

Optimised MLP Neural Network Model for Optimum Prognostic Learning of out of School Children Trend in Africa: Implication for Guidance and Counselling

Edith Edimo Joseph

Department of Educational Psychology, University of KwaZulu-Natal, Edgewood Campus, South Africa

Email: edimo8383@gmail.com

ORCID iD: <https://orcid.org/0000-0001-6148-9127>

Joseph Isabona*

Department of Physics, Federal University Lokoja, Lokoja, Kogi State, Nigeria

Email: joseph.isabona@fulokoja.edu.ng

ORCID iD: <https://orcid.org/0000-0002-2606-4315>

*Corresponding Author

Odaro Osayande

Centre for Learning Resources, Covenant University, Ota, Ogun State, Nigeria

Email: odaro.osayande@covenantuniversity.edu.ng

ORCID iD: <https://orcid.org/0000-0002-5771-9548>

Ikechi Irisi

Department of Physics, River State University Port Harcourt Nigeria

Email: ikechi.risi@ust.edu.ng

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Abstract: One crucial and intricate problem in the education sector that must be dealt with is children who initially enrolled in schools but later dropped out before finishing mandatory primary education. These children are generally referred to as out-of-school children. To contribute to the discuss, this paper presents the development of a robust Multilayer Perceptron (MLP) based Neural Network Model (NN) for optimal prognostic learning of out-of-school children trends in Africa. First, the Bayesian optimization algorithm has been engaged to determine the best MLP hyperparameters and their specific training values. Secondly, MLP-tuned hyperparameters were employed for optimal prognostic learning of different out-of-school children data trends in Africa. Thirdly, to assess the proposed MLP-NN model's prognostic performance, two error metrics were utilized, which are the Correlation coefficient (R) and Normalized root means square error (NRMSE). Among other things, a higher R and lower NRMSE values indicate a better MLP-NN precision performance. The all-inclusive results of the developed MLP-NN model indicate a satisfactory prediction capacity, attaining low NRMSE values between 0.017 - 0.310 during training and 0.034 - 0.233 during testing, respectively. In terms of correlation fits, the out-of-school children's data and the ones obtained with the developed MLP-NN model recorded high correlation precision training/testing performance values of 0.9968/0.9974, 0.9801/0.9373, 0.9977/0.9948 and 0.9957/0.9970, respectively. Thus, the MLP-NN model has made it possible to reliably predict the different patterns and trends rate of out-of-school children in Africa. One of the implications for counselling, among others, is that if every African government is seriously committed to funding education at the foundation level, there would be a reduction in the number of out-of-school children as observed in the out-of-school children data.

Index Terms: Africa, Bayesian Optimization Algorithm, Guidance and Counseling, Hyperparameters, MLP Neural Networks, Out-of-school children

1. Introduction

Passing through a quality education learning process at different stages in life is a non-negotiable human right to improve lives. This concrete right is plainly pronounced in the fourth driving goal of United Nations Sustainable Development Program, slated toward attainment in 2030. The agenda is such that every nation on the earth is rapt to trail good and across-the-board education for all school age in order enhance lifetime learning. Despite this agenda and other actions being taken by other agencies for the prompt realization of mission and agenda of education for all, however, there is still high rate of out-of-school children in Africa.

Out-of-school children is comprised of those kids that are within primary or secondary school age population, usually between 3-25 years old, who have not been formally registered in any school or pass through in any school system [1]. This perception of out-of-school kids simply implies that there exist a set of children who should be in school, however they are not. It can also be defined as kids who initially enrolled in schools but later dropped out before finishing the mandatory basic education. This population encompass poor and handicapped children from households living in abject poverty who lacks the privilege to go to schools. According the same UNESCO report [1], the population of out-of-school kids has reached up 98 million from the initial 20 million population that was recorded in 2009 for Sub-Sahara Africa. In Nigeria alone, the number of out-of-school number is around 20m. From the latest UNESCO and United Nations reports, 2022 [2], the out-of-school number within the school age has increased to 244 million worldwide.

Before the COVID-19 pandemic occurrence, the entire globe, particularly Africa continent, was already attacked by many learning challenges with about 53% of school children in middle and low-income countries living and learning in abject poverty. This global trend is already negatively impacting different lives, except concrete corrective measure with proactive action is taken, the negative incremental trend will likely continue.

One key method that can be engaged or adopted to deal with the issue of out-of-school problem is to reliably study the trend pattern over the years through robust data collection and prediction analysis to enable future planning. Though numerous prediction methods have been utilized to deal with the subject matter in literature, however, the precision accuracies of such methods are still below expectation. For example, Artificial neural networks (ANN) remained a distinctive soft computing learning-based models endowed with reliable functional approximation and prediction capacity. But, the ANN possesses many parameters sets that parameters must be selected fittingly to obtain the most preferred results. For instance, there is always the challenge of knowing the best neuron number, the most suitable layers number, best learning rate, or the right optimizer that is best suited a specific dataset. Choosing too few layers/neurons number may lead to underfitting results. Similarly choosing too many layers/neurons number may result to overfitting performance.

The leading objective of this paper is to develop a robust Multilayer Perceptron (MLP) based Neural Network Model (NNM) for optimal prognostic learning of school dropout trends in Africa. The MLP-NNM was developed by applying Bayesian optimization algorithm to obtain and determine the best MLP hyperparameters and its specific training values.

1.1 Outline

We commenced by providing an all-inclusive literature review and contribution to knowledge in Section. 2. We provide the methodology in section 3, which involves the Out-of-school data collection source, the developed MLP-NN structure, the model, and the implementation flowchart. It is followed by the provision of detailed results and discussion. In Section 4, the developed MLP-NN and prognostic learning impact on school dropout trends are presented. The concluding part of the work is described in section 5.

