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Application of Artificial Neural Network Tools for the Prediction of Water Quality Index of Hand Dug Well Water in Gboko Local Government Area of Benue State

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Abstract

This research assessed the ability of artificial neural network tools to accurately predict water quality index. Water from hand dug wells within Gboko Local Government area of Benue state were sampled using standard procedures of the American Public Health Association (APHA, 2017). Twelve water quality indices, namely; pH, TDS, EC, Alkalinity, TH, BOD, Mg, Cl^-, NO_3, Fe and Zn were evaluated and their concentrations used to determine the Water quality index (WQI) of hand dug well water in Gboko Local Government Area, making use of the weighted arithmetic water quality index (WAWQI) method. The FeedForward Neural Network (FNN) Tool was designed using the MATLAB APP. The FNN tool was designed with twelve input parameters, 10 hidden neurons, and one output parameter (WQI). The performance validation of the ANN tool was achieved at the 8^{th} run with a regression value greater than 0.8 and a mean square error of 0.6981.The FNN tool showed high accuracy in predicting the WQI. The accuracy of the results revealed that ANN tool can effectively be deployed in accurately predicting the WQI of a large dataset within a short time. Based on the findings, the study recommended the adaption of FNN tool for quicker and accurate determination of WQI.

Key Words: Artificial Neural network tool, feedforward neural network, hand dug wells, MATLAB, Neurons, Water quality index,.

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Introduction

Water is a vital natural resource with social and economic values for human beings [1]. According to [2], in its absence man's existence would be threatened. Safe water is one of humans' most precious resources and is essential for survival [3]. Lack of sustainable access to safe water can be the cause of many health related issues including diarrhea disease and nervous system damage [4]. Globally, at least 2 billion people use a drinking water source that is contaminated with faeces. Microbial contamination of drinking-water as a result of contamination with faeces, poses the greatest risk to drinking-water safety. In addition, water derived from various sources may also contain dissolved inorganic and organic substances which could cause health problems to the community [5]. The level of access to clean water varies over different populations; however, four criteria can determine whether users have or do not have access to this resource: i) a sufficient quantity, ii) an acceptable quality, iii) local availability, and iv) affordable price [6].

Drinking water quality is most often based on animal toxicity data, and more robust epidemiologic studies with an accurate exposure assessment are rare. The current risk assessment paradigm which deals mostly with one-by-one chemicals dismisses potential synergisms or interactions from exposures to mixtures of contaminants, particularly at the low-exposure range. Thus, evidence is needed on exposure and health effects of mixtures of contaminants in drinking water [7].

Sub-Saharan Africa contributes to approximately half the population that lacks access to improved drinking water sources [8]. The population that cannot access improved water and those in unsanitary conditions endure the severest health impacts including death from the scarcity of this resource. Unsafe drinking water can be a threat to human health if its level of contamination is significant enough. However, identifying harmful drinking water can be difficult because of the lack of knowledge of health risks, and a great variance in quality over time and distance. Water quality parameters that are important for public health include presence of microbiological indicators and pathogens, turbidity and suspended solids, and inorganic and organic pollutants. All of these parameters can have associated health risks, however, many have agreed that microbial contamination poses the greatest health risk to humans in developing world settings in regards to drinking water contaminants [9]. Exposure of a consumer to pathogens may be associated with the stomach flu, diarrhea, and vomiting. Turbidity itself is not a health risk; however, turbidity is associated with the concentration of suspended solids (SS) to which harmful microorganisms can be

attached. Turbid and odorous water can also be aesthetically unpleasing resulting in rejection by the user. Heavy metal contamination may cause acute or chronic health issues; this contamination can result from leaching from plumbing materials like galvanized iron and lead pipes, copper pipes, steel pipes, brass fittings and taps [10].

