Volume 6, Issue 12, December – 2021 International Journal of Innovative Science and Research Technology

ISSN No:-2456-2165

Modelling the Success of using Administrative Skills in Improving the Health Quality of People with Intellectual Disabilities using Adaptive Neuro-Fuzzy Inference System: A Case Study of Two Cities in Libya

[1*]Munsif J. Ahseen,
[1*]Department of Health care organization management,
Cyprus International University, Haspolat-lefkosa via Mersin 10, Turkey
[2]Special Education, Faculty of Education, Omar Al-Mukhtar University, Derna Libya

A. N. Salihu[3],
[3]Department of Public health Nursing, Faculty of Nursing, Near East University, 99138 Nicosia, Turkish Republic of Northern Cyprus

Afaf. A. Jibril[4]
[4]Faculty of Faculty of Clinical Sciences, Bayero University Kano

Abstract:- One of the major goals of employing any health care administrator in any health care center is to achieve success in improving the health quality of patients through the application of various administrative skills owing to the fact that in both developed and developing countries; quality in healthcare is increasingly becoming a major health policy concern. This research explored the application of adaptive neuro-fuzzy inference system (ANFIS) and the multilinear regression (MLR) in order to simulate the success of developing skills by administrative health worker for improving health quality of people with intellectual disabilities. Five different independent variables were used in predicting the dependent variables using the ANFIS and MLR models. The performance of ANFIS in both the calibration and verification stages indicates the ability of artificial intelligence techniques over classical models such as MLR in solving issues related to health care organization management.

Keywords:- *Health care management, health quality, intellectual disability, ANFIS, MLR, Administrative health workers.*

I. INTRODUCTION

In both developed and developing countries, quality in healthcare is increasingly becoming a major health policy concern. Significant economic, political, and social shifts have contributed to a major shift in healthcare policies around the world since the 1990s, with a stronger focus on improving performance and quality[1]. As a result, the argument has shifted from whether healthcare is suitable to policies and techniques for improving its quality[2].

Political and financial imperatives, such as restricted resources, rising medical expenses, and rising consumer expectations, have fueled interest in healthcare quality. Healthcare reforms in many countries have also contributed to a greater focus on the quality and efficiency of healthcare policies in both developed and developing countries, as well as a recognition of the existence of service quality issues in health services and the need for a systematic approach to analyzing and improving these issues[3].

Vretveit (2004) identified three key viewpoints that determine the quality of healthcare: managerial (economic efficiency), professional (clinical effectiveness), and patient.Patients' perspectives on healthcare services have become widely recognized as a central theme in healthcare policy in general and healthcare reform in particular [4]. As a result, quality is a multifaceted concept, and patients' perspectives are an important issue in this conversation[5].

Intellectual disability is defined as a handicap that occurs before the age of 18 and is characterized by significant limits in both adaptive behavior and intellectualism as evidenced by practical adaptive, conceptualization and social skills.Health policy formulation considers a variety of issues, including health care access, human behaviors, environmental conditions, societal situations, and hereditary characteristics, in order to investigate and give answers for individuals suffering from intellectual disability[6]. Various research, based on recent technical literature have been reported on people with intellectual disability who have diverse experiences such as a high likelihood of bad and harsh situations, and some even have concerns such as a lack of excellent health care services and health promotion issues[7].

According to the published literature, most of the studies conducted regarding people with intellectual disabilities employ the use of basic statistical approaches used in developing administrative skills. However, there is no single study so far that utilizes the implementation of artificial intelligence (AI) based models for the development of such skills.

Therefore, this study involve the implementation of a novel AI-based technique using the adaptive neuro-fuzzy inference system (ANFIS) with a traditional regression model multi-linear regression (MLR) for the prediction of success in using administrative skills in improving the quality of life for people with intellectual disabilities with factors such as their experiences in health care and government policies.

II. MATERIALS AND METHODS

A. Quantitative method

The employed method used for the purpose of this article is the quantitative method, that involves the data curation involving numerical values obtained from our study. The study composed of 209 instances generated based on our study using the questionnaire according to responses from administrative health workers of two hospitals from Derna and al-qubba in Libya.

