# HONG KONG JOURNAL OF SOCIAL SCIENCES

# 香港社會科學學報

第一的第 60 期 (2022 春/夏) Vol. 60 Autumn/Winter 2022

**Open Access Article** https://doi.org/10.55463/hkjss.issn.1021-3619.60.38


# Analysing Factors Influencing Women Unemployment Using a Random Forest Model


**Timothy T. Adeliyi[1], Lawrence Oyewusi[2], Ayogeboh Epizitone[1], Damilola Oyewusi**

[1] *ICT and Society Research Group, Durban University of Technology, Durban, South Africa*

[2] *Partners in Health, Maseru, Lesotho*



***Received: October 12, 2022*** ▪ ***Reviewed: November 1, 2022***

▪ ***Accepted: November 17, 2022*** ▪ ***Published: January 5, 2023***



**Abstract:**
The unemployment crisis has been a persistent issue for both developed and developing countries, resulting in an economic indicator deficit. Women are at a disadvantage and continue to encounter significant obstacles to gaining employment. Nigeria, like many other developing countries with high unemployment rates, has a 33% unemployment rate. Consequently, there has been minimal research on the factors that affect women's unemployment. As a result, the purpose of this study investigates the factors that influence women's unemployment in Nigeria. Although the Random Forest model has been widely applied to classification issues, there is a gap in the literature's use of the random forest as a predictor for analyzing factors influencing women's unemployment. The random forest model was employed in this study because of its characteristics such as strong learning ability, robustness, and feasibility of the hypothesis space. As a result, the Random forest prediction model was benchmarked with seven different cutting-edge classical machine learning prediction models, which include the J48 pruned tree, Support Vector Machine, AdaBoost, Logistic Regression, Naive Bayes, Logistic Model Tree, Bagging, and Random Forest. The experimental results demonstrate that Random Forest outperformed the other seven machine learning classifier models using ten commonly used performance evaluation metrics. According to the study's findings, age groups, ethnicity, marital status, and religion were the essential factors affecting women's unemployment in Nigeria.



**Keywords:** machine learning, National Demographic and Health Survey, random forest, influencing factors, women unemployment.


# 使用随机森林模型分析影响女性失业的因素


**摘要：**
机器学习，国家人口与健康调查，随机森林，影响因素，女性失业失业危机一直是发达国家和发展中国家

的一个长期问题，导致经济指标赤字。妇女处于不利地位，在获得就业方面继续遇到重大障碍。与许多其他高失业率的发展中国家一样，尼日利亚的失业率为 33%。因此，对影响妇女失业的因素的研究很少。 因此，本研究的目的是调查影响尼日利亚妇女失业的因素。尽管随机森林模型已广泛应用于分类问题，但文献中使用随机森林作为分析影响女性失业因素的预测因子存在差距。由于随机森林模型具有学习能力强、鲁棒性强、假设空间可行等特点，因此本研究采用了随机森林模型。因此，随机森林预测模型以七种不同的前沿经典机器学习预测模型为基准，包括杰 48 剪枝树、支持向量机、适应性提升、逻辑回归、朴素贝叶斯、逻辑模型树、装袋和随机 森林。实验结果表明，使用十种常用的性能评估指标，随机森林优于其他七种机器学习分类器模型。根据研究结果，年龄组、种族、婚姻状况和宗教是影响尼日利亚妇女失业的重要因素。

**关键词：**机器学习，全国人口与健康调查，随机森林，影响因素，女性失业.

# 1. Introduction

Unemployment is an intrinsic global issue with a never-ending economic ripple effect on the population. According to the International Labor Organization (ILO), unemployment includes people who are unemployed, underemployed, have actively looked for work in the last four weeks and are ready to start work within the next two weeks, or are unemployed and have accepted a job that will start within the two next weeks (Matandare, 2018). In the literature, unemployment is hypothesized to be a stifling catalyst for many large-scale developments and growth (Ajamobe, 2021). The unemployment crisis has been a persistent issue for both developed and developing countries, resulting in the waste of many resources. Recently, Africa has experienced an economic downturn characterized by high inflation and unemployment, which has affected African countries to varying degrees (Yaya et al., 2019). Nigeria, like many other developing countries, has high unemployment because of an economic indicator deficit (Ene, 2018). Nigeria is the most populous country in Sub-Saharan Africa and the tenth most populous country in the world, with an estimated population of 200 million people spread across 250 ethnic groups. an oil-rich country, with oil being one of the world's major natural resources and a major source of income. Men must lead the labor market in many countries around the world.

In Nigeria, there have been instances of women outperforming their male counterparts. Nigeria is a country where men are perceived to be superior to their female counterparts, owing to factors such as disparate cultural beliefs and gender inequality (Olonade et al., 2021). This is evident in the expectation of a woman's position being dedicated to housework, specifically the kitchen, and caring for her husband and children (Ciciolla & Luthar, 2019). These realities are more visible in northern Nigeria, where women are expected not to express themselves when men are present (Sinai et al., 2017). This has led to and promoted the belief among the average Nigerian man that it is unacceptable for the wife to be wealthier or more successful than the husband (Gibby et al., 2021). Modernization has introduced a new dimension to gender inequality, defining it as the unequal treatment of individuals based on their gender (Ewubare & Ogbuagu, 2017).

Despite these problems, the need for equal treatment of workers remains a large gap that must be filled by all stakeholders. Women make up 49% of the Nigerian population, which is more than one-third of the total national population. However, there is a 6.3% difference in unemployment rates between men and women (Ewing-Nelson, 2021). This disparity demonstrates that most women rely entirely on their male counterparts for a living and, as a result, are helplessly taken for granted or mistreated. Ewing-Nelson (2021) said that factors like education level, family background, maternal commitment, cultural beliefs, and household responsibilities may have contributed to the subliminal marginalization of men and women in the labor market.

Globally, female unemployment is estimated to be higher than male unemployment, and this is especially true in Sub-Saharan Africa, where males are thought to be more dominant than females. Men are expected to get more lucrative and better jobs, forcing women to accept low-wage jobs (Mihret, 2019). Furthermore, most studies on the factors causing women's unemployment in Nigeria have made no mention of other emerging ones that may be relevant to this problem. As a result, the dawn of modernization added a new dimension to gender inequality, defining it as the unequal treatment of individuals based on their gender. Despite this highlighting the need for equal treatment among workers, the unemployment gap remains a large gap that must be filled by all stakeholders. As a result, this paper delves deeper into other possible causes of this bias or inequality toward women in Nigeria. This paper investigates the factors that contribute to women's unemployment in Nigeria, with the main research question being what are the factors that contribute to women's unemployment in Nigeria?

The concise structure of this work is as follows. The relevant literature on women's unemployment in Nigeria is summarized in Section 2. The study's materials and methods are addressed in Section 3. The experimental findings and discussion are presented in Section 4. The paper's Section 5 contains the concluding statements.

