Genome Publications
https://doi.org/10.61096/978-81-990998-5-2_8

Chapter 8

Recession Trends Analyser: A Survey on Economic Downturn Detection Using Data Analytics and Machine Learning

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Abstract: Economic recessions exert systemic pressures across macroeconomics structures, posing critical risks to fiscal policy, financial markets and socio-economic stability. Traditional recession detection methodologies predominantly depend on lagging macroeconomic indicators such as GDP contraction, inflation surges and rising unemployment rates. These retrospective signals often hinder the timely formulation of responsive strategies. The Recession Trends Analyzer (RTA) address these constraints through a hybrid framework that fuses traditional economic indicators with high-frequency, real-time data sources- including google search volumes, equity market volatility, labor market postings and sentiment derived from news and social media streams. The analytical architecture employs advanced time series forecasting modes such as ARIMA, LSTM and Facebook Prophet to capture linear and non-linear temporal dependencies. In parallel, Natural Language Processing (NLP) techniques are applied for sentiment extraction and classification from unstructured text corpora, enhancing contextual awareness of economic narratives. This chapter provides a comprehensive survey of existing recession prediction systems, critiques their methodological limitations and proposes an integrated, sector-sensitive monitoring system. By coupling predictive modeling with real-time anomaly detection and interactive visualization interfaces, the RTA offers proactive decision-support tool for economic forecasting, capable of delivering early-warning signals and enhancing policy responsiveness.

Keywords: Recession Detection, Economic Indicators, Machine Learning, Sentiment Analysis, Time Series Forecasting, Economic Monitoring, Artificial Intelligence.

Citation: Raksha, Vanipriya C.H., Sowjanya Lakshmi A. Recession Trends Analyser: A Survey on Economic Downturn Detection Using Data Analytics and Machine Learning. Machine Learning in Research and Practice: A Multidisciplinary Perspective. Genome Publications. 2025; Pp71-77. https://doi.org/10.61096/978-81-990998-5-2_8

INTRODUCTION

Economic recessions exert profound effects on both national and global economics, often resulting in widespread industrial disruptions, heightened unemployment and diminished consumer confidence [2], [4], [6], [8], [9], [12], [15], [19]. Timely detection of such downturns is critical for enabling governments, business and individuals to implement preventive and corrective strategies. Traditionally, recession analysis has been grounded in lagging macroeconomic indicators such as GDP contraction, inflation trajectories and labor market statistics [1], [3], [5], [14], [19], [21]. While these metrics provide reliable post hoc assessment, they often fall short in delivering early warnings, as they typically reflect economic distress only after recessionary conditions are already underway [14], [16].

In recent years, advances in machine learning, coupled with the availability of high frequency and real-time data, have shifted the paradigm toward predictive economic diagnostics [10], [13]. Techniques such as time series forecasting and sentiment analysis are now being employed to anticipate economic trends with greater precision [10]. Moreover, alternative data sources- including Google search patterns, financial market signals, social media discourse and job listing activity, have emerged as valuable proxies for gauging public sentiment and market dynamics [10], [13]. These unconventional indicators, when integrated with traditional economic data, offer a more holistic and timely view of economic conditions.

The proposed RTA incorporates this hybrid methodology by integrating classical macroeconomic indicators with real-time digital signals. this composite framework enhances forecasting agility and enables dynamic, sector-specific insights for a diverse user base including economists, policymakers and corporate decision-makers. This chapter resents a comprehensive overview of existing recession detection methodologies, critiques their limitations and introduces an AI-driven, interactive platform designed to deliver early, actionable economic intelligence.

LITERATURE SURVEY

Current economic monitoring platforms such as the Federal Reserve Economic Data (FRED), OCED Economic Outlook and IMF databases provide comprehensive access to historical economic indicators including GDP, inflation, unemployment and interest rates [1], [5], [14]. These tools are primarily used for academic research and policy evaluation, offering data through charts and tables that support retrospective analysis [14], [19]. However, they are largely static, lack real-time monitoring and do not include predictive modelling and alert systems [10, [16].

Most of these platforms are designed for expert users and require substantial economic knowledge to interpret, making them less accessible to non-specialists [15], [18]. However, they fail to incorporate modern data sources such as Google Trends, social media sentiment, job market analytics, and stock market behaviour, which are critical for early recession detection [10], [9], [12]. They also lack sector-specific insights, behavioural economic indicators, and real-time sentiment analysis [2], [3], [6], [8]. The absence of user-centric dashboards, automated forecasting and adaptive learning limits their practical utility in fast-changing economic environments, leaving a significant gap for a more intelligent, interactive, and predictive recession analysis system [11], [13].

