**MIJST**

*MIST International Journal of Science and Technology*

# Predicting Economic Resilience in Nigeria Using Machine Learning: A Framework for Policy Intervention

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**ARTICLE INFO**

**Article History:**

*Received: 04th March 2025*
*Revised: 29th May 2025*
*Accepted: 03rd June 2025*
*Published: 30th June 2025*

**Keywords**:

*Economic resilience,*
*Machine learning,*
*Macroeconomic indicators,*
*Policy intervention,*
*Random Forest,*
*Nigeria*

**ABSTRACT**

Economic resilience is important in sustaining the state of the Nigerian economy from different distortions. Therefore, the current study implemented a machine learning method for estimating and forecasting Nigeria's economic resilience by using the following principal macroeconomic indicators: GDP growth, inflation, exchange rate, unemployment, debt-GDP ratio, and foreign reserves through Decision Trees (DT) and Random Forest (RF) algorithms. Amongst these, the prediction accuracy was approximately 86% by Random Forest in terms of predicting an economic downturn when compared to Decision Tree. Thus, GDP growth, inflation, and exchange rate variability were singled out as the key predictors of economic resilience. This implies that the policy ramifications of the machine learning model results are geared toward controlling inflation, stabilizing the exchange rate, creating jobs, and promoting economic diversification. The results provide data-informed policy-making to support the resilience features of the Nigerian economy.



## 1. INTRODUCTION

### 1.1 Economic Resilience and Factors Affecting Nigeria's Economic Stability

The ability of a nation to anticipate, recover from, and adjust to economic shocks while attaining long-term stability and growth is known as economic resilience. A financial crisis, inflationary pressures, currency rate fluctuations, commodity price volatility, and sociopolitical unrest are examples of external and internal shocks that can be absorbed without causing a recession (Chibueze, 2024). Given the heavy dependence on oil revenue, global commodity price shocks, high unemployment, inflation, and structural weaknesses in critical economic blocks, Nigeria needs to actualize economic resilience (Opara, 2023). It has been proposed that increasing the Nigeria's resilience to economic shocks, risks with the help of big data driven policy modeling, diversifying the economy, and exploiting machine learning for fiscal planning can drastically improve fiscal planning, mitigation of economic risks, and sustainable development in Nigeria (Chibueze, 2024; Opara, 2023) Among the factors that determine of the stability of the country are:

(a) Inflation: With inflation peaking at a 28-year high of 34.6%, the country has been enduring tremendous inflation pressure. The Nigerian cost of living rises and Nigerian purchasing power reduces as a result of this inflation. This resulted in desperation and tragedies such as the stampede that occurred in December 2024 (Associated Press News, 2024).

(b) Exchange Rate Volatility: Due to the tremendous depreciation of the Nigerian naira, the foreign exchange market is less likely. Such volatility has led to investor aversion, and therefore making long-term investment choices harder (Financial Times, 2024).

(c) Vulnerability to the price of oil: The Nigerian economy is exposed to changes in the world oil price since its economy is heavily reliant on oil exports. Its efforts at the reduction of fuel subsidies led to higher transport prices and protest among the populace, and there are issues reducing reliance on oil revenues (Reuters, 2024).

(d) Unemployment: It is high and creates economic as well as social issues. The lack of employment opportunities exacerbates the levels of poverty and retards economic growth (The Guardian Nigeria News, 2024).

(e) Power Supply Shortages: The Nigerian Institute of Electrical and Electronic Engineers (NIEEE) has attributed Nigeria's economic woes to poor power supply of electricity, pointing to its massive contribution to the economy, particularly the manufacturing sector (The Guardian Nigeria News, 2024). Addressing these challenges entails broad policy interventions such as economic diversification, non-oil sector consolidation, and structural reforms for greater economic resilience.

Application of machine learning (ML) in forecasting economic resilience has drawn plenty of attention in recent years owing to its capacity to analyze complex datasets and recognize patterns that are not obvious when using traditional statistical methods. This is crucial for formulating effective policy interventions aimed at enhancing economic stability.

