American Journal of Applied Mathematics and Statistics, 2020, Vol. 8, No. 2, 58-63
Available online at http://pubs.sciepub.com/ajams/8/2/4
Published by Science and Education Publishing
DOI:10.12691/ajams-8-2-4

On the Modeling of the Effects of COVID-19 Outbreak on the Welfare of Nigerian Citizens, Using Network Model

O. C. Asogwa[1,*], N. M. Eze[2], C. M. Eze[2], C. I. Okonkwo[1], C. U. Onwuamaeze[2]

[1]Department of Mathematics, Computer Science, Statistics and Informatics, Alex Ekwueme Federal University Ndufu-Alike Ikwo
[2]Department of Statistics, University of Nigeria, Nsukka
*Corresponding author: qackasoo@yahoo.com

Received June 27, 2020; Revised July 08, 2020; Accepted July 16, 2020

Abstract A multilayer perception algorithm based model was established in this research. The result from the test data evaluation showed that the established Artificial Neural Network model was able to correctly predict and classify the effects of COVID-19 outbreak on the well-being of Nigerian citizens with Mean Correct Classification Rate (CC_R) of 98.05%. The value of the AUC of the model which was classified as good (88.23%), also aligned with the result obtained from the Mean Correct classification rate. The architecture model also indicated a very high sensitivity and a low specificity values respectively. The study was able to show that some factors like economy, farming activities, religious activities, education, etc. were negatively affected whereas crime rates, unwanted pregnancy, relationship between parents and their children were positively influenced during the lockdown period of coronavirus pandemic outbreak in Nigeria.

Keywords: *mean correct classification rate, Artificial Neural Networks (ANNs), predictive models, COVID-19*

Cite This Article: O. C. Asogwa, N. M. Eze, C. M. Eze, C. I. Okonkwo, and C. U. Onwuamaeze, “On the Modeling of the Effects of COVID-19 Outbreak on the Welfare of Nigerian Citizens, Using Network Model.” *American Journal of Applied Mathematics and Statistics*, vol. 8, no. 2 (2020): 58-63. doi: 10.12691/ajams-8-2-4.

1. Introduction

Nigeria, officially known as the Federal Republic of Nigeria, is a country that is located on the western coast of Africa and has the highest population in African nation [1]. The country which has a total surface area of approximately 923,768 square kilometers with density of around 212.04 individuals per square kilometers [2], features 36 states with Federal Capital Territory, which is known as Abuja. Nigeria has over five hundred different ethnic groups, many different languages, and was declared independent from the United Kingdom on October 1, 1960. In the year 2020, the estimated population of this country was over 206.14 million, ranking 7th in the world, which suggests that the entire population of Nigeria accounts for about 2.35% of the entire earth’s population [3]. This means that about 1 out of every 43 people in the world is a Nigeria. It should be noted that these estimates by the Nigerian National Bureau of Statistics took into account the residual effects of the very high mortality rate, due to the rampant AIDS epidemic and other pandemics in the country.

However, the overall religious aspect of Nigeria is generally split among Christianity, Islam and Indigenous religions with majority of the population as Christians [4]. The culture of Nigeria is shaped by Nigerian multiple ethnic groups. The country has 527 languages, seven of them are extinct [5]. Nigeria also has over 1150 dialects and ethnic groups. The six largest ethnic groups are the Hausa and Fulani in the North, the Igbo in the Southeast, and the Yoruba predominate in the Southwest, the Tiv people of North Central Nigeria and the Efik - Ibibio. The Edo people are most frequent in the region between Yoruba land and Igbo land. Many of the Edo tend to be Christians. This group is followed [6] by the Ibibio/Annang/Efik people of the coastal South Southern Nigeria and the Ijaw of the Niger Delta. The Fulani and the Hausa are predominantly Muslims while the Igbo are predominantly Christians and so are the Efik, Ibibio, and Annang people. The Yoruba are equally likely to be either Christians or Muslims. Indigenous religious practices remain important to all of Nigerian ethnic groups, and frequently these beliefs are blended with Christian beliefs, a practice known as syncretism.

