International Journal of Religion
2024
Volume: 5| Number 11 | pp. 2295 – 2304
ISSN: 2633-352X (Print) | ISSN: 2633-3538 (Online)
ijor.co.uk
DOI: https://doi.org/10.61707/3dwt0k35

Fitting Machine Learning Models for the Identification of Social Vulnerability in the Event of Political Instability in Nigeria

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Abstract

Due to the high rate of poverty and the unequal distribution, social vulnerability is extremely common in rising economies around the world, including Nigeria. As a result of political instability in Nigeria, this research study's machine learning has been suitably fitted to identify potential social vulnerability. The outcomes of the machine learning optimizations indicate that a high incidence of social inequality, political unrest, natural disasters and agricultural instability will probably all contribute to the high degree of social vulnerability in Nigeria. The results of the predictor variables' contribution to the likelihood of high social vulnerability in Nigerian communities indicate that, at 100% and 74.8%, natural disasters related to flooding and political grievances respectively account for the majority of Nigeria's high level of vulnerability. Surpassing the logistic regression method, support vector machine, and random forest, the artificial neural network (ANN) attained the maximum prediction accuracy of 85% with a precision of 82%, according to the model performance evaluation. Therefore the best model for forecasting high social vulnerability in Nigerian currently, is the ANN. In order to reduce the high level of social vulnerability, the Nigerian government should establish an all-inclusive government that will resolve political grievances among citizens and also establish an efficient security network that will combat the country's current high level of insecurity. In the event that political instability, the government should then embrace the use of machine learning models for the future prediction of social vulnerability.

Keywords: *Machine learning, ANN, Political Instability, Natural disasters.*

INTRODUCTION

Social vulnerability globally pertains to an individual or group's capacity to withstand, manage, foresee, and recover from the effects of natural disasters or attacks. In the context of this study, it specifically refers to the ability of individuals or communities to handle or endure attacks resulting from insurgency or banditry during political instability in Nigeria [1, 2]. The current political turmoil in Nigeria is mostly attributed to ethnic tensions, insecurity, and religious intolerance, leading to significant societal vulnerabilities in both the northern and southern regions of the country [3].

Emeka-Isife [4] states that the widespread and persistent political instability in Nigeria is concerning. This leads to bad governance, crucial sector collapse, unemployment, widespread poverty, violent agitation, terrorism, and conflict. Political instability in Nigeria has resisted all leadership strategies implemented by successive governments and well-intentioned Nigerians. These techniques often do not align with the political views and comprehension of various indigenous ethnic groups. Conversely, the leadership of the Nigerian government frequently generates hostile atmospheres that disrupt political stability. Political instability has consistently characterised succeeding Nigerian political administrations.

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Additionally, the Nigerian government system inherited from colonial times disrupts the country's stability [5]. Post-independence, Nigeria continued the government structure established during the colonial period due to its legacy. The primary reform involved substituting expatriates with native politicians. These substitutions were controlled and forced upon the population, leading to a culture of pushing political candidates on the populace [6].

Post-independence Nigeria is marked by political manipulations, manoeuvring, coercion, and the imposition of political candidates on the populace, leading to societal fragility in the country. Furthermore, the Boko Haram insurgency, for instance, contributes to political instability in Nigeria. This group is advocating for the establishment of an Islamic state in Nigeria with strict adherence to Islamic law. Many government leaders from the northern area of Nigeria openly or indirectly endorse the actions of this insurgent group. These officials undermine government political initiatives to favour this group. This perspective supports Eckstein's [7] congruence thesis, which suggests that political instability in a society is influenced by how well the power structures of government and smaller entities align with each other and are consistent internally. These factors impact politics, the economy, security personnel, and the livelihood of the common people in the region. This undermines the political system and activities, resulting in ongoing political instability and high levels of socioeconomic vulnerability in Nigerian communities.