2. Literature Review

Several research investigations have addressed various aspects of out-of-school children's challenges in the society [3-5]. Some studies specifically examined the methods and tactics for tackling out-of-school student problems [6-8], while others concentrated on the risk, social and behavioral aspects of student dropout anomalies in the society [9-11].

Recently, the utilization of machine learning/artificial intelligence techniques in conducting predictive analytics to tackle out-of-school/drop-of-school problems is gradually rising. According to Neema [12], there is a pressing need to develop a robust machine-learning algorithm that can be explored to predict and address out-of-school problems. The authors in [13] opined that out-of-school prediction studies using machine learning techniques could efficiently identify school drop risk and find solutions to numerous societal problems.

Aguiar et al. (2015) [14] employed machine learning techniques involving Random Forest (RF), Logistic Regression (LR), and Cox Regression (CR) to investigate possible reasons why some students don't graduate early in the United States. The various machine models were trained utilizing school district datasets. The results disclosed that RF accomplished the most preferred performance over the LR and CR methods. A similar approach was also used in [15] to predict children's academic fitness. Generally, the precision accuracies of these aforementioned methods are still very visible to content with. Also, the authors didn't provide clear information of how each model's hyperparameters

were tuned or selected. The researchers in [16] employed a similar machine learning procedure to address secondary students' dropout problem. However, they used datasets acquired from Danish high schools. Again, the results disclosed that RF accomplished most preferred prediction accuracy. Also, the authors didn't provide clear information of how each model's hyperparameters were tuned or selected.

In [17], Feed-forward Neural Networks (FNN) and LR were employed by the researchers to conduct a predictive analysis of student dropout rate. From the outcome, the FNN outpaced the LR precision performance. By means of time dependent Cox (TD-Cox) and Cox proportional hazards (Cox-PH) models, the authors in [18], came up with a survival analysis framework to identify at-risk student's dropout problem and the resultant outcome reveals that the Cox-based framework got the best results. On the hand, the authors didn't provide clear information of how each aforementioned model's hyperparameters were tuned or selected

In [16], a four-Step LR Method is presented predict and identify student-teachers dropout risk in schools using least-developed country as a reference study. The results confirmed that aspirations and twin academic performance issues are the uppermost prognosticators of student-teacher attrition. The findings also highlight that prevention and early identification methods are the best means to constrain drop-out problems and boost retention and a healthy learning environment. In [19], prediction analysis of kindergarten-transition challenges is presented using statistical learning techniques and in concluding, the authors highlighted the need to support kindergarten children during their transition stage. In [20], Fuzzy and joint Neuro-Fuzzy Systems were adopted to Predict learning debilities in children within the school-age. The accuracy of the combined approach reveals that prediction performance is improved by engaging missing value based- imputing.

Most recently, many authors (e.g. [22-26]) renewed their interest in engaging neural networks (NN) modeling algorithms to study school drop-out problems and other children/students-related issues in the society. This may be due to their robust adaptive prediction outputs. However, clear information of how the NN model's hyperparameters were tuned or selected are not clearly revealed by authors.

There exist numerous NN architectures or models, but the most notable and explored one among them is the Multilayer perceptron (MLP). The MLP popularity may be due to its capability and robustness to learn real-time non-linear models via creative mapping between the output and input space. But a critical issue with MLP is that it requires many controlling hyperparameters that must be tuned effectively to obtain optimal precision results.

In this paper, optimal hyperparameter selection technic-based Bayesian optimization algorithm is proposed and explored to select the most appropriate MLP-NN prediction modelling parameter sets for the acquired school dropout data samples. The paper contribution to knowledge includes:

- Optimal selection of MLP-NN hyperparameters/values utilizing Bayesian optimization algorithm
- Selection of best MLP-NN training Algorithm through exhaustive research
- Development and effective application of MLP-NN Model with satisfactory prediction of out of school children's data in Africa.
- Implication analysis of predicted out-of-school children trend rate in guidance and counseling.

3. Methodology

This paper considers three crucial workflow steps to actualize the research as mentioned earlier, as summarized in Figure 2. The first step involves data collection, data loading, and preprocessing in Matlab format. The preprocessing is done to boost systematic MLP learning accuracy. This is followed by hypermeter tuning, the network building, and configuring. The next stage is the application and evaluation of the built MLP model via training and testing.

3.1 Data Collection

The out-of-school datasets used in this paper were directly obtained from UNESCO official website [27]. It is an organization set up by the United Nations; UNESCO is shouldered with the responsibility of looking into various educational, scientific, and cultural issues of the member nations. The specific dataset extracted from the website includes out-of-school children number belonging to Sub-Sahara Africa (SFA), North/Middle East Africa (NMA), Highly indebted poor Countries (HPIC), and Least Developed Countries (LDC). The dataset for each category mentioned above was from 1975-2020. The Organization has not less than 50 different field office locations globally, with its controlling headquarters centered in Paris.

3.2 The MLP-NN Model

Generally, NN remained a distinctive soft computing learning-based models endowed with reliable, functional approximation capacity [28-30]. As name denotes, the ANN are special networks that are interconnected structures of neurons, layers (input layer, output layer, hidden layer), and transfer functions.

Here, we consider an MLP-NN model consisting of three interconnected layers: the intermediate hidden layer, the resultant output layer, and the foremost input layer. Besides the input layer, every other layer holds a neuron that utilizes a non-linear transfer function that activates its switching output.

As displayed in figure 1, we engaged a three-layered MLP-NN model structure, and each layer possesses a particular a set of neurons number which form the NN standard computational elements.