An ANN is a signal processor composed of a multiplicity of nodes which receive one or more input signals and generate one or more output signals in a nonlinear fashion wherein those nodes are connected with one or two way signaling channels. Artificial neural networks (ANNs) are powerful tools in machine learning that are designed after the structure of the human brain. You can make use ANNs in various industries, including finance, engineering, and health care, to make predictions and gain insights based on inputted data. Warren McCulloch and Walker Pitts designed the first artificial neural circuit in 1943, but it wasn't until the 1980s that ANNs started to gain popularity in mainstream data operations. ANNs have since then exploded in popularity, becoming a popular tool across several industries. [11], averred that, recently, AI techniques have gained recognition as effective tools for modeling complex nonlinear phenomena in water systems and hydrology. Researchers have increasingly utilized ANN to model various engineering problems in several areas including material characterization, prediction of material properties like concrete. The application of ANN in water resource variables applications is also promising [12].

According to Yaseen [13] and Othman [14], ANNs are information driven modeling techniques with a flexible statistical structure capable of capturing complex and nonlinear relationships between input and output datasets without prior knowledge of the underlying phenomena. These networks typically consist of three or more layers: an input layer, hidden layers, and an output layer. The input layer solely transmits input information to the neurons of the primary hidden layer.

Wang *et al*. [15] reported that in a study on the prediction of WQI for surface water bodies in China, the authors utilized a Feed-forward Neural Network (FNN) to predict WQI based on parameters such as dissolved oxygen (DO), pH, temperature, and chemical oxygen demand (COD). The model showed high accuracy and was able to predict water quality in real-time, offering a better alternative to traditional empirical methods.

ANNs were used to predict WQI in rivers in the United States. The researchers employed a multi-layer perceptron (MLP) network, which was trained on water quality data from monitoring stations. The ANN model outperformed statistical methods, with the authors highlighting the ANN's ability to

handle large datasets and nonlinear relationships [16]

Mishra [17], have reported a study conducted in India using an ANN model to predict water quality in urban areas. The research focused on the use of input parameters such as turbidity, nitrate concentration, and pH, employing an RBF neural network. The results showed that the ANN could predict WQI with high precision, and the model was particularly valuable in monitoring water quality in real-time.

LSTM network were used for predicting the WQI of the Zayandeh-Rud River in Iran. The study demonstrated the efficiency of LSTM networks in processing temporal data and predicting future water quality indices based on historical trends, with a notable improvement in prediction accuracy compared to traditional models [18].

Kumar [19] focused on the development of a hybrid model combining ANNs with other machine learning algorithms (e.g., genetic algorithms or support vector machines) to optimize WQI prediction. Their results suggested that hybrid models can improve the accuracy and generalization capability of WQI prediction, making them promising for real-world applications.

Talent [20] reported in a case study of South African Basins that the ANN model demonstrated a comparatively high degree of accuracy, having an overall correlation coefficient (R) and coefficient of determination (R2) measuring 0.985 and 0.970, respectively. Furthermore, the R-values obtained are satisfactory, indicating higher predictive performance and a scientifically stable and well-defined neural network. The research findings suggest that artificial neural networks (ANNs) are robust and practical analytical tools for assessing surface water quality.

The results further exhibit the appropriateness of modelling ANNs as a powerful alternative to conventional and statistical modelling techniques, thereby satisfying the research hypothesis, which states that: “the ANN model should be more robust and scientifically stable, with better predictive performance than traditional WQI models”. Accordingly, the study encourages water resources professionals and scientists to consider neural networks to be an extensive and remarkably effective approach for assessing water quality patterns.

Against this background, artificial neural networks are recommended for routine monitoring of surface water resources. Chauhan [20], concluded in their case studies that ANNs can accurately predict water quality parameters. They discussed the advantages and limitations of using ANNs for water quality prediction. Hopefully, the study will provide meaningful contributions and a

valuable platform for applying artificial neural networks.

