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# Artificial Neural Network Regression Modelling of Poverty Index in Nigeria

Oloyede I.<sup>1</sup>, Abiodun A. A.<sup>1</sup>, Qaiser Abbas<sup>2</sup>

<sup>1</sup>Department of Statistics, University of Ilorin, Ilorin, Nigeria. <sup>2</sup>School of Economics and Management, Wuhan University, China

Corresponding author: oloyede.i@unilorin.edu.ng; Qabbas@gudgk.edu.pk

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#### **Abstract**

**RESEARCH ARTICLE** 

Due to the benefits of Artificial Neural Network (ANN) regression modelling over classical linear regression estimator with respect to faulty tolerance and generalization ability, the study adopted (ANN) regression modelling in order to investigate the impacts of economic variables indices on the poverty index of Nigeria in the years 2018/2019, artificial neural network regression modelling was adopted. This study examined poverty modelling in the realm of (ANN) regression and showcased the contribution of the weight of each predictor variable towards the nodes that determine the Multidimensional Poverty Index (MPI). Most literatures do not interpret the weights and bias of ANN regression, they only described the architecture of the procedures to obtain it. This is the gap this study filled. The study observed that Food insecurity has the highest relative importance with 0.085 magnitude to (MPI) while sanitation has lowest relative importance with magnitude of 0.045 to (MPI).

Keywords: Regression, Neural Network, Poverty, Modelling

#### 1. Introduction

Poverty remained one of the maximum pressing worldwide demanding situations affecting tens of millions of humans globally. Traditional methods to know-how and addressing poverty have often been restricted by using the complexity and variety of factors contributing to it. However, in latest years, the mixing of gadget getting to know strategies into poverty modeling has shown promising outcomes in improving accuracy, identifying key drivers, and guiding centered interventions, (Hand and Harper, 2020). Their study explored the improvements in gadget learning modeling of poverty and its potential packages in poverty relief efforts. One of the extensive breakthroughs in poverty modeling is the capability to harness big data from diverse assets, such as satellite imagery, social media, and governmental databases, (Hand and Harper, 2020). Machine studying algorithms, which includes Random Forests and Gradient Boosting, have confirmed superior predictive capabilities as compared to traditional statistical strategies, (Hendry and Baffour, 2019). These algorithms can predict poverty stages in unique areas, imparting precious insights for policymakers and corporations to allocate resources successfully, (Hendry and Baffour, 2019).

Geographic Information Systems (GIS) coupled with gadget studying have empowered researchers to carry out spatial analysis of poverty distributions. This lets in for figuring out high-density poverty regions and optimizing intervention strategies primarily based on spatial patterns (Chen *et al.*, 2021). Deep mastering techniques, particularly Convolutional Neural Networks (CNNs), have been implemented to research satellite imagery and extract features related to poverty signs, together with housing quality, urbanization, and flowers cover, (Jean et al., 2016).

Multidimensional Poverty Index (MPI) is the share of possible deprivations that negate humans experience value stages from zero to at least one, with 1 showing poverty. The National MPI 2022 survey questionnaire turned into consequently accelerated to encompass extra variables that were relevant given the brand-new context and national priorities-which include food protection, water reliability, underemployment, protection shocks and school lag, plus baby deprivations. The new survey layout was based on more than one consultation across authorities, civil society, academia and development partners, (NBS, 2022).

### 1.1 The Structure of the Nigeria MPI (2022)

In 2018, Nigeria posted its first national MPI, built by way of the National Bureau of Statistics, in the Human Development Report (UNDP, 2018). However, next consultations with stakeholder agencies concluded that additional signs have been needed to correctly reflect poverty following the pandemic—together with inclusion of children. The Nigeria MPI (2022) survey questionnaire therefore presented additional variables that were relevant given the brand-new context and countrywide priorities—consisting of food safety, water reliability, underemployment, safety shocks, school lag and toddler deprivations.