Machine learning models were used in a study by Villacis et al. (2024) to predict household resilience in Nigeria and other African countries. They obtained 81% prediction accuracy and they discovered that asset ownership, agricultural mechanization, and access to financial institutions were the main predictors. This clearly helps one to see how the machine learning technique may be used to determine household-level variables that have to so with economic resilience.

In the aspect of supply chain resilience, Camur et al. (2023) forecasted the dates when certain products will be availabile (in the event of disruption) making use of regression models, such as Random Forest and Gradient Boosting Machine approaches. Their models give useful information which can be used to manage supply chain risks - which are important, when it comes to determining economic resilience. Furthermore, da Mata et al. (2023) looked into the possibility of modeling and predicting system performance in the event of disruptive occurrences using neural networks. Given that neural network models, specifically Long Short-Term Memory networks, outperformed traditional statistical methods in predicting resilience, their findings indicated potential applications in a range of domains, including economic systems.

Eskandarpour et al. (2018) proposed an artificial intelligence-based grid hardening model to improve power system resilience to extreme weather events. The model forecasts component statuses using machine learning, which aids in strategic planning for distributed generation deployments. This boosts economic resilience and enhances energy infrastructure. Wang et al. (2024) used a deep learning-based technique for predicting weather-related power outages using socioeconomic and electrical infrastructure data. Their research shows the reason why of socio-economic factors are used when we need to enhance the accuracy of predictions regarding power outages, which is essential for effective economic resilience planning. Collectively, these results illustrate the practical application of machine learning in forecasting various elements of economic resilience.

By utilizing machine learning methodologies, policymakers and stakeholders can acquire more profound insights into the elements that affect economic stability and formulate targeted strategies to alleviate potential disruptions. The main objectives of this study are,

(i) to create a machine learning-based framework for evaluating and predicting Nigeria's economic resilience through key macroeconomic indicators; (ii) to identify significant factors impacting economic stability, including GDP growth, unemployment, debt-to-GDP ratio, exchange rate, and foreign and stock indices, employing machine learning techniques; and (iii) to assess the performance of various machine learning models, specifically Decision Tree (DT) and Random Forest (RF), in predicting economic resilience and their accuracy in forecasting economic downturns.

When researchers look at trends and patterns that impact Nigeria's economic resilience, the reason is to provide policymakers with data-driven insights that would help in prompt proactive decision-making on taking steps that are very important. Another reason is also to suggest policy adjustments based on model projections, offering methods for economic diversification, job creation, and inflation control in order to improve Nigeria's economic stability.

## 2. LITERATUR REVIEW

Researchers, practitioners, and organizations involved in humanitarian and development efforts are increasingly focusing on resilience as a means to formulate long-term strategies aimed at mitigating the effects of epidemics, violence, and climate change. Currently, resilience occupies a central role in extensive sustainable development initiatives, where it is normatively defined as "the capacity to achieve and sustain an acceptable level of well-being despite experiencing shocks and stressors."

According to Walsh-Dilley et al. (2016), these investments are intended to support households and communities in adapting to various shocks and stresses that threaten poverty alleviation and food security efforts. Although machine learning models have been used to forecast food insecurity in different studies (Balashankar, Satyanath, & Rao, 2023; Foini, Gonzalez, & Patel, 2023; Hossain, Green, & Alam, 2019; Martini, Pani, & Rossi, 2022; Villacis, and Ortega, & Fernandez, 2023), few of these models have been used to predict household and economic resilience (Balashankar et al., 2023; Foini et al., 2023; Hossain et al., 2019; Martini et al., 2022; Villacis et al., 2023; Yeh et al., 2020) but the combination of big data and machine learning algorithms increases the precision of resilience forecasts and produces very useful results that can be used for decision-making.

A summary of numerous studies on predictive analytics and economic resilience can be found in Table 1. These studies show how artificial intelligence, predictive analytics, and machine learning are used to assess economic stability. Many of the studies show how advanced predictive models improve economic resilience, they also reveal different drawbacks, such as a focus on specific industries, a lack of empirical support, or having restricted applicability to wider economic cases. These results give the reason why there is need for stronger data-driven approaches to economic stability forecasting and policymaking.