Nigeria has major sectors of occupation as Agriculture (Farming, Forestry and Fishing), Industry (Mining, Manufacturing, Energy production and Construction), Services (Government Activities, Communications, Transportation, Finance, and Others), [7]. It has been established that Agriculture accounts for 70% of the economy, followed by Industry with 10% and Services with 20% respectively [8]. However, the economy of

Nigeria is a middle -income mixed economy and emerging market, with expanding manufacturing, financial, services, communication, technology and entertainment sectors. It is ranked as the 27th largest economy in the world in term of normal GDP and the 22nd largest in term of purchasing power parity. Nigeria has the largest economy in Africa; her re - emergent manufacturing sectors became the largest on the continent in 2013 and it produces a large proportion of goods and services for the West African sub-continent [9]. Nigeria has about 2.7% of the world's oil supply [10] and has equally been proven to have an oil reserve of an estimated 35billion barrels natural gas reserve as well as over 100 trillion cubic feet. Nigeria which exports Bonny Light oil, Forcados crude oil, Qua Ibo crude oil, and Brass river crude oil [11] is a member of the Organization of Petroleum Exporting Countries (OPEC).

Nevertheless, in the early quarter of the year 2020, a deadly viral pandemic disease known as Coronavirus Disease (COVID - 19) was witnessed in Nigeria. On 27th February, the first confirmed case of the pandemic of Coronavirus Disease 2019 in Nigeria was announced, when an Italian citizen who works in Nigeria had returned on 25 February from Milan, Italy through the Murtala Muhammed International Airport, fell ill on 26 February and was transferred to Lagos State Biosecurity Facilities for isolation and testing [12]. This pandemic has infected a quite number of Nigerian citizens and has crippled all the major sectors of her economy. It has grossly affected Agriculture, Industry, Transportation, Religious Activities, Social Activities, Trade, etc. since its inception. This is because Nigerians were mandated by the government to stay at home for months.

In this paper, a Soft computing technique, which artificial neural network is part of, has been recognized as attractive alternatives to the standard, well-established hard computing paradigms. Soft computing techniques, which emphasize gains in understanding system behavior in exchange for unnecessary precision, have been proven to be able to efficiently solve complicated problems. Soft computing techniques have also enabled the development of more efficient model designed to evaluate and classify the impact of Coronavirus Disease on the welfare of Nigerian citizens, during the lockdown phase. Artificial Neural Networks (ANN) can recognize the rules to make right evaluation and provide assistance for decision-making because it has the characteristics of self-organizing and self-learning processes [13,14,15,16]. Artificial neural networks are computation systems that process information in parallel, using a large number of simple units that excel in tasks involving pattern recognition. These intrinsic properties of the neural networks have been translated into higher performance accuracy in outcome evaluation and prediction compared to expert opinion or conventional statistical methods [17,18,19,20].

Several researchers have conducted studies on the impact of pandemic diseases on the welfare of citizens. Liu et al. [21] used mathematical models to simulate the propagation status of COVID-19 in China and also noted the importance of the government policy in limiting public activities and the movement of infected people with no symptoms. Al-Qaness et al. [22] adopted the adaptive neuro-fuzzy inference system (ANFIS), an improvement from flower pollination algorithm and salp swarm algorithm, to predict the number of would be confirmed cases within the space of 10 days of the outbreak. The comparison with the ANFIS optimized with GA, PSO, ABC, and FPA indicated that the accuracy of the FPASSA-ANFIS model reached 0.97, and the predicted average increase in numbers of new cases within 10 days was 10% more than the number of already confirmed cases. In addition, [23] used the rate of increase together with delayed distribution estimation and statistical induction to establish a mathematical model, based on COVID-2019 case data reported before January 24. The predicted cumulative number of confirmed cases between the times of outbreak till January 24 was 6,924, and the predicted death ratio was 5.3%. These figures were within the 95% confidence interval. In line with previous methods for establishing mathematical models, [24] adopted a statistical method for predicting the floating population in Wuhan City. The experiment indicated that the floating population in Wuhan region was highly correlated with the number of daily confirmed cases. The residence time of the floating population for local cases was longer than that for non-local cases, which results in a lower predicted number of confirmed cases in the areas around Hubei Province. The prediction results indicate that approximately 80% of the epidemic will be centralized in the top 30 districts. Hu et al. [25] used an improved stacked auto-encoder and a cluster algorithm to group the instantaneous confirmed cases in every province which noted a high accuracy in AI-based methods for COVID-19 trajectory prediction. The epidemic was predicted to end in mid-April.