Other studies have utilised machine learning (ML) models such as random forest, logistic regression, support vector machines, and artificial neural networks to predict social vulnerabilities in the face of natural hazards. The accuracy and precision of these ML tools have proven them to be reliable in assessing social vulnerability in different communities worldwide [8, 9]. Social vulnerabilities in Nigeria can be determined by indicators like natural disaster frequency, agricultural instability, food insecurity, under-employment rate, lack of basic services, political unrest, social inequality, and ethnic or religious discrimination. These factors help identify community risks and susceptibilities to extremism (see Figure 1). Machine learning will be highly suitable for predicting the likelihood of high social vulnerability in Nigeria.

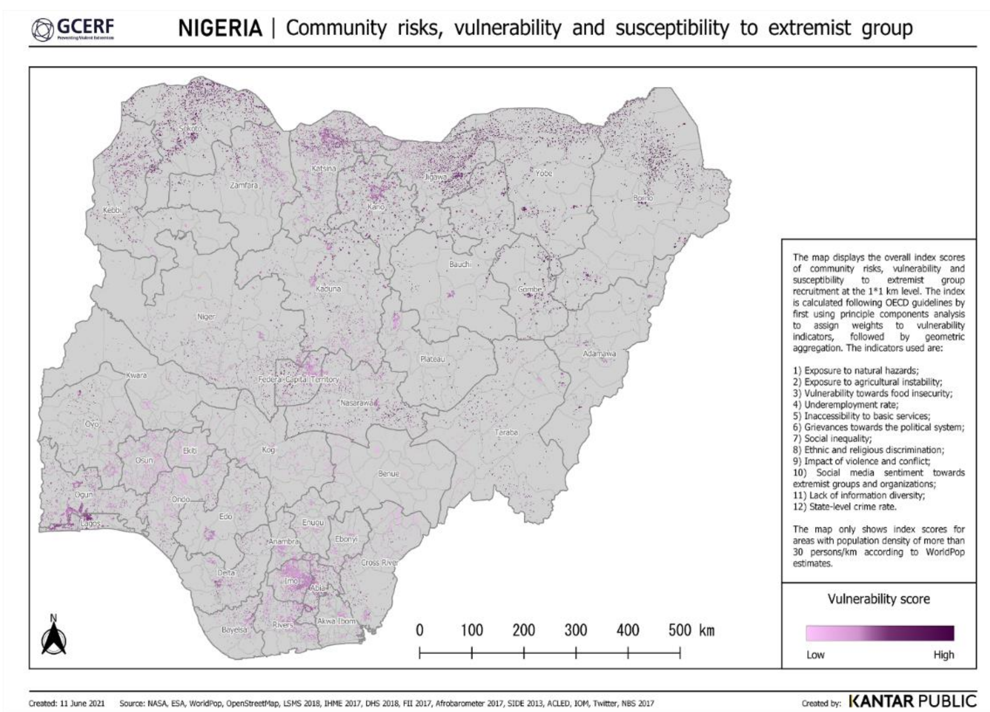

Figure 1: Social vulnerability indicators in Nigeria (Source: GCERF, 2023)

Machine learning is a proven data science technique for predicting social vulnerability with the aid of performance metrics like prediction accuracy, precision level, recall, and F1 score in the global world [10]. Therefore, this study will contribute differently by fitting machine learning models for the identification of the possibility of high social vulnerability in the event of political instability within the context of Nigerian communities.

RESEARCH METHOD

Nigeria is the most populous country in Africa, with a population exceeding 200 million, representing over 47% of West Africa's total population. The population density exceeds 151 individuals per square kilometre (Figure 2). The nation has a broad range of ethnic diversity, with more than 250 groups identified, as reported by the Central Intelligence Agency in 2015. This frequently results in friction, conflicts, and dissension, when an ethnic minority may feel marginalised or neglected. The population growth rate reached its highest point in the 1970s and has been steady since then, in comparison to the regional average of approximately 2.73% in Sub-Saharan Africa. Since 1980, Nigeria's population growth rate has been consistently below the global average, currently at 2.63% per year [11].