The Nigeria MPI (2022) has four dimensions: fitness, education, living standards, and work and shocks. The wide variety of indicators, and their ambition, have accelerated. Security shocks had been raised in consultations and had been brought to the minimum size, which additionally now includes underemployment. Food safety and time to healthcare have been delivered to the bearest size. School lag has been introduced to the education measurement as a proxy for first-rate, and water reliability introduced to dwelling citizens, (NBS, 2022).

Unemployment refers to the proportion of these in the labour pressure who have been actively seeking out jobs, however could not discover work for as a minimum 20 hours every week; underemployment captures individuals who work much less than full-time hours (forty hours), however, at least 20 hours a week on average and/or folks who work full time but are engaged in a pastime that underutilizes their competencies, time and educational Qualifications. NBS (2022) recorded that unemployment in Nigeria has been at the upward push with 2018 survey; increasing from 21.8% within the third region of 2018 to 33.3% at the end of 2020. Child mortality consequences are at the upward thrust and vitamins Health effects for kids in Nigeria stay extensively terrible (even though improving), partly due to vulnerable fitness structures and socio-economic elements which might be gradual to trade. Despite enhancements, the country stays one of the worst in sub-Saharan Africa for youngsters's heath, falling from 129 in 2013 to a 120 in 2018 and to 114 in 2020, with a huge difference among adult males (120) and girls (107), (World Bank, n.D.-c)

Poverty amongst useful people has been conceptualized to reflect a nation of deprivation which is manifested in financial deprivation, however also in the lack of basic services that make up residing requirements, inclusive of get right of entry to water and sanitation, cooking fuels and lights. Based on the 2018/19 Nigerian Living Standard Survey (NLSS) of NBS, reputable monetary poverty in 2019 was measured at 40.1%—that means that 82.9 million Nigerians had actual consistent with capital expenditure under the poverty line of #137,430 per year (or #376.50 per day) and have been consequently considered terrible (National Bureau of Statistics, 2019).

In 2018, 7.2 million youngsters (68.3% of children) in Nigeria have been attending early schooling which covered crèches, nurseries and kindergarten (Statista, 2022). In phrases of schooling time, despite the fact that a child is expected to have had 12 years of schooling (six in primary, 3 in junior secondary school and 3 in senior secondary school) by the time they are 18 years old, the Human Capital Index (HCI) outcomes show that the average years of schooling in Nigeria is 8.2 years. When disaggregated by means of gender, that is 8.7 years for boys and 7.6 years for ladies, with boys therefore having a couple of 12 months of schooling benefit, (National Bureau of Statistics, 2022).

Child MPI extends the Nigeria MPI to encompass suitable indicators for kids underneath 5, with the aid of including a 5th dimension of toddler survival and development. This additional dimension incorporates eight vital aspects of early childhood improvement in bodily and cognitive domain names—such as severe undernutrition, immunization, intellectually stimulating sports, and preschool. While it does not offer man or woman-level facts, it uncovers extra kids who in keeping with the greater dimension must qualify as multidimensionally poor.

Table 1: Depicts The Nigeria MPI (2022) - Dimensions, Indicators, Deprivation Cutoffs, Links to SDGs and Weights

Dimension	Indicator	Deprivation cutoff	SDG Goal, Target	weight
Health	Nutrition	A household is deprived if any child under the age of 5 is undernourished, i.e. stunted or underweight OR if there is anu adult household member wit a body mass index lower than 18.5	2.2.1/2	1/12
	Food insecurity	The household is severely food insecure according to FIES (the Food Insecurity Experience Scale,>=7 answers affirmatively)	2.1.2	1/12
	Time to healthcare	3.8	1/12	
Education	School attendance	A household is if any child between age 6 and 15 years is not attending school	4.1	3/32
	Year of schooling	A household is deprived if no member 15 years and above has completed primary school	4.6	1/8
	School lag	A household is deprived if any child aged school age + 2 years (8-17 years of age) is educationally lagging at least two years (grades) behind	4.1.1	1/32
Living Standards	Water	The household does not have access to safe drinking water (according to SDG guidelines)	3.9.2	1/24
	Water reliability	A household is deprived if they have drinking water available for less than 20 days per month OR for less than 4 hours per day	6.1	1/24
	Sanitation	The household's sanitation facility is not improved (according to SDG guidelines), or	3.9.2	1/24