Guo et al. [26] used deep learning-based virus host prediction to compare the gene sequence of 2019-nCoVs with those of Severe Acute Respiratory Syndrome Coronavirus (SARS-CoV), bat SARS corona virus, and Middle East respiratory syndrome-related coronavirus (MERS-CoV). The bat SARS coronavirus was discovered to have a more similar mode of infection to COVID-19. Further studies could be seen in [27,28,29,30].

However, the main objective of this work is to evaluate the accuracy of the Artificial Neural Network Model Architecture developed under a statistical programme (SPSS V.20) as a classifier, in evaluating the impact of Coronavirus on the welfare of Nigerian citizens using its Mean Correct Classification Rate {CCR (%)}, among others is: to report the order of predictor's significance to the model programmed. The factors that were considered under the welfare can be seen in the appendixes.

1.1. Coronavirus

The coronavirus belongs to a family of viruses that may cause various symptoms such as pneumonia, fever, breathing difficulty, and lung infection [31]. These viruses are common in animals worldwide, but very few cases have been known to affect humans [32]. The World Health Organization (WHO) used the term 2019 novel coronavirus to refer to a coronavirus that affected the lower respiratory tract of patients with pneumonia in Wuhan, China on 29 December 2019 [33,34,35]. The WHO announced that the official name of the 2019 novel coronavirus is coronavirus disease (COVID 19) [35]. And the current reference name for the virus is severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). It was reported that a cluster of patients with pneumonia of unknown cause was linked to a local Huanan South China Seafood Market in Wuhan, Hubei Province, China in December 2019 [36]. However, Standard recommendations to prevent the spread of COVID-19 include frequent cleaning of hands using alcohol-based hand rub or soap and water; covering the nose and mouth with a flexed elbow or disposable tissue when coughing and sneezing; and avoiding close contact with anyone that has a fever and cough.

2. Materials and Methods

The data used in this work were primary data collected through questionnaire. A total number of 480 questionnaires were sent through social media across the six geopolitical zones in Nigeria. In each geopolitical zone, a random sample technique was used to select four States, and in each State, twenty friends in my social media accounts were administered the questionnaire. The geopolitical zones and the states that were randomly selected in each were as follows: North Central (Middle Belt) - Benue State, Kogi State, Niger State and Abuja; North East - Adamawa State, Bauchi State, Taraba State and Yobe State; North West - Kaduna State, Kano State, Kebbi State and Sokoto State; South East - Anambra State, Enugu State, Ebonyi State and Imo State; South South (Niger Delta Region) - Akwa Ibom State, Bayelsa State, River State and Delta State; and South West - Lagos State, Ondo State, Ogun State and Ekiti State.

However, through an extensive review of literatures, on the coronavirus outbreak, a number of factors which has an impact direct or indirect on the welfare of Nigerian citizens were discovered. Some of these factors were religions activities, education, economy, transportation, trading, security, health, family peace, social activities, clubbing, prostitution, etc. Total evaluation of these impacts of COVID - 19 on the welfare of Nigerian citizens during the period of lockdown as responded were carefully studied and harmonized into a manageable number suitable for computer coding within the context of the Artificial Neural Network modeling. These influencing factors were categorized as input variables (units). The output variables on the other hand represented the total evaluation of the impact of COVID - 19 on the welfare of Nigerian citizens during the period of lockdown (Above 50% - Positive Impact, below 50% - Negative Impact, Unaffected). That is, the output was categorically classified. SPSS version 20 was used as a statistical tool for the analysis. In addition, a Multi-Layer Artificial Neural Network (ANN) model with a Softmax Transfer Function, trained with back-propagation algorithm was programmed; the model was able to evaluate and classify Nigerian citizens into three categories: those that perceived the impact positively, those that agreed to the impact negatively and those that said that their welfare were unaffected.

