International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Can Machine Learning Predict the Indian Recession?

***Mayank Rajput*[1], *Meeta Rajput*[2]**

[1]Indian Institute of Management, Sirmaur : mba08107@iimsirmaur.ac.in
[2]Indian Institute of Technology, Delhi : ch7200179@iitd.ac.in

ABSTRACT

This research project aims to develop a predictive model using random forest regression to forecast the possibility of a recession in India. The study utilizes key economic indicators, including Consumer Price Index (CPI), Interest Rates, Government Securities, Bonds, M3 money supply, and Global WTI crude price. By analyzing these variables, the research seeks to identify their impact on the likelihood of an economic recession in India. The results will provide valuable insights for policymakers and investors to make informed decisions regarding economic stability and mitigate potential risks.

Keywords: Recession, Consumer Price Index, Interest Rates, Government Securities, Bonds, M3 money supply, Global WTI crude price, COVID-19, Great Recession, Random Forest Regression

1. Introduction

Economic recessions have significant implications for countries, affecting various sectors and individuals' livelihoods. These effects can have a ripple effect throughout the economy, leading to further economic decline. Accurate predictions of such downturns are crucial for policymakers, financial institutions, and investors to implement timely measures and reduce adverse consequences.

This research focuses on developing a predictive model using random forest regression to forecast the possibility of a recession in India. Random forest regression is a machine learning algorithm that can be used to predict categorical outcomes, such as whether or not a recession will occur, using the data of the past 23 years. It considers a range of economic indicators, including CPI, Interest Rates, Government Securities, Bonds, M3 money supply, and Global WTI crude price, to capture both domestic and international factors affecting India's economy, as discussed by DUA et al. [1].

2. Literature Review

This study by Hossein et al. [2] employs the singular spectrum analysis (SSA) method to forecast and analyze the values of a time series representing the economic indicators of the United Kingdom before, during, and after the 2008 recession. SSA is utilized to decompose the time series data into its constituent components, including trends, seasonalities, and noise, allowing for a comprehensive understanding of the series' behavior during this critical period. The application of SSA provides valuable insights into the economic landscape, facilitating accurate predictions and a deeper understanding of the factors contributing to the recession.

Puglia et al. [3] aimed to assess the predictive ability of Term spreads and other financial variables in forecasting recessions in the United States. They employed neural networks as a tool for analysis and compared their performance with that of probit regression, a traditional statistical technique. To validate and evaluate the machine learning classifiers, a three-step econometric method was utilized. This method consisted of NTS Cross-Validation, McNemar's Tests, and Shapley Value Decomposition, which facilitated statistical inference and explanation of the forecasts. Ultimately, the study demonstrated the efficacy of neural networks in classification tasks and shed light on the potential of macro-financial variables in predicting recessions.

The research done by Nyberg et al. [4] investigates the forecasting power of variables for the probability of recessions in both United States and Germany. The examined variables include the domestic term spread, stock returns, and the differential of interest rate between the given countries. After analyzing these indicators, the study aims to assess their effectiveness in forecasting economic downturns in both nations.

While the research carried out by Anderson et al. [5] focuses on constructing autoregressive leading nonlinear indicator models to predict the growth of GDP, using the spread of interest rate and increase in M2 as crucial indicators. The study utilizes data from FRED, which provides a comprehensive economic dataset for the US. The primary objective of this analysis is to utilize GDP growth as a predictor for a recession. By incorporating these leading indicators and studying their relationship with GDP growth, the research aims to develop a reliable framework for forecasting economic downturns and capturing nonlinear dynamics in the data.

Gogas et al. [6] focused on evaluating the predictive capability of the yield curve in relation to the real GDP cycle of the U.S. They employed the Support Vector Machines (SVM) technique for classification, achieving a noteworthy accuracy of 66.7% for the overall classification and 100% accuracy specifically for predicting 6 recessions. These results were then compared to the performance of alternative standard models, such as the logit and probit models. The study highlights the effectiveness of using the yield curve as a predictive technique for anticipating changes in the real DP cycle of the U.S. and demonstrates the superior performance of SVM compared to traditional models in recession forecasting.