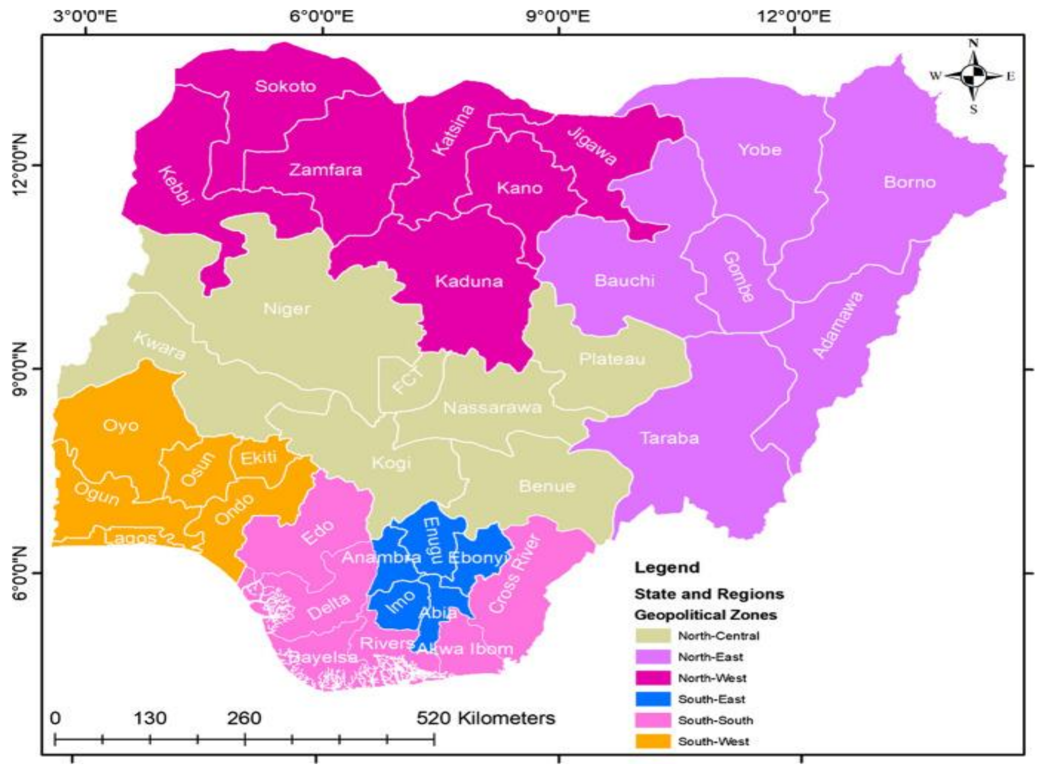

Figure 2: Population density of states in Nigeria

Cross-sectional data of social vulnerability indexes like natural disasters (ND), particularly cases of flood, agricultural instability (AI), food insecurity (FI), underemployment rate (UR), inaccessibility to basic services (IBS), political grievances (PG), and social inequality (SI) from the 75 communities in the northern and southern parts of Nigeria with the most vulnerability to violent extremism in Nigeria via the Nigeria pilot project conducted daily by the Global Community Engagement and Resilience Fund (GCERF) [12] and a total sample of 750 were extracted after cleaning the dataset to remove errors from the GCERF report for the purpose of the analysis of this study.

This study utilises machine learning models including random forest, artificial neural network (ANN), logistic regression, and support vector machine. The most effective model will be selected to identify the potential for high social vulnerability during political instability in Nigerian communities. Python is well-suited for applying machine learning techniques and visualising datasets due to its structures, libraries, and user-friendly syntax.

MACHINE LEARNING PREDICTION MODEL

Various machine learning binary prediction models, including random forest, artificial neural networks (ANN), logistic regression, and support vector machines, were evaluated to predict the likelihood of high social vulnerability during political instability in Nigerian communities. The data went through cleansing process to eliminate mistakes and outliers before evaluating the final valid dataset. The four machine learning models employed in this study are suitable for detecting high social vulnerability in Nigeria during political instability due to their binary nature. These models are designated as 1 for identifying high social vulnerability and 0 for other cases.

Random forest and ANN are versatile algorithms suitable for both classification and regression problems, unlike logistic regression and support vector machine (SVM) which are limited to binary classification. The R programming language will be extensively used to create the three predictive models.