2.1. Artificial Neural Network Model

Artificial Neural Network (ANN) model proposed by [37] was used. The model which considered a transfer function as softmax, is given below as;

$$y = \varphi + \epsilon_i \tag{1}$$

where $\varphi = f(X, W)$.

Then equation (1) will be

$$y = f(X, W) + \epsilon_i. \tag{2}$$

From equation (2) above,

$$y = \alpha X + \sum_{h=1}^{H} \beta_h g(*)\{\sum_{i=0}^{I} \gamma_{h_i} x_i\} + \epsilon_i. \tag{3}$$

This equation (3) can rewritten as,

$$y = \alpha X + \sum_{h=1}^{H} \beta_h \left(\frac{e^{\alpha_i}}{\sum_h e^{\alpha_h}} \right) \{\sum_{i=0}^{I} \gamma_{h_i} x_i\} + \epsilon_i \tag{4}$$

Where $g(*) = \dfrac{e^{\alpha_i}}{\sum_h e^{\alpha_h}}$

$$X = (x_0 = 0, x_1, \ldots, x_I);\ W = (\alpha, \beta, \gamma)$$

Where: y is the output variable; X is the input variables; α is the weight of the input unit(s); β is the weight of the hidden unit(s); γ is the weight of the output unit(s); $g(*)$ is the softmax transfer function which classify the output; and ϵ_i is the error term.

2.1.1. Network Architecture and Design

Multi-layer Perceptions (MLPs) are layered feed forward networks typically trained with static back propagation. These networks have found their way into countless applications requiring static pattern classification [38]. Therefore, given the computational capabilities of a multilayer perception as a classifier, a three-layered feed forward neural network was programmed in this research work. The first layer (input level) comprised of twenty two neurons (processing elements) - one for each profile parameter (input). The third layer (output level) comprised of three neurons (“positive impact”, “negative impact” & “unaffected”) as seen in the appendix. However, upon recommendations from [39] and [40], one hidden-layer network is sufficient to model any complex system. Hence the network model was designed with only one hidden layer. Besides, eighty neurons in the hidden layer were most suitable, as the network performance was most favored. The network was trained with back-propagation learning algorithm and softmax activation function adopted at the hidden layer.

2.1.2. Data Set Grouping

The data were divided into three categories in supervised training; the training set, verification set (hide out) and the testing set. The training set enables the system to observe relationships between input data and resulting outputs, so that it can develop relationship between the input and the expected output [38]. A heuristic statement is that the number of the training set data should be at least a factor of 10 larger than the number of network weight to accurately classify test data with 90% accuracy [41]. A total of 480 respondents were used in the analysis. About (58.0%) of the total data (i.e. 278 candidates) was used as the training set, (32.0%) (i.e. 154 candidates) as the testing set, and (10.0%) (i.e. 48 candidates) was used for cross validation as each network was run for 1000 epochs.

2.1.3. Model Performance Measures

There can be many performance measures for predictors; the most important measure of performance is the prediction accuracy that can be achieved with the training data [38]. The most frequently used is the Mean Correct Classification Rate (CC_R) [42,43], which is defined as

$$CC_R = \frac{\sum_{k=0}^{C-1} CC_R}{n} \quad (5)$$

Where CC_R is the number of correctly classified observations and n is the number of observations in the class. A model with a high Correct Classification Rate has a better performance. In general, CC_R is used to judge the functional network classifier performance. The better classifier is the one with a high CC_R value.

3. Results

After the training and cross validation, the network was tested with the test data set and the following results were obtained. This involve given the input variable data to the network without the output variable results. The output from the network is then compared with the actual variable data and the mean correct classification rate was evaluated using equation (5). The comparison is summarized in the matrix bellow in Table 1.