This research by Fornari et al. [7] tried to forecast the probability of recession for Germany, the United States, and Japan. This study combined a widely-used probit approach with a Vector AutoRegressive (VAR) model to endogenize the dynamics of regressors, resulting in a combined model referred to as a 'ProbVAR.' The research consists of two strands: one aims to forecast the industrial production or GDP growth rates, while the other seeks to forecast expansion and recession phases in the business cycle. By incorporating both strands, the study provides a comprehensive analysis of recession probabilities in these three economies and sheds light on the forecasting power of the yield curve slope.

Other research by Puglia et al. [8] employed ML techniques to analyze the effectiveness of Term spreads and other macroeconomic and financial variables in forecasting recessions of US, comparing them to probit regression. Contrary to expectations, the authors proposed a more conservative cross-validation strategy, which suggests that probit regression needs to be favored rather than machine learning methods. The study highlighted the importance of considering the bias-variance tradeoff, especially when working with small and sparse datasets. It emphasizes the significance of having experience in tuning the hyperparameters of each algorithm to achieve optimal performance in such scenarios.

Davig et al. [9] explored the utilization of a model of Naïve Bayes as a tool for predicting recessions. The approach was closely associated with both Logistic regression and Markov-switching model techniques. By leveraging the Naïve Bayes model, the study aimed to capture the underlying patterns and relationships in economic data that are indicative of recessionary periods. This approach drew upon the principles of probabilistic modeling and conditional independence assumptions to make predictions.

Gour et al. [10] examined the use of ANN models for predicting inflation, as measured by the Consumer Price Index of India. The researchers compared the performance of ANN models with other traditional models such as ARIMA and VAR. The findings indicated that ANN models achieve better accuracy in inflation forecasting compared to the alternative models. Additionally, the study explored the factors that influence inflation, which are also interconnected with the occurrence of recessions.

In the study done by Cadahia et al.[11], decision-tree ensemble methods are utilized to analyze the variable importance of Treasury term spreads in predicting economic recessions in the United States. The researchers aim to develop an interpretable forecasting model by understanding the term structure and yield curve dynamics. Through their analysis, they identify several term spreads, which prove to be effective predictors of recessions in the US. By focusing on these key indicators, the study provides valuable insights into creating an accurate and interpretable forecasting model for future recessions.

Kaur et al. [12] investigated the role of leading indicators in predicting business cycles and identifying expansion, contraction, or recession phases within the economy. Data from various sources, including the Bureau of Economic Indicators, the OECD, Handbook of Statistics on the Reserve Bank of India, the Indian Economy, was utilized. The study employed a probit model to analyze the data and attempt to forecast growth.

The research done by Coulombe et al. [13] provides a comprehensive review of forecasting economies using machine learning. The findings indicate that ML methods generally outperform traditional forecasting approaches, particularly in volatile and uncertain environments. However, the paper highlights a gap in research regarding the use of ML for forecasting. The results show that nonlinear ML methods with extrapolation capabilities demonstrate particular effectiveness in forecasting during this unprecedented crisis.

While Tang et al.[14] highlighted the significance of time series forecasting technology for stock price analysis and decision-making based on historical data. Their study specifically focused on the application of Long Short-Term Memory (LSTM) models and identified optimal parameters. The research further explored the connection between stock price prediction and economic recessions, utilizing the accuracy of different models with the help of MAPE values. The findings demonstrated that the LSTM model is better in accurately forecasting economic recessions through stock price prediction.

The previous studies examining recession prediction have shown a limited utilization of machine learning models such as random forests. However, it is evident that there is a need to explore the potential of these models further. In our research paper, we aim to address this research gap by incorporating machine learning techniques, specifically random forest, to predict recessions in India. Additionally, we recognize the importance of considering real-time variables. By incorporating real-time data into our models, we aim to enhance the accuracy and timeliness of recession predictions.