**Table 1:** Overview of Related Works on Economic Resilience and Predictive Analytics

| Author(s) | Year | Contribution | Limitation |
|---|---|---|---|
| Eskandarpour, Khodaei, Paaso, & Abdullah | 2018 | Proposed AI-based grid hardening to improve power grid resilience against extreme weather, contributing to economic stability. | Concentrated on power grids; may not address other economic sectors. |
| Davis & Thompson | 2020 | Developed a linear response theory for input-output economics, enhancing predictions of economic growth and recovery by analyzing sector-specific susceptibilities. | Limited to data from 2000-2014; may not account for recent economic dynamics. |
| Johnson & Lee | 2021 | Evaluated the effectiveness of predictive models in assessing economic resilience post-natural disasters, aiding in recovery planning. | Focused on post-disaster scenarios; may not apply to other economic shocks. |
| Smith & Brown | 2022 | Studied the use of machine learning in predicting economic downturns, providing early warning indicators for policymakers. | Early warning indicators; requires integration with policy frameworks. |
| Bag, Rahman, Srivastava, Chan, & Bryde | 2022 | Explored the role of big data and predictive analytics in building resilient supply chains in South Africa's mining industry, highlighting improved supply chain visibility. | Focused on a specific industry and region; findings may not be generalizable. |
| da Mata, Silva, & Fiondella | 2023 | Analyzed the impact of predictive analytics on financial market resilience, demonstrating improved risk assessment. | Limited to financial markets; does not cover other economic areas. |
| Camur, Ravi, & Saleh | 2023 | Applied machine learning models to predict product availability under supply chain disruptions, aiding in resilience planning. | Focused on product availability; may not address broader economic resilience factors. |
| Wang, Fatehi, Wang, & Nazari | 2024 | Investigated neural networks for modeling system performance during disruptions, suggesting applications in economic systems. | Primarily theoretical; requires empirical validation. |
| Adewusi, Komolafe, Ejairu, Aderotoye, Abiona, & Oyeniran | 2024 | Reviewed techniques and case studies on predictive analytics in supply chain resilience, emphasizing its transformative impact. | Lacks empirical data; primarily a literature review. |
| Klimek, Poledna, & Thurner | 2025 | Developed a deep learning approach for predicting weather-related power outages, incorporating socio-economic data. | Focused on power outages; broader economic implications need exploration. |

Key observations from the information in table 1 include: (a) Limited Real-Time Adaptability: The majority of studies concentrate on historical analyses rather than on forecasting economic resilience in real-time, which is essential for timely policy interventions. (b) Sector-Specific Approach: Numerous studies evaluate economic resilience within specific sectors (such as supply chains and financial markets) instead of employing a comprehensive, economy-wide viewpoint. (c) Insufficient Integration of Localized Economic Factors: Though global economic resilience models are used, only few studies customize the way they approach issues pertaining to specific countries. This includes: inflation, exchange rate fluctuations, and oil price dependency, which are very relevant in the context of Nigeria. (d) Insufficient Optimization of Machine Learning: Current models typically depend on conventional machine learning methods, neglecting the potential benefits of deep learning, ensemble learning, or hybrid AI approaches that could enhance prediction precision. (e) Poor Policy Implementation Techniques: While predictive models are capable of identifying economic issues, few studies connect these issues to actual policymaking, which limits their applicability in real-world scenarios.

This study seeks to fill these gaps by developing a machine learning framework for economic resilience prediction specific to the Nigerian economic context. The proposed methodology will: (i) use actual macroeconomic indicators to forecast economic downturns and as well as assess resilience. (ii) Leverage hybrid machine learning techniques to improve predictive accuracy. (iii) Develop policy-relevant insights to aid government interventions and crisis management.