Raval et al. [19] focus on Global recession and its impact on Indian economy and discusses the 2008 financial crisis with sectoral analysis and implications for India. Singh et al. [18] also focus on Global recession and India's turnaround and describes India's resilience and post-recession strategies, laying a base for comparative analysis. Thansum et al. [17] worked on focused case study that examines industry-specific vulnerabilities. Their work establishes economic patterns and vulnerabilities before modern data-driven tools became central. Later, the shift toward industry-level studies, institutional roles, and economic recovery modelling begins. Khudyakova et al. [16] focus on financial sustainability in industrial companies and evaluates the impact of recession on corporate finance and sustainability. Gunaseelan et al. [15] focus on recession during COVID-19 in India and captures COVID-triggered economic contraction, signalling a major shift in recession dynamics. Kose et al. [14] focus on Global recessions and offers quantitative global recession frameworks, key indicators, and stylized facts from 150 years. Their research builds the framework for predictive economic modeling and benchmarking.

Further, there is an emergence of machine learning, data analytics, and behavioral models for recession analysis. Kolluru et al. [13] focus on Recovery strategies in high-GDP EU countries and case-based exploration of post-recession fiscal and economic planning. Iheanacho [12] focus on Job satisfaction under recession and studies micro-level sentiment indicators. Gupta et al. [11] focus on Liquidity impact on Power Grid Corporation and applies financial ratio analysis during downturns. Chandra et al. [10] focus on Stock prediction using Google Trends & Twitter and provides web-scraped and social media data for recession trend modeling. Tiwari [9] focus on Global recession's impact on Indian economy and an updated macroeconomic survey using data visualization and indicators. These methodologies provide strong integration of real-time data sources, moving from qualitative to predictive modeling. Doetsch et al. [8] focus on Recession's impact on perinatal health in Portugal and illustrates how downturns affect social health metrics. Solorzano-Rivas et al. [7] focus on water table recession modeling and though environmental, it introduces analytical rigor in time-series modeling, useful in economic domains. Schaffartzik et al. [6] focus on material inequality post-Great Recession in the EU and on resource disparity and inequality analytics. Seio et al. [5] develops Policy models: Taylor Rule, Phillips Curve & Okun's Law and Models recession detection through macroeconomic rules. Leal et al. [4] focus on Brazil's tale of two recessions and provides a narrative comparison model, essential for case-based AI training. These research work lays groundwork for deep learning, cross-country modeling, and policy-based detection systems. Further, pioneering studies blending AI, innovation analysis, and behavioral forecasting and Kumar et al. [3] focus on Recessions, institutions & innovation and panel regression and patent analysis reveal exploration under economic pressure. Bietenbeck et al. [2] focus on Prosocial behavior shaped by recessions and highlights psychological and behavioral evolution. Arguelles et al. [1] focus on Combustion recession modeling (engineering). Though from engineering, offers computational diagnostic methodology relevant for economic simulations. This tier marks the transition to simulation-based, AI-driven recession understanding and forecasting.

There is a gradual shift from macro-description, industry-specific diagnosis, behavioral impact, data-driven detection to AI-enhanced prediction. The chapter proposes a hybrid machine learning framework integrating, Microeconomic indicators, Sectoral financials, Behavioral analytics, Real-time web data and Innovation metrics. While this survey offers a comprehensive overview of the literature spanning macroeconomic analyses, sector-specific impacts, behavioral shifts, and data-drive recession modeling, several limitations emerge from the review. First, a significant number of earlier studies focus predominantly on descriptive macroeconomic impacts without employing advanced computational techniques [17], [18], [19], thereby limiting their utility for real-time detection or forecasting. Moreover, while data-driven approaches are gaining traction [10], [11], [14], many of these methods rely on small datasets, single-country studies, or lack rigorous validation across temporal or geographic variations, reducing their generalizability. Additionally, behavioral and institutional studies [2], [6], [8] often emphasize long-term effects, but lack integration with real-time economic indicators or machine learning models, leaving a gap in dynamic recession prediction frameworks. Another limitation is the under representation of cross-disciplinary models that combines economic, social, and technological variables, despite emerging interest in hybrid analytics [1], [3], [5]. Finally, many studies employ retrospective analysis [4], [9], [12], [13], making them less applicable for proactive or anticipatory economic policy making. Bridging these gaps requires the development of real-time, multi-variable, and AI-integrated frameworks for holistic recession detection and response.

PROPOSED METHODOLOGY

The dynamic and multifaceted nature of economic recessions necessitates a holistic and adaptive analytical approach. Based on the progression of existing literature and identified limitations, this chapter proposes a Hybrid Machine Learning Framework for real-time recession detection and trend analysis. The framework is designed to integrate diverse data sources and analytical dimensions, combining traditional economic metrics with contemporary digital and behavioral signals for robust, proactive economic monitoring. The framework components include

(i) Macroeconomic Indicators

Core macroeconomic variables such as GDP growth rate, inflation, unemployment rate, industrial production, and interest rates serve as the foundational layer of the framework. These indicators offer historical and structural insights into economic performance and are traditionally used by policymakers and economists to declare recessions. Incorporating them into machine learning models allows for capturing established recession signals while calibrating predictive accuracy over time [14], [17], [19].