Furthermore, previous studies have identified certain variables that are significant in predicting recessions in India. In our research, we will focus on incorporating these key variables into our models and exploring their predictive power. Additionally, alternative bivariate nonlinear models that consider the relationship between output and spread will be examined to provide a more comprehensive understanding of recession dynamics in India. We will also explore the use of averages of financial variables from various countries to assess the forecasting power of financial factors. By considering a broader set of variables beyond those explored in previous studies, we aim to gain a more comprehensive understanding of the factors influencing recessions in India. Lastly, we acknowledge the need to effectively handle hyperparameters in machine learning models to optimize their performance, and we will incorporate this in our research methodology. Ultimately, our research aims to contribute to filling the research gap by providing insights into the most effective machine-learning methods for recession prediction in India during 2008 and that posed by the COVID-19 pandemic using the data for the past 23 years.

3. Methodology

3.1 Data Collection:

The historical information used to calculate the selected economic indicators came from reputable sources such as the RBI, Ministry of Fin, FRED, foreign economic databases. The dataset will cover the last 23 years, during which time it will be sure to record various economic cycles, such as recessionary and non-recessionary times.

3.2 Data Preprocessing:

The data that was obtained was prepared for analysis by being thoroughly cleaned, arranged, and formatted using Excel in the most effective manner. In order to guarantee the dataset's completeness, quality, and integrity, the missing values, outliers, and inconsistencies were dealt with in an acceptable manner.

3.3 Feature Selection:

Relevant features were chosen on the basis of the theoretical significance of those features as well as their statistical association with recessions derived from the continuous testing of the model. CPI, interest rates, government securities, bond prices, M3 money supply, and the global price of WTI crude oil will be among the selected features.

3.4 Model Development:

Random forest regression, a robust machine learning algorithm, was employed to build the predictive model, as discussed by Liu et al. [15]. In order to conduct an appropriate evaluation of the model's performance, the dataset was first split into training and testing sets. Methods of hyperparameter tweaking were utilized in order to fine-tune the model and bring forth its full potential. The Random Forest Regression provides an estimate of the likelihood of a recession, with a value of 0.5 on a scale from 0 to 1 serving as the threshold for a recession.

4. Datasets

The dataset used for this analysis was compiled from a variety of reliable sources, including the Reserve Bank of India (RBI), the Ministry of Finance, and the Federal Reserve Economic Data (FRED) maintained by the Research Division of the Federal Reserve Bank of St. Louis. These organizations are renowned for their accurate and comprehensive economic data, making them ideal sources for collecting information on the Indian economy. Additionally, foreign economic databases were also consulted to ensure a global perspective.

The dataset covers a substantial time period of the last 23 years, enabling the inclusion of multiple economic cycles, including both recessionary and non-recessionary periods. This extended time frame allows for a comprehensive analysis of economic trends and patterns over time, providing valuable insights into the Indian economy's performance. By including various economic cycles, the dataset can capture the fluctuations and dynamics of the economy during different phases, offering a more nuanced understanding of its behavior and performance.

