundation for developing more robust and reliable economic forecasting systems capable of supporting early warning mechanisms for financial crises.

4.0 RESULTS

The findings of this study highlight the effectiveness of artificial intelligence (AI) models in improving the prediction of economic recessions when combined with multi-source data. By analyzing previous empirical studies and conceptual frameworks, the results demonstrate that AI-based predictive models provide significant advantages

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over traditional econometric forecasting techniques. These advantages include improved prediction accuracy, better handling of nonlinear relationships, and the ability to process large and diverse datasets.
One of the key findings from the reviewed studies is that machine learning models can detect early recession signals more effectively than conventional statistical models. Traditional econometric approaches often rely on a limited number of macroeconomic indicators and assume linear relationships among variables. In contrast, AI models such as neural networks, decision trees, and ensemble learning algorithms can identify complex interactions among multiple economic indicators. Research conducted by Molepo (2022) shows that machine learning techniques can improve recession prediction accuracy by analyzing multiple macroeconomic variables simultaneously, including GDP growth, unemployment rates, and financial market indicators.
The results also indicate that financial market data plays an important role in recession prediction models. Variables such as government bond yields, stock market indices, and credit spreads often reflect investor expectations regarding future economic conditions. Studies have shown that incorporating financial market signals into AI-based forecasting models improves the early detection of economic downturns (Castellani & Santos, 2006). These indicators frequently respond to economic uncertainty before traditional macroeconomic statistics are released, making them valuable inputs for predictive systems.
Another significant finding is the role of multi-source data integration in improving forecasting performance. Data fusion techniques allow predictive models to combine different types of economic information, including macroeconomic indicators, financial market data, global economic signals, and alternative data sources. According to Li et al. (2021), integrating heterogeneous datasets enhances the ability of predictive models to capture complex economic relationships and detect subtle patterns associated with recession risks.
Furthermore, the results show that deep learning models offer additional advantages in analyzing large-scale economic datasets. Advanced architectures such as recurrent neural networks and temporal fusion transformers can learn temporal dependencies within time-series data and forecast economic trends across different time horizons. Laborda et al. (2023) demonstrated that deep learning models can improve multi-country GDP forecasting accuracy by capturing dynamic interactions between economic variables.
The findings also suggest that hybrid predictive models that combine machine learning algorithms with traditional econometric methods can further enhance forecasting performance. Hybrid models benefit from the interpretability of statistical methods while leveraging the pattern recognition capabilities of AI techniques. This integration allows researchers to develop more robust forecasting systems capable of handling both structured economic indicators and large-scale datasets.
In addition to improved predictive accuracy, the results emphasize the potential policy implications of AI-based recession prediction systems. Early detection of economic downturns enables governments and financial institutions to implement preventive measures such as monetary policy adjustments, fiscal interventions, and financial risk management strategies. As a result, AI-driven forecasting tools can contribute to the development of more effective economic early warning systems.
Overall, the results indicate that artificial intelligence models combined with multi-source data provide a powerful framework for predicting economic recessions. These models offer significant improvements in predictive accuracy, data processing capabilities, and early detection of recessionary trends, making them valuable tools for economic analysis and policy decision-making.

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