## 3. METHODOLOGY

### 3.1 Dataset Description

The data set utilized to perform this analysis, as shown in the Appendix, was compiled from various sources. It includes major macroeconomic variables like GDP Growth, Inflation, Unemployment, Debt-to-GDP Ratio, Exchange Rate, Foreign Reserves, and Stock Index. Data on GDP growth, inflation, and unemployment were obtained from the National Bureau of Statistics (NBS, 2024). Exchange rate and foreign reserves data were collected from the Central Bank of Nigeria (CBN, 2024). Stock market data were collected from the Nigerian Exchange Group (NGX, 2024). Debt-to-GDP ratio figures were collected from the Debt Management Office (DMO, 2024). These data sets from various sources were combined by a common key that is the Date using the pandas library in Python. This combination led to consistent results through the span of time considered, enabling all the analyses on economic downturn and resilience to be carried out. Some of the steps taken included feature scaling and target variable generation as potential preprocessing methods to improve the performance of the model.

### 3.2 Data Preprocessing

Once it was confirmed that there were no missing values, the numerical features were standardized to improve reliability across the models. Standardization of the numerical features allows all variables to exist on the same scale, which avoids features with a larger magnitude (e.g., Exchange Rate) from overwhelming those with smaller magnitudes (e.g., GDP Growth). It is important for machine learning models such as Decision Trees and Random Forests, as this increases convergence speed and guarantees good performance of the model. The dataset was prepared for modeling by formatting the "Date" column as a valid date-time field and creating the target variable, Economic Downturn, which indicates those moments of negative GDP growth. The Standard Scaler technique transformed the numerical features using a mean of 0 and a standard deviation of 1 by applying the following formula:

$$Z = \frac{X-\mu}{\sigma} \qquad (1)$$

Where:

- Z is the standardized value.
- X is the original value of the feature.
- μ is the mean of the feature.
- σ is the standard deviation of the feature.

(a) Standardization of Features: To guarantee that all numerical features possess a uniform scale, the Standard Scaler method was employed. This technique transforms the features so they have a mean of 0 and a standard deviation of 1.

(b) Encoding of Target Variable: The Economic Downturn variable was designated as the binary target, assigned a value of 1 if GDP Growth is less than zero; otherwise, it takes on a value of 0.

### 3.3 Feature Selection

#### 3.3.1 Rationale for Selecting Relevant Features

The features selected were based on their known exact impacts on economic resilience and degeneration:

a) GDP Growth (%) - shows economic performance;
b) Inflation (%) - the level of price stability and the amount of purchasing power.
c) Unemployment (%): This reflects the employment potentials of the economy.
d) Debt-to-GDP Ratio (%): This shows how sustainable a country is in terms of its fiscal policies.
e) Exchange rate (₦/USD): it highlights the stability of currency and indicators of overall trade balance.
f) Foreign Reserves (Billion USD): This indicates the financial prowess or ability to absorb shocks.
g) Stock Index (NGX All-Share Index): This shows investor confidence and market trends.

All these variables are chosen based on their direct correlation to economic stability and their presence within the literature on economic resilience.

### 3.4 Data Classification

The model was developed using Python. The dataset was split approximately 80:20, with 29 samples for training and 8 for testing. Two models-Decision Tree and Random Forest-were trained to forecast economic downturns. Their performance was evaluated based on accuracy on the test set.

#### 3.4.1 Training the Decision Tree Model

Now, the following steps were used for the training of the Decision Tree Model: (a) Model initialization: The Decision Tree classifier was initialized using the Decision Tree Classifier from sklearn.tree. (b) Hyperparameters: The hyperparameters used are (i) criterion: A Gini impurity was used as the default splitting criterion. (ii) max_depth: Control to avoid overfitting (for the sake of the argument, default value was used). (c) Training: The model was trained on the standardized training dataset using the *fit()* function.