The hidden layer neurons output can be express as:

$$y_j(a) = f(\sum_{q=1}^Q w_{qj}x_q(a) - G_q) \quad (1)$$

$q \in \{1, 2, \dots, Q\}, j \in \{1, 2, \dots, J\}$

where f and Q indicate the sigmoid transfer function and the input number from neuron j.

For the entire NN layer, the neurons output can be obtained using:

$$y_t(a) = f(\sum_{i=1}^I w_{it}(a)x_{it}(a) - G_t) \quad (2)$$

where I indicates the input number from neuron k. x_i (i=1, 2, 3 ...I) designate input data, x_i (i=1, 2, 3 ...I) with, w_{it} being the connecting weights.

The error per epoch, E and the neurons gradient of error, G_t in the output layer re computed using:

$$E = E + \frac{(e_t(a))^2}{2} \quad (3)$$

$$G_t(a) = f' e_t(a) \quad (4)$$

$$e_t(a) = y_{d,t}(a) - y_t(a) \quad (5)$$

where $y_{d,t}(a)$ and $y_t(a)$ describes the input and MLP output.

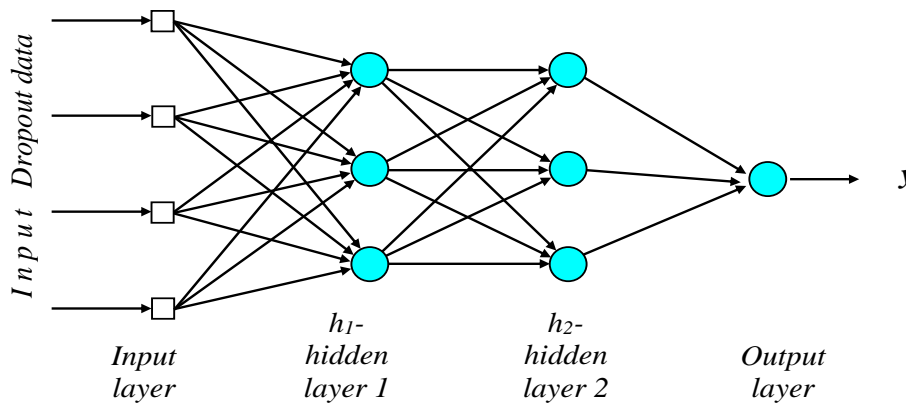


Fig. 1. MLP Model Architecture

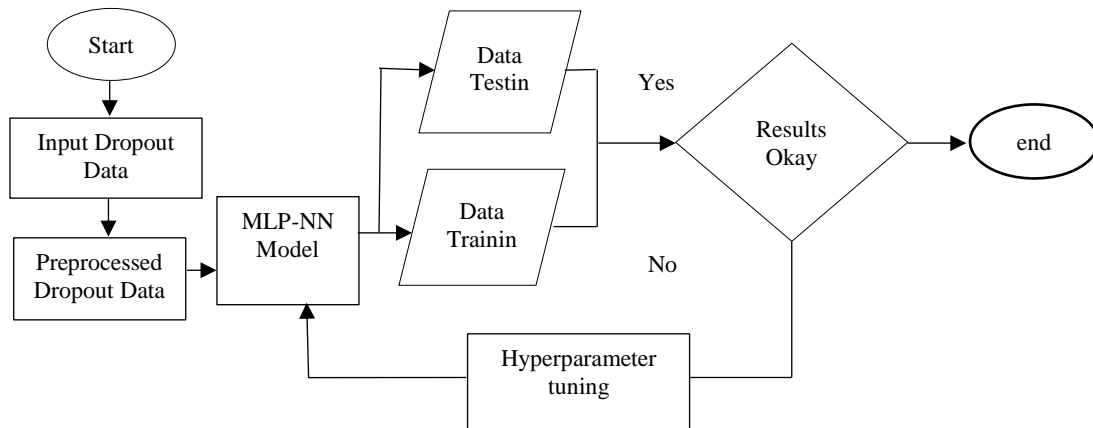


Fig. 2. Method Proposed MLP-NN Model Development

3.3 Hyperparameters and Tuning Based-Selection

Neural networks need a specific parameter set (hyperparameters) for engagement during data training and testing in order to attain the desired results. Therefore, effective hyperparameter-tuning is crucial to conducting search and determining the possible best parameter sets to come up with a robust NN model to handle a particular dataset [31].

However, the NN possesses many parameter sets that must be selected fittingly to obtain the most preferred results. For instance, there is always the challenge of knowing the best neuron number, the most suitable layers number, the best learning rate, or the right optimizer that best suits a specific dataset. Choosing too few layers/neurons number may lead to underfitting results. Similarly choosing too many layers/neurons number may result to overfitting performance [31-33]. This paper explores the optimal hyperparameter selection technique-based Bayesian optimization algorithm to select the most appropriate NN prediction modelling parameter sets for the acquired school drop-out data samples.

3.4 Precision Evaluation Index

Two key precision evaluation indexes (PEI) were utilized to ascertain the developed Bayespot-based MLP-ANN model accuracy in this study. The first PEI is called Normalized Root Mean Square Error (NRMSE) and it expresses the L_1 -norm precision of the mean prediction [34, 35]. The second one is the Correlation coefficient (R) and it indicates connection strength between the developed model and target input variables [36]. The NRMSE value is preferred when it closer to zero, but R, its value is preferred when it is closer to 1 [37-40]. The NRMSE and R can be computed by:

$$RMSE = \sqrt{MSE} = \frac{1}{N} \sqrt{\sum_{q=1}^N [y_q - d_q]^2} \quad (6)$$

$$NRMSE = RMSE / \max(y_q) - \min(d_q) \quad (7)$$

$$R = \frac{\sum_{q=1}^N (y_q - \bar{y}_k)(y_q - \bar{d}_k)}{\sqrt{\left[\sum_{q=1}^N [(y_k - \bar{y}_k)^2] \right] \left[\sum_{q=1}^N [(y_k - \bar{d}_k)^2] \right]}} \quad (8)$$

where y_q and d_q describe the observed and predicted out-of-school children's data.