B. Proposed methodology

Regarding the modelling of success in using administrative skills in increasing health status related with people with intellectual disabilities (SAH) by administrative health status of two cities; Derna and al-qubba in Libya. Five different input variables based on the experience of the health workers on health care and government policies, which consists of; Physical working conditions (PWC), Opportunities to use your abilities (OUA), Your remuneration money for job (YRM), Rate by which government agency visits your work site to follow up and inspect for safety on people with intellectual disabilities (RGV) and Rate by which the government support safety management of people with intellectual disabilities (RGS). The data was curated based on responses from the administrative health workers using the questionnaire. The ANFIS and MLR models were further developed based on the following studies [8], [9], [10], [11], [12] and [13]. Hence, the results were divided into calibration and verification phases.

C. Adaptive neuro-fuzzy inference system (ANFIS)

As a result of its resilience in imitating with a high complex link between the input and output models of data collections, ANNs tools are one of the widely used AI-based models that are motivated by replicating the brain of a human being.ANFIS has shown to be an effective technology that includes the fuzzy Sugeno model's approach, which combines through both fuzzy logic and ANN in one platform. ANFIS has recently been applied in complicated dataset prediction and modeling [14]. Because of its ability to estimate real functions, ANFIS is a genuine estimator [15]. In reality, membership functions such asGaussian, sigmoidandtrapezoidal are employed. Despite the fact that the Gaussian function is the most common MF. Figure 1 shows the architecture of ANFIS model.

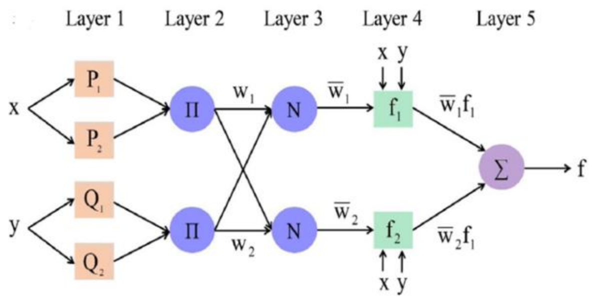


Fig. 1: The architecture of the ANFIS model

D. Multi-linear regression (MLR)

MLR is the most frequent linear method used by modelers to predict several variables in various fields of study such as science, engineering, health science, and social sciences [16]. It aids in the comprehension of the predictor's linear relationship with the input variables [17]. By holding the independent variables constant and modifying one, it investigates the interaction between the variables and describes the relationship between them. Usman et al., (2020a)[18] found that the n regressor variables and the dependent variable y could be correlated:

$$y = b_0 + b_1x_1 + b_2x_2 + b_3x_3 + \cdots + b_ix_i + \xi \qquad (1)$$

Whereby, x_i is defined as the values of the i^{th} predictor, while b_i represents the coefficient for the i^{th} predictor, b_0 is the constant of regression and ξ is the error term.

E. Performance evaluation metrics and Model validation

The basic objective of data-driven models is to gain an accurate fit of models based on available data in order to obtain a dependable prediction of an unknown new dataset [19]. Due to overfitting issues, there is discrepancy between training and testing performances[20]. The validation process employs a variety of validation techniques, including cross-validation (k-fold cross-validation), leave one out, and holdout. Among the various methods of k-fold cross-validation, the holdout approach is considered to be the most straightforward. The data is randomly divided into two phases in this method: training and testing. The primary advantage of the k fold cross validation testing method is that each cycle of testing is independent of the validation and training sets [21]. This results in a performance objective, which serves as a solid foundation for model optimization. As previously stated, the acquired data is divided into two samples: 75% for calibration and 25% for verification, taking into account the 4-fold cross-validation. Despite this, additional pertinent ways for validating and segmenting the data can be applied [22], [23], [24], [25], [26] and [27].

$$R^2 = 1 - \frac{\sum_{j=1}^{N}\left[(Y)_{obs,j} - (Y)_{com,j}\right]^2}{\sum_{j=1}^{N}\left[(Y)_{obs,j} - \overline{(Y)}_{obs,j}\right]^2} \qquad (2)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(Y_{obsi} - Y_{comi})^2}{N}} \qquad (3)$$

ISSN No:-2456-2165

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}(Y_{obsi} - Y_{comi})^2 \tag{4}$$

$$R = \frac{\sum_{i=1}^{N}(Y_{obs}-\bar{Y}_{obs})(Y_{com}-\bar{Y}_{com})}{\sqrt{\sum_{i=1}^{N}(Y_{obs}-\bar{Y}_{obs})^2 \sum_{i=1}^{N}(Y_{com}-\bar{Y}_{com})^2}} \tag{5}$$

Where N, Y_{obsi}, $\bar{Y}$ and$Y_{comi}$are data number, observed data, average value of the observed data and computed values, respectively.