Table 1. The table of Prediction and Classification of the Model

Model Performances	Positive Impact	Negative Impact	Unaffected
Positive Impact	25 (96.15%)	1 (3.85%)	0 (0.00%)
Negative Impact	0 (0.00%)	124 (99.20%)	1 (0.80%)
Unaffected	1 (33.33%)	0 (0.00%)	2 (66.67%)
Mean Correct Class ($\boldsymbol{CCR}$) = 98.05%			

From Table 1 above, each row represents a case of interest and each cell represents the number of the cases of the interest in the rows as evaluated by the classifier. The network was able to predict accurately 25 out of 26 for people which attested that COVID-19 impacted positively to the welfare of the Nigerian citizens, 124 out of 125 for the respondents that saw the impact of COVID-19 negatively on the welfare of Nigerian citizens, and 2 out of 3 for those that responded that COVID-19 did not affected the welfare of Nigerian citizens, as used to test the Network's topology. An accuracy of 96.15% was attributed to those that stood for positive impact, 99.20% for the candidate that agreed that COVID-19 affected the citizens of Nigeria negatively, and 66.67% for those that said that COVID-19 did not affect the welfare of Nigerian citizens. The Mean Correct Classification Rate or accuracy of about 98.05% for the Artificial Neural Network model architecture developed which shows a good performance according to results from some literatures is like: [41,44,45].

However, from the result obtained, it was observed that some factors responded in support and against the effect of COVID-19 on the welfare of Nigerian citizens. Religious Activities, farming activities, prostitution rates, employment level and economy, including others were negatively affected whereas crime rates, relationship between the parents and their children, unwanted pregnancy, etc. were positively influenced during the lockdown period of COVID-19 pandemic in Nigeria.

The AUC of the model indicated that the model was able to correctly predict and classify the Nigerian opinion on the effect of COVID-19 pandemic on her welfare during the lockdown phase of the pandemic. This was observed by a good value of the model's AUC which was 88.23%. The model indicated a very high sensitivity and a low specificity values as classified.

4. Conclusion

This paper has clearly expressed the potentials of the Artificial Neural Network for accurate prediction and classification of the effect of the outbreak of pandemic diseases on the well-being of Nigerian citizens, having the consideration of the model's CCR value. The model was developed based on some designed input variables that concerns the Nigerian citizens as related to the outbreak of COVID-19 epidemic. It achieved an accuracy of over 98.05%, which elucidates the potential efficacy of Artificial Neural Network as a prediction tool and a selection criterion for classifying the effect of an outbreak of pandemic diseases on the welfare of citizens.

Acknowledgements

Friends on my social media platform that helped in responding to the designed questionnaire which formed the data set for this research work were strongly acknowledged.

References

[1] http://www.cia.gov/library/publications/the-word-factbook/goes/ni.html.

[2] http://www.nigerianstat.gov.ng/index.php.

[3] Nigeria population. (2020). Demographics, Maps and Graphs _1586361654411.pdf-adobe reader.

[4] http://hdl.handle.net/10419/29449.

[5] Lewis, M. Paul; Gary F. Simons; & Charles D. Fennig, eds. (2016). *"Nigeria". Ethnologue: Languages of the World (19th ed.). Dallas, Texas: SIL International Publications.*

[6] https://en.Nigeria/Culture%20of%20Nigeria%20-%20Wikipedia.htm#cite_ref-1.

[7] http://www.indexmundi.com/site_map.html).

[8] http://www.indexmundi.com/site_map.html).

[9] Manufacturing sector report, (2015). Manufacturing in Africa. KPMG.

[10] http://en.m.wikipedia.org/wiki/Petrolum#production.

[11] http://en.m.wikipedia.org/wiki/Economy_of_Nigeria.

[12] *FIRST CASE OF CORONA VIRUS DISEASE CONFIRMED IN NIGERIA, (NCDC-2020)". Nigeria Centre for Disease Control. 28 February 2020. Retrieved 10 March 2020*

[13] Becerikli, Y., Konar, A. F., & Samad, T. (2003). Intelligent optimal control with dynamic neural networks. *Neural Netw.* 16: 251-259.