Material and Methods

Description of the Study Area

The study area for this research was Gboko Local Government Area of Benue State, Nigeria. It is one of the largest and most populous Local Government Areas in Benue State. It has a land mass of 1,835 km², Density, 196.9 in h./km² with a population of 361, 325 people according to National Population Commission census of (2006). It is bounded by Tarka Local Government on the North, Ushongo Local Government to the South, Buruku Local Government on the East and Gwer on the West. It lies between latitude 7°05′–7°31′N and longitude 9°13′–9°35′E in the savannah region of Nigeria with typical savannah vegetation and climate. The research covered 18 sample points listed below with their geographical location points and shown the map.

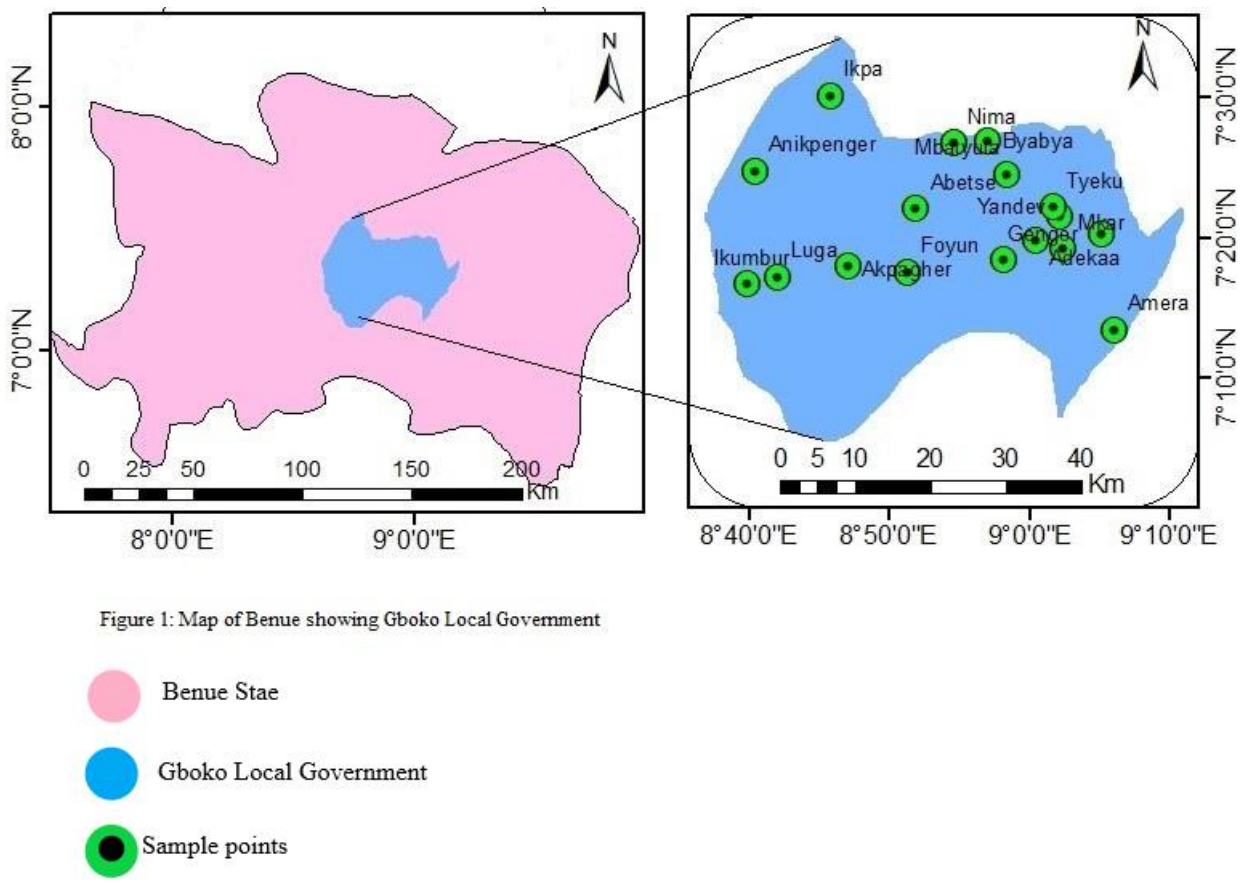


Figure 1: Map of Benue showing Gboko Local Government

The eighteen villages where samples were collected are listed below with their location described by their geographic coordinates using GPRS