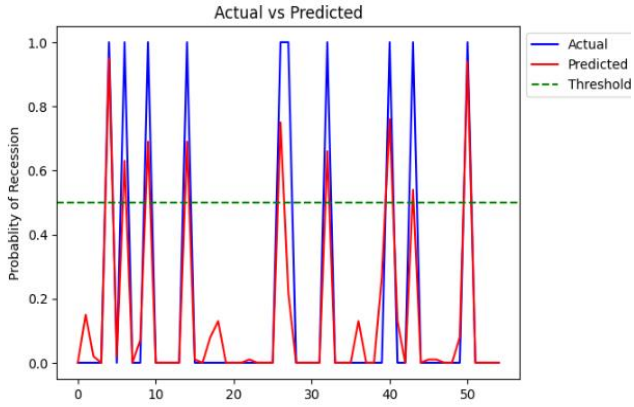
5. Results

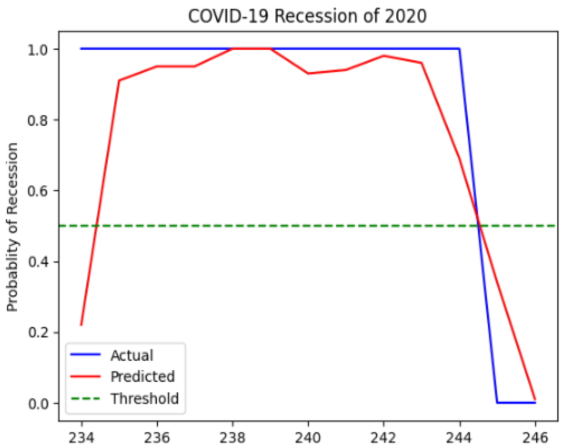
The developed model exhibits a strong fit with the seasonal patterns observed in the data, yielding an impressive R-squared value of 0.80984. By considering multiple variables such as the Consumer Price Index (CPI), interest rates, government securities, bond prices, M3 money supply, and the global price of WTI crude oil, the model takes a comprehensive approach to assess the economic landscape during the recession.

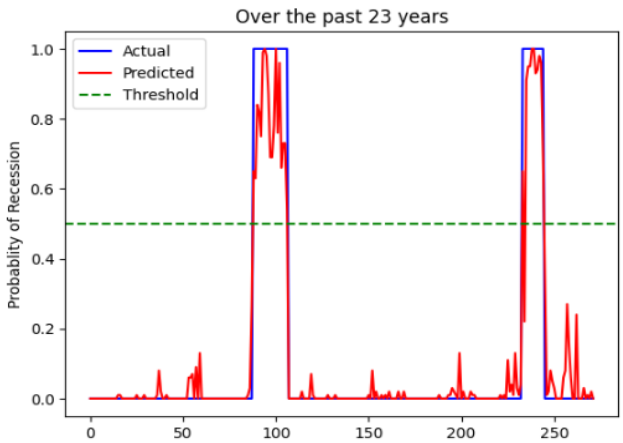
Moreover, the model's ability to generate values between 0 and 1 is a valuable asset for identifying the signs of a recession. With a threshold set at 0.5, where values above this indicate the presence of a recession, the model effectively distinguishes between recessionary and non-recessionary periods. Additionally, the proximity of the model's values to 1 signifies the magnitude and significance of the predicted recession.

The model was trained to predict the economic downturn of the Great Recession in 2008 and successfully applied this knowledge to forecast the recession triggered by the COVID-19 pandemic in 2020. These findings indicate the model's ability to recognize patterns and provide accurate predictions in the context of economic recessions. Furthermore, the model attributes varying levels of importance to different variables, shedding light on the key drivers of the recession. Among the factors considered, interest rates, government securities, bond prices, and the global price of WTI crude oil emerge as the most influential contributors. This finding underscores the interconnectedness of financial markets, as fluctuations in interest rates and the prices of government securities and bonds impact the overall economic conditions, as confirmed by the research conducted by Vidyakala et al. [16].

Additionally, the significant role of the global price of WTI crude oil highlights the influence of external factors on domestic economic conditions, as confirmed by Candila et al. [17]. By discerning the relative importance of these variables, the model enhances our understanding of the underlying mechanisms driving recessions, providing valuable insights for policymakers and researchers alike. Overall, the developed model's robust fit, high R-squared value, and ability to predict the presence of a recession highlight its effectiveness in analyzing and forecasting economic downturns. By considering multiple variables and identifying the most impactful factors, the model offers a comprehensive approach to understanding the Recession of 2008 and 2020. The insights provided by this model can guide policymakers and researchers in formulating effective strategies to mitigate the impact of recessions and promote sustainable economic growth.