III. APPLICATION OF RESULTS AND DISCUSSION

Simulation approaches such as ANFIS and MLR can be generally used in modelling various health care administrative qualities such as the success of developing new skills in improving the health conditions of different patients. These variables can be predicted using different independent variables based on their demographic result, their working experience as health care administrators and different government policies. This study involve the use of five different independent variables namely; Physical working conditions (PWC), Opportunities to use your abilities (OUA), Your remuneration money for job (YRM), Rate by which government agency visits your work site to follow up and inspect for safety on people with intellectual disabilities (RGV) and Rate by which the government support safety management of people with intellectual disabilities (RGS) as shown in the previous section. The dependent variable was selected to be, success in using administrative skills in increasing health status related with people with intellectual disabilities (SAH), so as to evaluate and predict the performance of each of the health care administrative workers involve in the study.

Before dwelling into the modelling process two different preliminary analysis were conducted namely correlation and descriptive statistics analysis in order to have an idea on the nature and the chemistry of the data.

	PWC	*OUA*	*YRM*	*RGV*	*RGS*	*SAH*
Mean	6.39	2.49	6.23	6.17	5.84	6.57
Median	6.00	3.00	6.00	6.00	6.00	7.00
Mode	6.00	3.00	6.00	6.00	7.00	7.00
Standard Deviation	1.35	1.05	1.36	1.35	1.66	1.29
Sample Variance	1.81	1.10	1.85	1.83	2.75	1.66
Kurtosis	0.11	-0.14	0.31	0.74	-0.10	0.36
Skewness	-0.36	-0.89	-0.32	-0.57	-0.55	-0.33
Minimum	2.00	0.00	2.00	2.00	1.00	2.00
Maximum	9.00	4.00	10.00	9.00	10.00	10.00
Confidence Level(95.0%)	0.18	0.14	0.19	0.18	0.23	0.18

Table 1: Descriptive statistics of the study

Table 1 demonstrates the descriptive statistics of both the dependent and independent variables used in the study for the prediction of the success of administrators in developing skills that can help and assist the life of people with intellectual disabilities, which is denoted as SAH. Ten factors including, mean, median, mode, standard deviation, sample variance, kurtosis, skewness, minimum, maximum and confidence limit at 95% were used in evaluating and checking the statistics of the data.

	PWC	OUA	YRM	RGV	RGS	SAH
PWC	1.00					
OUA	0.19	1.00	0.13			
YRM	0.51	0.14	1.00			
RGV	0.55	0.14	0.48	1.00		
RGS	0.14	-0.12	0.10	0.15	1.00	
SAH	0.56	0.25	0.57	0.47	0.13	1.00

Table 2: Correlation analysis of the variables

Table 2 depicts the correlation analysis of the data explored in this current study. Based on the correlation analysis result it can be observed that there is strong correlation between the dependent variable (SAH) and the independent variables, especially RGV, YRM and PWC. This indicates that as far the response giving by the respondents in this study the physical working condition, the money they receive as salary or incentive and government policies plays a Signiant role in developing skills that can improve the health status of people with intellectual disabilities.

	R^2	RMSE	MSE	R
		Calibration		
ANFIS	0.991	0.080	0.006	0.990
MLR	0.741	0.437	0.191	0.861
		Verification		
ANFIS	0.961	0.240	0.058	0.980
MLR	0.694	0.673	0.453	0.833

Table 3: Performance of both the MLR and ANFIS models based different evaluation indices

Table 3 depicts the comparative performance of the two models, ANFIS and MLR in both the calibration and

ISSN No:-2456-2165

verification phases respectively using four different evaluation metrics namely; R^2, RMSE, MSE and R. According to the performances of the models, it can be observed that ANFIS outperformed the MLR model in both the calibration and verification phases. Moreover, based on the determination co-efficient values it can be observed that ANFIS increased the performance skills of MLR up to 25 and 27% in both the calibration and verification stages accordingly.

More also, to compare the performance of the two models graphical approaches can be used in indicating the results so as to support the quantitative result demonstrated in Table 3.

Figure 2 demonstrates the response plot, which showed the variation, trend and performance of the predicted values of each model in response to the observed values.

