FUDMA Journal of Sciences (FJS)
ISSN online: 2616-1370
ISSN print: 2645 - 2944
Vol. 7 No. 1, February, 2023, pp 284 - 289
DOI: https://doi.org/10.33003/fjs-2023-0701-2052

APPLICATION OF ARTIFICIAL NEURAL NETWORK FOR PREDICTING HYPERTENSION STATUS AND INDICATORS IN HADEJIA METROPOLITAN

[*1]Usman Abubakar, [1]Abbas Abubakar, [2]Aminu Sulaiman, [1]Haruna Ibraim Ringim, [2]Iliyasu Abubakar Salisu, [2]Abduhamid Ado Osi, [2]Ismaila James, [3]Auwal Muhammad Sani, [4]Ibrahim Sule Haruna

[1]Department of Statistics, Jigawa State Polytechnic Dutse, Jigawa State.
[2]Department of Statistics, Aliko Dangote University of Science and Tech, wudil, Kano State
[3]Department of Actuarial Science, Federal University Dutse, Jigawa State.
[4] Directorate of ICT, Federal University Dutse, Jigawa State

*Corresponding authors' email: Usmanabubakar@Jigpoly.edu.ng

ABSTRACT

The responsibilities of hypertension or long blood pressure is rapidly increasing worldwide. Jigawa state in Nigeria seems to be one of the most affected states in the country. The frequency of hypertension in Hadejia forms an ongoing section of the overall responsibility in Jigawa state because of its population among local governments in the state. The purpose of this research is to determine the frequency and classification of a case of hypertension in Hadejia. A survey for some factors was conducted to identify which among the factors impact the prevalence of long blood pressure in Hadejia. It can be seen that the overall prevalence of hypertension in the study was found to be 45.97156% and 54.02844% were found to be non-hypertensive among the categories, those who are married have a higher prevalence of 35.07109%. The study produced the results shown in Table 2, which show the frequency of hypertensive and non-hypertensive patients among the categories and the prevalence of hypertension among those categories. Non-diabetic and those whose parents are hypertensive have the same prevalence of 34.12322% whereas those at or below 25 years of age have a less prevalence of 1.421801% of hypertension. Likewise, in Table 4, ANN with 64.3% of accuracy (sensitivity). The outcome for the testing sample performed better with an accuracy of 64.35% than that for the training sample with an accuracy of 70.4%, and the result shows that Age, Diabetics, and parental Hypertension Status are contributing to the prevalence of Hypertension or long blood pressure.

Keywords: Artificial Neural Network, Multilayer Perceptron, Hypertensive Status, Hypertension Related information, Hadejia metropolis

INTRODUCTION

Long blood pressure (LBP) (Heart Association, 2021) is a terrific medical condition that purposefully intensifies the feats of the heart (Asemu et al., 2021, Singh et al., 2017), stroke (Asemu et al., 2021, Usman et al., 2022) brain, kidney (Schutte et al., 2021, Joshi et al., 2014), and other diseases. In 2010, 31.1% of adults (1.39 billion) (Mills et al., 2020) were estimated to have LBP worldwide, and it is predicted to be 1.56 billion adults with LBP in 2025 (Singh et al., 2017b), where the majority remain in low and middle-income countries (Mills et al., 2020). Worldwide, hypertension is the primary cause and main risk factor for cardiovascular (Usman et al., 2022) events and adult death (Heart Association, 2021, Goit & Yang, 2019). LBP is found in 60% of older persons with Peal arterial disease, 74% of adults with LBP, 69% of adults with first myocardial infarction, 77% of adults with first stroke, and 74% of adults with LBP (Goit & Yang, 2019). Long blood pressure is responsible for about 13.5% of yearly agonies globally. Moreover, Long blood pressure is also directly accountable for 47% of all coronary heart diseases and 54% of all stroke artery diseases worldwide. The population of those aged 45 to 69 is the most productive segment of those making up more than half of these responsibilities (Asemu et al., 2021) and is a major cause of the agony of productive age worldwide. Reducing the prevalence of hypertension by 33% between 2010 and 2030 (Adeloye et al., 2015) is among the world's missions for illnesses that are not contagious. Half of the current health responsibilities in developing nations are related to non-communicable diseases (Joshi et al., 2014). By 2020 it is projected that non-communicable diseases, long blood pressure, will surpass communicable diseases as the main factor contributing to agony (Joshi et al., 2014).