The generalised machine learning binary prediction model can be stated as follows [13, 14].

$$In\left(\frac{p}{1-p}\right) = \beta_o + \beta_1 ND_1 + \beta_2 AI_2 + \beta_3 FI_3 + \beta_4 UR_4 + \beta_5 IBS_5 + \beta_6 PG_6 + \beta_7 SI_7 + \varepsilon\ldots\ldots \quad (1)$$

Where β_0 is the constant term and β_1 to β_7 are the slope of the predictor variables, ε is the error term and the predictor variables are stated below with their respective measurements.

ND = Natural disasters (it is the count of the natural disasters/hazards that occurred in the selected communities).

AI = Agricultural instabilities (measured in percentage).

FI = Food insecurity (measured in percentage).

UR = Underemployment rate (measured in percentage).

IBS = Inaccessibility to basic services (measured in percentage).

PG = Political grievances (measured in percentage).

SI = Social inequality (Ratio of the poor to the rich)

Accuracy, precision, recall and f1-score are the four main performance criteria used to identify the best machine learning system [15].

In the context of Nigerian communities, accuracy refers to the ratio between True Positives and all Positives when creating the optimal machine learning algorithm for identifying the possibility of high social vulnerability in the case of political instability.

Recall is a measure of our model's accuracy in identifying True Positives. Accuracy is defined as the ratio of all correct forecasts to all forecasts. Although it is reasonable to use accuracy as the model's defining parameter, it is also usually advisable to use precision and recall. There might be other situations in which we are very accurate but not very precise or recalling [15]. Besides, f1-scire is the harmonic mean of the precision and recall with it best value approaching 1 and worst score at zero.

Additionally, the four machine learning models' performance metrics formulas are listed below;

$$Accuracy = \frac{True\ Positive + True\ Negative}{(True\ Positive + False\ Positive + True\ Negative + False\ Negative)} \ldots\ldots\ldots \quad (2)$$

$$Precision = \frac{True\ Positive\ (TP)}{(True\ Positive\ (TP) + False\ Positive\ (FP)} \ldots\ldots\ldots \quad (3)$$

$$Recall = \frac{True\ Positive\ (TP)}{(True\ Positive\ (TP) + False\ Negative\ (FN)} \ldots\ldots\ldots \quad (4)$$

$$f1 - score = \frac{2\ (TP)}{(2\ (TP) + FP + FN)} \ldots\ldots\ldots \quad (5)$$

The ML models-Prototype illustrated the ML full implantation process, which may be summed up as follows:

Testing the machine learning system: The suggested ML models that was fully implemented for this research project is the machine learning (ML) system. First, the dataset will be cleaned by transforming the data and removing associated measurement errors. Finally, the ML models will be tested and cleaned by evaluating the dataset using performance metrics like accuracy, precision, and recall (See Figure 3).