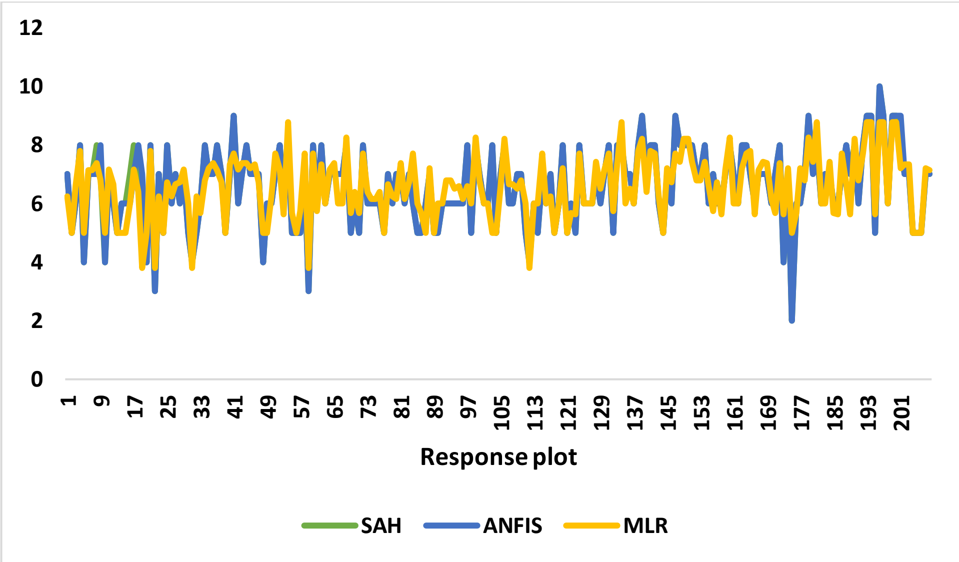
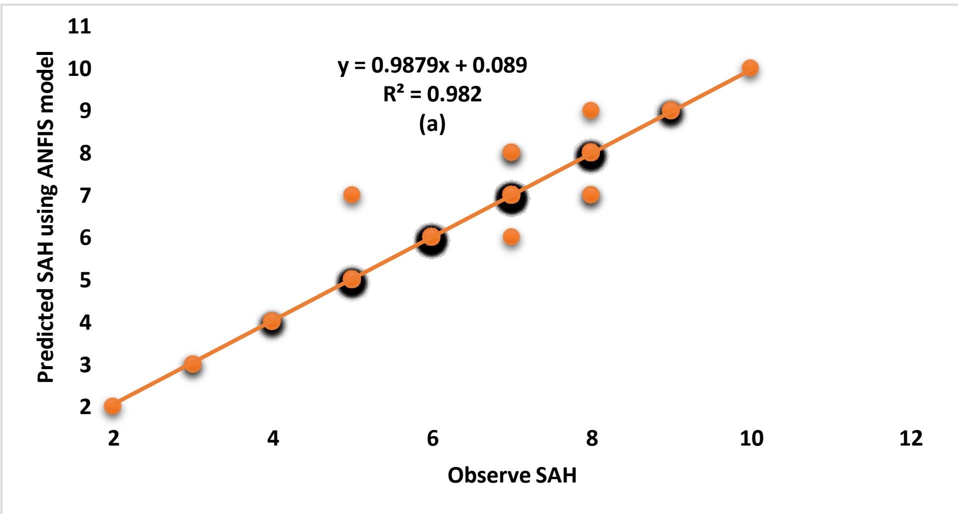


Fig. 2: Response plot indicating the performance of the ANFIS and MLR models towards the dependent variable SAH



Furthermore, the scatter plot shown in Figure 3 below depicts the relationship between the predicted and observed values of SAH.