		it is improved but shared with other households		
	Housing materials	The household has natural/rudimentary floor, roof or wall	11.1.1	1/24
	Cooking fuel	The household cooks with dung, wood or charcoal etc.	3.9.1	1/24
	Assets	The household has less than two assets and does not own a car	1	1/24
Work & Shocks	Un- employment	The household is deprived if any member 15 years and above is unemployed- not in employment, but looking for work and available for work	8.5.2	1/10
	Under- employment	A household is deprived if at least one household member 15 years and above is working for less than 40 hours per week but is available and willing to do extra hours of work	8.5	1/20
	Security shock	A household is deprived if it experienced at least one shock, over the past 12 months	16.1.1/3/4	1/10

Source: National bureau of Statistics, 2022

In table 1 above, the dimension as well indicators were displayed. According to the 2022 MPI, 62.9% of people – just under 133 million people- are multidimensionally poor, meaning that they experience deprivations in more than one dimension, or in at least 26% of weighted indicators. The average deprivation score among poor people, which shows the intensity of poverty is 40.9%. Nigeria National MPI is 0.257, showing that poor people in Nigeria experience just over one-quarter of all possible deprivations. Multidimensional poverty is higher in rural areas, where 72% of people are poor, compared to 42% of people living in urban areas. Approximately 70% of Nigeria's population live in rural areas and 30% in urban areas. Yet rural areas are home to 80% of people living in poverty, and their intensity of poverty is also higher, at 42% in rural areas compared to 37% in urban areas, (NBS, 2022).

**Table 2: Showed the Intensity of the Population** 

Area	MPI	Incidence (H,%)	Intensity (A,%)	Population Share (%)	Number of poor (million)
National	0.257	62.9	40.9	100.0	132.92
Rural	0.302	72.0	41.9	69.6	105.98
Urban	0.155	42.0	36.9	30.4	26.94

Source: National bureau of Statistics, 2022

Strategies to lessen MPI in rural areas are barely extraordinary from city techniques. In urban regions, protection shocks and unemployment make contributions greater to multidimensional poverty than in rural areas. While health deprivations make a contribution strongly in both areas, meals insecurity is contributing more in city areas. Rural priorities could also include skill training and lifelong getting to know opportunities for adults who in no way finished primary education and best housing substances. Over poverty is simply excessive in rural areas, (NBS, 2022).