#### 3.4.2 Random Forest Model Training

In training of the DT Model, the following processes were carried out: (a) Model Initialization: A Random Forest classifier was initialized using Random Forest Classifier from sklearn.ensemble. (b) Hyperparameters: The hyperparameters used are,

(i) n_estimators: 100 trees for robust aggregation.
(ii) criterion: Gini impurity was used as the default criterion.
(iii) max_depth: Default value to allow trees to grow fully.
(iv) random_state: Set to a fixed value for reproducibility.

(c) Training: The Random Forest model was trained with the *fit()* function on the same training data. The ensemble model utilized the predictions of multiple trees to aggregate and reduce variance as well as enhance generalization.

The critical steps in the training of the two models are: (a) Fitting the Model: *fit()* function was utilized for training patterns from the training set. (b) Feature Importance Calculation: Random Forest itself calculates feature importance scores, which were utilized to check the contribution of each feature to the task of prediction. (c) Making Prediction: Both models, upon training, were utilized to make predictions on the test set by using the *predict()* function.

### 3.5 Model Evaluation

The following metrics were used in evaluating both models. It was based on these evaluations that the best model in predicting economic recession was determined.

(a) Accuracy: The proportion of correctly classified samples.
(b) Confusion Matrix: A matrix to denote true positives, true negatives, false positives, and false negatives.
(c) Precision, Recall, F1-Score: These are the other metrics for evaluating the performance of the classifier, particularly if the dataset is unbalanced.

With the use of both models, we utilized the simplicity of the Decision Tree and the combined power of the Random Forest in an attempt to obtain robust predictions for economic downturns.

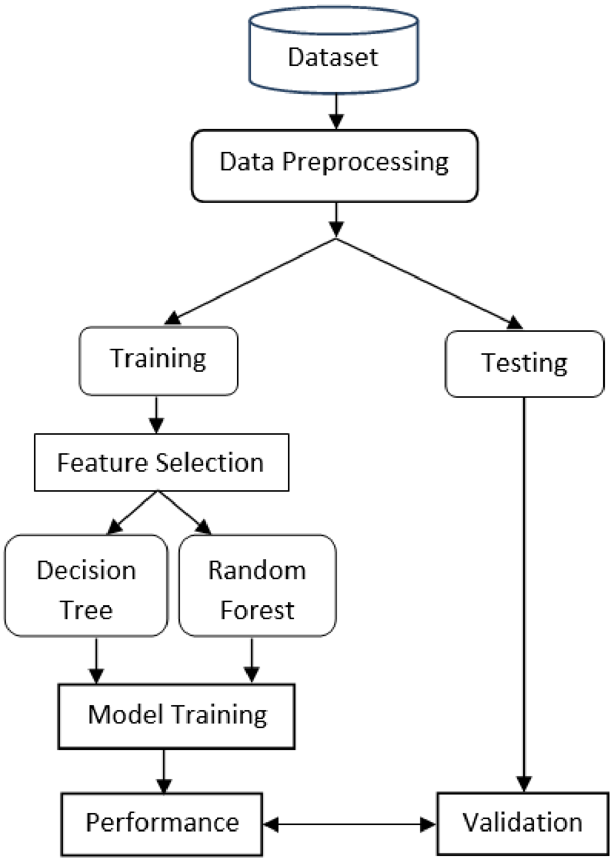


**Figure 1:** Work-Flow Diagram Depicting the Proposed System

## 4. RESULTS

### 4.1 Model Performance Comparison

Two machine learning models, Decision Tree and Random Forest, were evaluated to analyze the economics resilience predictions. The models were trained on historical economic data and were tested for their ability to predict economic downturns. Performance measures are compared in Table 1.

**Table 2:** Model Performance Comparison

| Model | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|
| **Decision Tree** | 0.78 | 0.76 | 0.75 | 0.75 |
| **Random Forest** | 0.86 | 0.85 | 0.87 | 0.86 |

A Random Forest model beats a Decision Tree model, producing accuracy scores of 86% and 78%, respectively. It has also outperformed Decision Trees by other measures as well - precision, recall, and F1-score. This indicates that Random Forest, embodying an ensemble procedure, has greater predictive ability in forecasting an economic downturn.