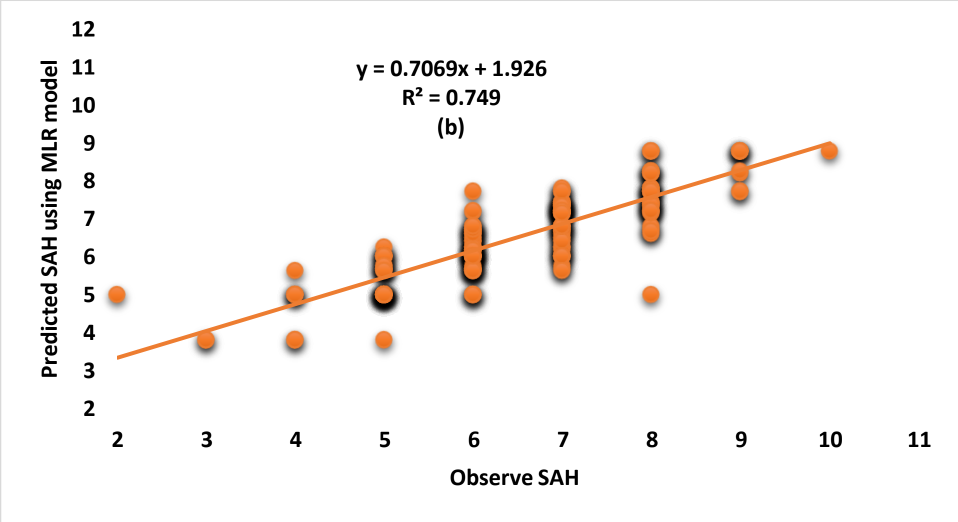


Fig. 3: Relationship between the observed SAH values and (a) ANFIS predicted values and (b) MLR predicted values

To compare the correlation co-efficient values of the models in both the calibration and verification phases, Figure 4 presents the radar plot. More references can be found in [28], [29], [30], [31], [32], [33], [34] and [35]regarding the radar plot.

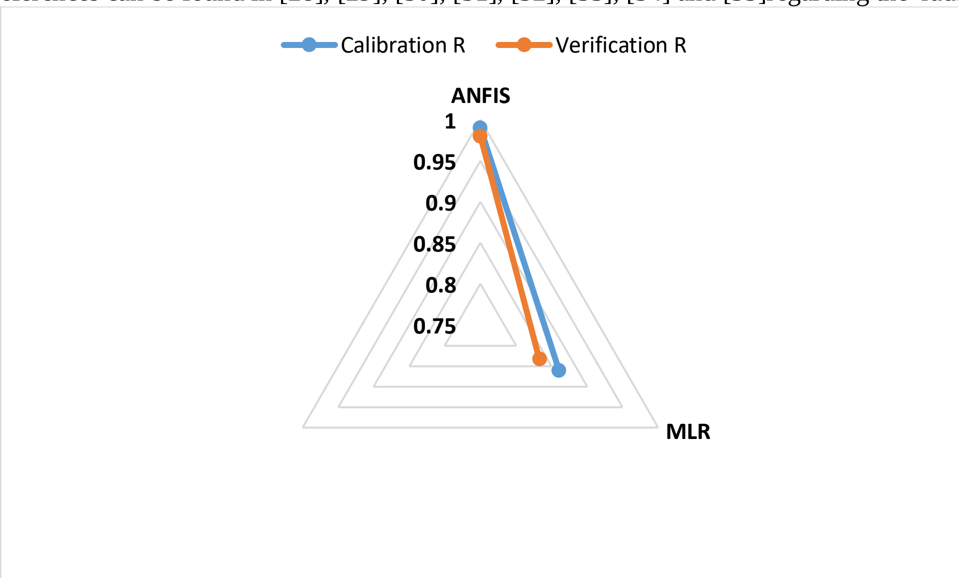


Fig. 4: Radar plot of the models

The error depicted by each model can be presented based on their MSE-values as shown in Table 3. Therefore, the MSE-values of the MLR and ANFIS models are shown in Figure 5 using a bar chart.