# 2. Related Works

The International Labour Organization defines unemployment as "the proportion of the economically active population who are unemployed but available and seeking work within the previous five weeks" (Ewing-Nelson, 2021; Ewubare & Ogbuagu, 2017). Many studies show that unemployment is more common among women, and this has been proven to be due to various factors (Matandare, 2018). According to some studies, women are usually exceptional in most businesses and have the same level of productivity as men, but they are not in a better position (Berman, 2018; Zulqaram et al., 2021). However, there is a report in the literature on the high unemployment rate in women, as a cursory glance at gender astute reveals the unemployment rate to be higher for females than their male counterparts due to the predominantly stout challenges they face when attempting to enter the labor force due to early motherhood and a lack of education (Okolie & Igbini, 2020). According to Mihret (2019), women's unemployment is higher than men's unemployment on a global scale.

Existing literature holds unemployment primarily responsible for various societal ills, including crime, suicide, poverty, alcoholism, the spread of HIV/AIDS, gender violence, and prostitution (Biancone & Radwan, 2018; Fakih et al., 2020; Okonko & Okoli, 2020). Furthermore, unemployment has had a significant impact on household income, health, government revenue, GDP, and overall development. Despite women's critical role in the economic development of their families and communities, unemployment, among other factors, impedes their effective performance (Ene, 2018). According to National Bureau statistics from 2010, approximately 68% of 164 million Nigerians are in relative poverty, with the highest rate of 77.7% in the North-West and 76.3% in the North-East geographical zones. Their survey also revealed a trend among women to enter the labor force in pursuit of careers and financial independence, owing to improvements in female education and living standards (Okolie & Igbini, 2020).

Despite ongoing reforms and consolidation in many corporations in certain sectors facilitate women's employment. Additionally, a cost of women's unemployment is an increase in gender-based violence. According to the authors, unemployed women are more vulnerable to violence and abuse because they rely on their spouses for financial support (Tadesse et al., 2022). As a result, Okonko and Okoli (2020) reported a high prevalence of HIV among unemployed pregnant women. Existing literature details the global woes of unemployment, with varying impacts and severity (Hammell, 2019). These consequences are felt globally, with more than 200 million people out of work in 2011 (Ewing-Nelson, 2021).

Unemployment in Nigeria is a consistent and persistent uprising phenomenon. Even though Nigeria is known as one of the world's oil giants, brought significant economic and financial reforms, there are reports of an alarming increase in unemployment (Osiobe & Oseghe, 2020). Consequently, unemployment is a developmental issue that affects every developing economy, including Nigeria. The literature also emphasizes Nigeria's governments' and policymakers' failure to deal with the unemployment phenomenon, attributing this to a lack of adequate job creation provision (Shimfe & Wajim, 2020; Tukur & Aguiyi, 2022). According to the literature, the inadequacies of the fundamental structural changes presenting a structural shift in Nigeria have failed to provide significant sustainable economic growth and development that addresses unemployment.

According to (Olorunfemi, 2021), most of the unemployed youth are females in general, and he could also reveal that approximately 50% of females in Nigeria were unemployed between 2008 and 2012. Considering at the Nigerian system critically, some employers do not want to hire women because they require more leave days than their male counterparts, and this is due to pregnancy, during which most women are not as productive as they may suffer from many pregnancy-related medical conditions throughout most of their pregnancies. It does not end there; they will also need maternity leave once the baby arrives. Employers, particularly those in small businesses, face a low productivity level, which may have a significant impact on the sustainability of such businesses, particularly in areas where most employees are women.

Furthermore, there is a cultural value, which is an important factor to consider regarding unemployment in Nigeria. Cultural practices in Nigeria do not favor women in terms of employment compared to their western counterparts (Enfield, 2019). Furthermore, it is widely believed and supported in many parts of the country that women cannot inherit their parents' properties because they are expected to marry into another family and receive whatever they require from that new family. Regardless, they have no right to inherit in whatever family they are married to; their husbands are the only ones eligible for any inheritance that may be available.

Prior research has revealed an alarming rate of unemployment in Nigeria, which can be attributed to various factors such as a lack of proper training and essential employable skills, the state economy and economic activities, the political agenda, security reasons, cultural factors, skewed budget allocation, and an inadequate intervention program (Ewubare & Ogbuagu, 2017).

Despite all these consequences, there have been numerous attempts to reduce unemployment in Nigeria, including educational curriculum changes that include vocational courses; the Programme Life for Rural Women; the Family Support Programme; and the National Directorate of Employment (NDE), which was established on November 22, 1986. Furthermore, numerous studies have been conducted to investigate youth unemployment in Nigeria (Adebimpe et al., 2021; Uju & Racheal, 2018). This creates a gap and emphasizes the need for studies that take a different approach and include women because of their critical role in the economy and society. As a result, investigating unemployment as it relates to women is critical. It is expected that researching the factors influencing women's unemployment will make a significant contribution to efforts to address the issues raised.

## 3. Materials and Methods

The dataset came from the National Demographic and Health Survey (NDHS) (National Population Commission, 2019), a cross-sectional descriptive survey of the total population that focused primarily on the empowerment of women. The 2018 Nigeria Demographic and Health Survey was conducted by the National Population Commission (NPC), which supported data collected from 14 August to December 29, 2018. The data include 41821 study participants, who were women between the ages of 15 and 49. No pre-processing of the data was required. The selection of features is important for machine learning classifier models. Finding the right features for a classification model to employ helps it function more effectively (Mqadi et al., 2021). The dataset in this instance had 13 features; however, 12 of the features were chosen, as shown in Table 1. (1) highest education level, (2) Wealth index, (3) type of place of residence, (4) currently pregnant, (5) currently breastfeeding, (6) currently marital, (7) households age, (8) woman age at the first birth, (9) occupational status, (10) region, (11) ethnicity and (12) age.

Table 1. Description of the NDHS data (n = 41821)

| Features | Categories | Frequency | Percentage (%) |
|---|---|---|---|
| Region | Northcentral | 7772 | 18.6 |
| | Northeast | 7639 | 18.3 |
| | Northwest | 10129 | 24.2 |
| | Southeast | 5571 | 13.0 |
| | South-south | 5080 | 12.1 |
| | Southwest | 5630 | 13.5 |
| The type of place of residence | Urban | 24837 | 59.4 |
| | Rural | 16984 | 40.6 |
| Age | 15–19 | 8423 | 20.2 |
| | 20–24 | 6844 | 16.4 |
| | 25–29 | 7203 | 17.2 |
| | 30–34 | 5997 | 14.3 |
| | 35–39 | 5406 | 12.9 |
| | 40–44 | 4057 | 9.7 |
| | 45–49 | 3891 | 9.3 |
| Educational level | Higher | 4342 | 10.4 |
| | No education | 14398 | 34.4 |
| | Primary | 6383 | 15.3 |
| | Secondary | 16698 | 39.9 |
| Ethnicity | Ekoi | 275 | 0.7 |
| | Fulani | 2953 | 7.1 |
| | Hausa | 10765 | 25.7 |
| | Ibibio | 801 | 1.9 |
| | Igala | 457 | 1.1 |
| | Igbo | 5714 | 13.7 |
| | Ijaw | 1201 | 2.9 |
| | Kanuri | 873 | 2.1 |
| | Tiv | 976 | 2.3 |
| | Yoruba | 5372 | 12.8 |
| | Continuation of Table 1 | | |
| | Others | 11404 | 27.3 |
| | Don’t know | 30 | 0.1 |
| Religion | Catholic | 4436 | 10.6 |
| | Islam | 20959 | 50.1 |
| | Other | 200 | 0.5 |
| | Other Christian | 16070 | 38.4 |
| | Traditionalist | 156 | 0.4 |
| Household Head Gender | Female | 7207 | 17.2 |
| | Male | 34614 | 82.8 |
| Wealth index | Middle | 8859 | 21.2 |
| | poorer | 8346 | 20.0 |
| | poorest | 7747 | 18.5 |
| | Richer | 8840 | 21.1 |
| | Richest | 8029 | 19.2 |
| Current marital Status | Divorced | 543 | 1.3 |
| | Partnership | 1047 | 2.5 |
| | Married | 27841 | 66.6 |
| | Never in union | 10669 | 25.5 |
| | Separated | 604 | 1.4 |
| | Widowed | 1117 | 2.7 |
| Age of respondents at 1st birth | 0–20 | 19524 | 46.7 |
| | 21–40 | 10453 | 25.0 |
| | 40–41 | 15 | 0.0 |
| | Undisclosed | 11829 | 28.3 |
| Currently pregnant | No and Unsure | 37630 | 90.0 |
| | Yes | 4191 | 10.0 |
| Pregnancy Term | 0-3 Months | 1149 | 2.7 |
| | 4-6 Months | 1596 | 3.8 |
| | 7-10 Months | 1446 | 3.5 |
| | Undisclosed | 37630 | 90.0 |