6. Statistical Analysis

6.1 Correlation Test:

	Consumer Price Index	Interest Rates, Government Securities, Bonds	M3 for India	Global WTI crude price	Recession Yes=1, No=0
Consumer Price Index	1				
Interest Rates, Government Securities, Bonds	-0.395959224	1			
M3 for India	0.967464968	-0.330083084	1		
Global WTI crude price	0.247141965	0.426188432	0.248529425	1	
Recession Yes=1, No=0	-0.203063995	-0.031847661	-0.18264973	0.217628468	1

There is a negative correlation between a recession and the Consumer Price Index (CPI). The research highlights the impact of reduced consumer spending during a recession. When individuals face financial constraints, they tend to purchase fewer goods and services, resulting in a decrease in overall demand.

This decline in consumer demand puts downward pressure on prices, leading to a lower CPI, as studied by Nicholas et al.[18]. Moreover, businesses also experience reduced sales and lower revenues during a recession, as people's earnings and disposable income are typically reduced.

As a result, businesses may lower their prices to stimulate demand, further contributing to a negative correlation between a recession and the CPI.

The Correlation Test asserts a negative correlation between a recession and interest rates, government securities, and bonds. Research has shown that during a recession, central banks often adopt expansionary monetary policies to stimulate economic activity. These policies involve lowering interest rates to encourage borrowing and investment. As the demand for loans slows down during a recession, the reduced loan demand leads to a decrease in interest rates. Lower interest rates also make government securities and bonds relatively more attractive to investors seeking safer investment options.

The findings suggest a negative correlation between a recession and the M3 money supply in India. Research indicates that during a recession, the growth rate of money supply tends to slow down. Although the M3 money supply may still increase, the rate of growth is typically lower compared to periods of economic expansion. Central banks often implement monetary policies to stabilize the economy during a recession, which can affect the pace of money supply growth, as determined by Cochrane [19].

There is a positive correlation between recession and global WTI crude price because, during a recession, demand for oil decreases as businesses and consumers cut back on spending. However, the supply of oil does not decrease as much, as oil-producing countries are reluctant to lower prices and lose revenue. This leads to an increase in the price of oil, which can further exacerbate the recession.

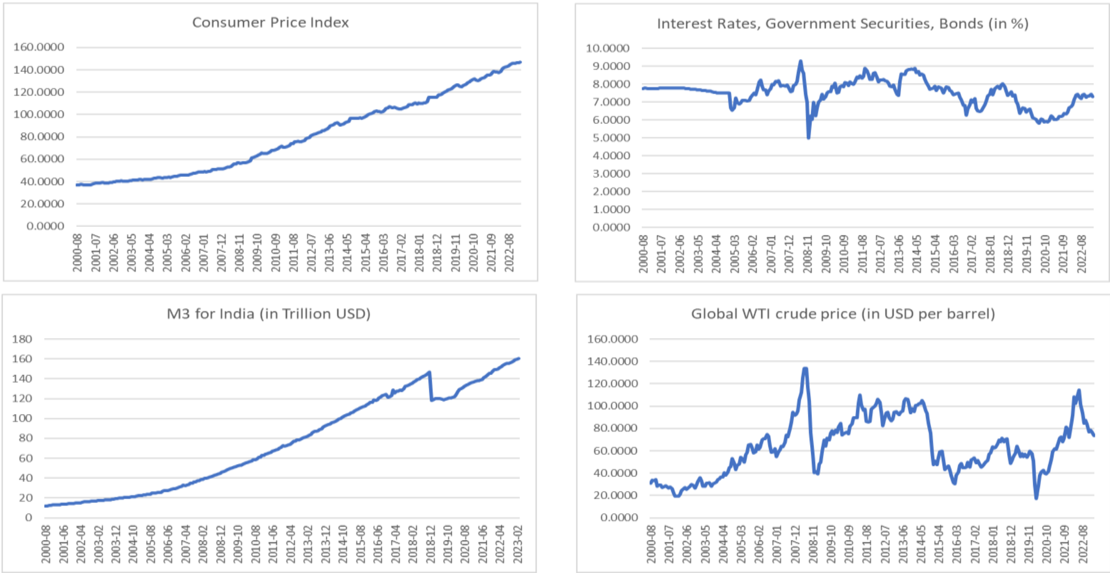
6.2 Regression Test:

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	0.070980976	0.01290841	5.4988182	9.0206E-08	0.045564447	0.096397504	0.045564447	0.096397504
Consumer Price Index	-0.29696599	0.05785066	-5.133321	5.52814E-07	-0.410873391	-0.18305859	-0.410873391	-0.183058589
Interest Rates, Government Securities, Bonds	-0.12431410	0.02049298	-6.066181	4.5212E-09	-0.164664583	-0.08396363	-0.164664583	-0.083963626
M3 for India	0.19430226	0.05499077	3.5333615	0.000484229	0.086025963	0.302578557	0.086025963	0.302578557
Global WTI crude price	0.46145164	0.07815422	5.9043725	1.08481E-08	0.307566721	0.61533656	0.307566721	0.61533656

The obtained p-values, significantly below the chosen significance level of 0.01, provides strong evidence to reject the null hypothesis and establish a statistically significant relationship of recession, CPI, interest rates, M3 money supply, and global WTI crude price. This suggests a mutual dependency among these variables. Additionally, the p-value obtained in the regression test supports the findings of the correlation test, strengthening the validity of the observed relationships. Statistical hypothesis testing relies on p-values to assess the likelihood of observing the relationships by chance.

When p-values are markedly lower than the significance level, it indicates that the observed association is unlikely due to randomness. Hence, the null hypothesis is discarded, and a meaningful relationship between recession and the independent variables is established. The regression analysis, considering multiple independent variables simultaneously, reinforces the evidence of interdependence. Overall, these findings highlight the statistical significance and interconnectedness of recession with CPI, interest rates, M3 money supply, and global WTI crude price.

7. Visualization of Dataset



The Great Recession of 2008 was characterized by a noticeable but not statistically significant decrease in the Consumer Price Index (CPI) after December 2007. It was accompanied by a sharp dip in interest rates and a slower increase in the M3 money supply. Additionally, there was a significant surge in global West Texas Intermediate (WTI) crude oil prices during this period, which further exemplified the economic downturn.

In contrast, the Recession of 2020, triggered by the COVID-19 pandemic, also saw the Consumer Price Index experiencing a fall, although not a significant one, throughout the year. Similarly, there was a sharp decline in interest rates, but the M3 money supply actually decreased during this recession. Interestingly, contrary to the 2008 recession, the Global WTI crude oil prices started rising rapidly during the 2020 recession, further underscoring the unprecedented nature of the economic crisis caused by the COVID-19 virus.

These two distinct periods of economic recession demonstrate varying trends in key indicators. While both exhibited a lack of significant decrease in the Consumer Price Index, they differed in terms of the M3 money supply. The Great Recession of 2008 witnessed a slower growth rate, whereas the Recession of 2020 experienced an actual decrease. Furthermore, the sharp dip in interest rates was a common characteristic of both recessions. However, the direction of Global WTI experienced a surge during both the 2008 and 2020 recessions.

Overall, the divergent patterns observed in the CPI, M3 money supply, interest rates, and crude oil prices during the Recession of 2008 as well as the Recession of 2020 highlight the unique circumstances and triggers that led to each economic downturn. Understanding these distinctive factors is crucial for policymakers and economists to formulate effective strategies to mitigate the impact of future recessions and ensure economic stability and resilience.