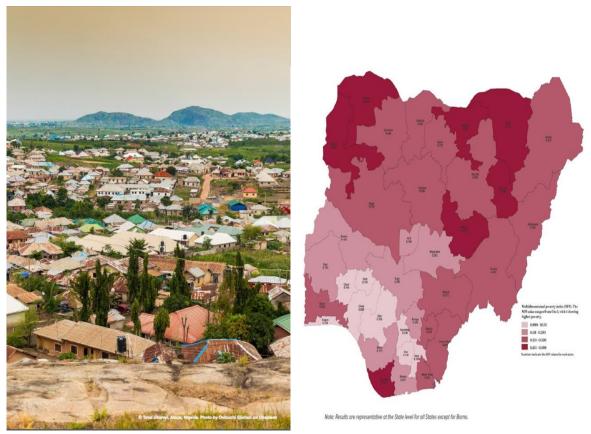


Figure 1. Showing the Map of Nigeria

#### **Methodical Designs**

The neural learning fashions which are stimulated through the organic neurons' networks of animals, every of which similar to an organic neuron that is related to and can transmit alerts with other neurons. Neural Networks is a shape of nonlinear regression technique that is stimulated via the neuron within the human brain. In the artificial neural community (ANN) diagram, the primary node is referred to as the enter layers which corresponds to the set of independent variables, the following nodes are the hidden layers which corresponding to instant calculation that are not usually discovered. If there exist one hidden layer, it's far mentioned an Artificial Neural Network (ANN) however if the hidden layer exceeds one (this is two or extra), it is appeared as deep learning. Thus, the neural network is composed of many logistics' regression model, sequel to the kind of activations adopted. Each input layer has corresponding arrow to a particular hidden layer node having coefficient similar to regression evaluation, that is known as weight, there is an awesome arrow with node labelled '1' that's called bias. The hidden layer node implemented the sigmoid characteristic  $s(x) = \frac{1}{(1+e^{-1})}$  to the linear equation of hidden layer. The final results variable is model with the aid of the intermediate or unobserved variable called hidden layers, it employed the nonlinear characteristic g(.), it depends on the choice of the researcher. The study followed sigmodal; the model is stated as:

$$h_k k = g\left(\beta_0 + \sum_{i=1}^p x_i \beta_{jk}\right) \tag{1}$$

$$h_k k = g(\beta_0 + \sum_{i=1}^p x_i \beta_{jk})$$

$$g = \frac{1}{(1+e^{-1})}$$
(2)

where  $x_i$  is a set of predictor valuables of economy indicator they are. The  $\beta_{ik}$  is the effect of predictor in the  $k_{th}$  hidden layers.

The research involved collecting data from World Bank database. Machine learning algorithms Artificial Neural Network was employed to develop predictive models. Given a set of m training points  $\{(\bar{x}_1, \bar{y}_1), \dots, (\bar{x}_m, \bar{y}_m)\}$  where  $\bar{x}_i \in \mathbb{R}^n$ ,  $\bar{y}_i \in \mathbb{R}$  are features vector(independent variables) and the target output respectively; thus in linear regression, the linear function  $f(\bar{x}) : \mathbb{R}^n \to \mathbb{R}$  minimizes error of least squares:  $\sum_{i=1}^m (y_i - f(\bar{x}_i))^2$ . Supposed  $f(\bar{x})$  is linear then, we have:  $f(\bar{x}) = \bar{w}^T \bar{x} + b, \bar{w} \in \mathbb{R}^n$ , thus obtaining the following optimization problem:

$$\min_{\overline{w}, b} \sum_{i=1}^{m} (y_i - \overline{w}^T \overline{x} - b)^2 \text{ with } \overline{w} \in \mathbb{R}^n \text{ } b \in \mathbb{R}$$
(3)

Three key statistics which were used to describe multidimensional poverty:

• Incidence (H), which is the proportion of the population who are multidimensionally poor. It is sometimes called the poverty rate. Intensity (A), which is the average percentage of weighted indicators in which poor people are deprived – that is, the average deprivation score among poor people. MPI, which is the share of possible deprivations that poor people experience. The MPI is computed by multiplying the incidence by the intensity (MPI=H x A).

#### 3. ANN-Artificial Neural Network

In the neural network regression analytics, there are three layers which are Input, Hidden and Output. Each input layer has numerous neurons whose activations are determined by activations of neurons from past layer that contain both weights and bias. The structure of the poverty model in neural network is displaced as follow:

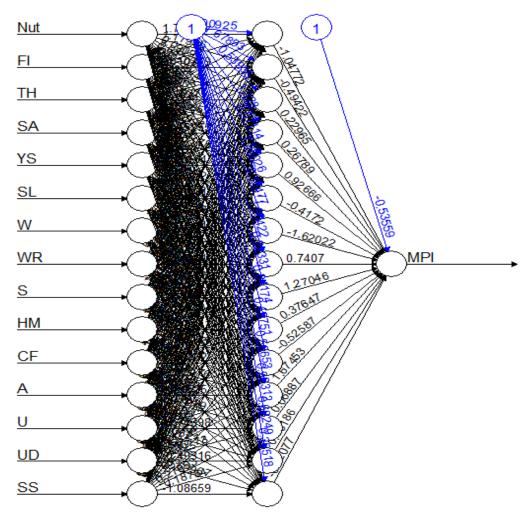


Figure 2. Showing the ANN Structure of the Poverty Modelling

"SSE: 0.0883" Figure 1 showing Artificial Neural Network Regression model on MPI

The first column of fifteen nodes in Figure 1 is called the input layer, which corresponds to the fifteen independent variables namely NUT, FI, TH, SA, YS, SL, W, WR, S, HM, CF, A, U, UD and SS. The third column with a single node is the output layer, which corresponds to the dependent variable MPI. The middle column of two nodes is called a hidden layer, which corresponds to intermediate calculations that were typically not observed (hence, "hidden"). This particular neural network is composed of many logistic regression models. The top node in the middle-hidden layer has directed arrow connections from all fifteen input layer nodes, with numerical coefficients as labels, as well as a sixteenth arrow from a node bias term in the linear equation with coefficient -0.5365 and is regarded as bias. All the arrows for the fifteen input nodes contribute to each hidden node. The hidden layer node then applies the sigmoid function  $s(x) = \frac{1}{1+e^{-x}}$  to the linear equation.

Table 3: Depicts Hidden Neuron 1 to Response Variable MPI

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u <i>)</i>								
nodes	1	2	3	4	5	6	7	8
bias	0.909	-1.68	0.539	1.328	0.571	1.96	0.165	1.904
NUT	<b>1.711</b>	1.179	0.091	1.047	0.997	-0.099	-0.329	1.263
FI	0.162	-0.1	1.025	1.69	0.994	-0.528	1.861	-0.328
TH	-1.65	1.441	0.164	-0.469	-0.29	0.003	0.663	-0.809
SA	1.256	-2.7	1.145	-0.153	-0.872	0.147	0.619	1.22
YS	0.368	1.164	0.837	1.06	0.472	0.352	-0.414	-1.127
SL	-0.539	0.047	0.371	0.919	0.283	1.087	0.282	-0.204
W	-0.56	-2.32	0.343	0.124	-0.054	-1.67	0.455	0.475
WR	0.368	-0.67	1.265	0.869	1.046	-0.076	-0.802	1.949
S	-0.295	-0.21	-1.245	-0.171	-0.554	-2.285	2.135	-0.498
HM	-0.807	-1.24	0.433	-1.175	1.265	0.323	-0.265	-0.511
CF	-1.555	-0.77	1.296	1.151	1.614	-0.684	-1.02	-1.521
A	-0.133	0.883	-0.351	-0.671	1.824	0.316	0.012	-1.691
U	-0.612	0.529	-0.781	-0.504	0.613	-0.213	-0.066	-1.866
UD	0.597	-1.03	-1.65	-1.227	0.278	0.691	-2.465	0.115
SS	1.099	2.516	0.387	1.348	-0.415	0.693	-0.23	-0.701
mpi	-1.048	-0.494	0.23	0.268	0.927	-0.417	-1.62	0.741

