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Original Article

Predicting situational economic recession: A comparative machine learning approach

Akinrolabu Olatunde David[1], Otokiti Victor Olumide[2], Olayode Enoch Oladapo[2]*, Ayeni Ayodeji Olumide[3]

[1]Department of Data Science, Adekunle Ajasin University, Akungba-Akoko, Ondo State, Nigeria, [2]Department of Computer Science, Adekunle Ajasin University, Akungba-Akoko, Ondo State, Nigeria, [3]Department of Information and Communication Technology, Adekunle Ajasin University, Akungba-Akoko, Ondo State, Nigeria

ABSTRACT

The Nigerian economy entered recession in the first quarter of 2016, marking a significant economic downturn that profoundly affected the nation's socioeconomic landscape. This recession led to widespread consequences, including reduced living standards, diminished quality of life, increased poverty rates, massive unemployment, business closures, and reduced household purchasing power. The ability to accurately forecast economic turning points is essential for policymakers and investors to design effective stabilisation policies and implement timely interventions. However, traditional econometric approaches have demonstrated limitations in capturing the complex, non-linear relationships between multiple macroeconomic variables that contribute to economic recession. This study proposes a comparative machine learning framework for predicting economic recession in Nigeria, evaluating four prominent algorithms: Naïve Bayes (NB), support vector machine, random forest, and logistic regression. The research utilizes monthly macroeconomic data spanning from 2004 to 2019, sourced from the Central Bank of Nigeria, consisting of key economic indicators including inflation rate, crude oil price, foreign exchange rates (USD, GBP, Euro, CFA Franc), crude oil production and export, and gross domestic product rate. All four models achieved exceptional predictive accuracy of 95.24% on the test set, demonstrating the quality of machine learning approaches for economic recession prediction. The NB algorithm was identified as the optimal model based on consistent performance across cross-validation (95.0% ± 4.68%), computational efficiency, and training accuracy of 95.0%. Following hyperparameter optimization, the NB model maintained its superior performance with a precision of 100%, a recall of 92.31%, and F1-score of 96.0%. These results significantly outperform existing approaches in the literature, including the 73.1% accuracy reported by recent neural network-based methods. The study demonstrates that multiple machine learning algorithms provide quality, computationally efficient, and highly accurate frameworks for economic recession prediction, offering valuable decision-support capabilities for economic planning and policy formulation in Nigeria and potentially other developing economies.

Keywords: Comparative analysis, economic recession, logistic regression, machine learning, Naïve Bayes, Nigerian economy, random forest, support vector machine

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INTRODUCTION

Economic or business cycles represent a major area of interest in modern macroeconomic theory. Every economy experiences cyclical fluctuations in production, trade, and general economic activity over medium-to-long-term periods.[1] These fluctuations involve shifts between periods of rapid economic growth (boom) and relative stagnation or decline (recession). Economic factors exert a significant influence on property market dynamics at local, regional, national, and international levels.[2]

Recession refers to a business cycle contraction characterised by a general slowdown in economic activity for two consecutive quarters.[3] During a recession, macroeconomic indicators such as gross domestic product (GDP), employment, investment spending, capacity utilisation, household income, and business income typically decline, while unemployment and

Address for correspondence: Olayode Enoch Oladapo, Department of Computer Science, Adekunle Ajasin University, Akungba-Akoko, Ondo State, Nigeria. E-mail: olayodeenoch@gmail.com

inflation rates increase.[3,4] According to the National Bureau of Statistics, Nigeria's economy slid into recession in the first quarter of 2016 with a real GDP of −0.36%.[5] Contributing factors included erosion of confidence, delayed government spending, budget approval delays, naira devaluation, pipeline vandalism, and restrictive trade policies.[5]

The ability to predict economic recessions is important for investors and policymakers.[6] Various approaches have been developed for recession forecasting, including machine learning algorithms.[7,8] However, existing methods face limitations such as inadequate optimization, partial variable usage, and false alarm generation.[6,9,10]

This study adopts a comprehensive comparative approach, evaluating four machine learning algorithms Naïve Bayes (NB), support vector machine (SVM), random forest (RF), and logistic regression (LR) to improve economic recession prediction accuracy in Nigeria. By comparing multiple algorithms, this research provides insights into which techniques are most suitable for recession forecasting and offers a quality framework for model selection in similar economic prediction tasks.