In the literature, there are various cross-validation techniques for choosing a sample to use as training data. Actual samples were separated into k equal-sized subsamples using the k-fold cross-validation approach. The classification model is tested using each subsample as the validation data, and the process is repeated k times. This method has an advantage over repeated random subsampling because training and validation are performed for each at least once (Raju et al., 2018). Because it helps reduce the variability of accuracy estimations for statistical comparison, 10-fold cross-validation was performed in this study (Berrar, 2019). To determine the relevant elements that impact women's employment in Nigeria, a machine learning approach was used. All eight machine learning classifier models had their classification rules adopted during the training stage; as a result, the testing stage is used to evaluate the classification rules' accuracy. To execute algorithms and acquire statistical findings, WEKA, a data mining tool, was employed. The design of the NDHS women unemployment in Nigeria used in this study is depicted in Figure 1.

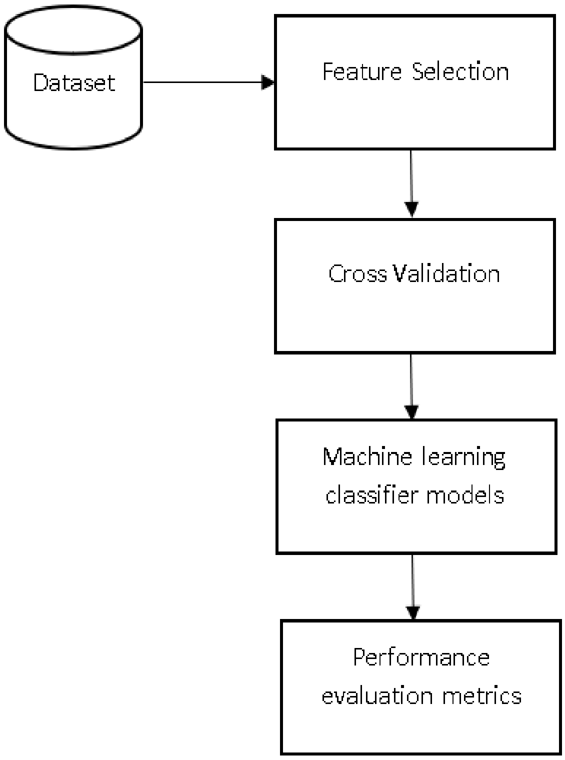


Figure 1. The study design of women unemployment in Nigeria using machine learning classifier models

### *3.1. J48 Pruned Tree*

Using information gain, J48 pruned tree constructs the decision tree from the training data set and evaluates the same after selecting an attribute for data splitting. The algorithm then iterates over smaller selections. If every instance in a subset belongs to the same class, the splitting process comes to an end. The decision tree's leaf node, which presents the outcomes, is then formed. Considering that decisions are made using the Depth-first technique, J48 is marginally improved from C4.5 (Ratra et al., 2021).

### *3.2. Support Vector Machine*

To separate and organize features, a support vector machine built a hyperplane. To determine the best hyperplane, support vectors are produced on either side of the hyperplane, with each vector maximizing the distance between them. A more precise decision boundary between the category features is produced by a larger vector distance around the hyperplane (Hansrajh et al., 2021; Mqadi et al., 2021). Depending on where they are on the hyperplane, the data points are divided into several classes. The primary goal is to increase the gaps between the hyperplane and the data point. Support vector machines, which have been successful in many real-world applications, give conspicuous qualities including margin maximization and nonlinear classification using kernel tricks (Naicker et al., 2020).

### *3.3. AdaBoost*

AdaBoost, an ensemble learning algorithm, is used to improve the precision of decision trees and other weak binary classifiers. Here, weak classifiers add sequentially in contrast to random forest. A dataset with N feature variables will produce N decision stump. All decision stumps were initially given equally weighted data. Based on the lower value of Entropy, the base model, which is the first stump, will be chosen. Following that, each observation is updated with a new weight adjusted depending on performance and overall inaccuracy (Chhillar, 2021).

### *3.4. Logistic Regression*

In each data set, the Logistic Regression inducer looks for a link between the independent variable and the class label that is based on likelihood. The objective is to develop a probability function that accepts features as inputs and outputs the likelihood that an instance belongs to a particular class. The logistic regression needs significantly fewer computational resources and does not require scaling of the input features (Mutanga et al., 2022).

### *3.5. Naïve Bayes*

A straightforward machine learning technique called Naive Bayes (NB) uses the Bayes theorem to calculate class probabilities while assuming that the features are independent. The class with the highest likelihood then receives the predictions. Their probability distributions must be estimated to derive probabilities from continuous features. Usually, kernel density estimation is used for this. The classifier has demonstrated that it can compete with more sophisticated classifiers even though the independence assumption of NB rarely holds in practice (Ijaz et al., 2021).

### *3.6. Logistic Model Tree*

The C4.5 method and logistic regression (LR) functions are combined in the logistic model tree. The LogitBoost approach is used to fit the logistics regression functions at a tree node after the information gain ratio technique has been used to divide the tree into nodes and leaves. The C4.5 algorithm chooses features using the entropy strategy since it is the quickest way to produce accurate classification results (Nhu et al., 2020).

### *3.7. Bagging*

Bootstrap aggregating, also known as bagging, entails giving each model in the ensemble the same weight when voting (Kabari & Onwuka, 2019). The different iterations of the base predictive model are created by bootstrap replications, which use one of the most widely used methods for data resampling in statistical research. Predictive model bagging is a framework that reduces variance and avoid overfitting (Lin et al., 2022).

### *3.8. Random Forest*

The random forests framework is an ensemble learning method that, during training, integrates a collection of decision trees and creates a class representing the mode of the classes found inside the various trees (Lin et al., 2022).