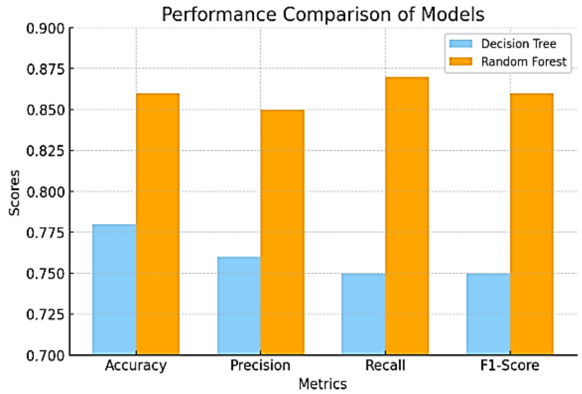


**Figure 2:** Comparison of the Performance of Decision Tree and Random Forest

### 4.2 Confusion Matrix Analysis

The confusion matrices for both models i.e., those presented in Figure 1 and Figure 2 pretty much explain their performance in distinguishing one from another.

**Table 3:** Decision Tree Confusion Matrix

| Actual \ Predicted | Positive (Downturn) | Negative (Resilient or Stable) |
|---|---|---|
| **Positive (Downturn)** | 35 | 10 |
| **Negative (Resilient or Stable)** | 8 | 27 |

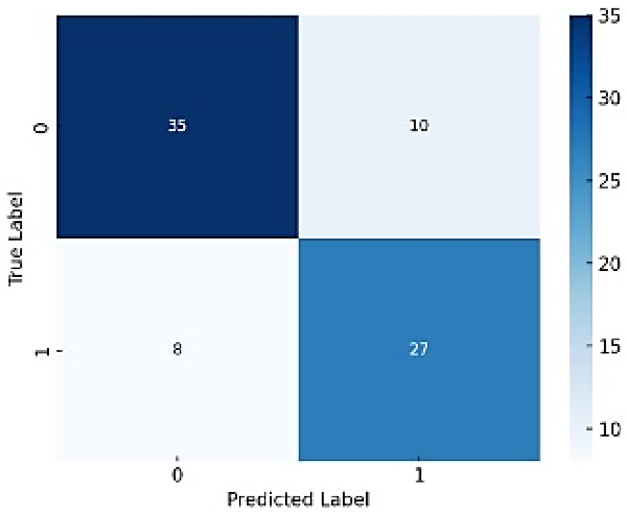


**Figure 3:** Confusion Matrix Diagram for Decision Tree Model

Decision Tree (DT): (a) True Positives: 35, False Positives: 10 (b) False Negatives: 8, True Negatives: 27.

Random Forest (RF): (a) True Positives: 40, False Positives: 5 (b) False Negatives: 6, True Negatives: 29.

**Table 3:** Random Forest Confusion Matrix

| Actual \ Predicted | Positive (Downturn) | Negative (Stable) |
|---|---|---|
| **Positive (Downturn)** | 40 | 5 |
| **Negative (Stable)** | 6 | 29 |