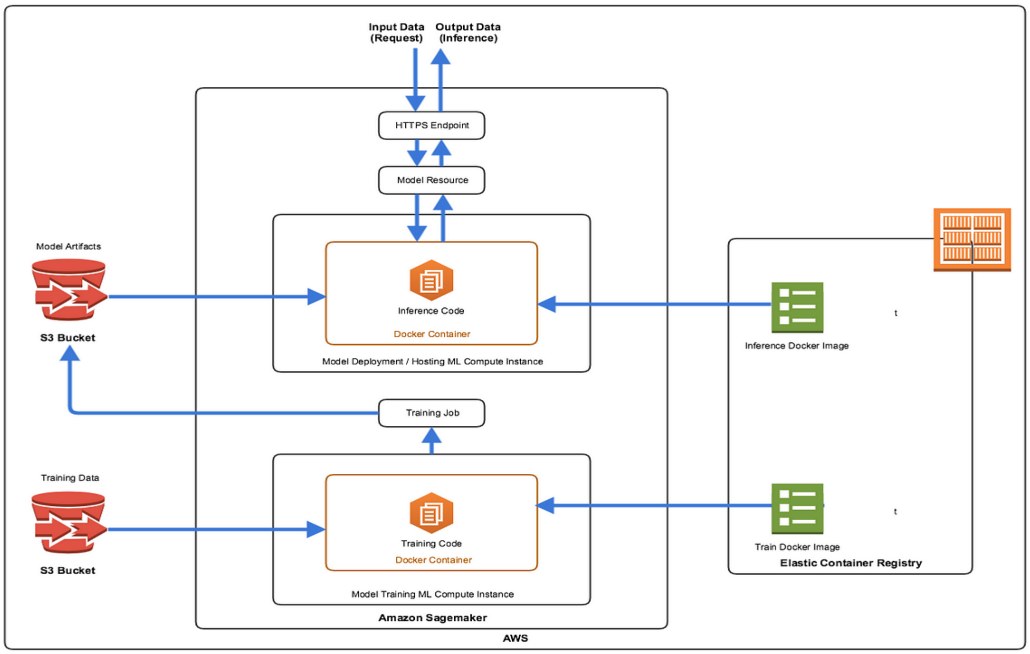

Figure 3: ML models-Prototype

LITERATURE REVIEW

Authors worldwide have utilised machine learning to forecast social vulnerability, especially during natural disasters such as earthquakes and floods. They have assessed the effectiveness of various machine learning methods in their research [8 9, 10]. Upon further examination of the vulnerability aspect in the previously mentioned risk equations, it becomes evident that individuals and locations can influence the risk of experiencing loss, whether it be in terms of life or property. Vulnerability can be influenced by biophysical or social factors [16]. Biophysical vulnerability refers to the susceptibility caused by the physical condition of a place or the characteristics of a hazard event. Social vulnerability refers to the characteristics and societal circumstances that can increase individuals' and society's susceptibility to the adverse impacts of a hazard event or disaster [17].

The Hyogo Framework for Action 2005–2015 has not been effectively implemented, despite the growing focus on disaster management in poor countries and the formation of emergency and disaster management agencies in many African states [18]. Therefore, emphasising the obstacles encountered by a specific area in executing the subsequent Sendai Framework for Disaster Risk Reduction. Research is being conducted to map and measure social vulnerability and resilience in low- and middle-income countries to enhance catastrophic risk management [19]. This indicates an increase in proficiency and comprehension.

Edkrantz and Said [14] examined the correlation between vulnerabilities and Proof-of-Concept (PoC) exploits with machine learning binary prediction models, including logistic regression and support vector machines (SVM). By utilising performance characteristics such as recall, precision, and prediction accuracy, they successfully predicted vulnerability exploits. The logistic regression achieved an 80% prediction accuracy, outperforming the support vector machine in binary classification. Edkrantz and Said [14] demonstrate that the dataset's quality significantly influences the accuracy of the model's predictions. This study aims to enhance previous research by employing four machine learning prediction models: logistic regression, support vector machines, random forest models, and artificial neural networks. This study will utilise the performance measures accuracy, precision, and recall to forecast the likelihood of high social vulnerability in Nigerian communities during times of political unrest.

Abhirami et al. [13] conducted a comparative evaluation of various machine learning algorithms, including K-nearest neighbour, decision tree, LR, and random forest, focusing on identifying e-commerce fraud. Logistic regression (LR) outperforms other methods in fraud detection investigations. The experiment utilised the Kaggle dataset. There are 284807 records in the collection, with 492 being incorrect. The Decision Tree Algorithm was the least successful strategy [13]. This research is primarily limited by the use of Kaggle data that does not reflect current real-world conditions. This study will utilise appropriate data-driven machine learning techniques to evaluate social vulnerability data in a real-world context.

RESULTS AND DISCUSSION

An overview of the variables examined in this investigation is shown in Table 1. It indicates that, on average, 121 natural disasters resulting from flooding occur in the communities that are being examined. Due to insurgency and insecurity, agricultural activity is only 4% on average. The average percentage of food insecurity is almost 69%, which is significant and consistent with the state of affairs in Nigeria at the moment. Underemployment, which includes both unemployed people and underutilized workers, has an average rate of about 21%. About 33% of people are unable to get basic services on average. Furthermore, the average social inequality ratio - a measure of the difference between the rich and the poor - is approximately 0.47, whilst the average level of political grievances is approximately 32%. This shows that because of the unequal distribution of resources, the wealthiest in Nigerian communities have access to resources that are noticeably better than those of the poor.