8. Discussion

The results of this research paper provide valuable insights into the economic dynamics of the Great Recession of 2008 and the Recession of 2020 due to COVID-19. The strong fit of the developed model with the seasonal patterns observed in the data with high R-squared value of 0.80984, demonstrates its effectiveness in capturing the complexities of these recessions. By considering multiple variables such as the Consumer Price Index, interest rates, government securities, bond prices, M3 money supply, and the global price of WTI crude oil, the model offers a comprehensive approach to analyzing economic downturns. These findings contribute to our understanding of the interconnectedness of financial markets [20] and external factors on domestic economic conditions [21].

Furthermore, the identification of key drivers of recessions is significant for policymakers and researchers. The importance attributed to variables such as interest rates, government securities, bond prices, and the global price of WTI crude oil highlights their role in shaping economic conditions during recessions.

Policymakers can utilize this information to devise effective strategies to mitigate the impact of recessions while researchers gain insights into the underlying mechanisms and transmission channels during these economic downturns [22]. Overall, this research provides a solid foundation for further exploration and analysis of recessions, aiding in the development of proactive measures to foster sustainable economic growth and stability.

9. Conclusion

In conclusion, the findings of this research paper shed light on the economic landscape during the Recession of 2008 and the Recession of 2020, offering valuable insights for policymakers, economists, and researchers. The developed model's strong fit with the data, high R-squared value, and ability to predict the presence of a recession demonstrate its effectiveness in analyzing and forecasting economic downturns. By considering multiple variables and identifying key drivers, such as interest rates, government securities, bond prices, and the global price of WTI crude oil, the model provides a comprehensive understanding of the intricate relationships within the economic system.

Looking ahead, there are several avenues for future research. First, researchers can explore the impact of specific policy responses and interventions during recessions to assess their effectiveness and identify best practices. Furthermore, investigating the spillover effects of recessions across different sectors and regions can provide valuable insights into the interconnectedness of economies. Finally, considering the lessons learned from the Recessions discussed, policymakers can develop proactive measures and policies to better mitigate the impact of future recessions and promote economic resilience. By addressing these research gaps, scholars can contribute to the ongoing understanding of recessions and support evidence-based decision-making for sustainable economic development.