4. Results and Discussion

4.1 The Developed MLP-NN and Prognostic Learning impact on School Drop-out Trend

Specifically, in this paper, the considered MLP-NN is configured with 2-hidden layered architecture which runs 0.001, 0.1 and 0.3 values of error goal, momentum value and learning rate, respectively. The learning rate value, the hidden layer plus the neuron number were determined using the Bayesian optimization tuning algorithm in MALTAB software interface. In terms of training/testing, Bayesian regularization (br), which gotten through exhaustive search process, was utilised. To attain optimal NN learning, the acquired out-of-school data were divided using 70%:15%:15% ratio. While first portion was for training, the remaining two portions were used for testing and validation. Furthermore, the out-of-school datasets inputs were first scaled to be in the [-1, 1] range to enhance the adaptive MLP-NN learning speed. Also, early stopping measures were utilized in order to avert MLP-NN overtraining. Also, to assess the proposed MLP-NN model's prognostic performance, two error metrics were utilized, which are the Correlation coefficient (R) and Normalized root means square error (NRMSE). A higher R and lower NRMSE values indicate a better MLP-NN precision performance.

Figure 1-4 reveals that the developed MLP-NN model reliably predict the school dropout data during training and testing with minimal NRMSE values. Particularly, for Sub-Sahara Africa (SAF) out of school children's data in figure 3, MLP-NN model attained as low 0.017 and 0.182 NRMSE values during training and testing. Similarly, for North Africa/ Middle East (NMA), least developed countries (LDC) and heavily indebted poor countries (HPIC), the developed MLP-NN model also attained enhanced learning accuracies with 0.063/0.053; 0.031/0.033 and 0.026 and 0.048 RMSE values, during the out of school data training and testing.

Displayed in figures 4-8 are correlation coefficient performance fits between the predicted and observed out of school data the developed MLP-NN model. From the results, the MLP-NN recorded high correlation precision training/testing performance values of 0.9968/0.9974, 0.9801/0.9373, 0.9977/0.9948 and 0.9957/0.9970, respectively.

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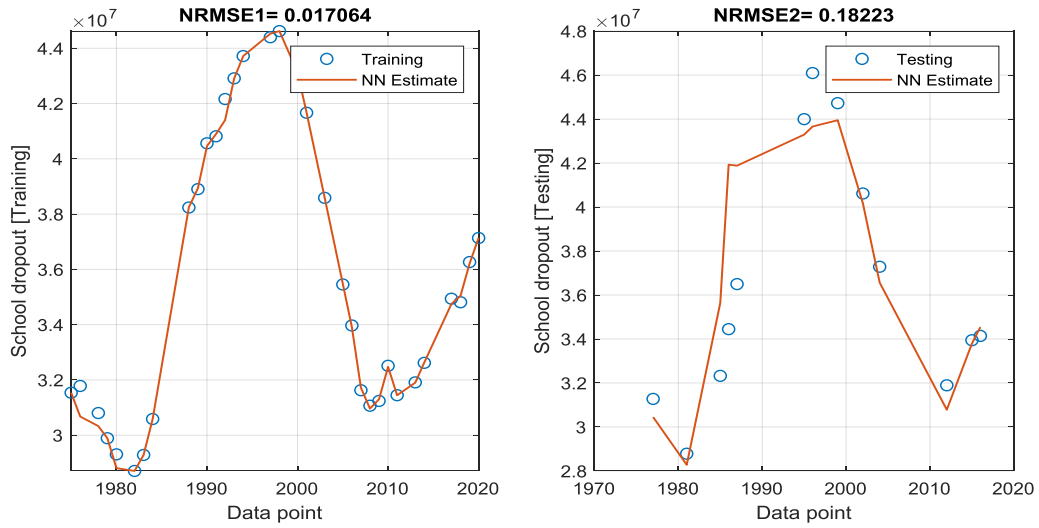


Fig. 3. Predicted out of school children trend rate for Sub-Sahara Africa using the MLP-NN model during Training and Testing

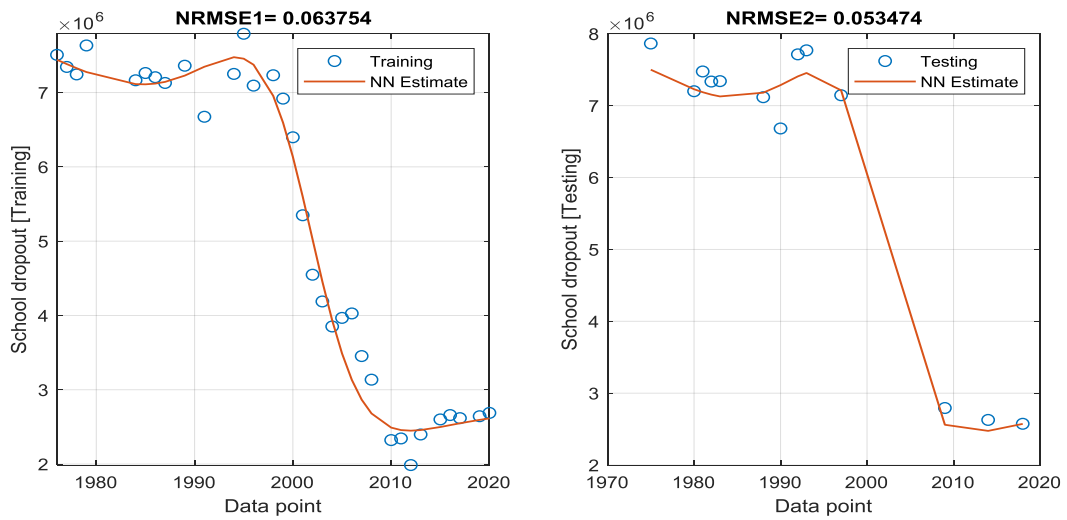


Fig. 4. Predicted out of school children trend rate for North/Middle East Africa using the MLP-NN model during Training and Testing