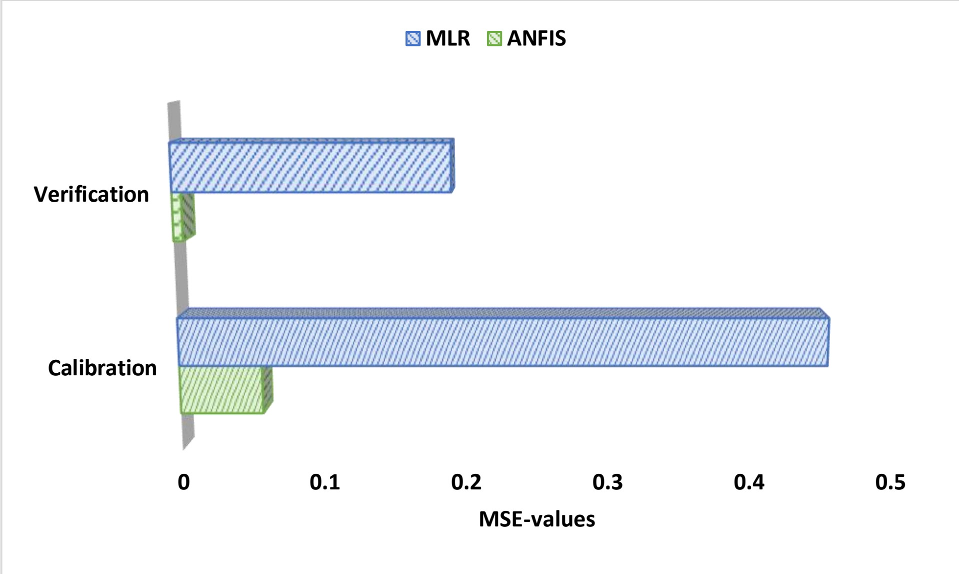


Fig. 5: Performance of the MSE-values of the MLR and ANFIS models

Concerning the error performance of different models, it's not necessary that only MSE values can be graphically compared but other error evaluation metrics such as RMSE, MAE and MAPE can also be demonstrated as reported in[36], [37], [38], [39], [40], [41], [42] and [43].

IV. CONCLUSION

The evaluation of success of developing administrative skills that can be used in improving the quality of life of people with intellectual disabilities is of paramount importance, owing to the role of administrative health workers in the health care system.

The current work explored the application of ANFIS as an AI-based approach and MLR model in order to predict SAH using five different input variables. The result indicates the ability of ANFIS over the MLR model, based on both the graphical and quantitative performance using four various evaluation metrics.

REFERENCES

[1.] L. G. Kalb, J. Beasley, A. Klein, J. Hinton, and L. Charlot, "Psychiatric hospitalisation among individuals with intellectual disability referred to the START crisis intervention and prevention program," *J. Intellect. Disabil. Res.*, vol. 60, no. 12, pp. 1153–1164, 2016.

[2.] O. Doody and M. E. Bailey, "Interventions in pain management for persons with an intellectual disability," *J. Intellect. Disabil.*, vol. 23, no. 1, pp. 132–144, 2019.

[3.] T. Buchner *et al.*, "Same Progress for All ? Inclusive Education , the United Nations Convention on the Rights of Persons With Disabilities and Students With Intellectual Disability in European Countries," 2020.

[4.] G. Kritsotakis *et al.*, "Attitudes towards people with physical or intellectual disabilities among nursing, social work and medical students," *J. Clin. Nurs.*, vol. 26, no. 23–24, pp. 4951–4963, 2017.

[5.] S. Arora, S. Goodall, R. Viney, and S. Einfeld, "Societal cost of childhood intellectual disability in Australia," *J. Intellect. Disabil. Res.*, vol. 64, no. 7, pp. 524–537, 2020.

[6.] J. L. Roberts *et al.*, "Soles of the Feet Meditation Intervention for People with Intellectual Disability and Problems with Anger and Aggression—a Feasibility Study," *Mindfulness (N. Y).*, vol. 11, no. 10, pp. 2371–2385, 2020.

[7.] J. Trollor *et al.*, "Positive cardiometabolic health for adults with intellectual disability: An early intervention framework," *Aust. J. Prim. Health*, vol. 22, no. 4, pp. 288–293, 2016.

[8.] U. M. Ghali *et al.*, "Advanced chromatographic technique for performance simulation of anti-Alzheimer agent: an ensemble machine learning approach," *SN Appl. Sci.*, vol. 2, no. 11, 2020.

[9.] A. G. Usman, S. Isik, S. I. Abba, and F. Mericli, "Artificial intelligence based models for the qualitative and quantitative prediction of a phytochemical compound using HPLC method," *Turkish J. Chem.*, vol. 44, no. 5, 2021.

[10.] A. G. Usman, M. H. Ahmad, R. N. Danraka, and S. I. Abba, "The effect of ethanolic leaves extract of Hymenodictyon floribundun on inflammatory biomarkers: a data-driven approach," *Bull. Natl. Res. Cent.*, vol. 45, no. 1, 2021.

[11.] S. I. Abba *et al.*, "Emerging evolutionary algorithm integrated with kernel principal component analysis for modeling the performance of a water treatment plant," *J. Water Process Eng.*, vol. 33, 2020.