[14] Dassen, W. R., Mulleneers, R. G., Den, Dulk K., Smeets, J. R., Cruz, F., Penn, O. C., & Wellens, H. J. (1990). An artificial neural network to localize atrioventricular accessory pathways in patients suffering from the Wolff-Parkinson-White syndrome. *Pacing Clin. Electrophysiol.*13, (12): 1792-1796.

[15] Kao, J. J, & Huang, S. S. (2000). Forecasts using neural network versus Box-Jenkins methodology for ambient air quality monitoring data. *J. Air Waste Manag. Assoc.* 50: 219-226.

[16] Mohamed E. I., Linder, R., Perriello, G., Di, Daniele. N., Poppl, S. J. & De, Lorenzo. A. (2002). Predicting Type 2 diabetes using an electronic nose based artificial neural network analysis. *Diabetes Nutr. Metab*. 15: 215-221.

[17] Augusteijn, M. F, & Shaw, K. A. (2002) Constructing a query-able radial basis function artificial neural network. *Int. J. Neural Syst.* 12: 159-175.

[18] Castellaro, C., Favaro, G., Castellaro, A., Casagrande, A., Castellaro, S., Puthenparampil, D. V., & Salimbeni, C. F. (2002) An artificial intelligence approach to classify and analyses EEG traces. *Neurophysiol. Clin*. 32: 193-214.

[19] Cimander, C., Bachinger, T., & Mandenius, C. F. (2003) Integration of distributed multi-analyzer monitoring and control in bioprocessing based on a real-time expert system. *J. Biotechnol.* 103: 237-248

[20] Yen, G.G. & Meesad, P. (2001). Constructing a fuzzy rule-based system using the ILFN network and Genetic Algorithm. *Int. J. Neural Syst.* 11: 427-443.

[21] Z. Liu, P. M., O. Seydi, & G. Webb, (2020). Predicting the cumulative number of cases for the COVID-19 epidemic in China from early data.

[22] Al-Qaness, M. A. A.; Ewees, A. A.; Fan, H.; & El Aziz, M., (2020) Optimization Method for Forecasting Confirmed Cases of COVID-19 in China. *J Clin. Med.* 9, (3).

[23] Jung, S. M., Akhmetzhanov, A. R., Hayashi, K., Linton, N. M., Yang, Y., Yuan, B., Kobayashi, T., Kinoshita, R. & Nishiura, H. (2020). Real-Time Estimation of the Risk of Death from Novel Coronavirus (COVID-19) Infection: Inference Using Exported Cases. *Journal of Clinical Medicine*. 9, (2).

[24] Fan, C.; Liu, L.; Guo, W.; Yang, A.; Ye, C.; Jilili, M.; Ren, M.; Xu, P.; Long, H.; & Wang, Y., (2020). Prediction of Epidemic Spread of the 2019 Novel Coronavirus Driven by Spring Festival Transportation in China: A Population-Based Study. *Int. J. Environ. Res. Public Health*. 17, (5).

[25] Zixin Hu, Q. G., Shudi Li, Li Jin & Momiao Xiong. (2020). Artificial Intelligence Forecasting of Covid-19 in China.

[26] Guo, Q.; Li, M.; Wang, C.; Wang, P.; Fang, Z.; tan, J.; Wu, S.; Xiao, Y. & Zhu, H. (2020). Host and infectivity prediction of Wuhan 2019 novel coronavirus using deep learning algorithm.

[27] Liu, T., Hu, J., Xiao, J., He, G., Kang, M., Rong, Z., Lin, L., Zhong, H., Huang, Q., Deng, A., Zeng, W., Tan, X., Zeng, S., Zhu, Z., Li, J., Gong, D., Wan, D., Chen, S., Guo, L., Li, Y., Sun, L., Liang, W., Song, T., He, J.,& Ma, W. (2020) Time-varying transmission dynamics of Novel Coronavirus Pneumonia in China.