In random forests, each tree in the group is constructed using a bootstrap sample, or an example is drawn with substitution, from the training set (Dutta et al., 2018). Similarly, when dividing a node during tree construction, the split that is chosen is no longer the best split across all features. Instead, the split that is chosen is the best split among a selection of traits that were chosen at random. The bias of the forest slightly increases due to this unpredictability, but because of averaging, its volatility also decreases, often more than making up for the increase in propensity, leading to an overall superior model. Overfitting is a general problem in decision trees; hence, random forests help prevent it.

## 4. Results and Discussion

The random forest learning model outperformed the other seven classical learning models with an accuracy of 86.9% as shown in Table 2. The J48 pruned tree achieved an accuracy of 75.2%, followed by Support Vector Machine (71.1%), AdaBoost (71.0%), Logistic Regression (72.0 %), Naive Bayes (68.0 %), Logistic Model Tree (74.2 %), and Bagging (70.7 %). Because random forest had the advantage of guaranteeing greater levels of accuracy and efficiency, it outperformed the next conventional learning model, Bagging, by 9.6% in terms of accuracy.

Table 2. Performance evaluation metrics of the machine learning classifier models

| | **Accuracy (%)** | **Precision** | **Recall** | **F-measure** | **MCC** |
|---|---|---|---|---|---|
| Random Forest | 86.9 | 0,869 | 0,869 | 0,869 | 0,713 |
| J48 pruned tree | 75.2 | 0,746 | 0,752 | 0,744 | 0,436 |
| Support Vector Machine | 71.1 | 0,700 | 0,711 | 0,699 | 0,335 |
| AdaBoost | 71.0 | 0,700 | 0,710 | 0,686 | 0,320 |
| Logistic Regression | 72.0 | 0,710 | 0,720 | 0,709 | 0,357 |
| Naive Bayes | 68.0 | 0,692 | 0,680 | 0,684 | 0,323 |
| Logistic Model Tree | 74.2 | 0,735 | 0,742 | 0,734 | 0,413 |
| Bagging | 77.7 | 0,773 | 0,777 | 0,772 | 0,498 |

Furthermore, Table 1 results show that the Random Forest learning model outperforms other traditional learning models. The bagging learning model is the closest to the RF learning model, with precision, recall and F-measure scores of 0.773, 0.777, and 0.772 respectively. RF achieved the greatest average precision, recall and F-measure score of 0.869. Consequently, MCC essentially measures the correlation between the predicted and actual series. The bagging learning model reached second best with a score of 0.498, while the random forest learning model had the best score of 0.713 for MCC.

The largest portion of the ROC and PRC areas is covered by RF (0.945) as shown in Table 3. Higher values for kappa statistics, which range from 0 to 1, assume a stronger inter-rate agreement. It is a more accurate projection of a Percentage treaty than usual. As shown in Table 3, RF continues to perform better than other traditional learning models, recording a kappa statistic score of 0.713.

Additionally, it can be shown that AdaBoost outperforms other learning models in terms of MAE value, having the highest value (0.371), while Random Forest has the lowest value (0.244). Finally, the length of time needed to construct the model differs, with Naive Bayes recording the shortest training time (11.9 seconds) and Random Forest recording the longest training time (18.9 seconds). RF outperformed the other seven classical learning models on all nine performance evaluation parameters, despite having the highest training time.

Table 3. ROC area, PRC area, the Kappa statistics, mean absolute error and training time of the machine learning classifier models

| | **ROC Area** | **PRC Area** | **Kappa Statistics** | **Mean Absolute Error** | **Training Time (s)** |
|---|---|---|---|---|---|
| Random Forest | 0,945 | 0,945 | 0.713 | 0.224 | 18.5 |
| J48 pruned tree | 0,775 | 0,776 | 0.429 | 0.352 | 12.6 |
| Support Vector Machine | 0,653 | 0,653 | 0.327 | 0.289 | 12.8 |
| AdaBoost | 0,756 | 0,750 | 0.297 | 0.371 | 13.2 |
| Logistic Regression | 0,768 | 0,768 | 0.350 | 0.367 | 12.0 |
| Naive Bayes | 0,736 | 0,738 | 0.322 | 0.351 | 11.9 |
| Logistic Model Tree | 0,792 | 0,798 | 0.407 | 0.348 | 12.6 |
| Bagging | 0,850 | 0,851 | 0.494 | 0.317 | 16.1 |

The confusion matrix for the random forest, which produced the most accurately categorized class for the unemployed women in Nigeria in the NDHS dataset, is shown in Figure 2.

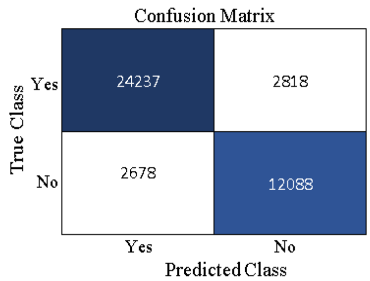


Figure 2. Random forest confusion matrix

## 5. Conclusion

Ensemble classifiers like Random Forest used in this work outperformed other classical machine learning models because of the inherent problem of significant variation, which makes it difficult for classical machine learning models to correctly categorize the dataset. The factors examined in this study provide significant insights with potential recommendations to reduce women's unemployment and assist the primary drivers of sustainable employment in Nigeria in the investigation of factors influencing women's unemployment in Nigeria. Only secondary data from the Nigeria Demographic and Health Survey were used in this study (NDHS). In this study, the twelve factors identified to be explored and investigated were as follows: highest education level, wealth index, type of place of residence, currently pregnant, currently breastfeeding, currently marital, households ages, woman age at the first birth, occupational status, region, ethnicity and age. In this study, a random forest was used to analyze each of these factors and determine their effects on women unemployed in Nigeria. Because the results were acquired using the NDHS dataset, the variables and models developed can be used to estimate new data produced in the future to analyze factors influencing women's unemployment. Instead of traditional attempts to analyzing the influencing factors associated with women's unemployment, this study applied machine learning, a current statistical, algorithmic approach. The outcome shows that, out of the twelve categories, age groups, ethnicity, marital status, and religion are the four main factors affecting women's unemployment in Nigeria. As a result, the results might not be representative of the unemployment problem in other developing countries. Generalization, on the other hand, was not intended because the goal was to emphasize the significance of the identified factors that influence women's unemployment in Nigeria. This study offers insightful information on the phenomenon of women's unemployment for governmental and non-governmental issues. To strengthen future research on women unemployment, the criteria considered during data collection should be expanded as literature has shown that women are more susceptible to unemployment, which might be caused by gender health inequality (Acevedo et al., 2020).