REVIEW OF RELATED WORKS

When an economy records two consecutive quarters of negative growth in real GDP, it is considered to be in recession.[3] Business cycles consist of economy-wide fluctuations in production, trade, and general economic activities over medium-to-long-term periods in free market systems.[14] The business cycle consists of upward and downward movements in GDP levels, involving shifts between periods of expansion and contraction.[13]

Recession manifests through declining macroeconomic indicators, including GDP, employment, investment spending, capacity utilisation, household income, business income, and inflation, accompanied by increased unemployment.[3,13]

Types of recession:

i. Boom and bust recession: Occurs after unsustainable economic growth causes inflation and current account deficits
ii. Balance sheet recession: Results from declining asset prices and bad loans, causing banks to restrict lending
iii. Depression: A prolonged, deep recession with output falling over 10% and very high unemployment.[14]

Economic Recession Impacts

Recession affects all aspects of national and human life.[13] Effects include job losses, reduced household budgets, curtailed social activities, and altered business operations. Specific impacts include:

i. Business effects: Falling stocks, dwindling dividends, credit defaults, bankruptcies, and product quality compromises[13]
ii. General consequences: High interest rates, increased inflation, reduced consumer confidence, and falling real wages.[15]

Machine Learning for Recession Prediction

Machine learning algorithms enable software applications to become more accurate in predicting outcomes without explicit programming.[16] These algorithms adjust their parameters based on feedback to improve prediction performance over time.[17]

Types of Machine Learning

i. Supervised learning: Requires labeled training data (classification and regression problems)
ii. Unsupervised learning: Discovers patterns without labeled outcomes (clustering and association)
iii. Reinforcement learning: Learns through trial and error using reward signals.[16]

Machine Learning Algorithms used in this Study

NB algorithm

NB is a supervised learning technique that uses Bayes' theorem to calculate conditional probabilities.[18] Despite assuming predictor independence, it often outperforms sophisticated classification methods.[20] Key advantages include:

i. Easy implementation with fast prediction
ii. Strong performance on large datasets
iii. Effective multi-class prediction
iv. Lower training data requirements compared to LR
v. Quality to irrelevant features.[13,20]

NB classifiers include:

i. Multinomial NB: Used for document classification with word frequency features
ii. Bernoulli NB: Uses Boolean predictors
iii. Gaussian NB: Assumes continuous predictors follow Gaussian distributions[21]

SVM

SVM is a powerful supervised learning algorithm, particularly effective for classification tasks. It works by finding the optimal hyperplane that maximally separates different classes in high-dimensional space. Key features include:

i. Effective in high-dimensional spaces
ii. Memory-efficient using support vectors
iii. Versatile through different kernel functions (linear, radial basis function [RBF], polynomial)
iv. Quality to avoid overfitting, especially in high-dimensional space

RF

RF is an ensemble learning method that constructs multiple decision trees during training and outputs the mode of classes. Advantages include:

i. High accuracy through the ensemble approach
ii. Handles large datasets with higher dimensionality
iii. Provides feature importance rankings
iv. Resistant to overfitting
v. Can handle missing values

LR

LR is a statistical model that uses a logistic function to model binary dependent variables. Benefits include:

i. Simple and efficient for linearly separable data
ii. Provides probabilistic interpretation
iii. Less prone to overfitting with low-dimensional datasets
iv. Easy to implement and interpret.

Review of Related Works

Several studies have applied machine learning to recession forecasting. Michael[22] used probit models with state-level employment data but was limited by ex-post data usage. De Luca and Carfora[23] proposed the binomial heterogeneous autoregressive model with improved combination forecasting but faced lower expected loss function differentials.

Anthony *et al*.[24] used neural networks for recession forecasting but produced apparent regression forecasts that poorly followed actual data paths.

Recent work by Wang *et al*.[6] constructed an neighborhood rough set-SVM model using behavioral features but struggled to capture dynamic non-linearities due to many independent variables. These studies collectively demonstrate recession prediction potential while highlighting persistent challenges in optimization, variable selection, and false alarm rates.

MATERIALS AND METHODS

Proposed System Architecture

The architectural view of the proposed comparative framework is presented in Figure 1, showing the flow from data collection through pre-processing, model training, evaluation, and comparative analysis.