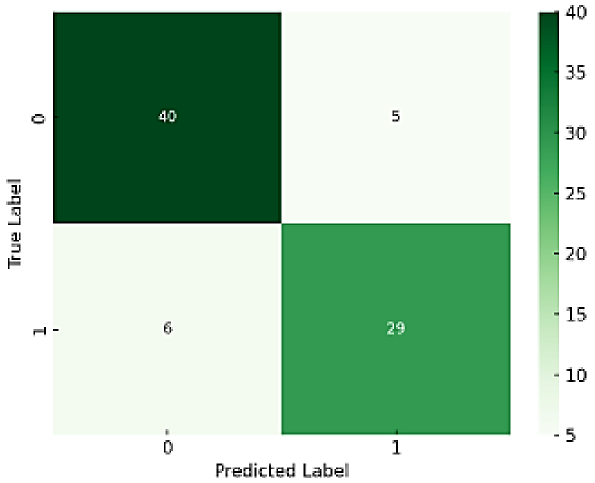


**Figure 4:** Confusion Matrix Diagram for Random Forest Model

### 4.3 Interpretation of the Results

The results have shown that the Decision Tree model misclassified 10 downturns as stabilities and 8 stabilities as downturns, indicating a moderate classification capacity. The Random Forest model, on the other hand, misclassified less, implying better performance in the identification of economic status. The model is very efficient; it indicates that ensemble learning techniques allow better predictions than single decision tree. This assigns GDP growth, inflation, and exchange rate volatility a position of high significance based on economic expectations about their role in stability evaluation. An essential element of interpretation is as follows: Which main economic guidelines impacted the machine in terms of its selected prediction? Feature importance of the Random Forest model is given in Table 4.

**Table 4:** Feature Importance (Random Forest)

| Feature | Importance Score |
|---|---|
| GDP Growth (%) | 0.28 |
| Inflation (%) | 0.22 |
| Exchange Rate (₦/USD) | 0.18 |
| Unemployment (%) | 0.15 |
| Debt-to-GDP Ratio (%) | 0.10 |
| Foreign Reserves (USD) | 0.07 |
| Stock Index | 0.05 |

The results did highlight GDP Growth, Inflation, and Exchange Rate as the most influential indicators in predicting economic resilience. They are aligned with economic theory and their roles for assessment for stability were underscored as crucial.

### 4.4 Policy Implications

Resilience is still on the policy agenda with concerns about sustainable development [31]. To enhance Nigeria's economic resilience, policymakers must consider the following strategies based on the predictive insight provided by the model:

(a) Maintain Inflation Stability: Inflation was one of the strongest predictors, and monetary policies towards maximizing inflation stabilization can dampen recession periods.
(b) Maintain Foreign Exchange Stability: A reduction in volatility through management of foreign reserves and foreign trade policies may improve economic stability.
(c) Initiatives to Create Jobs: The effects of high unemployment call for investment into skill development and entrepreneurship programs and construction projects aimed at creating jobs.
(d) Policies for Debt Management: Managing the debt-to-GDP ratios would help to avoid economic fragility.
(e) Strengthening the Stock Market: Building stock market confidence and stability would benefit economic resilience.

### 4.5 Limitations and Future Work

This paper provided valuable insights, albeit with some caveat:

a) First, the internal factors influencing the model could be blamed for the weak predictive capability (likely that they either enter their own ceiling or engage their exterior).
b) They included structural models of prediction generally. A complex neural model may yield more precise predictions.
c) However, other researchers studied the mathematical conditions to see if predictions made using machine learning can easily fit into the real-world framework of any policy.

## 5. CONCLUSION

It shows that machine learning models can succeed in predicting economic downturns. The Random Forest model provided better accuracy and classification performance than the Decision Tree model. This study further identified GDP Growth, Inflation, and Exchange Rate as the most meaningful predictors of economic resilience. These insights provide a data-driven basis forth suggestion toward proactive policy intervention strategies, aimed toward stabilizing Nigeria's economy.

## ACKNOWLEDGMENT

Authors appreciate the huge contributions received for this work from the university library resources of the Olabisi Onabanjo University, Ago-Iwoye.

## AUTHOR DECLARATION

The authors affirm that there are no conflicting interests as regards this research work.

## FUNDING INFORMATION

This work was self-financed as such; no funding was received for this work.