## References


[1] ACEVEDO, P., MORA-URDA, A.I., & MONTERO, P. (2020). Social inequalities in health: duration of unemployment unevenly effects on the health of men and women. *European Journal of Public Health*, 30(2), 305-310. https://doi.org/10.1093/eurpub/ckz180

[2] ADEBIMPE, O.I., ADETUNJI, A.T., NWACHUKWU, C., & HIEU, V.M. (2021). Covid 19 pandemic challenges: The youth unemployment in Nigeria. *Journal of Contemporary Issues in Business and Government*, 27(1), 2004-2012. Retrieved from https://www.cibgp.com/article_8447_afae9a228dc4ba680a0191c4ed4b7dfc.pdf

[3] AJAMOBE, J. O. (2021). Risk taking capacity and entrepreneurship inclination of graduates among postgraduate students in public universities in Lagos State, Nigeria. *Jurnal Pendidikan Nonformal*, 16(2), 94-103. http://dx.doi.org/10.17977/um041v16i2p94-103

[4] AKTURK, S.O., TUGCU, G., & SIPAHI, H. (2022). Development of a QSAR model to predict comedogenic potential of some cosmetic ingredients. *Computational Toxicology*, 21, 100207. https://doi.org/10.1016/j.comtox.2021.100207

[5] AL-TAIE, R.R.K., SALEH, B.J., SAEDI, A.Y.F., & SALMAN, L.A. (2021). Analysis of Weka data mining algorithms Bayes net, random forest, MLP and SMO for heart disease prediction system: A case study in Iraq. *International Journal of Electrical and Computer Engineering*, 11(6), 5229. http://doi.org/10.11591/ijece.v11i6.pp5229-5239

[6] ALI, R.A., IBRAHIM, N.N.L.N., GHANI, W.A.A.K., SANI, N.S., & LAM, H.L. (2022). A Hybrid P-Graph And Weka Approach In Decision-Making: Waste Conversion Technologies Selection. *Journal of Applied Science and Engineering*, 26(2), 261-267. https://doi.org/10.6180/jase.202302_26(2).0012

[7] ALON, T., DOEPKE, M., OLMSTEAD-RUMSEY, J., & TERTILT, M. (2020). This time it's different: The role of women's employment in a pandemic recession. *National Bureau of Economic Research*, 27660. https://doi.org/10.3386/w27660

[8] BERMAN, R. (2018). Women are more productive than men, according to new research. *World Economic Forum*. Retrieved from https://www.weforum.org/agenda/2018/10/women-aremore-productive-than-men-at-work-these-days

[9] BERRAR, D. (2019). Cross-Validation. *IEEE Transactions on Knowledge and Data Engineering*, 32, 1586-1594. http://dx.doi.org/10.1016/B978-0-12-809633-8.20349-X

[10] BIANCONE, P.P., & RADWAN, M. (2018). Social finance and unconventional financing alternatives: an overview. *European Journal of Islamic Finance*, 10. http://dx.doi.org/10.13135/2421-2172/2818

[11] CHHILLAR, R.S. (2021). Analyzing predictive algorithms in data mining for cardiovascular disease using Weka tool. *International Journal of Advanced Computer Science and Applications*, 12(8), 144-150. https://dx.doi.org/10.14569/IJACSA.2021.0120817

[12] CICIOLLA, L., & LUTHAR, S.S. (2019). Invisible household labor and ramifications for adjustment: Mothers as captains of households. *Sex Roles*, 81(7), 467-486. https://doi.org/10.1007/s11199-018-1001-x

[13] DUTTA, D., PAUL, D., & GHOSH, P. (2018). Analysing feature importances for diabetes

prediction using machine learning. Proceedings of the 9th IEEE Annual Information Technology, Electronics and Mobile Communication Conference, 01-03 November 2018. https://doi.org/10.1109/IEMCON.2018.8614871

[14] DVOULETÝ, O., LUKEŠ, M., & VANCEA, M. (2020). Individual-level and family background determinants of young adults' unemployment in Europe. *Empirica*, 47(2), 389-409. https://doi.org/10.1007/s10663-018-9430-x

[15] ENE, E.E. (2018). An empirical analysis of the budget deficit and unemployment nexus in Nigeria. *International Journal of Contemporary Applied Researches*, 5(9), 23-45. Retrieved from http://ijmrap.com/wp-content/uploads/2018/09/IJMRAP-PP2258Y18.pdf

[16] ENFIELD, S. (2019). Gender roles and inequalities in the Nigerian labour market. *K4D*. Retrieved from https://assets.publishing.service.gov.uk/media/5d9b5c88e5274a5a148b40e5/597_Gender_Roles_in_Nigerian_Labour_Market.pdf

[17] EWING-NELSON, C. (2021). All of the jobs lost in december were women's jobs. *National Women's Law Center*. Retrieved from https://nwlc.org/wp-content/uploads/2021/01/December-Jobs-Day.pdf

[18] EWUBARE, D.B., & OGBUAGU, A.R. (2017). Unemployment Rate, Gender Inequality and Economic Growth in Nigeria: A Short-Run Impact Analysis. *Global Journal of Human Resource Management*, 5(5), 12-41. Retrieved from http://www.eajournals.org/wp-content/uploads/Unemployment-Rate-Gender-Inequality-and-Economic-Growth-in-Nigeria-%E2%80%9CA-Short-Run-Impact-Analysis%E2%80%9D-1.pdf

[19] FAKIH, A., HAIMOUN, N., & KASSEM, M. (2020). Youth unemployment, gender and institutions during transition: evidence from the Arab Spring. *Social Indicators Research*, 150(1), 311-336. https://doi.org/10.1007/s11205-020-02300-3

[20] GIBBY, A.L., PETTIT, L., HILL, E.J., YORGASON, J., & HOLMES, E.K. (2021). Implicit and explicit childhood financial socialization: Protective factors for marital financial disagreements. *Journal of Family and Economic Issues*, 42(2), 225-236. https://doi.org/10.1007/s10834-020-09695-8

[21] HAMMELL, K.W. (2019). Building globally relevant occupational therapy from the strength of our diversity. *World Federation of Occupational Therapists Bulletin*, 75(1), 13-26. https://doi.org/10.1080/14473828.2018.1529480

[22] HANSRAJH, A., ADELIYI, T.T., & WING, J. (2021). Detection of online fake news using blending ensemble learning. *Scientific Programming*, 2021, 3434458. https://doi.org/10.1155/2021/3434458

[23] IJAZ, M., ZAHID, M., & JAMAL, A. (2021). A comparative study of machine learning classifiers for injury severity prediction of crashes involving three-wheeled motorized rickshaw. *Accident Analysis & Prevention*, 154, 106094. https://doi.org/10.1016/j.aap.2021.106094

[24] KABARI, L.G., & ONWUKA, U.C. (2019). Comparison of bagging and voting ensemble machine learning algorithm as a classifier. *International Journals of Advanced Research in Computer Science and Software Engineering*, 9(3), 19-23. Retrieved from https://www.researchgate.net/publication/332353572_Comparison_of_Bagging_and_Voting_Ensemble_Machine_Learning_Algorithm_as_a_Classifier

[25] LEVANTESI, S., & PISCOPO, G. (2020). The importance of economic variables on London real estate market: A random forest approach. *Risks*, 8(4), 112. https://doi.org/10.3390/risks8040112

[26] LI, Y. (2018). Against the odds? – A study of educational attainment and labour market position of the second-generation ethnic minority members in the UK. *Ethnicities*, 18(4), 471-495. https://doi.org/10.1177/1468796818777546

[27] LIN, E., LIN, C.-H., & LANE, H.-Y. (2022). A bagging ensemble machine learning framework to predict overall cognitive function of schizophrenia patients with cognitive domains and tests. *Asian Journal of Psychiatry*, 69, 103008. https://doi.org/10.1016/j.ajp.2022.103008