Table 2 shows that the overall ML model is statistically significant, indicating that the possibility of high social vulnerability in Nigerian communities is significantly associated with natural disasters, agricultural instabilities, food insecurity, underemployment, inaccessibility to basic services, political grievances, and social inequality. The results also show that natural disasters, agricultural instabilities, political grievances, and social inequality have a positive and significant contribution to the social vulnerability in Nigeria, while food insecurity has a negative and significant contribution to the social vulnerability in the Nigerian community, indicating that a high level of natural disasters, agricultural instabilities, political grievances, and social inequality will more likely contribute to the high level of social vulnerability in the Nigerian communities.

Table 3 displays the model accuracy assessment of four machine learning predictive models. The artificial neural network achieved the highest prediction accuracy of 85% with a precision of 82%, surpassing the logistic regression algorithm, support vector machine, and random forest. The artificial neural network is the champion model for predicting high social vulnerability during political instability in Nigerian communities.

Table 4 presents the predictor variables' contribution to the likelihood of high social vulnerability in Nigerian communities. It is evident that the natural disasters linked to flooding and political grievances account for the largest share of the high level of vulnerability in Nigeria, at 100% and 74.8%, respectively. These findings are consistent with the current state of affairs in Nigeria.

Table 1: Summary statistics

Variables	Mean	Std Dev	Samples
Natural disasters	120.74	32.020	750
Agricultural instabilities	3.84	3.370	750
Food insecurity	68.98	19.509	750
Underemployment	20.49	15.919	750
Inaccessibility to basic services	33.17	11.709	750
Political grievances	31.959	7.927	750
Social inequality	0.474	0.332	750

Social Vulnerability	Frequency	Percentage	
High	260	34.7	
Otherwise	490	65.3	

Source: Author's computation using Python programming language

Table 2: Model Optimization Results

ML: LLR P-value = 0.000

Social Vulnerability	**Coefficient**	**Std err**	**z**	**P-value**
Constant	-7.6545	0.818	-9.352	0.000
Natural disasters	0.0309	0.004	7.749	0.000
Agricultural instabilities	0.1121	0.038	2.959	0.003
Food insecurity	-0.0157	0.006	-2.558	0.011
Underemployment	-0.0004	0.008	-0.058	0.954
Inaccessibility to basic services	0.0196	0.011	1.786	0.074
Political grievances	0.0839	0.019	4.529	0.000
Social inequality	0.7723	0.363	2.129	0.033

Source: Author's computation using Python programming language

Table 3: The four machine learning performance metrics evaluation

	Prediction classification			
Metrics	**Logistic regression**	**Support vector machine**	**Random forest**	**Artificial neural network**
Precision	0.80	0.68	0.72	0.82
Recall	0.66	0.64	0.48	0.68
f1-score	0.73	0.70	0.58	0.75
Accuracy	0.83	0.79	0.75	0.85

Source: Author's computation using Python programming language

Table 4: Predictor Variable Importance

	Importance	**Normalized Importance**
Natural disasters	0.264	100.0%
Agricultural instabilities	0.108	41.0%
Food insecurity	0.111	42.0%
Underemployment	0.069	26.3%
Inaccessibility to basic services	0.094	35.7%
Political grievances	0.197	74.8%
Social inequality	0.157	59.6%

Source: Author's computation using Python programming language

Figure 4 shows the interaction activities or pattern between the social vulnerability and the predictors, and we can see that natural disasters and political grievances demonstrated high volume activities and contributed to the high level of social vulnerability in the Nigerian communities.