(ii) Sectorial Financial Data

The financial performance of key industries-especially IT/ITES, manufacturing, power, and infrastructure-can offer early clues of economic distress [11], [16], [17]. Sector-specific ratios (e.g., liquidity, profitability, asset turnover) from company balance sheets provide granular visibility into economic slowdowns that macro indicators may obscure. Machine learning models can be trained to detect sectoral stress patterns that precede broader economic contraction.

(iii) Behavioral Analytics

Behavioral changes in consumer sentiment, job satisfaction, prosocial attitudes, and investor psychology, especially during or following economic turbulence, are increasingly measurable and valuable [2], [8], [12]. Surveys, labor market trends, and sentiment analysis from social data can serve as soft indicators of recession onset or recovery. These metrics allow the framework to reflect how real people and businesses are reacting, adding a socio-economic dimension to purely financial or macroeconomic models.

(iv) Real-Time Web Data

The use of real-time, highly-frequency data such as Google Trends, Twitter sentiment, news media analytics, and web-scraped data has gained prominence in recent research [10]. These data streams can serve as leading indicators, detecting shifts in search behavior, market concern, or consumer demand before formal statistics are published. Natural Language Processing (NLP) techniques, combined with real-time dashboards, enable timely alerts systems for economic downturns.

(v) Innovation and Technology Metrics

Innovation resilience plays a crucial role during recessions, as technological adoption often accelerates in times of disruption. Tracking patent filings, R&D investments, start-up

activity, and digital transformation indices provides insights into the economy's adaptability and recovery potential [3], [13]. These innovation indicators also help to differentiate between structural downturns and cyclical slowdowns.
The hybrid model employs a multi-level machine learning architecture is shown in fig (a).

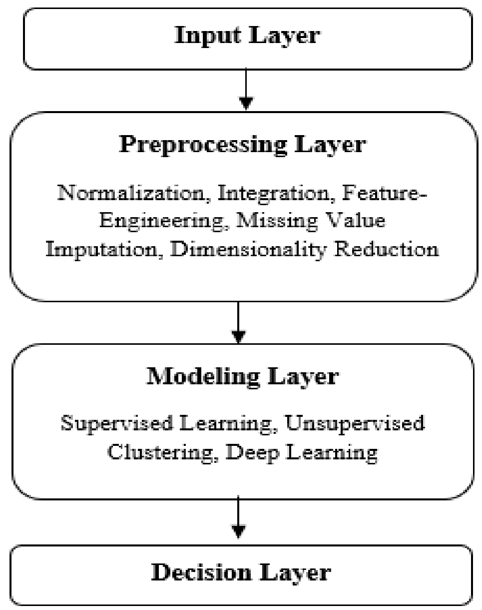

Fig 1: Hybrid Machine Learning Schematic Diagram

Input Layer- gathers data from structured (economic reports, financial statements) and unstructured (tweets, search trends) sources. *Preprocessing Layer* - normalizes and integrates data using feature engineering, missing value imputation, and dimensionality reduction. *Modeling Layer* - uses a combination of supervised learning (e.g., Random Forest, XGBoost), unsupervised clustering (e.g., K-means for pattern recognition), and deep learning (LSTM for time-series forecasting). *Decision Layer* - synthesizes outputs into a recession risk score, supported by visual dashboards and alert systems.

CONCLUSION

This chapter provides a broad spectrum of literature and empirical studies addressing economic recessions, with particular attention to India and global economies. It covered traditional economic perspectives, the effects on sectoral domains (e.g., IT/ITES, industrial sustainability, health, and labor), and transitioned into the emerging use of data analytics and machine learning for recession detection and analysis. The growing availability of real-time and behavioral data sources, such as Google Trends and social medial feeds, presents a transformative opportunity for early warnings systems and impacts assessment during downturns. However, current models often rely on siloed datasets or traditional econometric tools that do not capture the complexity and interconnectedness of modern economic systems.

FUTURE SCOPE

The next phase in recession analysis lies in the integration of hybrid machine learning architectures combining, Macroeconomic Variables (GDP, inflation, interest rates), Sector-Specific Financial Metrics (liquidity ratios, stock indices), Behavioral Analytics (consumer sentiment, employment behavior), Web-Sources Real-Time Data (Google trends, Twitter sentiment, news), Innovation Indicators (patent filings, R&D investment shifts).

Future research can explore the automated detection of early economic stress signals using deep learning and ensemble models that weigh multiple data streams dynamically. There is also significant potential in regionalized economic risk modeling, allowing policymaker to deploy targeted interventions. Finally, interdisciplinary collaboration across economics, data science, and behavioral research will be vital in designing robust, explainable, and ethically-aligned AI models for economic downturn prediction.

This hybrid framework, once validated, can become a decision support system for governments, financial institutions, and business to prepare for and mitigate the impact of future recessions more effectively.

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