[28] MATANDARE, M. (2018). Botswana unemployment rate trends by gender: Relative analysis with upper middle income Southern African countries (2000-2016). *Dutch Journal of Finance and Management*, 2(2), 4. https://doi.org/10.20897/djfm/3837

[29] MIHRET, Y.A. (2019). Factors associated with women unemployment in Ethiopia. *International Journal of Theoretical and Applied Mathematics*, 5(5), 68-73. Retrieved from https://www.sciencepublishinggroup.com/journal/paperinfo?journalid=347&doi=10.11648/j.ijtam.20190505.11

[30] MQADI, N., NAICKER, N., & ADELIYI, T. (2021). A SMOTE based oversampling data-point approach to solving the credit card data imbalance problem in financial fraud detection. *International Journal of Computing and Digital Systems*, 10(1), 277-286. http://dx.doi.org/10.12785/ijcds/100128

[31] MQADI, N.M., NAICKER, N., & ADELIYI, T. (2021). Solving misclassification of the credit card imbalance problem using near miss. *Mathematical Problems in Engineering*, 2021, 7194728. https://doi.org/10.1155/2021/7194728

[32] MUTANGA, R.T., NAICKER, N., & OLUGBARA, O.O. (2022). Detecting Hate Speech on Twitter Network using Ensemble Machine Learning. *International Journal of Advanced Computer Science and Applications*, 13(3). https://dx.doi.org/10.14569/IJACSA.2022.0130341

[33] NAICKER, N., ADELIYI, T., & WING, J. (2020). Linear support vector machines for prediction of

student performance in school-based education. *Mathematical Problems in Engineering*, 2020, 4761468. https://doi.org/10.1155/2020/4761468

[34] NATIONAL POPULATION COMMISSION (2019). *Nigeria Demographic and Health Survey 2018: key indicators report*. Abuja: National Population Commission.

[35] NHU, V.-H., SHIRZADI, A., SHAHABI, H., SINGH, S.K., AL-ANSARI, N., CLAGUE, J.J., JAAFARI, A., CHEN, W., MIRAKI, S., & DOU, J. (2020). Shallow landslide susceptibility mapping: A comparison between logistic model tree, logistic regression, naïve bayes tree, artificial neural network, and support vector machine algorithms. *International Journal of Environmental Research and Public Health*, 17(8), 2749. https://doi.org/10.3390/ijerph17082749

[36] OKOLIE, U.C., & IGBINI, M.D. (2020). Leadership failure and acute youth unemployment in Nigeria. *RUDN Journal of Public Administration*, 7(3), 254-271. https://doi.org/10.22363/2312-8313-2020-7-3-254-271

[37] OKONKO, I.O., & OKOLI, E.M. (2020). Determination of antibodies to human immunodeficiency virus type 1&2&O and P24 – antigen in pregnant women in port harcourt Nigeria. *Journal of Immunoassay and Immunochemistry*, 41(2), 208-218. https://doi.org/10.1080/15321819.2019.1708387

[38] OLONADE, O.Y., OYIBODE, B.O., IDOWU, B.O., GEORGE, T.O., IWELUMOR, O.S., OZOYA, M.I., EGHAREVBA, M.E., & ADETUNDE, C.O. (2021). Understanding gender issues in Nigeria: the imperative for sustainable development. *Heliyon*, 7(7), e07622. https://doi.org/10.1016/j.heliyon.2021.e07622

[39] OLORUNFEMI, G.C. (2021). Addressing the State of Youth Unemployment in Nigeria. *International Journal of Innovative Psychology & Social Development*, 9, 102-113. Retrieved from https://seahipaj.org/journals-ci/dec-2021/IJIPSD/full/IJIPSD-D-10-2021.pdf

[40] OSIOBE, E.U., & OSEGHE, O.M. (2020). Analyzing the Jobless Recovery Phenomenon in the Nigerian Economy. *Journal of Applied Business and Economics*, 22(9), 181-196. https://doi.org/10.33423/jabe.v22i9.3678

[41] RAJU, K.S., MURTY, M.R., RAO, M.V., & SATAPATHY, S.C. (2018). Support Vector Machine with k-fold cross validation model for software fault prediction. *International Journal of Pure and Applied Mathematics*, 118(20), 321-334. https://doi.org/10.1016/j.procs.2021.01.074

[42] RATRA, R., GULIA, P., & GILL, N.S. (2021). Performance Analysis of Classification Techniques in Data Mining using WEKA. *SSRN*, 3879610. https://dx.doi.org/10.2139/ssrn.3879610

[43] SHIMFE, H.G., & WAJIM, J. (2020). Youth unemployment: the cause of ethnic conflict and criminal activities in Takum local government area of Taraba state Nigeria. *The International Journal of Social Sciences and Humanities Invention*, 7(04), 5882-5890. https://doi.org/10.18535/ijsshi/v7i04.01

[44] SINAI, I., ANYANTI, J., KHAN, M., DARODA, R., & OGUNTUNDE, O. (2017). Demand for women's health services in northern Nigeria: a review of the literature. *African Journal of Reproductive Health*, 21(2), 96-108. https://doi.org/10.29063/ajrh2017/v21i2.11

[45] TADESSE, A.W., TAREKEGN, S.M., WAGAW, G.B., MULUNEH, M.D., & KASSA, A.M. (2022). Prevalence and associated factors of intimate partner violence among married women during COVID-19 pandemic restrictions: a community-based study. *Journal of Interpersonal Violence*, 37(11-12), 8632-8650. https://doi.org/10.1177/0886260520976222

[46] TUKUR, I.T., & AGUIYI, C.C. (2022). Poor Education, Unemployment and National Security in Nigeria. *KIU Journal of Social Sciences*, 8(1), 187-197. Retrieved from https://www.ijhumas.com/ojs/index.php/kiujoss/article/view/1428

[47] UJU, M., & RACHEAL, J.-A. C. (2018). Impact of entrepreneurial skills in reducing youth unemployment in Nigeria. *European Journal of Business, Economics and Accountancy*, 6(3), 1-12. Retrieved from https://www.idpublications.org/wp-content/uploads/2018/04/Full-Paper-IMPACT-OF-ENTREPRENEURIAL-SKILLS-IN-REDUCING-YOUTH-UNEMPLOYMENT-IN-NIGERIA.pdf

[48] YAYA, O.S., OGBONNA, A.E., & MUDIDA, R. (2019). Hysteresis of unemployment rates in Africa: new findings from Fourier ADF test. *Quality & Quantity*, 53(6), 2781-2795. https://doi.org/10.1007/s11135-019-00894-6

[49] ZULQARAM, M.S., ZAINAL, H.S.H., MAHAT, N.F., SULTAN MOHIDEEN, R., ILYAS, I.Y., RAMLAN, A.F., JAAPAR, I., SUYURNO, S.S., & AMAIRUDIN, M.F. (2021). The level of gender bias in workplace and household. *E-Journal of Media and Society*, 4(2), 37-60. Retrieved from https://myjms.mohe.gov.my/index.php/ejoms/article/view/15600