[12.] A. G. Usman, S. Işik, and S. I. Abba, "Hybrid data-intelligence algorithms for the simulation of thymoquinone in HPLC method development," *J. Iran. Chem. Soc.*, vol. 18, no. 7, pp. 1537–1549, 2021.

[13.] K. Mahmoud *et al.*, "Prediction of the effects of environmental factors towards COVID-19 outbreak using AI-based models," *IAES Int. J. Artif. Intell.*, vol. 10, no. 1, pp. 35–42, 2021.

[14.] A. G. Usman, S. Işik, and S. I. Abba, "A Novel Multi-model Data-Driven Ensemble Technique for the Prediction of Retention Factor in HPLC Method Development."

[15.] U. M. Ghali *et al.*, "Applications of Artificial Intelligence-Based Models and Multi- Linear Regression for the Prediction of Thyroid Stimulating Hormone Level in the Human Body," vol. 29, no. 4, pp. 3690–3699, 2020.

[16.] M. H. Ahmad, A. G. Usman, and S. I. Abba, "Comparative performance of extreme learning machine and Hammerstein–Weiner models for modelling the intestinal hyper-motility and secretory inhibitory effects of methanolic leaf extract of Combretumhypopilinum Diels (Combretaceae)," *Silico Pharmacol.*, vol. 9, no. 1, 2021.

[17.] W. Asnake Metekia, A. Garba Usman, B. Hatice Ulusoy, S. Isah Abba, and K. Chirkena Bali, "Artificial intelligence-based approaches for modeling the effects of spirulina growth mediums on total phenolic compounds," *Saudi J. Biol. Sci.*, no. xxxx, 2021.

[18.] A. G. Usman, S. Işik, S. I. Abba, and F. Meriçli, "Chemometrics-based models hyphenated with ensemble machine learning for retention time simulation of isoquercitrin in Coriander sativum L. using high-performance liquid chromatography," *J. Sep. Sci.*, vol. 44, no. 4, pp. 843–849, 2021.

[19.] G. M. Khalid and A. G. Usman, "Application of data-intelligence algorithms for modeling the compaction performance of new pharmaceutical excipients," 2021.

[20.] S. I. Abba *et al.*, "Emerging evolutionary algorithm integrated with kernel principal component analysis for modeling the performance of a water treatment plant," *J. Water Process Eng.*, vol. 33, no. December 2019, p. 101081, 2020.

[21.] Q. B. Pham *et al.*, "Potential of Hybrid Data-Intelligence Algorithms for Multi-Station Modelling of Rainfall," *Water Resour. Manag.*, vol. 33, no. 15, 2019.

[22.] A. G. Usman, S. Işik, and S. I. Abba, "Hybrid data-intelligence algorithms for the simulation of thymoquinone in HPLC method development," *J. Iran. Chem. Soc.*, no. 0123456789, 2021.

[23.] A. G. U. Selin and I. S. I. Abba, "A Novel Multi - model Data - Driven Ensemble Technique for the Prediction of Retention Factor in HPLC Method Development," *Chromatographia*, no. 0123456789, 2020.

[24.] S. I. Malami *et al.*, "Implementation of soft-computing models for prediction of flexural strength of pervious concrete hybridized with rice husk ash and calcium carbide waste," *Model. Earth Syst. Environ.*, 2021.

[25.] A. G. USMAN, S. IŞIK, S. I. ABBA, and F. MERİÇLİ, "Artificial intelligence–based models for the qualitative and quantitative prediction of a phytochemical compound using HPLC method," *Turkish J. Chem.*, vol. 44, no. 5, pp. 1339–1351, 2020.

[26.] S. I. Haruna *et al.*, "Compressive Strength of Self-Compacting Concrete Modified with Rice Husk Ash and Calcium Carbide Waste Modeling: A Feasibility of Emerging Emotional Intelligent Model (EANN) Versus Traditional FFNN," *Arab. J. Sci. Eng.*, vol. 46, no. 11, pp. 11207–11222, 2021.

[27.] H. U. Abdullahi, A. G. Usman, S. I. Abba, and H. U. Abdullahi, "Modelling the Absorbance of a Bioactive Compound in HPLC Method using Artificial Neural Network and Multilinear Regression Methods," *Dutse J. Pure Appl. Sci.*, vol. 6, no. 2, 2020.