The global responsibilities associated with high blood pressure have been reported for 1997, 2001, 2005, and 2010 in detail. Information from around the world on responsibilities According to the 2015 Infection, harm, and Risk Component Study, 41% of all years of life with disability were impacted by risk factors (Forouzanfar et al., 2017). The estimated responsibility of heart disease is projected to double from 1999 to 2020 with an immense negative role on the progress of the economy in several aspects, including the excessive value of medication, a low rate of output, and increasing disparity and is rapidly increasing worldwide, and according to statistics from the 2013 World Health Day on High blood pressure, Africa has the greatest rates (Siziya, 2012). The professionals in public health and interested parties of the world health organization have declared non-communicable diseases a global distinction, as noted at the 2011 United Nations high-level gathering, to lessen this expanding problematic responsibility in Africa and other countries with the lower and middle class. About 17 million people worldwide suffer agonies from cardiovascular illnesses, with obstacles, causing roughly 7.5 million pains due to elevated blood pressure and 57 million inability-adjusted life years globally (Adeloye et al., 2015), both contributing roughly 12.8 (Singh et al., 2017b) and 3.7% of global agonies and inability adjusted life years, respectively. Nigeria happens to be the most populated nation in Africa, with a population of over 216 million, since the incidence of high blood pressure in the nation significantly contributes to Africa's overall responsibility (Akinlua et al., 2015). The

World Health Organization calculated that 42.8% of Nigerians had hypertension in 2008. The Risk factors for long blood pressure include increasing Age (above 65 years), sex (males are more than females), heart rate (greater than 80 beats/min) (Unger et al., 2020) low education sedentary lifestyle, family history (Siziya, 2012) increased body weight, diabetes (Unger et al., 2020) alcohol tobacco (Schutte et al., 2021)

In Nigeria, there are many obstacles in managing hypertension at one's own organizational, societal, and physician stages. Despite the years-long advancement of systolic therapies, these hurdles are substantially to blame for the reported rise in the occurrence of problems among hypertension patients (Nelson I, 2021). The Nigerian national non-communicable diseases survey committee in 1997 reported a long blood pressure 11.2% of men and women had hypertension, which at the time accounted for around 4.33 million cases in adults who were over 15 years of age (Adeloye et al., 2015).

The fact that hypertension has received little attention in Nigerian society and has been poorly managed (Kayima et al., 2015) is one of the challenging variables influencing how this task is carried out (Nelson I, 2021, Kayima et al., 2015). Therefore, the health facilities related to cardiovascular difficulties, including ischemic cardiac disease, strokes, and heart failure affect people who live with long blood pressure in many cases (Asemu et al., 2021). Research findings show that long blood pressure is diagnosed in many people as an incidental finding when admitted for unrelated sickness. Since this was the theme of the 2013 World Health Organization Day, the WHO emphasized the need for increased long blood pressure literacy to reduce the total burden of the disease, particularly at the national and societal levels. In addition, long blood pressure and related cardiovascular issues have a high economic cost in Nigeria (Adeloye et al., 2015), as evidenced by initial expenses like the price of antihypertensive drugs, management costs, laboratory fees, and other health expenditures, as well as indirect costs like loss of savings from repeated medical expenses, medical centre waiting times, and lateness from work. For instance, in a region where most people make less than 2000 Naira a day, the average monthly cost of medication was relatively expensive. Accuracy in categorization is used to gauge the model's performance.

MATERIALS AND METHODS

A multilayer perceptron (MLP) neural network was applied with its functions using IBM SPSS 27v (Corporation, 1989), In this study, the multilayer perceptron design consisted of three layers: an input layer, a hidden layer that describes the hidden neurons using radially symmetric functions, and an output layer with a categorical node that enables us to obtain the weighted sum from the hidden layer outputs and to determine the index class for the input pattern (Bekesiene et al., 2021).

The construction of the model was based on the display of various node mergers in one or more hidden layers. In an experiment, the dataset's partition rates for testing and training were allocated at random: ANN = 70%-30% (Corporation, 1989). Given that a neural network creates a model by taking into account a potential relationship between two different types of explanatory and dependent variables, ANNs can validate the model's findings by tying the projected values to the actual values. With this benefit, neural network systems outperform conventional calculations that execute a series of rules to obliterate a fact.