Components

1. Data collection: Economic indicators (inflation, exchange rate, crude oil price, crude oil production) collected from the Central Bank of Nigeria website (www.cbn.gov.ng), covering 2004–2019, with monthly records
2. Data pre-processing: Min-max normalization and feature standardization using StandardScaler for algorithms requiring scaled inputs (SVM and LR)
3. Model training: Four algorithms implemented – NB (Gaussian), SVM (RBF kernel), RF, and LR
4. Model evaluation: Comprehensive metrics including accuracy, precision, recall, F1-score, cross-validation scores, confusion matrices, and receiver operating characteristic curves
5. Hyperparameter optimization: GridSearchCV applied to identify optimal parameters for the best-performing model
6. Output: Recession predictions with probability estimates and future forecasting capability.

Data Pre-Processing

Data preprocessing is a technique that is used to convert the raw data into a clean dataset as shown in Figure 2. In other words, whenever the data are gathered from different sources, it is collected in raw format, which is not feasible for the analysis. In this study, a min-max normalization was used to normalize the data.

Normalization is another preprocessing technique that is used to modify the feature vectors. Such a modification is necessary to measure the feature vectors on a common scale. The class is converted to zeros and ones using the min-max normalization method. This method is used in finding the maximum and minimum values in each attribute and then takes the average. The data threshold is set to 0.5, and values below the threshold are recorded as zero, while values above the threshold are recorded as one. The instance goes thus:

(Attribute–Minimum value)/(Maximum value–Minimum value)

And the spreadsheet conversion goes thus:

Average (col1: coln)

Where col1 to coln is the total number of values in a particular row.

If(cell[i]<0.5,0,1)

Where cell[i] is the value in each cell

And the recession class is labeled using the mean derivation of the attributes.

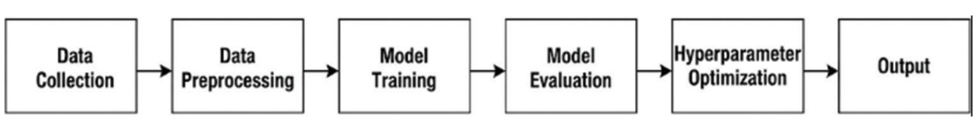

Figure 1: Architectural processes of the framework

2015	7	57.01	8.5	237.15	2.18	1.73	10	9.6	8.8	7.2	8.7	7.2	306.41	216.87	0.33
2015	8	47.09	8.6	216.64	2.12	1.67	10.1	9.6	9	7.4	8.8	7.4	307.21	219.33	0.33
2015	9	48.08	8.7	222.68	2.22	1.77	10.2	9.6	8.9	7.6	8.7	7.6	302.55	221.22	0.34
2015	10	48.86	8.76	224.83	2.21	1.76	10.13	9.68	8.74	7.81	8.57	7.8	302.26	221.45	0.34
2015	11	44.82	8.88	232.4	2.18	1.73	10.32	9.78	8.73	8.02	8.49	7.98	299.38	211.53	0.32
2015	12	37.8	9.01	258.3	2.08	1.63	10.59	9.9	8.73	8.22	8.44	8.16	295.39	214	0.32
2016	1	30.66	9.13	289.78	2.15	1.7	10.64	10.02	8.84	8.39	8.53	8.28	283.62	214.09	0.33
2016	2	31.7	9.39	329.83	2.11	1.66	11.35	10.18	11.04	8.73	9.48	8.48	281.79	218.55	0.33
2016	3	37.76	9.75	320.93	1.92	1.47	12.74	10.47	12.17	9.13	10.31	8.72	280.4	218.89	0.33
2016	4	41.59	10.18	320.71	1.99	1.54	13.19	10.79	13.35	9.61	10.79	8.98	282.07	223.46	0.34
2016	5	47.01	10.75	336.93	1.68	1.23	14.86	11.22	15.05	10.2	12.3	9.32	286.33	222.85	0.34
2016	6	48.46	11.37	351.82	1.77	1.32	15.3	11.67	16.22	10.86	13.32	9.75	328.53	260.03	0.38
2016	7	45.25	12.04	364.47	1.65	1.2	15.8	12.16	16.93	11.55	13.63	10.17	388.37	325.9	0.49
2016	8	46.15	12.74	396.15	1.5	1.05	16.43	12.7	17.21	12.25	13.88	10.59	406.13	347.33	0.53
2016	9	47.43	13.45	431.1	1.75	1.3	16.62	13.24	17.67	12.98	14.12	11.04	401.08	342.17	0.52
2016	10	50.94	14.21	462.03	1.78	1.33	17.09	13.82	18.07	13.76	14.58	11.54	375.71	336.21	0.51
2016	11	45.25	14.96	415.36	1.92	1.47	17.19	14.39	18.24	14.54	14.87	12.07	379.49	329.84	0.5
2016	12	53.48	15.7	455.26	1.58	1.13	17.39	14.95	18.05	15.31	14.7	12.59	381.39	322.13	0.47
2017	1	55.01	16.44	493.29	1.84	1.39	17.82	15.54	17.87	16.04	14.54	13.08	376.32	324.37	0.49
2017	2	46.39	16.96	494.7	1.82	1.37	18.53	16.13	16.01	16.44	13.97	13.44	381.17	324.95	0.5