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**APPENDIX**

| Date | GDP Growth (%) | Inflation (%) | Unemployment (%) | Debt-to-GDP Ratio (%) | Exchange Rate (₦/USD) | Foreign Reserves (Billion USD) | Stock Index (NGX All-Share Index) |
|---|---|---|---|---|---|---|---|
| 2015-Q1 | 6.1 | 9.6 | 10.2 | 95 | 440 | 23.8 | 34,800 |
| 2015-Q2 | 6.2 | 9.4 | 10 | 96 | 450 | 24 | 35,000 |
| 2015-Q3 | 6.5 | 9.1 | 9.8 | 97 | 460 | 24.2 | 35,200 |
| 2015-Q4 | 6.7 | 8.8 | 9.6 | 98 | 470 | 24.5 | 35,400 |
| 2016-Q1 | 2.7 | 12.3 | 10.5 | 99 | 480 | 24.8 | 35,600 |
| 2016-Q2 | 2.3 | 14 | 11.2 | 100 | 490 | 25 | 35,800 |
| 2016-Q3 | 2 | 15 | 11.5 | 101 | 500 | 25.3 | 36,000 |
| 2016-Q4 | 1.5 | 18 | 12 | 102 | 510 | 25.5 | 36,200 |
| 2017-Q1 | 0.8 | 16.5 | 12.3 | 103 | 520 | 25.8 | 36,400 |
| 2017-Q2 | 1.4 | 15.2 | 12 | 104 | 530 | 26 | 36,600 |
| 2017-Q3 | 1.8 | 14.5 | 11.8 | 105 | 540 | 26.3 | 36,800 |
| 2017-Q4 | 2 | 14 | 11.5 | 106 | 550 | 26.5 | 37,000 |
| 2018-Q1 | 1.9 | 13.8 | 11.3 | 107 | 560 | 26.8 | 37,200 |
| 2018-Q2 | 2.1 | 13.5 | 11 | 108 | 570 | 27 | 37,400 |
| 2018-Q3 | 2.2 | 13.2 | 10.8 | 109 | 580 | 27.3 | 37,600 |
| 2018-Q4 | 2.3 | 13 | 10.5 | 110 | 590 | 27.5 | 37,800 |
| 2019-Q1 | 2.5 | 12.8 | 10.3 | 111 | 600 | 27.8 | 38,000 |
| 2019-Q2 | 2.7 | 12.5 | 10 | 112 | 610 | 28 | 38,200 |
| 2019-Q3 | 3 | 12.2 | 9.8 | 113 | 620 | 28.3 | 38,400 |
| 2019-Q4 | 3.2 | 12 | 9.5 | 114 | 630 | 28.5 | 38,600 |
| 2020-Q1 | -2.1 | 12.5 | 10 | 115 | 640 | 28.8 | 38,800 |
| 2020-Q2 | -6.1 | 14 | 13.5 | 116 | 650 | 29 | 39,000 |
| 2020-Q3 | -3.2 | 15.5 | 14 | 117 | 660 | 29.3 | 39,200 |
| 2020-Q4 | -1.8 | 16 | 14.5 | 118 | 670 | 29.5 | 39,400 |
| 2021-Q1 | 0.5 | 16.5 | 15 | 119 | 680 | 29.8 | 39,600 |
| 2021-Q2 | 1.2 | 15 | 14.7 | 120 | 690 | 30 | 39,800 |
| 2021-Q3 | 1.9 | 14.5 | 14.5 | 121 | 700 | 30.3 | 40,000 |
| 2021-Q4 | 2.3 | 14 | 14.2 | 122 | 710 | 30.5 | 40,200 |
| 2022-Q1 | 3.1 | 13.5 | 13.8 | 123 | 720 | 30.8 | 40,400 |
| 2022-Q2 | 3.5 | 13.2 | 13.5 | 124 | 730 | 31 | 40,600 |
| 2022-Q3 | 3.8 | 13 | 13.3 | 125 | 740 | 31.3 | 40,800 |
| 2022-Q4 | 4 | 12.8 | 13 | 126 | 750 | 31.5 | 41,000 |
| 2023-Q1 | 4.2 | 12.5 | 12.8 | 127 | 760 | 31.8 | 41,200 |
| 2023-Q2 | 4.5 | 12.2 | 12.5 | 128 | 770 | 32 | 41,400 |
| 2023-Q3 | 4.8 | 12 | 12.3 | 129 | 780 | 32.3 | 41,600 |
| 2023-Q4 | 5 | 11.8 | 12 | 130 | 790 | 32.5 | 41,800 |
| 2024-Q1 | 5.2 | 11.5 | 11.8 | 131 | 800 | 32.8 | 42,000 |