Artificial Neural Network (ANN) Approach

The ANN is a widely used analytical technique that simulates the functioning of the human brain to help solve complex issues (Bekesiene et al., 2021). It was motivated by the biological operations of the human nervous system. The artificial nerves known as nodes are covered by neural networks of the perceptron type. In neural networks of the perceptron type, these nodes serve as the information processing units. Artificial neurons are also organized in layers and connected to one another. Under this method of information processing, the neurons can screen the information and convey it in a way that is commonly used for administration to build an analytical model that can categorize the information stored in the memory.

As previously mentioned, ANNs are often built as three-layer network models of connected artificial neurons. It may also enable the formation of one or more hidden layers by the researchers between the neurons of the input and output layers. Additionally, there are no connections between neurons in the same layer, but each neuron can still connect to another neuron in the layer above it. Forecasting is one of the main applications for ANNs (Zhang et al., 1998). ANNs offer a desirable alternative method for forecasting for both scholars and practitioners. The vast majority of ANNs' distinctive qualities make them useful and desirable for forecasting jobs (Zhang et al., 1998). ANN approaches were used in the data analysis and modelling, and they produced positive results. The data analysis and modelling using ANN techniques as a methodology, and have provided good results in prediction for literature (Bekesiene et al., 2021)

Model performance

There are various ways to examine and assess the model's performance, but in this study, we'll discuss how it performed using the receiver operating characteristic curve, classification result table, and model summary table.

Model summary

(Corporation, 1989) Model summary table shows the total and by partitioning neural network results, including a sum of squares error, relative error (% of wrong predictions), and training time. Depending on the levels of measurement for the dependent variable, relative errors or percentages of inaccurate predictions are also shown.

Classification results

(Corporation, 1989) Model summary table shows the total and by partitioning neural network results, including the sum of squares error, relative error (% of wrong predictions), and training time. Depending on the levels of measurement for the dependent variable, relative errors or percentages of inaccurate predictions are also shown.

ROC curve

(Corporation, 1989) Receiver Activity for every response categorical variable, the characteristic curve. Additionally, a table showing the space under each curve is included. The ROC graph shows one curve for each category for a certain dependent variable. Each curve treats the relevant category as the positive state vs the other category if the dependent variable has two categories. Each curve treats the relevant category as the positive state versus the sum of all other categories if the dependent variable has more than two categories.

Data Coding and Description

The data of Age Sex, Marital status, Employment status, Diabetics status, Hypertensive, Lifestyle, exercise, Educational qualification, and Parent hypertension status. The variables contain the response and explanatory variable, for the dependent variable is Hypertension (1 for hypertension and 0 representing the non-hypertension), likewise for the independent variables are Sex (1 for male and 2 for female), Age (1 represent age less than or equal to 25, 2 for 26-35, 3 for 36-45, 4 for 46-55, and 5 for 56 and above), Marital status (1 for married, 2 for divorce, 3 for widow/widower, 4 for single), Employment status (1. For self-employment, 2. For employment, 3. For unemployment, and 4. For retirement), Diabetics status (0 for non-diabetic, and 1 for diabetic), Lifestyle and exercise (1 for sedentary 2 for light and 3 for moderate), Educational qualifications (1 for primary, 2 for secondary, 3 for tertiary, and 4 for uneducated), Parent hypertension status (0 for non-hypertensive, 1for hypertensive).

RESULTS AND DISCUSSION

The frequency of high blood pressure

The result in Table 1 below shows the frequency of hypertensive and non-hypertensive patients among the categories and the prevalence of hypertension among those categories, it can be seen that In this research, high blood pressure was generally prevalent at a rate of found to be 45.97156% which averages out of the 211 samples 97 of them were found to be hypertensive and 114 people were found to be non-hypertensive corresponding to 54.02844%, among the categories, those that are married has a higher prevalence of 35.07109%. Non-diabetic and those whose parents are hypertensive have the same prevalence of 34.12322% whereas those at or below 25 years of age have less prevalence of 1.421801% of hypertension.