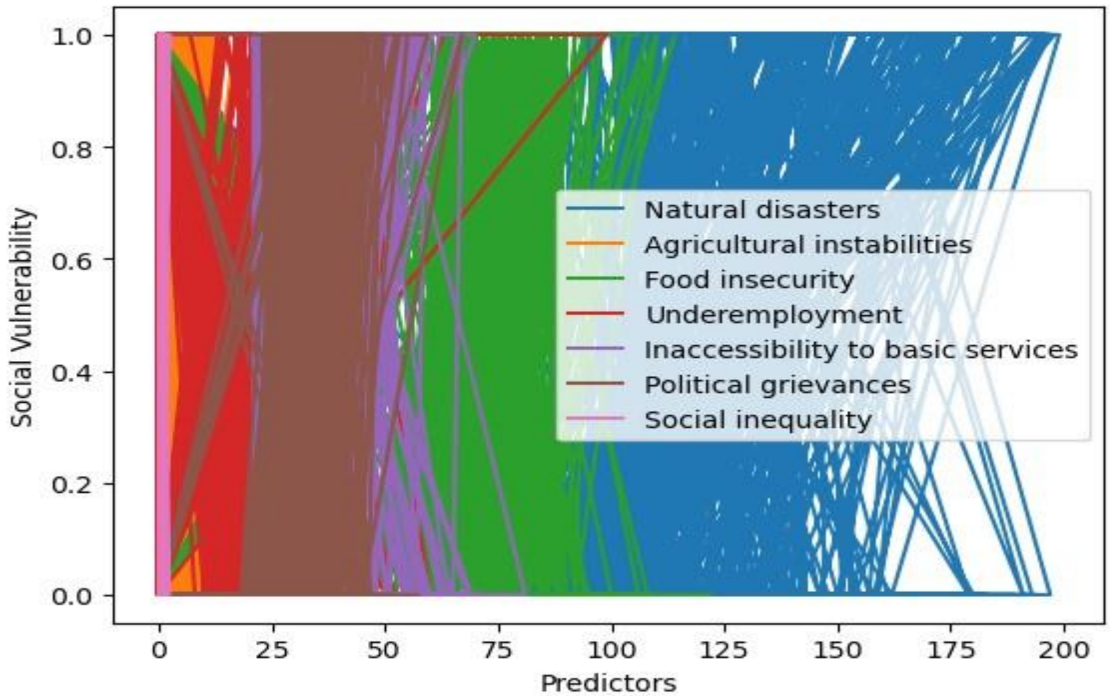

Figure 4: Interactive plot between the social vulnerability and the predictors' variables

CONCLUSION

Social vulnerability is widespread in emerging economies like Nigeria, mostly due to high poverty levels and unequal distribution of resources within communities, resulting in a significant gap between the wealthy and the impoverished. This research work has effectively applied suitable machine learning techniques to determine the potential social vulnerability during political instability in Nigeria.

The machine learning optimisations indicate that a strong correlation exists between high levels of natural disasters, agricultural instabilities, political grievances, and social inequalities with the increased social vulnerability in Nigerian communities. The predictor variables indicate that flooding and political grievances are the main factors contributing to high social vulnerability in Nigerian communities, accounting for 100% and 74.8% of the vulnerability, respectively. The findings align with the present situation in Nigeria. This supports the findings of Lawal and Arokoyu (2015) regarding society's vulnerability to hazard events or disasters. It is also consistent with Manyena's (2016) conclusion about the increasing attention to disaster management in developing countries and the establishment of emergency and disaster management organisations in various African nations.

The model evaluation shows that the artificial neural network outperformed the logistic regression algorithm, support vector machine, and random forest by achieving the maximum prediction accuracy of 85% with a precision of 82%. The artificial neural network is the most effective model for forecasting high social vulnerability in Nigerian communities during political instability. Edkrantz and Said (2015) studied the relationship between vulnerabilities and Proof-of-Concept (PoC) exploits using machine learning binary prediction models like logistic regression and support vector machines (SVM). By analysing performance metrics such as recall, precision, and prediction accuracy, they were able to predict vulnerability exploits successfully. Logistic regression achieved an 80% prediction accuracy, surpassing the support vector machine in binary classification.

The Nigerian government should establish an inclusive administration to address political grievances among all parties. Additionally, they should implement a robust security system to combat the prevalent insecurity in

Nigerian communities, thereby reducing social vulnerability. Furthermore, they should adopt machine learning models to predict fuiture social vulnerability in the event of political instability in Nigeria.

ACKNOWLEDGEMENTS

I would like to express my sincere appreciation to all those who contributed to the completion of this paper. Special thanks to all the co-authors, whose insightful guidance and expertise greatly enriched the content as well as for their invaluable support and encouragement throughout the research process. Their contributions have been instrumental in shaping the outcome of this work, and I extend my heartfelt thanks to each one of them.