**参考文:**

[1] ACEVEDO, P., MORA-URDA, A.I., 和 MONTERO, P. (2020). 健康方面的社会不平等：失业持续时间对男性和女性健康的影响不均衡。欧洲公共卫生杂志，30(2), 305-310. https://doi.org/10.1093/eurpub/ckz180

[2] ADEBIMPE, O.I., ADETUNJI, A.T., NWACHUKWU, C., 和 HIEU, V.M. (2021). 新冠肺炎大流行挑战：尼日利亚的青年失业问题。商业和政府当代问题杂志，27(1), 2004-2012。从...获得 https://www.cibgp.com/article_8447_afae9a228dc4ba680a0191c4ed4b7dfc.pdf

[3] AJAMOBE, J. O. (2021). 尼日利亚拉各斯州公立大学研究生毕业生的风险承担能力和创业倾向。非正式学报, 16(2), 94-103. http://dx.doi.org/10.17977/um041v16i2p94-103

[4] AKTURK, S.O., TUGCU, G., 和 SIPAHI, H. (2022). 开发定量构效关系模型以预测某些化妆品成分的致粉刺潜力。计算毒理学, 21, 100207. https://doi.org/10.1016/j.comtox.2021.100207

[5] AL-TAIE, R.R.K., SALEH, B.J., SAEDI, A.Y.F., 和 SALMAN, L.A. (2021). 维卡数据挖掘算法贝叶斯网、随机森林、多层感知器和心脏病预测系统的顺序最小优化分析：伊拉克案例研究。国际电气与计算机工程杂志, 11(6), 5229. http://doi.org/10.11591/ijece.v11i6.pp5229-5239

[6] ALI, R.A., IBRAHIM, N.N.L.N., GHANI, W.A.A.K., SANI, N.S., 和 LAM, H.L. (2022). 决策中的混合 P 图和维卡方法：废物转化技术选择。应用科学与工程杂志, 26(2), 261-267. https://doi.org/10.6180/jase.202302_26(2).0012

[7] ALON, T., DOEPKE, M., OLMSTEAD-RUMSEY, J., 和 TERTILT, M. (2020). 这次有所不同：女性就业在大流行性衰退中的作用。国家经济研究局, 27660. https://doi.org/10.3386/w27660

[8] BERMAN, R. (2018). 根据最新研究, 女性比男性更有生产力。世界经济论坛。从...获得 https://www.weforum.org/agenda/2018/10/women-aremore-productive-than-men-at-work-these-days

[9] BERRAR, D. (2019). 交叉验证。电气与电子工程师协会知识与数据工程汇刊, 32, 1586-1594. http://dx.doi.org/10.1016/B978-0-12-809633-8.20349-X

[10] BIANCONE, P.P., 和 RADWAN, M. (2018). 社会融资和非常规融资方案：概述。欧洲伊斯兰金融杂志, 10. http://dx.doi.org/10.13135/2421-2172/2818

[11] CHHILLAR, R.S. (2021). 使用维卡工具分析心血管疾病数据挖掘中的预测算法。国际高级计算机科学与应用杂志, 12(8), 144-150. https://dx.doi.org/10.14569/IJACSA.2021.0120817

[12] CICIOLLA, L., 和 LUTHAR, S.S. (2019). 无形的家务劳动和调整的后果：母亲是一家之主。性别角色, 81(7), 467-486. https://doi.org/10.1007/s11199-018-1001-x

[13] DUTTA, D., PAUL, D., 和 GHOSH, P. (2018). 使用机器学习分析糖尿病预测的特征重要性。第九届电气和电子工程师协会年度信息技术、电子和移动通信会议论文集，2018 年 11 月 1 日至 3 日. https://doi.org/10.1109/IEMCON.2018.8614871

[14] DVOULETÝ, O., LUKEŠ, M., 和 VANCEA, M. (2020). 由欧洲年轻人失业的个人水平和家庭背景决定。经验主义, 47(2), 389-409. https://doi.org/10.1007/s10663-018-9430-x

[15] ENE, E.E. (2018). 尼日利亚预算赤字与失业关系的实证分析。 国际当代应用研究杂志，5(9), 23-45。从...获得 http://ijmrap.com/wp-content/uploads/2018/09/IJMRAP-PP2258Y18.pdf

[16] ENFIELD, S. (2019). 尼日利亚劳动力市场中的性别角色和不平等。知识促进发展。从...获得 https://assets.publishing.service.gov.uk/media/5d9b5c88e5274a5a148b40e5/597_Gender_Roles_in_Nigerian_Labour_Market.pdf

[17] EWING-NELSON, C. (2021). 12 月份失去的所有工作都是女性的工作。国家妇女法律中心。从...获得 https://nwlc.org/wp-content/uploads/2021/01/December-Jobs-Day.pdf

[18] EWUBARE, D.B., 和 OGBUAGU, A.R. (2017). 尼日利亚的失业率、性别不平等和经济增长：短期影响分析。全球人力资源管理杂志，5(5), 12-41。从...获得 http://www.eajournals.org/wp-content/uploads/Unemployment-Rate-Gender-Inequality-and-Economic-Growth-in-Nigeria-%E2%80%9CA-Short-Run-Impact-Analysis%E2%80%9D-1.pdf

[19] FAKIH, A., HAIMOUN, N., 和 KASSEM, M. (2020). 转型期间的青年失业、性别和制度：来自阿拉伯之春的证据。社会指标研究, 150(1), 311-336. https://doi.org/10.1007/s11205-020-02300-3

[20] GIBBY, A.L., PETTIT, L., HILL, E.J., YORGASON, J., 和 HOLMES, E.K. (2021). 隐性和显性童年财务社会化：婚姻财务分歧的保护因素。家庭与经济问题杂志, 42(2), 225-236. https://doi.org/10.1007/s10834-020-09695-8

[21] HAMMELL, K.W. (2019). 凭借我们的多元化优势，建立全球相关的职业治疗。世界职业治疗师联合会公告, 75(1), 13-26. https://doi.org/10.1080/14473828.2018.1529480

[22] HANSRAJH, A., ADELIYI, T.T., 和 WING, J. (2021). 使用混合集成学习检测在线假新闻。科学规划, 2021, 3434458. https://doi.org/10.1155/2021/3434458

[23] IJAZ, M., ZAHID, M., 和 JAMAL, A. (2021). 机器学习分类器对三轮机动人力车碰撞严重程度预测的比较研究。事故分析与预防, 154, 106094. https://doi.org/10.1016/j.aap.2021.106094

[24] KABARI, L.G., 和 ONWUKA, U.C. (2019). 套袋和表决集成机器学习算法作为分类器的比较。计算机科学与软件工程高级研究国际期刊, 9(3), 19-23. 从...获得 https://www.researchgate.net/publication/332353572_Comparison_of_Bagging_and_Voting_Ensemble_Machine_Learning_Algorithm_as_a_Classifier

[25] LEVANTESI, S., 和 PISCOPO, G. (2020). 经济变量对伦敦房地产市场的重要性：随机森林管理方法。风险, 8(4), 112. https://doi.org/10.3390/risks8040112

[26] LI, Y. (2018). 逆势而行？– 英国第二代少数民族成员的教育程度和劳动力市场地位研究。种族, 18(4), 471-495.