Table 1: The frequency of high blood pressure

Variables	Categories	Hypertension Status			
		Non-hypertension Count	Hypertensive Count	Non-hypertension Prevalence %	Hypertensive Prevalence %
Gender	Female	58	61	27.48815	28.90995
	Male	56	36	26.54028	17.06161
Age Group	<=25	5	3	2.369668	1.421801
	26-35	13	8	6.161137	3.791469
	36-45	26	22	12.32227	10.42654
	46-55	27	36	12.79621	17.06161
	55+	43	28	20.37915	13.27014
Marital Status	Married	83	74	39.33649	35.07109
	Divorced	9	8	4.265403	3.791469
	Widow	9	10	4.265403	4.739336
	Single	13	5	6.161137	2.369668
Employment Status	Self-Employed	26	27	12.32227	12.79621
	Employed	60	49	28.43602	23.22275
	Unemployed	9	4	4.265403	1.895735
	Retired	19	17	9.004739	8.056872
Educational Qualification	Primary	17	13	8.056872	6.161137
	Secondary	30	22	14.21801	10.42654
	Tertiary	60	57	28.43602	27.01422
	Uneducated	7	5	3.317536	2.369668
Diabetic Status	Non-diabetic	64	72	30.33175	34.12322
	Diabetic	50	25	23.69668	11.84834
Life Style And Exercise	Severe	11	3	5.21327	1.421801
	Light	30	39	14.21801	18.48341
	Sedentary	73	55	34.59716	26.06635
Parent Hypertension Status	No	52	25	24.64455	11.84834
	Yes	62	72	29.38389	34.12322
Hypertension Status	Non-hypertension.	114	0	54.02844	0
	Hypertensive	0	97	0	45.97156

ANN Result

The data consist of 9 variables (Table 1) for 211 patients in Hadejia. Here, the variable name Hypertensive is categorical for each patient that is either Hypertensive or Non-Hypertensive in Table 3. To classify the 211 patients into Hypertensive and Non-Hypertensive, by using the Artificial Neural Network on the known information.

The data is divided into training samples and testing samples, with 148 (70%) samples taken for the training sample and the other 63 (30%) samples taken to be tested from the starting point. This allows us to test the effectiveness on both 148 and 63 samples of the 211 observations, resulting in slightly too little data to obtain a precise Classifying rule, as shown in Table 2 below. So the model learned on the train and predicted based on the testing samples.

The ANN Result using the Multilayer perceptron from 211 observations to re-classify them gives the result shown in Table 4 below which summarizes the percentage of incorrect classification (misclassification) which can also be used to determine the percentage of correct classification as well as the specificity and sensitivity in Figure 2. However, in Table 3 below ANN method correctly classify 62 out of 86 as Non-Hypertensive, and 24 patients were misclassified and correctly classify 39 out of 71 as Hypertensive also 32 patients were misclassified resulting in an accuracy of 64.35%, training data. While for testing, ANN correctly classifies 19 out of 28 as Non-Hypertensive, and 9 patients were misclassified and correctly classify 19 out of 26 as Hypertensive also 7 patients were misclassified causing an accuracy of 70.4%. This result shows that the testing sample performs better than the training samples by comparing their accuracy.

Table 2: Case Processing Summary

		N	Percent
Sample	Training	148	70.1%
	Testing	63	29.9%
Valid		211	100.0%
Excluded		0	
Total		211	

The case processing summary shows that 148 cases were assigned to the training sample, 63 to the testing samples, and 0 cases were excluded from the analysis.

Table 3: Classification result

		Predicted		
Sample	**Observed**	**.0**	**1.0**	**Percent Correct**
Training	.0	62	24	72.1%
	1.0	32	39	54.9%
	Overall Percent	59.9%	40.1%	64.3%
Testing	.0	19	9	67.9%
	1.0	7	19	73.1%
	Overall Percent	48.1%	51.9%	70.4%