[28.] S. I. Abba and A. G. Usman, "Modeling of Water Treatment Plant Performance using Artificial Neural Network: Case Study Tamburawa Kano-Nigeria," no. September, 2020.

[29.] S. I. Abba *et al.*, "Comparative implementation between neuro-emotional genetic algorithm and novel ensemble computing techniques for modelling dissolved oxygen concentration," *Hydrol. Sci. J.*, vol. 66, no. 10, pp. 1584–1596, 2021.

[30.] A. G. Usman, M. H. Ahmad, N. Danraka, and S. I. Abba, "The effect of ethanolic leaves extract of Hymenodictyon floribundun on inflammatory biomarkers : a data - driven approach," *Bull. Natl. Res. Cent.*, 2021.

[31.] S. I. Abba, A. G. Usman, and S. Işik, "Simulation for response surface in the HPLC optimization method development using artificial intelligence models: A data-driven approach," *Chemom. Intell. Lab. Syst.*, p. 104007, 2020.

[32.] U. M. Ghali, M. Alhosen, A. Degm, A. N. Alsharksi, Q. Hoti, and A. G. Usman, "Development Of Computational Intelligence Algorithms For Modelling The Performance Of Humanin And Its Derivatives In HPLC Optimization Method Development," vol. 9, no. 08, pp. 110–117, 2020.

[33.] H. U. Abdullahi, A. G. Usman, and S. I. Abba, "Modelling the Absorbance of a Bioactive Compound in HPLC Method using Artificial Neural Network and Multilinear Regression Methods," vol. 6, no. 2, pp. 362–371, 2020.

[34.] S. I. Abba et al., "Modeling of Water Treatment Plant Performance using Artificial Neural Network: Case Study Tamburawa Kano-Nigeria," *Dutse J. Pure Appl. Sci.*, vol. 6, no. 3, pp. 135–144, 2020.

[35.] S. I. Abba *et al.*, "Effluents quality prediction by using nonlinear dynamic block-oriented models: A system identification approach," *Desalin. Water Treat.*, vol. 218, no. April, pp. 52–62, 2021.

[36.] F. Khademi, S. M. Jamal, N. Deshpande, and S. Londhe, "Predicting strength of recycled aggregate concrete using Artificial Neural Network, Adaptive Neuro-Fuzzy Inference System and Multiple Linear Regression," *Int. J. Sustain. Built Environ.*, vol. 5, no. 2, pp. 355–369, 2016.

[37.] S. I. Abba, L. Aliyu, and S. I, "Treatability Study of Color Reduction from Textile Waste Water Effluent Sample by Coagulation- flocculation Method using different Coagulants and Dosing Compositions," *J. Civ. Eng. Environ. Technol. Print ISSN*, vol. 2, no. 12, pp. 2349–8404, 2015.

[38.] S. I. Abba, R. A. Abdulkadir, M. S. Gaya, M. A. Saleh, P. Esmaili, and M. B. Jibril, "Neuro-fuzzy ensemble techniques for the prediction of turbidity in water treatment plant," *2019 2nd Int. Conf. IEEE Niger.*

Comput. Chapter, Niger. 2019, no. October, pp. 1–6, 2019.

[39.] S. I. Abba, G. Elkiran, and V. Nourani, “Improving novel extreme learning machine using pca algorithms for multi-parametric modeling of the municipal wastewater treatment plant,” *Desalin. Water Treat.*, vol. 215, no. March, pp. 414–426, 2021.

[40.] S. I. Abba, V. Nourani, and G. Elkiran, “Multi-parametric modeling of water treatment plant using AI-based non-linear ensemble,” *J. Water Supply Res. Technol. - AQUA*, vol. 68, no. 7, pp. 547–561, 2019.

[41.] S. Abba and J. Lee, “Microprocessors and Microsystems A parametric-based performance evaluation and design trade-offs for interconnect architectures using FPGAs for networks-on-chip,” *Microprocess. Microsyst.*, no. May, 2014.

[42.] R. Costache *et al.*, “Flash-flood susceptibility assessment using multi-criteria decision making and machine learning supported by remote sensing and GIS techniques,” *Remote Sens.*, vol. 12, no. 1, 2020.

[43.] S. I. Abba, S. J. Hadi, and J. Abdullahi, “River water modelling prediction using multi-linear regression, artificial neural network, and adaptive neuro-fuzzy inference system techniques,” *Procedia Comput. Sci.*, vol. 120, pp. 75–82, 2017.