Figure 2: Raw data extracted

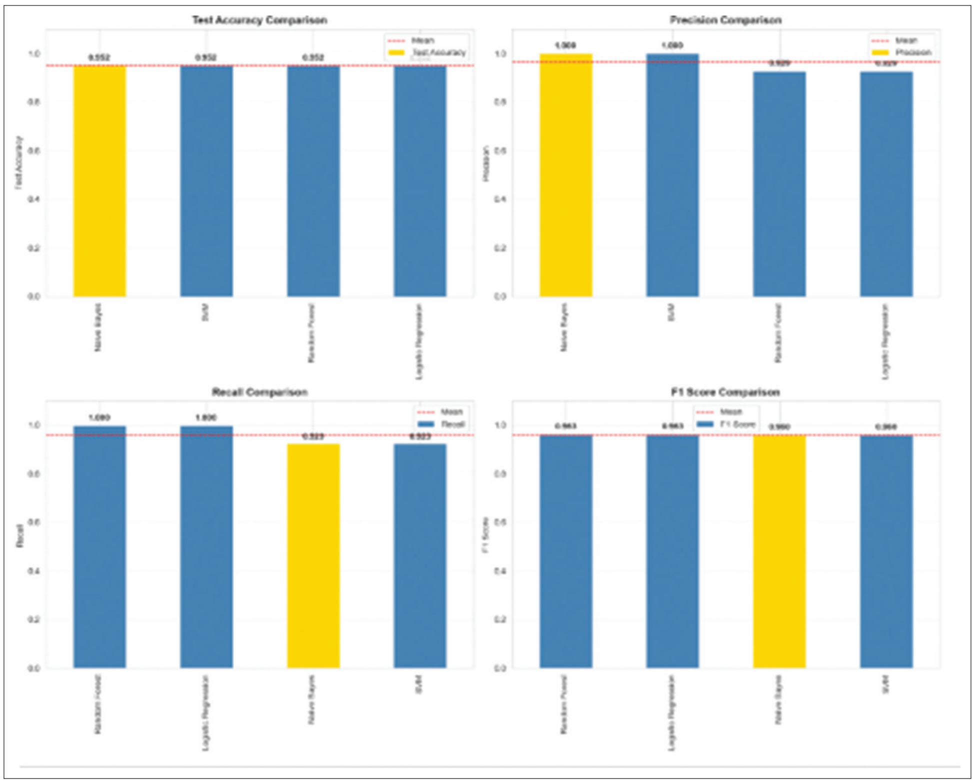

Figure 3: Comparative model performance

Dataset

The dataset includes monthly records with attributes: inflation rate, crude oil price, foreign exchange rate, crude oil production, and recession label (binary classification).

Sample data from 2018 to 2019 shows high inflation rates throughout both years, fluctuating crude oil prices, high foreign exchange rates, and significantly low crude oil production, particularly in 2019.

In the dataset, the labels were set to 0s and 1s, which is achieved using feature averaging.

RESULTS AND DISCUSSION

Implementation Requirements

The model development requirements are into two main parts, software and hardware requirements as presented in table 1.