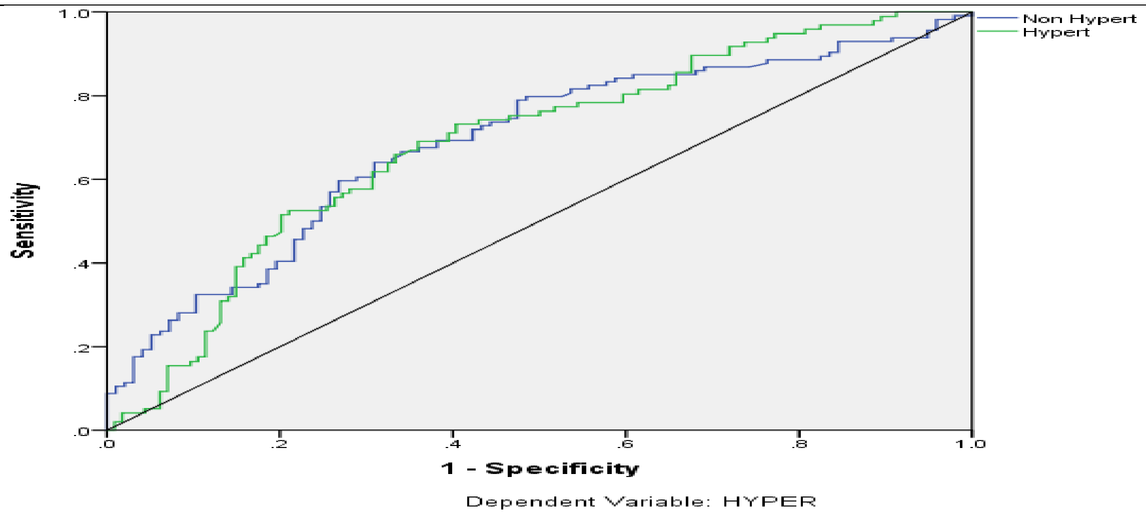

Figure 1: Receiver Operating Characteristics (ROC) Curve

The importance chart is simply arranged by significance value in descending order as shown in Figure 2. Age, diabetes, and parent hypertension status data appear to have the biggest influence on how the network categorizes people; however, it is impossible to determine the "direction" of the association between these variables and the anticipated chance of default. You might assume that the risk of hypertension increases with age. Similarly, the longer or higher the level of diabetes, the higher the risk of hypertension.

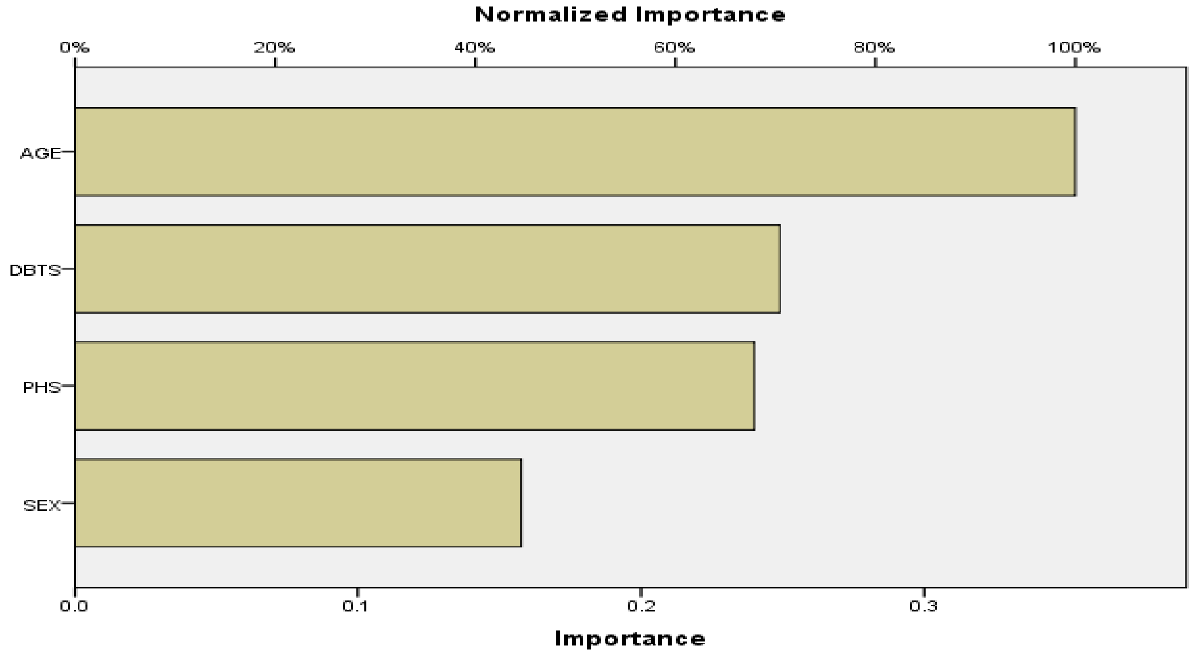

Figure 2: Normalized importance by the artificial neural network (ANN) model.