https://doi.org/10.1177/1468796818777546

[27] LIN, E., LIN, C.-H., 和 LANE, H.-Y. (2022). 一个套袋集成机器学习框架，用于预测具有认知域和测试的精神分裂症患者的整体认知功能。亚洲精神病学杂志, 69, 103008. https://doi.org/10.1016/j.ajp.2022.103008

[28] MATANDARE, M. (2018). 博茨瓦纳按性别划分的失业率趋势：与中高收入南部非洲国家的相对分析（2000-2016 年）。荷兰金融与管理杂志, 2(2), 4. https://doi.org/10.20897/djfm/3837

[29] MIHRET, Y.A. (2019). 与埃塞俄比亚妇女失业相关的因素。国际理论与应用数学杂志，5（5），68-73。从...获得 https://www.sciencepublishinggroup.com/journal/paperinfo?journalid=347&doi=10.11648/j.ijtam.20190505.11

[30] MQADI, N., NAICKER, N., 和 ADELIYI, T. (2021). 一种基于合成少数过采样技术的过采样数据点方法来解决金融欺诈检测中的信用卡数据不平衡问题。国际计算与数字系统杂志, 10(1), 277-286. http://dx.doi.org/10.12785/ijcds/100128

[31] MQADI, N.M., NAICKER, N., 和 ADELIYI, T. (2021). 使用有惊无险解决信用卡不对问题的错误分类。工程中的数学问题, 2021, 7194728. https://doi.org/10.1155/2021/7194728

[32] MUTANGA, R.T., NAICKER, N., 和 OLUGBARA, O.O. (2022). 使用集成机器学习检测推特网络上的仇恨言论。国际高级计算机科学与应用杂志, 13(3). https://dx.doi.org/10.14569/IJACSA.2022.0130341

[33] NAICKER, N., ADELIYI, T., 和 WING, J. (2020). 用于预测校本教育中学生表现的线性支持向量机。工程中的数学问题, 2020, 4761468. https://doi.org/10.1155/2020/4761468

[34] 国家人口委员会 (2019). 2018 年尼日利亚人口与健康调查：关键指标报告。阿布贾：国家人口委员会.

[35] NHU, V.-H., SHIRZADI, A., SHAHABI, H., SINGH, S.K., AL-ANSARI, N., CLAGUE, J.J., JAAFARI, A., CHEN, W., MIRAKI, S., 和 DOU, J. (2020). 浅层滑坡敏感性映射：逻辑模型树、逻辑回归、朴素贝叶斯树、人工神经网络和支持向量机算法之间的比较。国际环境研究与公共卫生杂志, 17(8), 2749. https://doi.org/10.3390/ijerph17082749

[36] OKOLIE, U.C., 和 IGBINI, M.D. (2020). 尼日利亚的领导失败和严重的青年失业问题。人民民主共和国公共行政学报, 7(3), 254-271. https://doi.org/10.22363/2312-8313-2020-7-3-254-271

[37] OKONKO, I.O., 和 OKOLI, E.M. (2020). 尼日利亚哈科特港孕妇人体免疫缺陷病毒 1&2&O 和 P24 抗原抗体的测定。免疫分析与免疫化学杂志, 41(2), 208-218. https://doi.org/10.1080/15321819.2019.1708387

[38] OLONADE, O.Y., OYIBODE, B.O., IDOWU, B.O., GEORGE, T.O., IWELUMOR, O.S., OZOYA, M.I., EGHAREVBA, M.E., 和 ADETUNDE, C.O. (2021). 了解尼日利亚的性别问题：可持续发展的当务之急。赫利永, 7(7), e07622. https://doi.org/10.1016/j.heliyon.2021.e07622

[39] OLORUNFEMI, G.C. (2021). 解决尼日利亚青年失业状况。国际创新心理学与社会发展杂志，9，102-113。从...获得 https://seahipaj.org/journals-ci/dec-2021/IJIPSD/full/IJIPSD-D-10-2021.pdf

[40] OSIOBE, E.U., 和 OSEGHE, O.M. (2020). 分析尼日利亚经济中的失业复苏现象。应用商业与经济学杂志, 22(9), 181-196. https://doi.org/10.33423/jabe.v22i9.3678

[41] RAJU, K.S., MURTY, M.R., RAO, M.V., 和 SATAPATHY, S.C. (2018). 用于软件故障预测的具有 k 折交叉验证模型的支持向量机。国际理论与应用数学杂志, 118(20), 321-334. https://doi.org/10.1016/j.procs.2021.01.074

[42] RATRA, R., GULIA, P., 和 GILL, N.S. (2021). 使用维卡进行数据挖掘中分类技术的性能分析。社会科学研究网, 3879610. https://dx.doi.org/10.2139/ssrn.3879610

[43] SHIMFE, H.G., 和 WAJIM, J. (2020). 青年失业：尼日利亚塔拉巴州塔库姆地方政府地区种族冲突和犯罪活动的起因。国际社会科学与人文发明杂志, 7(04), 5882-5890. https://doi.org/10.18535/ijsshi/v7i04.01

[44] SINAI, I., ANYANTI, J., KHAN, M., DARODA, R., 和 OGUNTUNDE, O. (2017). 尼日利亚北部妇女保健服务的需求：文献综述。非洲生殖健康杂志, 21(2), 96-108. https://doi.org/10.29063/ajrh2017/v21i2.11

[45] TADESSE, A.W., TAREKEGN, S.M., WAGAW, G.B., MULUNEH, M.D., 和 KASSA, A.M. (2022). 新冠肺炎大流行限制期间已婚妇女亲密伴侣暴力的发生率和相关因素：一项基于社区的研究。人际暴力杂志, 37(11-12), 8632-8650. https://doi.org/10.1177/0886260520976222

[46] TUKUR, I.T., 和 AGUIYI, C.C. (2022). 尼日利亚贫困的教育、失业和国家安全。坎帕拉国际大学社会科学杂志，8(1), 187-197。从...获得，8(1), 187-197. 从...获得 https://www.ijhumas.com/ojs/index.php/kiujoss/article/view/1428

[47] UJU, M., 和 RACHEAL, J.-A. C. (2018). 创业技能对减少尼日利亚青年失业的影响。欧洲商业、经济和会计杂志，6(3), 1-12。从...获得 https://www.idpublications.org/wp-content/uploads/2018/04/Full-Paper-IMPACT-OF-ENTREPRENEURIAL-SKILLS-IN-REDUCING-YOUTH-UNEMPLOYMENT-IN-NIGERIA.pdf

[48] YAYA, O.S., OGBONNA, A.E., 和 MUDIDA, R. (2019). 非洲失业率的滞后现象：傅里叶增强迪基-富勒检验的新发现。质量和数量，53(6), 2781-2795. https://doi.org/10.1007/s11135-019-00894-6

[49] ZULQARAM, M.S., ZAINAL, H.S.H., MAHAT, N.F., SULTAN MOHIDEEN, R., ILYAS, I.Y., RAMLAN, A.F., JAAPAR, I., SUYURNO, S.S., 和 AMAIRUDIN, M.F. (2021). 工作场所和家庭中的性别偏见程度。媒体与社会电子期刊，4(2), 37-60 。从 ... 获得 https://myjms.mohe.gov.my/index.php/ejoms/article/view/15600