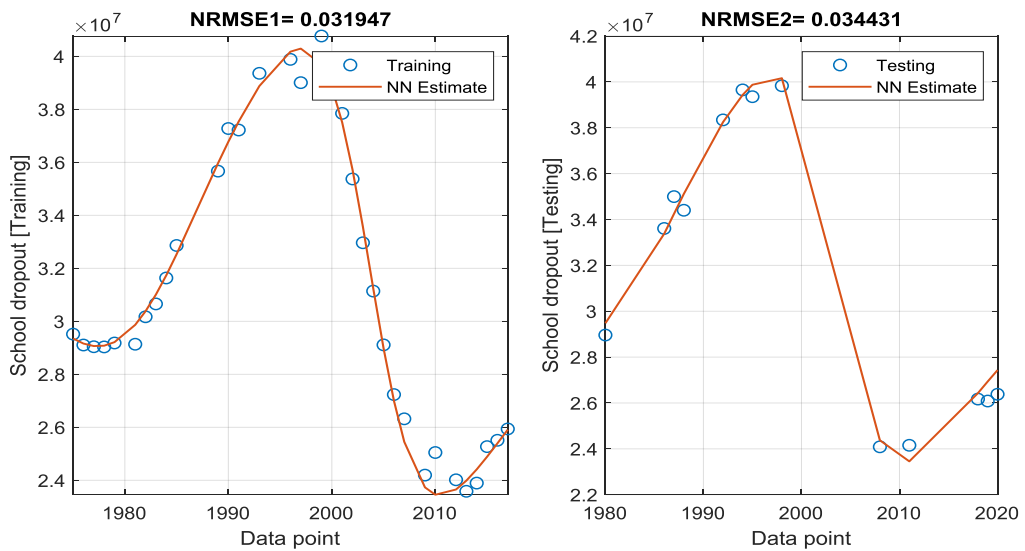


Fig. 5. Predicted out of school children trend rate for Heavily Indebted Poor Countries using the MLP-NN model during Training and Testing

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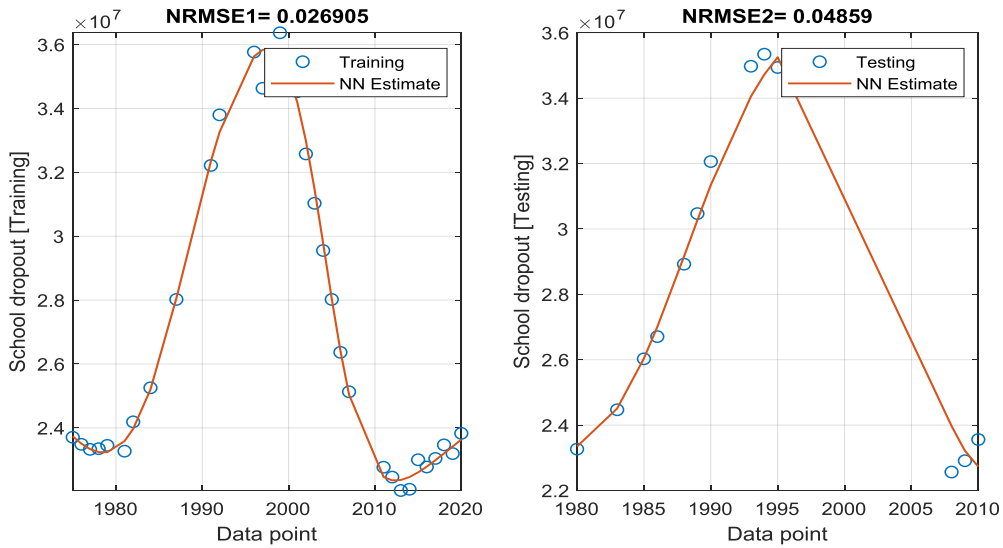


Fig. 6. Predicted out of school children trend rate for least Developed Countries using the MLP-NN model during Training and Testing

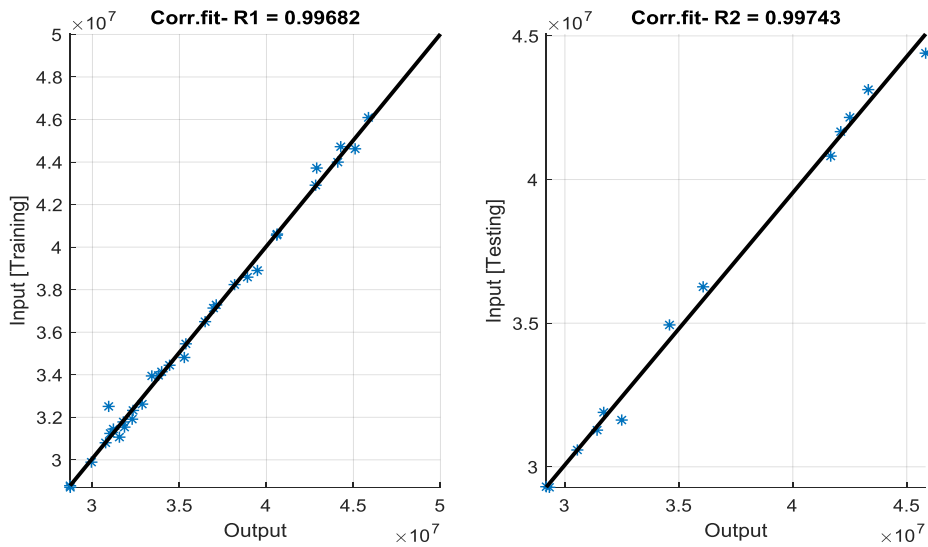


Fig. 7. Correlation performance of predicted out of school children trend rate for Sub-Sahara Africa using the MLP-NN model during Training and Testing