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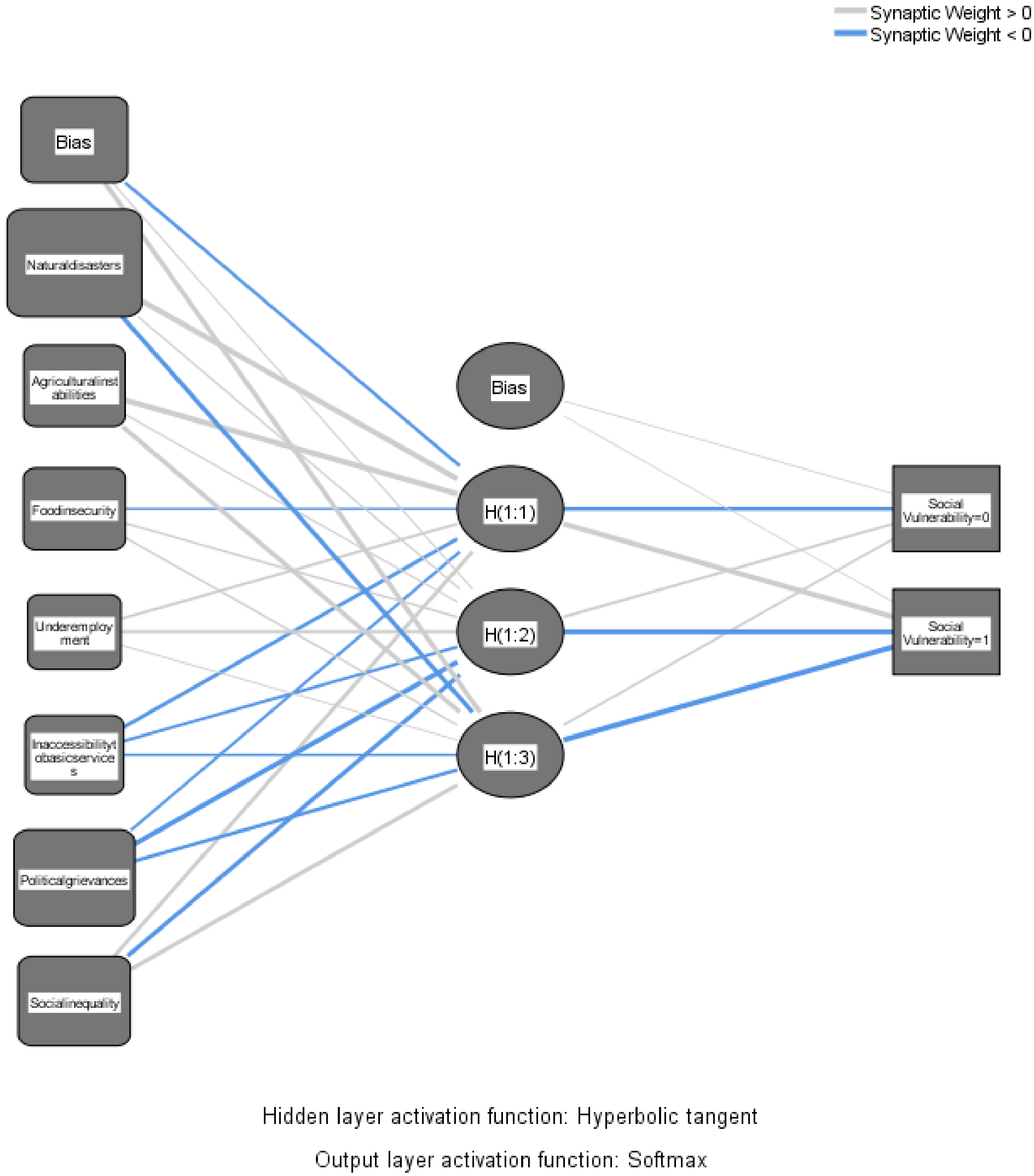
Appendix



ANN Structure

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