As seen in Figure 2, the importance chart is simply arranged in decreasing order by the value of importance. Age, diabetes, and parent hypertension status data appear to have the biggest influence on how the network categorizes people; however, it is impossible to determine the "direction" of the association between these variables and the anticipated chance of default. You might assume that the risk of hypertension increases with age. Similarly, the risk of LBP increases with the duration or level of diabetes.

CONCLUSION

The research performs here demonstrates of artificial neural network in pattern recognition and Classification of the Hypertension Status into hypertensive and Non-hypertensive. The performance was based on correct Classification rates for the method. Thus, the model performed well with an overall accuracy of 64.35%, for training data and 70.4% for testing samples as shown in Table 5. The ROC curve, however, provides a visual representation of the sensitivity and shows that the probability that the model predicts correct classification is around 0.7. The overall prevalence of LBP in this study was found to be 45.97156% which averages that out of the 211 samples 97 people were found to be hypertensive and 114 people were found to be non-hypertensive, among the categories, those that are married had a higher prevalence of hypertension which is 35.07109%. Non-diabetic and those whose parents are hypertensive have the same prevalence of 34.12322% of hypertension cases whereas those at or below 25 years of age have a less prevalence of 1.421801% of hypertension as shown in Table 2. The research carried out, is therefore recommended that: (Nelson I, 2021, Unger et al., 2020) Those with long blood pressure and diabetics should limit the potential advantages of a healthy diet, maintaining a healthy weight, and engaging in regular exercise for all people with LBP because these lifestyle changes have the potential to improve blood pressure control and possibly even lessen the need for medication. Those with LBP should avoid harmful habits, smoking, and alcohol consumption, and reduce the intake of salt. Patients with LBP should regularly monitor their blood pressure, take prescription drugs as directed, and take the time to learn stress management techniques. Salted potato or corn chips, reduced saturated fat, salted peanuts, and fried chicken or other fried meals should all be avoided by those with LBP. Patients with LBP should strive to consume whole wheat bread, whole grain cereals like pasta, and potatoes regularly, as well as more fiber-rich foods like beans, nuts, low-fat cheeses, low-fat glasses of milk, and fish. A patient without LBP should keep a healthy weight, exercise frequently, refrain from smoking and drinking, consume fewer high-cholesterol foods, adopt a healthy eating regimen, and consume less salt overall. The research performed also recommended that the neural network approach is much better with large amounts of data to provide good performance.

REFERENCES

Adeloye, D., Basquill, C., Aderemi, A. V., Thompson, J. Y., & Obi, F. A. (2015). An estimate of the prevalence of hypertension in Nigeria: A systematic review and meta-analysis. *Journal of Hypertension*, *33*(2), 230–242. https://doi.org/10.1097/HJH.0000000000000413

Akinlua, J. T., Meakin, R., Umar, A. M., & Freemantle, N. (2015). Current prevalence pattern of hypertension in Nigeria: A systematic review. *PLoS ONE*, *10*(10). https://doi.org/10.1371/journal.pone.0140021

Akwensi, P. H., Brantson, E. T., Niipele, J. N., & Ziggah, Y. Y. (2021). Performance evaluation of artificial neural networks for natural terrain classification. *Applied Geomatics*, *13*(3), 453–465. https://doi.org/10.1007/s12518-021-00360-9

Asemu, M. M., Yalew, A. W., Kabeta, N. D., & Mekonnen, D. (2021). Prevalence and risk factors of hypertension among adults: A community-based study in Addis Ababa, Ethiopia. *PLoS ONE*, *16*(4 April). https://doi.org/10.1371/journal.pone.0248934

Bekesiene, S., Smaliukiene, R., & Vaicaitiene, R. (2021). Using artificial neural networks in predicting the level of stress among military conscripts. *Mathematics*, *9*(6). https://doi.org/10.3390/math9060626

Corporation, I. (1989). *IBM SPSS Neural Networks 21*. http://www.ibm.com/spss.