[28] Metsky, H. C., Freije, C. A., Kosoko-Thoroddsen, T. S. F., Sabeti, P. C. & Myhrvold, C. (2020) CRISPR-based surveillance for COVID-19 using genomically-comprehensive machine learning design.

[29] Ming, W.-K., Huang, J. & Zhang, C. J. P. (2020). Breaking down of healthcare system: Mathematical modelling for controlling the novel coronavirus (2019-nCoV) outbreak in Wuhan, China.

[30] Riou, J. & Althaus, C. L. (2020). PATTERN OF EARLY HUMAN-TO-HUMAN TRANSMISSION OF WUHAN 2019-NCOV.

[31] WMHC. (2020) Wuhan Municipal Health and Health Commission's Briefing on the Current Pneumonia Epidemic Situation in Our City. 2020. http://wjw.wuhan.gov.cn/front/web/showDetail/2019123108989.

[32] Sasmita, P. A., Sha M., Yu-Ju W., Yu-Ping M., Rui-Xue Y., Qing-Zhi W., Chang S., Sean S., Scott R., Hein R., and Huan Z. (2020). Epidemiology, causes, clinical manifestation and diagnosis, prevention and control of coronavirus disease (COVID-19) during the early outbreak period: a scoping review. Infectious Diseases of Poverty. 9, (29).

[33] CDC. (2019) Novel coronavirus, Wuhan, China. https://www.cdc.gov/coronavirus/2019-nCoV/summary.html.

[34] Li Q, Guan X, Wu P, Wang X, Zhou L, Tong Y, et al. (2020). Early transmission dynamics in Wuhan, China, of novel coronavirus-infected pneumonia. N Engl. J. Med.

[35] WHO. Novel Coronavirus-China. (2020). https://www.who.int/csr/don/12-january-2020-novel-coronavirus-china/en/. Accessed 1 Feb 2020.

[36] Zhu N, Zhang D, Wang W, Li X, Yang B, Song J, et al. (2019). A novel coronavirus from patients with pneumonia in China. N Engl. J. Med.

[37] Anders, U. (1996) Model selection in neural networks, ZEW Discussion Papers 96-21.

[38] O. C. Asogwa and A. V. Oladugba (2015). Of Students Academic Performance Rates Using Artificial Neural Networks (ANNs). *American Journal of Applied Mathematics and Statistics.3, (4):* 151-155.

[39] Cybenko, G. (1989) Approximation by superpositions of a sigmoidal function. *Journal Mathematics of Control, Signals, and Systems*, 2, (4): 303-314.

[40] Hornik, K., Stinchcombe, M. & White, H. (1989). "Multilayer feed forward networks are universal approximators," *Neural Networks*. 2, (5): 359-366.

[41] Adefowoju, B. S. & Osofisan, A. O. (2004). Cocoa Production Forecasting Using Artificial Neural Networks. *International Centre for Mathematics and Computer Science Nigeria*. ICMCS 117-136.

[42] El-Sebakhy, E. A., Hadi, A. S. & Faisal, K. A. (2007). Iterative Least Squares Functional Networks Classifier. *IEEE Transactions on Neural Networks*. 18, (3): 844-850.

[43] Ritchie, S. G & Oh, C. (2007). Recognizing vehicle classification information from blade sensor signature, *Pattern Recognition Letters*. 28, (9): 1041-1049.

[44] Oladokun, V. O., Charles-Owaba. O. E. & Adebanjo, O. E. (2008) Predicting Student's Academic performance using artificial neural network: A case study of an engineering course. *The pacific Journal of Science and Technology*. 9, (1): 72-79.

[45] Thipsuda, W. & Pusadee, S. (2010) A comparison of classical Discriminant Analysis and Artificial Neural Network in predicting student graduation outcomes. *Proceedings of the Second International Conference of knowledge and Smart technologies*: 24-25.