**(b)** 

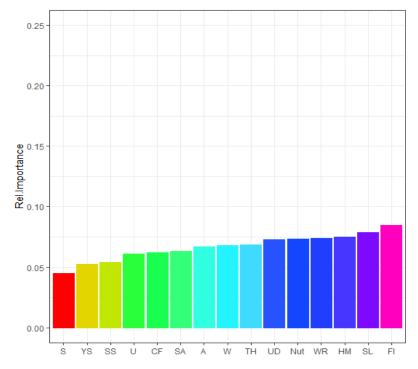
nodes	9	10	11	12	13	14	15
bias	0.223	-0.842	0.408	-0.557	-0.963	0.622	0.355
NUT	1.879	1.032	0.596	1.121	0.844	0.749	-0.125
FI	1.035	-1.114	-1.349	-1.201	-1.575	-0.809	-0.549
TH	0.645	-0.906	-1.036	0.795	-0.334	-1.971	-0.912
SA	-0.638	0.809	0.027	1.22	1.405	-0.182	0.061
YS	1.399	-2.166	-0.645	-0.533	0.229	0.094	-0.379
SL	0.108	-0.151	0.947	-0.057	1.858	-0.894	-3.132
W	1.016	-1.563	-0.566	-1.072	1.691	1.71	-0.351
WR	0.739	1.711	-0.856	-1.783	-0.794	-0.854	0.091
S	1.681	0.199	0.675	-0.731	0.932	-0.853	1.236
HM	-0.752	-0.487	-0.255	-1.616	1.681	1.04	0.98
CF	-1.162	-0.218	0.208	-0.546	-0.899	0.099	0.447
A	0.735	0.729	1.094	1.215	1.573	-0.438	-0.308
U	-1.057	-0.321	-0.319	1.093	-0.744	1.032	0.283
UD	0.774	0.487	-2.814	0.217	-0.058	-0.493	-0.7
SS	-0.347	-0.613	-0.243	-0.896	0.279	-0.188	-1.087
mpi	1.27	0.376	-0.526	1.675	0.069	0.362	-0.321

Table 3 (a and b) above described the. In ANN models, there is obviously no one-to-one correspondence between weights (parameters) and explanatory variables. More importantly, the marginal effect of a certain explanatory variable on the conditional expectation of the dependent variable is a (non-constant) function of all explanatory variables. A perceptron multilayer network with backpropagation was used. The ANN consisted of input, one hidden and one output layer. The number of nodes of the input layer corresponds to the number of variables describing the attributes being tested, while the number of neurons in the output layer is unit. In the hidden and output layer each neuron was connected to all of the nodes in the proceeding layer by an associated numerical weight. The weight connecting the neurons regulates the magnitude of the signal that passes between them. From nodes 1 to fifteen in the table 1 above, all highlighted weights are positively contributed to the weights that determined MPI, for illustration in node one, NUT, FI, SA, YS, WR, UD and SS contributed positively towards the weight that determine MPI while other variables contributed negatively. Ditto for all other nodes. Nodes 3,4,5, 8,9, 10, 12, 13, 14 were in all contributed positively to determine the MPI. The absolute bias to MPI is 0.536 which is invariably intercept.

Table 4: Depict Variable Importances of the Economic Variables

Variables	rel_imp	Rank
Nut	0.073	6
FI	0.085	1
TH	0.069	7
SA	0.063	10
YS	0.052	15
SL	0.079	2
W	0.068	8
WR	0.074	4
S	0.045	14
HM	0.075	3

0.062	11
0.067	9
0.061	12
0.073	5
0.054	13
	0.067 0.061 0.073



**Figure 3.** Showing the Variable Importance of the Economic Variables

The relative importance of each predictor is shown in the above table 4 and figure 3 respectively. The results suggest that FI is the most important predictor of MPI, followed by SL and HM. The relative importance of each predictor is showed in figure 2 above. The figure depicts the importance of each variable, the higher the bar, the more important the variable, variable FI has the highest value which implies the most important variable in all whereas variable S has the lowest values depicted the bar, the implication is that the variable S is less importance in all, ditto for all other variables shown in the figures as well as table 4. Table 4 showed the magnitude while figure 3 display the pictorial view.

#### 4. Conclusion

The integration of machine learning in poverty modeling has emerged as a powerful approach to address the multidimensional challenges of poverty. Advancements in data integration, predictive modeling, spatial analysis, and image processing have opened new avenues for understanding poverty dynamics and designing targeted interventions. This study examined poverty modelling in the realm of artificial neural network regression and showcased the contribution of the weight of each predictor variable towards the nodes that determine the MPI. Most literature do not interpret the weights and bias of ANN regression; they only described the architecture of the procedures to obtain it. This is the gap this study filled.

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