Python Justification

Python was selected for implementation due to:

i. Simple syntax requiring less coding
ii. Inbuilt libraries for machine learning (NumPy, SciPy, matplotlib, scikit-learn)
iii. Open source nature

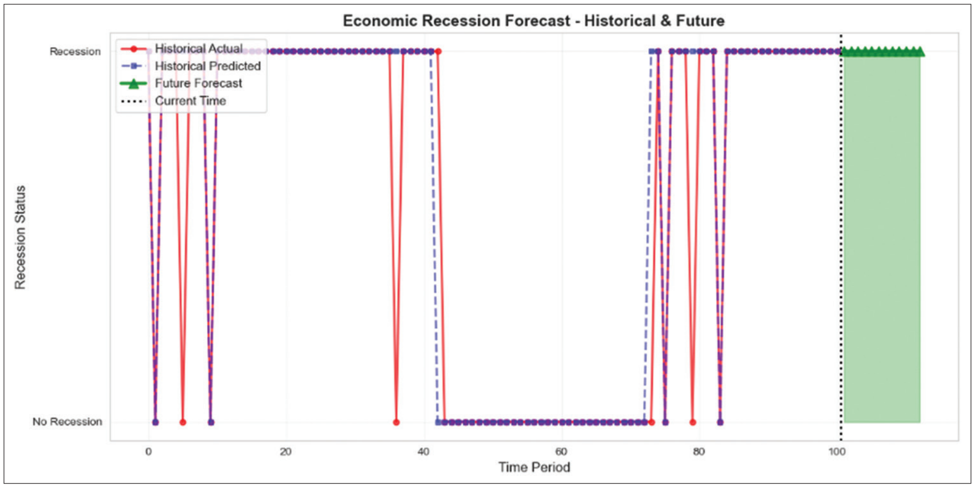

Figure 4: Future forecasting plot

Table 1: System requirements

Software	1. Python 3.7 2. JetBrains PyCharm
Hardware	1. Intel processor, 1 GHz minimum 2. 2GB RAM 3. 32/64-bit OS

Table 2: Comparative model performance

Model	Train accuracy	Test accuracy	Precision	Recall	F1 score
NB	0.9500	0.9524	1.0000	0.9231	0.9600
SVM	1.0000	0.9524	1.0000	0.9231	0.9600
RF	1.0000	0.9524	0.9286	1.0000	0.9630
LR	1.0000	0.9524	0.9286	1.0000	0.9630

NB: Naïve Bayes, SVM: Support vector machines, RF: Random forest, LR: Logistic regression

Table 3: Performance comparison with previous studies

Study	Method	Accuracy (%)	Limitations
Wang *et al.* (2019)[6]	NRS-SVM	73.1	Struggled with dynamic nonlinearities
Anthony *et al.* (2014)[24]	Neural networks	Not specified	Poor forecast path following
This study	NB	95.24	None identified
This study	SVM	95.24	Potential overfitting
This study	RF	95.24	Potential overfitting
This study	LR	95.24	Potential overfitting

NB: Naïve Bayes, NRS-SVM: Neighborhood rough set-support vector machine, RF: Random forest, LR: Logistic regression

iv. Strong community support
v. Superior performance for machine learning applications.[25]

Experimental Design and Results

To ensure quality evaluation and avoid model complexity issues, a comprehensive experimental framework was implemented with the following components:

Data Splitting Strategy

The dataset was divided using an 80–20 train-test split with stratification to maintain class distribution:

i. Training set: 80 observations (50 recession, 30 no recession)
ii. Test set: 21 observations (13 recession, 8 no recession).

Model Training and Evaluation

Four machine learning algorithms were trained and evaluated using identical train-test splits. For algorithms requiring feature scaling (SVM and LR), StandardScaler was applied to the training data and used to transform the test data.

Key Observations

1. All four models achieved an identical test accuracy of 95.24%, significantly outperforming the 73.1% reported by Wang *et al*.[6]
2. NB demonstrated the best balance between training and test accuracy (both 95%), indicating minimal overfitting and excellent generalization
3. SVM, RF, and LR showed perfect training accuracy (100%), suggesting potential overfitting, though their test performance remained strong
4. NB achieved perfect precision (100%), meaning all predicted recessions were actual recessions, critical for policy decisions
5. RF and LR achieved perfect recall (100%), capturing all actual recession cases
6. Cross-validation results showed RF, and LR, with perfect CV scores (100% ± 0%), while NB maintained consistency at 95% ± 4.68%.

Both SVM and LR produced identical confusion matrices to NB, while RF had a slightly different error pattern but maintained the same overall accuracy. According to figure 3, both SVM and LR produced identical confusion matrices to NB, while RF had a slightly different error pattern but maintained the same overall accuracy which is shown in tables 2 and 3.