10. References

1. DUA, PAMI, and ANIRVAN BANERJI. "An Indicator Approach to Business and Growth Rate Cycles: The Case of India." *Indian Economic Review*, vol. 36, no. 1, 2001, pp. 55–78. *JSTOR*, http://www.jstor.org/stable/29794225. Accessed 2 July 2023.
2. Hossein Hassani, Saeed Heravi, Gary Brown & Daniel Ayoubkhani (2013) Forecasting before, during, and after recession with singular spectrum analysis, Journal of Applied Statistics, 40:10, 2290-2302, DOI: 10.1080/02664763.2013.810193
3. Puglia, Michael & Tucker, Adam. (2021). Neural Networks, the Treasury Yield Curve, and Recession Forecasting. The Journal of Financial Data Science. 3. jfds.2021.1.061. 10.3905/jfds.2021.1.061.
4. Nyberg, Henri. (2010). Dynamic Probit Models and Financial Variables in Recession Forecasting. Journal of Forecasting. 29. 10.1002/for.1161.
5. Anderson, Heather & Vahid, Farshid. (2001). Predicting the Probability of a Recession with Nonlinear Autoregressive Leading Indicator Models. Macroeconomic Dynamics. 5. 482-505. 10.1017/S1365100500000432.
6. Gogas, Periklis & Papadimitriou, Theophilos & Matthaiou, Maria & Chrysanthidou, Efthymia. (2014). Yield Curve and Recession Forecasting in a Machine Learning Framework. Computational Economics. to appear. 10.1007/s10614-014-9432-0.
7. Fornari, Fabio & Lemke, Wolfgang. (2010). Predicting Recession Probabilities with Financial Variables Over Multiple Horizons. SSRN Electronic Journal. 10.2139/ssrn.1685168.
8. Puglia, Michael, and Adam Tucker (2020). "Machine Learning, the Treasury Yield Curve and Recession Forecasting," Finance and Economics Discussion Series 2020-038. Washington: Board of Governors of the Federal Reserve System, https://doi.org/10.17016/FEDS.2020.038.
9. Davig, Troy & Hall, Aaron. (2019). Recession forecasting using Bayesian classification. International Journal of Forecasting. 35. 848-867. 10.1016/j.ijforecast.2018.08.005.
10. Gour Sundar Mitra Thakur, Rupak Bhattacharyya, Seema Sarkar Mondal, Artificial Neural Network Based Model for Forecasting of Inflation in India, Fuzzy Information and Engineering, Volume 8, Issue 1, 2016, Pages 87-100, ISSN 1616-8658, https://doi.org/10.1016/j.fiae.2016.03.005
11. Cadahia Delgado, Pedro & Congregado, Emilio & Golpe, Antonio & Vides, José Carlos. (2022). The Yield Curve as a Recession Leading Indicator. An Application for Gradient Boosting and Random Forest. International Journal of Interactive Multimedia and Artificial Intelligence. 7. 7-19. 10.9781/ijimai.2022.02.006.
12. Kaur, Sumanpreet. (2019). An Attempt to Predict Recession for the Indian Economy Using Leading Indicators. Asian Development Policy Review. 7. 171-190. 10.18488/journal.107.2019.73.171.190.
13. Coulombe, Philippe & Marcellino, Massimiliano & Stevanovic, Dalibor. (2021). CAN MACHINE LEARNING CATCH THE COVID-19 RECESSION?. National Institute Economic Review. 256. 71-109. 10.1017/nie.2021.10.
14. Tang, YM & Chau, Ka Yin & Li, Wenqiang & Wan, TW. (2020). Forecasting Economic Recession Through Share Price in Logistics Industries with Artificial Intelligence (AI). Computation. 8. 10.3390/computation8030070.
15. Liu, Yanli & Wang, Yourong & Zhang, Jian. (2012). New Machine Learning Algorithm: Random Forest. 7473. 246-252. 10.1007/978-3-642-34062-8_32.

16. Vidyakala, K. & Madhuvanthi, S. & Poornima, S.. (2009). Recession in Indian Banking Sector. SSRN Electronic Journal. 10.2139/ssrn.1494873.
17. Candila, V.; Maximov, D.; Mikhaylov, A.; Moiseev, N.; Senjyu, T.; Tryndina, N. On the Relationship between Oil and Exchange Rates of Oil-Exporting and Oil-Importing Countries: From the Great Recession Period to the COVID-19 Era. *Energies* **2021**, *14*, 8046. https://doi.org/10.3390/en14238046
18. Nicholas Kaldor, Inflation and Recession in the World Economy, *The Economic Journal*, Volume 86, Issue 344, 1 December 1976, Pages 703–714, https://doi.org/10.2307/2231447
19. Cochrane, John. (2010). Understanding Policy in the Great Recession: Some Unpleasant Fiscal Arithmetic. European Economic Review. 55. 2-30. 10.1016/j.euroecorev.2010.11.002.
20. King, Thomas B. and Levin, Andrew and Perli, Roberto, Financial Market Perceptions of Recession Risk (October 2007). FEDS Working Paper No. 2007-57, Available at SSRN: https://ssrn.com/abstract=1049081 or http://dx.doi.org/10.2139/ssrn.1049081
21. Morana, Claudio & Bagliano, Fabio. (2010). The Great Recession: US Dynamics and Spillovers to the World Economy. Journal of Banking & Finance. 36. 10.2139/ssrn.1709955.
22. Giannone, D., Lenza, M. & Reichlin, L. Market Freedom and the Global Recession. *IMF Econ Rev* 59, 111–135 (2011). https://doi.org/10.1057/imfer.2010.14