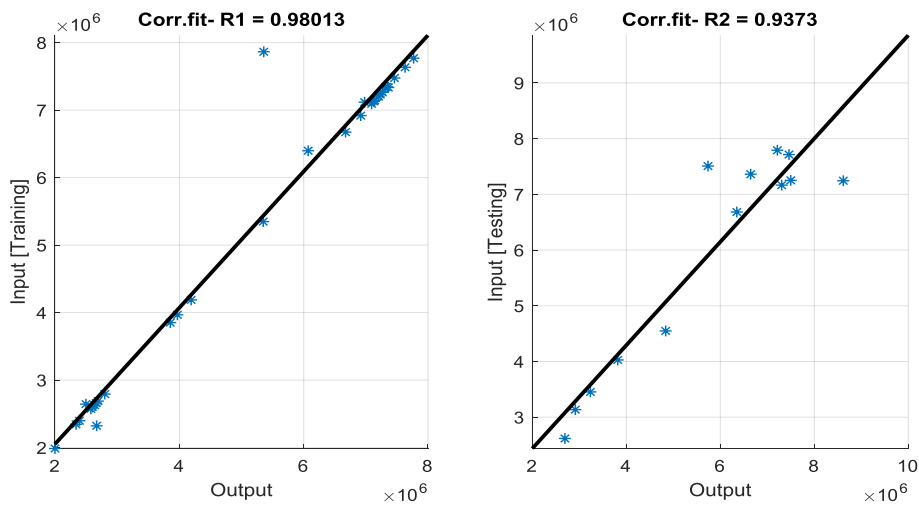


Fig. 8. Correlation performance of predicted out of school children trend rate for North/Middle East Africa using the MLP-NN model during Training and Testing

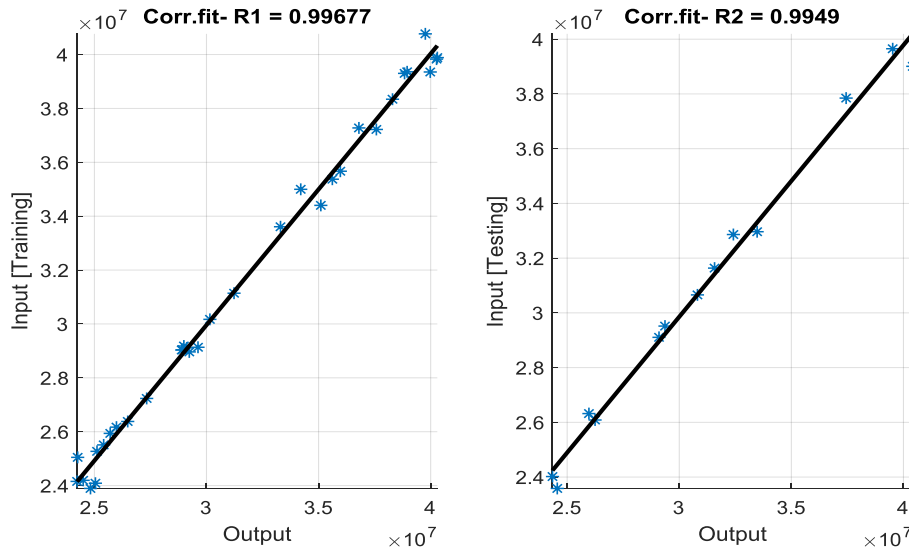


Fig. 9. Correlation performance of predicted out of school children trend rate for Highly Indebted Countries using the MLP-NN model during Training and Testing

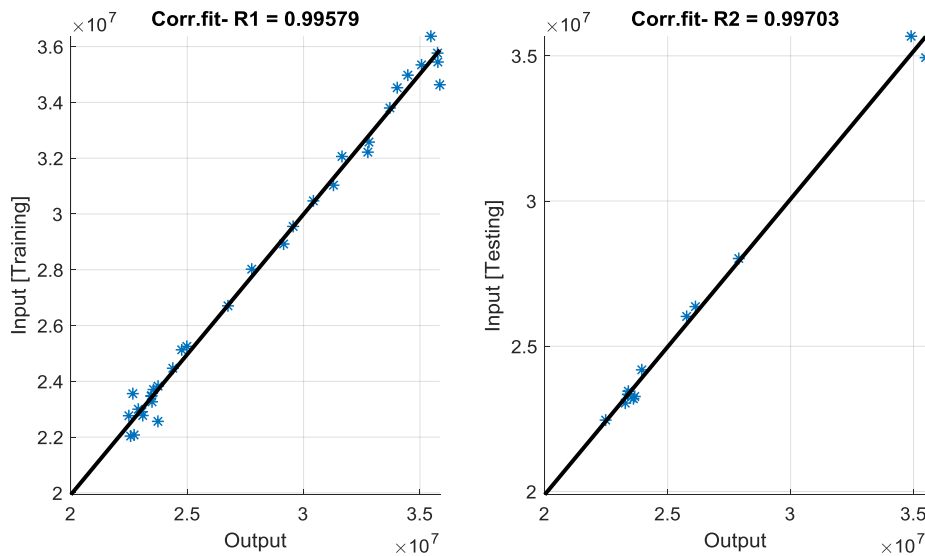


Fig. 10. Correlation performance of predicted out of school children trend rate for Least Developed Countries using the MLP-NN model during Training and Testing