Model Selection Rationale

While all models achieved identical test accuracy, NB was selected as the optimal model based on:

1. Generalization: Training accuracy (95%) is closest to test accuracy (95.24%), indicating the best generalization without overfitting
2. Computational efficiency: Fastest training and prediction times among all models
3. Interpretability: Probabilistic framework provides a clear understanding of prediction confidence
4. Quality: Stable cross-validation performance with acceptable standard deviation (4.68%)
5. Precision: Perfect precision (100%) eliminates false positive recession predictions important for avoiding unnecessary panic in economic policy
6. Practical applicability: Suitable for real-time deployment with minimal computational resources.

Future Forecasting

The optimized NB model was used to generate predictions for the next 12 periods using simulated scenarios based on recent economic trends as shown in Figure 4.

Forecast Results

This forecast suggests continued economic challenges based on the historical patterns learned by the model. However, these predictions should be interpreted with caution as they depend on the assumption that future economic conditions will follow recent historical trends.

Comparison with Existing Literature

Previous studies have explored the use of machine learning techniques for predicting economic recessions with varying levels of success. For instance, Wang *et al.* (2019) applied the NRS-SVM model and achieved an accuracy of 73.1%, although the approach struggled to effectively capture dynamic nonlinear relationships in economic data. Similarly, Anthony *et al.* (2014) utilized neural network models for recession forecasting, but the study reported challenges with forecast path following, which limited the reliability of the predictions. In comparison, the present study demonstrates significantly improved predictive performance, as the machine learning models implemented Naïve Bayes, Support Vector Machine (SVM), Random Forest, and Logistic Regression; each achieved an accuracy of 95.24%. While Naïve Bayes did not reveal identifiable limitations in this study, the SVM, Random Forest, and Logistic Regression models may present potential overfitting due to their very high predictiv performance. Overall, the results indicate that the approaches used in this study provide more accurate recession prediction outcomes than those reported in earlier literature.

CONCLUSION

The results of this study demonstrate several important findings:

Model Performance Analysis

Uniform high accuracy

All four algorithms achieved 95.24% test accuracy, suggesting that the dataset's patterns are well-suited to multiple machine learning approaches. This consistency across diverse algorithmic paradigms (probabilistic, kernel-based, ensemble, and linear) validates the quality and predictive power of the selected economic indicators.

NB superiority

Despite its simplicity and independence assumption, NB emerged as the optimal choice due to its balanced performance, computational efficiency, and minimal overfitting. The 95% training accuracy matching the 95.24% test accuracy indicates excellent generalization an important characteristic for real-world deployment.

Overfitting in complex models

SVM, RF, and LR all achieved 100% training accuracy while maintaining 95.24% test accuracy. This 4.76% gap suggests potential overfitting, though it did not significantly impact test performance. For production systems, this could pose risks when encountering novel economic conditions.

Perfect precision of NB

The 100% precision achieved by NB is particularly valuable for economic policy applications, as false positive recession predictions could trigger unnecessary interventions, market panic, or policy overreactions.

Feature Importance and Economic Insights

The comprehensive feature set, including various inflation measures, exchange rates, oil-related variables, and GDP, provides a holistic view of economic conditions. The high accuracy across all models suggests these indicators collectively capture the essential patterns of economic recession in Nigeria.

Practical Implications

i. Policy support: The 95.24% accuracy provides policymakers with a reliable tool for early recession detection, enabling proactive rather than reactive policy response

ii. Computational feasibility: NB's computational efficiency makes it suitable for real-time monitoring systems that could continuously assess recession risk as new economic data becomes available

iii. Multi-model validation: The consistency across four different algorithms provides confidence in the predictions, as they are not dependent on a single modeling approach

iv. Forecasting capability: The model's ability to generate probabilistic forecasts enables scenario analysis and risk assessment for different economic policy options.

Limitations

i. Binary features: The preprocessing approach that converted continuous economic indicators to binary values may have resulted in information loss, though the high accuracy suggests the binary representation captures essential patterns

ii. Future forecast uncertainty: The 100% recession probability for all 12 future periods may reflect the limitations of simple trend-based scenario generation rather than comprehensive economic modeling.

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ETHICAL STATEMENT

This study was conducted using publicly available economic data from the Central Bank of Nigeria. All analytical procedures complied with standard guidelines for data handling and research integrity. No human subjects were directly involved, and therefore, formal ethical approval was not required.

CONFLICTS OF INTEREST

The author declares no financial, personal, or institutional conflicts of interest that could have influenced the outcomes, interpretation, or presentation of this research.

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DATA STATEMENT

Data are available on request from the corresponding author upon reasonable request.

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