Appendixes

S/N	Variables	Data type	Location	Code	Selected Number
1	Gender	Categorical	Input	0 = Female, 1 = Male	
2	State	Categorical	Input	0= Kano, 1=Kebbi, 2=Sokoto, 3=Kaduna, 4=Benue, 5=Kogi, 6=Niger, 7=Abuja, 8=Adamawa, 9=Bauchi, 10=Taraba, 11=Yobe, 12=Enugu, 13=Anambra, 14=Ebonyi, 15=Imo, 16=Akwa-Ibom, 17=Bayelsa, 18=Rivers, 19=Delta, 20=Lagos, 21=Ondo, 22=Ogun, 23=Ekiti	
3	Geopolitical Zone	Categorical	Input	0 = North Central, 1 = North East, 2 = North West, 3 = South East, 4 = South South, 5 = South West	
4	Age	Categorical	Input	0 = Adult, 1 = Adolescence	
5	Marital Status	Categorical	Input	0 = Married, 1 = Single, 2 = Divorced	
6	Occupation	Categorical	Input	0 = Public servant, 1 = Private servant, 2 = Company worker, 3 = Apprentice, 4 = Freelance, 5 = Unemployed, 6 = Others	
7	Education Status	Categorical	Input	0 = Uneducated, 1 = Educated, 2 = Others	
8	Religious Status	Categorical	Input	0 = Christian, 1 = Pagan, 2 = Muslim	
9	Does the Outbreak of COVID-19 Effected the Religious Activities of Nigerian citizens	Categorical	Input	0 = Yes, 1 = No, 2 = can't say	
10	Does the Outbreak of COVID-19 Aided in Settlement of Family Conflict	Categorical	Input	0 = Yes, 1 = No, 2 = can't say	
11	What was the Effect of COVID-19 on the Social Activities of Nigerian Citizens	Categorical	Input	0 = Positive effect, 1 = Negative effect, 2 = Others	
12	Does COVID-19 Outbreak Promoted Unwanted Pregnancy in Nigeria	Categorical	Input	0 = Yes, 1 = No, 2 = can't say	
13	Does the Outbreak of COVID-19 Affected Funereal Activities of Nigerian Citizens	Categorical	Input	0 = Yes, 1 = No	
14	What was the Effect of COVID-19 Outbreak on the Economy of Nigeria	Categorical	Input	0 = Positive, 1 = Negative, 2 = Unaffected	
15	What was the Effect of COVID-19 Pandemic on the Education Sector of Nigerian	Categorical	Input	0 = Positive, 1 = Negative, 2 = Unaffected	
16	COVID-19 Affected the Prizes of Commodities in Nigerian Markets	Categorical	Input	0 = Yes, 1 = No, 2 = can't say	
17	COVID-19 Affected the Farming Activities of Nigerian Citizens During the Lockdown Period	Categorical	Input	0 = Yes, 1 = No, 2 = can't say	
18	What was the Crime Impact of COVID-19 on Nigerian Citizens During Quarantine Period	Categorical	Input	0 = Increased crime, 1= Decreased crime, 2 = Unaffected	
19	How was the Impact of the Relationship Between Parents and their Children During the Quarantine Period of COVID-19 in Nigeria	Categorical	Input	0 = Positive, 1 = Negative, 2 = Others	
20	The Effect of COVID-19 on the Prostitution Rates on Nigerian Citizens During Quarantine Phase	Categorical	Input	0 = Promoted prostitution, 1 = Decreased prostitution, 2 = Unaffected	
21	The Impact of COVID-19 Outbreak on the Poverty Level of Nigerian Citizens	Categorical	Input	0 = Increased poverty, 1 = Decreased poverty, 2 = Unaffected	
22	The effect of COVID-19 Outbreak on the Employment Level of Nigerian Citizens	Categorical	Input	0 = Positive influenced, 1 = Negative influenced, 2 = Unaffected	
23	Total Evaluation of the Impact of COVID-19 on the Welfare of Nigerian Citizens During the Stay at Home Phase	Categorical	Output	0 = Above 50% Positive Impact, 1 = Below 50% Negative Impact 2 = Unaffected	