4.2 Impact of MLP-NN Learning Algorithms

As mentioned earlier, the algorithm employed when engaging the MLP for data training/testing also play key role in its overall adaptive learning performance. This paper adopted the Bayesian regularization algorithm (br) through exhaustive research. The optimum performance of the adopted BR over other popular ones during drop-of-school data training and testing is exhibited in Figure 1, Table 1 and Table 2. These popular ones include the Gradient descent combined with momentum backpropagation (gdm), Levenberg-Marquardt backpropagation (lm), BFGS quasi-Newton backpropagation (bfg), One-step secant backpropagation (oss). Others include Scaled conjugate gradient backpropagation (scg), Resilient backpropagation (rp) and Conjugate gradient backpropagation combined with Powell-Beale restarts (cgf). The figure visibly show that adopted BR outperform other algorithms by 10 -20%, due to its optimum adaptive learning and generalization ability. Here, the NRMSE value is preferred when it closer to zero. It clear from table 11 that br algorithm is mostly preferred as it attains lowest NRMSE values during SAF, NMA, LDC and HPIC training. Such cute performance may be ascribed to optimal generalization capacity of the br. The optimal generalization performance is followed by scg algorithm, and then LM algorithm. The worst performance is achieved particularly by the gdm algorithm, which attaced as high as 2.09 NRMSE value during training with NMA out-of-school children's data.

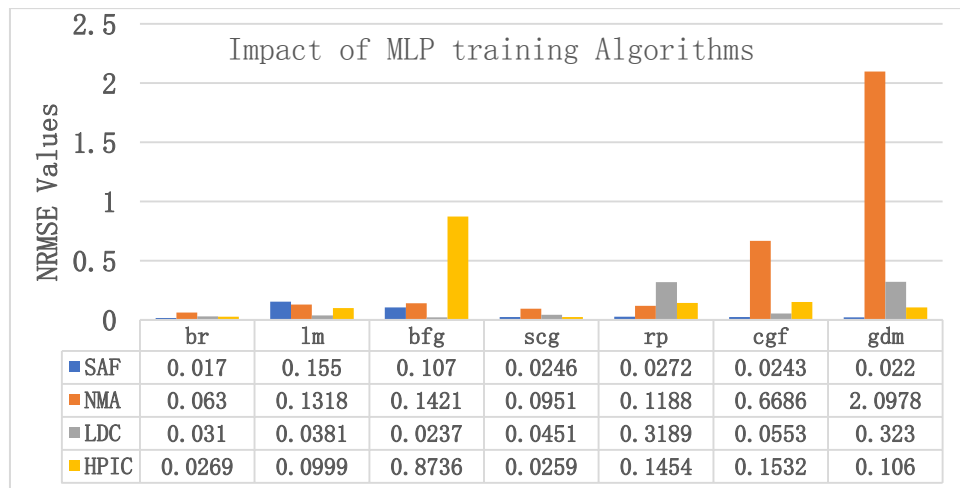


Fig. 11. NRMSE Predicted performance values of out of school children trend rate data using the MLP-NN model using different Training Algorithms

Table 1. Predicted performance summary of out of school children trend rate data using the MLP-NN model using different Training Algorithms

	SAF		MNA		LDC		HPIC	
	NRMSE	R	NRMSE	R	NRMSE	R	NRMSE	R
br	0.017	0.9956	0.063	0.9801	0.031	0.9967	0.0269	0.9957
lm	0.155	0.8548	0.1318	0.9194	0.0381	0.9949	0.0999	0.9595
bfg	0.107	0.4775	0.1421	0.8271	0.0237	0.7648	0.8736	0.4754
scg	0.0246	0.9938	0.0951	0.4467	0.0451	0.9919	0.0259	0.9923
rp	0.0272	0.9739	0.1188	0.9425	0.3189	0.7659	0.1454	0.8501
cgf	0.0243	0.9843	0.6686	0.9898	0.0553	0.9877	0.1532	0.8854
gdm	0.0220	0.8810	2.0978	0.9338	0.3230	0.9338	0.1060	0.7086
oss	0.066	0.7081	0.3483	0.5536	0.0461	0.9332	0.0361	0.9159

Table 2. Predicted performance summary of out of school children trend rate data using the MLP-NN model using different Testing Algorithms

	SAF		MNA		LDC		HPIC	
	NRMSE	R	NRMSE	R	NRMSE	R	NRMSE	R
br	0.1822	0.9974	0.0534	0.9373	0.0344	0.9949	0.0485	0.9970
lm	0.1813	0.6952	0.1551	0.9054	0.0938	0.9696	0.1778	0.8983
bfg	3.5877	0.4878	0.7886	0.8222	0.3238	0.6917	1.1671	0.2306
scg	0.0243	0.9979	0.1422	0.8882	0.0617	0.9880	0.0603	0.9919
rp	0.1313	0.9314	0.1822	0.8011	0.3623	0.8880	0.1942	0.8803
cgf	0.1219	0.9287	0.8845	0.9867	0.10883	0.9622	0.1532	0.8803
gdm	0.3657	0.8522	2.4471	0.9070	0.3359	0.6056	1.0051	0.6583
oss	0.2091	0.6990	0.3560	0.5694	0.0931	0.9819	0.3059	0.9971

4.3 Out-of-School Children Trends Rate in Africa: Implication for Guidance and Counselling

One notable aim of guidance counselling is to encourage students' academic, emotional, social, and personal development. To achieve this aim, students should be helped to understand themselves better and to be able to make well-informed decision in their daily lives.