Forouzanfar, M. H., Liu, P., Roth, G. A., Ng, M., Biryukov, S., Marczak, L., Alexander, L., Estep, K., Abate, K. H., Akinyemiju, T. F., Ali, R., Alvis-Guzman, N., Azzopardi, P., Banerjee, A., Bärnighausen, T., Basu, A., Bekele, T., Bennett, D. A., Biadgilign, S., … Murray, C. J. L. (2017). Global burden of hypertension and systolic blood pressure of at least 110 to 115mmHg, 1990-2015. *JAMA - Journal of the American Medical Association*, *317*(2), 165–182. https://doi.org/10.1001/jama.2016.19043

Goit, L. N., & Yang, S. (2019). Treatment of Hypertension: A Review. *Yangtze Medicine*, *03*(02), 101–123. https://doi.org/10.4236/ym.2019.32011

Heart Association, A. (2021). *What is High Blood Pressure?*

Joshi, M. D., Ayah, R., Njau, E. K., Wanjiru, R., Kayima, J. K., Njeru, E. K., & Mutai, K. K. (2014). Prevalence of hypertension and associated cardiovascular risk factors in an urban slum in Nairobi, Kenya: A population-based survey. In *BMC Public Health* (Vol. 14, Issue 1). BioMed Central Ltd. https://doi.org/10.1186/1471-2458-14-1177

Kayima, J., Nankabirwa, J., Sinabulya, I., Nakibuuka, J., Zhu, X., Rahman, M., Longenecker, C. T., Katamba, A., Mayanja-Kizza, H., & Kamya, M. R. (2015). Determinants of hypertension in a young adult Ugandan population in epidemiological transition - The MEPI-CVD survey. *BMC Public Health*, *15*(1). https://doi.org/10.1186/s12889-015-2146-y

López-Martínez, F., Núñez-Valdez, E. R., Crespo, R. G., & García-Díaz, V. (2020). An artificial neural network approach for predicting hypertension using NHANES data. *Scientific Reports*, *10*(1). https://doi.org/10.1038/s41598-020-67640-z

Mills, K. T., Stefanescu, A., & He, J. (2020). The global epidemiology of hypertension. In *Nature Reviews Nephrology* (Vol. 16, Issue 4, pp. 223–237). Nature Research. https://doi.org/10.1038/s41581-019-0244-2

Nelson I, O. (2021). Management of hypertension in Nigeria: The barriers and challenges. *Journal of Cardiology and Cardiovascular Medicine*, *6*(1), 023–025. https://doi.org/10.29328/journal.jccm.1001112

Schutte, A. E., Srinivasapura Venkateshmurthy, N., Mohan, S., & Prabhakaran, D. (2021). Hypertension in Low- And Middle-Income Countries. *Circulation Research*, 808–826. https://doi.org/10.1161/CIRCRESAHA.120.318729

Singh, S., Shankar, R., & Singh, G. P. (2017a). Prevalence and Associated Risk Factors of Hypertension: A Cross-Sectional Study in Urban Varanasi. *International Journal of Hypertension*, *2017*. https://doi.org/10.1155/2017/5491838

Singh, S., Shankar, R., & Singh, G. P. (2017b). Prevalence and Associated Risk Factors of Hypertension: A Cross-Sectional Study in Urban Varanasi. *International Journal of Hypertension*, *2017*. https://doi.org/10.1155/2017/5491838

Siziya, S. (2012). Prevalence and Correlates of Hypertension among Adults Aged 25 Years or Older in a Mining Town of Kitwe, Zambia. *Journal of Hypertension: Open Access*, *01*(03). https://doi.org/10.4172/2167-1095.1000105

Unger, T., Borghi, C., Charchar, F., Khan, N. A., Poulter, N. R., Prabhakaran, D., Ramirez, A., Schlaich, M., Stergiou, G. S., Tomaszewski, M., Wainford, R. D., Williams, B., & Schutte, A. E. (2020). 2020 International Society of Hypertension Global Hypertension Practice Guidelines. *Hypertension*, *75*(6), 1334–1357. https://doi.org/10.1161/HYPERTENSIONAHA.120.15026

Usman, U., Arkilla, B. M., Ismail, A. A., & Dauda, U. (2022). Time-To-Optimal Control of Hypertension Using Kaplan-Meier Estimator, Cox Proportional Hazard and Weibull Model. *Fudma Journal of Sciences*, *6*(5), 71–75. https://doi.org/10.33003/fjs-2022-0605-1096

Zhang, G., Eddy Patuwo, B., & Y. Hu, M. (1998). Forecasting with artificial neural networks: The state of the art. *International Journal of Forecasting*, *14*(1), 35–62. https://doi.org/10.1016/S0169-2070(97)00044-7