As shown in figures 3-6, the out-of-school number in Africa displayed a high reduction trend over 12 years, mainly falling from 7.5×10^6 million in 1988 to 2.5×10^6 million in 2010. The reduction in the number of out-of-school children within this period was when world leaders agreed to work towards achieving Education for All by 2015, which was the commitment they made in the World Education Forum that took place in the year 2000 at Dakar. This result calls for regular organization of such World Education Forum. The result implies that a lot of the reduction in the number of out-of-school children was observed; hence if every African government is seriously committed to funding education at the foundation level, there could be a high reduction of out-of-school children.

On the other hand, a swift rise in the number of out-of-school children across Africa can be seen in the graphs in millions, particularly between 2019-2020. The surge may be attributed to school closure problems during COVID-19 epidemic emergence and lockdown that ravages the whole world of resources and convenience, principally in the area

of health and income. Though, distance learning was introduced in some countries, but the above results have shown that its effectiveness was limited, probably due to poor access to digital capital for teaching and learning and technical know-how by many teachers and children. Thus, to ensure the number of out-of-school children is reduced drastically, there is an urgent need for collective mobilization by the government, parents, individuals and Non-governmental organizations to ensure that every single child has access to primary quality education is valued and respected.

5. Conclusion

Generally, ANN remained a distinctive soft computing learning-based models endowed with reliable functional approximation capacity. ANN are special networks that are interconnected structure of neurons, layers (input layer, output layer, hidden layer) and transfer functions. However, the though NN possesses many parameters sets, but there that parameters must be selected fittingly to obtain the most preferred results. For instance, there is always the challenge of knowing the best neuron number, the most suitable layers number, best learning rate, or the right optimizer that is best suited a specific dataset. Choosing too few layers/neurons number may lead to underfitting results. Similarly choosing too many layers/neurons number may result to overfitting performance.

In this paper, optimal hyperparameter selection technic-based Bayesian optimization algorithm is explored to select the most appropriate NN prediction modelling parameter sets for the acquired school dropout data samples. From the findings, the explored MLP-NN model attained as low 0.017 and 0.182 NRMSE values it was employed for the training and testing the school drop-out data acquired for Sub-Sahara Africa. Similarly, for school dropout data training/testing for Middle East /North Africa, least developed and heavily indebted poor countries, the developed MLP-NN model also attained enhanced learning accuracies with 0.063/0.053; 0.031/0.033 and 0.026 and 0.048 RMSE values, respectively. In terms of correlation coefficient fits to the school drop-out data, the developed MLP-NN model recorded high correlation precision training/testing performance values of 0.9968/0.9974, 0.9801/0.9373, 0.9977/0.9948 and 0.9957/0.9970, respectively. Particularly, our finding during the out-of-school children data training reveals that the br algorithm is mostly preferred as it attains lowest NRMSE values during SAF, NMA, LDC and HPIC training. Such cute performance may be ascribed to optimal generalization capacity of the br. The optimal generalization performance is followed by scg algorithm, and then LM algorithm. The worst performance is achieved particularly by the gdm algorithm, which attained as high as 2.09 NRMSE value during training with NMA out-of-school children's data.

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Authors' Profiles



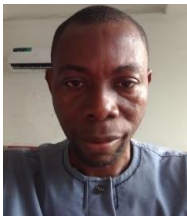
Edith Edimo Joseph, Ph.D, received the Bachelor of Arts in Education/English (B.Ed) from the University of Nigeria, Nsukka and Master of Education in Counselling Psychology from the University of Benin, Benin City. She recently completed her PhD studies from the University of KwaZulu-Natal, Durban South Africa. Her research interest includes Invitational Education, Menstruation and Learning and Out-of-School Children. She is currently a Lecturer at Federal University Lokoja, Kogi state, Nigeria. She can be reached with edimo8383@gmail.com



Joseph Isabona, Ph.D, is a Professor of Physics. He received his Ph.D. and M.Sc. degrees in Physics with Electronics, 2013 and 2007 respectively, and a B.Sc in Applied Physics in 2003. He is the author of more than 100 scientific contributions including articles in international Peer-review Journals and Conferences in the area of Wireless Mobile communications. The Author is a Postdoctoral Research Fellow of the Department of Electronic Engineering, Howard College, University of KwaZulu-Natal, Durban, South Africa. His area of interest includes Signal Processing, Machine Learning, RF Propagation Modelling and Radio Resource Management in Telecommunication Networks. His email is joseph.isabona@fulokoja.edu.ng



Odaro Osayande, Ph.D. is a professional Librarian and an information services Manager. He bagged his Ph.D. and M.L.I.S (Master, Library and Information Studies in 2020 and 2010 from the University of KwaZulu-Natal, Pietermaritzburg campus, South Africa, and the prestigious University of Ibadan respectively. He got his BSc. Ed. In Library Science and Political. He is the author of several peer-reviewed local and international journal articles and conference proceedings. His research areas include library security, library administration, library induction ICT in library services, etc. His email is: odaro.osayande@covenantuniversity.edu.ng



Ikechi Risi is lecturer at Rivers State University, Nigeria in Physics Department where he lectures physics. He obtained his B.Sc and M.Sc in Solid State Physics at the university in 2013 and 2019 respectively and currently pursuing his Ph.D at Ignatius Ajuru University of Education, Port-Harcourt. His interest areas are electronic circuit design/construction, embedded system, and radio signal propagation engineering. He can be contacted through ikechi.risi@ust.edu.ng

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