S1-Mkar
7.3213°N, 9.0419°E
S2-Ameradu
7.3380°N, 9.0871°E
S3-Amera,
7.3162°N, 8.9017°E
S4-Akpaher
7.2997°N, 8.7853°E
S5-Ikumbur
7.4631°N, 9.3506°E
S6- Foyun
7.1930°N, 9.0180°E
S7-Yandev
7.3602°N, 9.0378°E
S8-Tyeku
7.7346°N, 8.5340°E
S9-Byabya
7.7136°N, 8.6230°E
S10-Abetse
7.3685°N, 8.8662°E
S11-Nima
7.2693°N, 8.9940°E
S12- Mbatyula
7.4782°N, 8.9388°E
S13-Adekaa
7.3307°N, 9.0090°E
S14-Akaajime
6.5930°N, 9.5149°E
S15-Genger
7.3072°N, 8.9703°E
S16-Ikpa
7.5035°N, 8.7633°E
S17-Luga
7.2881°N, 8.7004°E
S18s-Anikpenger.
7.4324°N, 8.5003°E

To evaluate the quality of water in Gboko Local Government Area of Benue State, 108 samples were collected from selected eighteen wells within a period of six months covering two seasons (June to November for rainy season, and December to May for dry season. The well water samples were collected using standard procedures of the American Public Health Association [22]. Locations were marked with the help of global positioning system (GPS). Samples from the study area were labelled as: S1, S2, S3 ……. S18.

Analytical Technique

The physical parameters which shall be analyzed and their levels directly recorded in the field are: Temperature, pH, Dissolved oxygen, Electrical conductivity. The analyses of the parameters followed the guide lines established by [22]. Heavy metals in all the samples collected for this research were analyzed using a Perkin Elmer Atomic

Absorption Spectrophotometer (AAS) Model Optima 8300 series using acetylene, nitrous oxide and compressed air for burning. Duplicate analysis were done on each water sample and the mean values recorded.

Water Quality Index Calculation

The weighted arithmetic water quality index (WAWQI) was used to establish the water quality index of Gboko local government area of Benue State. Twelve water quality indices were used to produce the water quality index, namely: pH, TDS, E.C, DO, ALK. TH, BOD, Mg, Cl-, NO3, Fe and Zn.

WQI has a value between 0 and 100 which indicates the quality of the water. The classification on WAWQI is as follows:

0 – 25 (Excellent), 26- 50 (Good), 51 – 75(poor), 76 – 100 (very poor), < 100 (unsuitable for drinking)

The WQI was calculated using the following equations:

$$WAWQI = \frac{\sum \mathrm{Wiqi}}{\sum \mathrm{Wi}} \qquad 1$$

where:

qi represents a relative value of the water quality, specific to each parameter;

i represents the number of parameters taken into consideration;

Wi is a factor that measures the importance of a parameter in the calculation of the WQI index (relative weight)

$$\mathrm{qi} = 100 \times \frac{\mathrm{Vi}-\mathrm{Vo}}{\mathrm{Si}-\mathrm{Vo}} \qquad 2$$

where:

Vi, represents the value experimentally determined of the i analyzed parameter;

Vo represents the ideal value of that parameter;

Si represents the standard value for the water category in which the analyzed water sample was included.

$$\mathrm{Wi} = \frac{\mathrm{K}}{Si} \qquad 3$$

Training and Selection of an ANN Tool

Figure 2 shows the training of the FNN tool using the MATLAB software and Excel software for data modelling, basic statistical analysis and data visualization (plotting graphs and charts). FNN was adopted for this research. The input for the FNN tool was the twelve water quality parameters used in the computation of WQI and output is the predicted WQI. The FNN tool was designed with twelve input parameters, one hidden neurons of 10, and one output parameter which was the WQI. Figure 3 shows the performance validation of the ANN tool at 8th run.

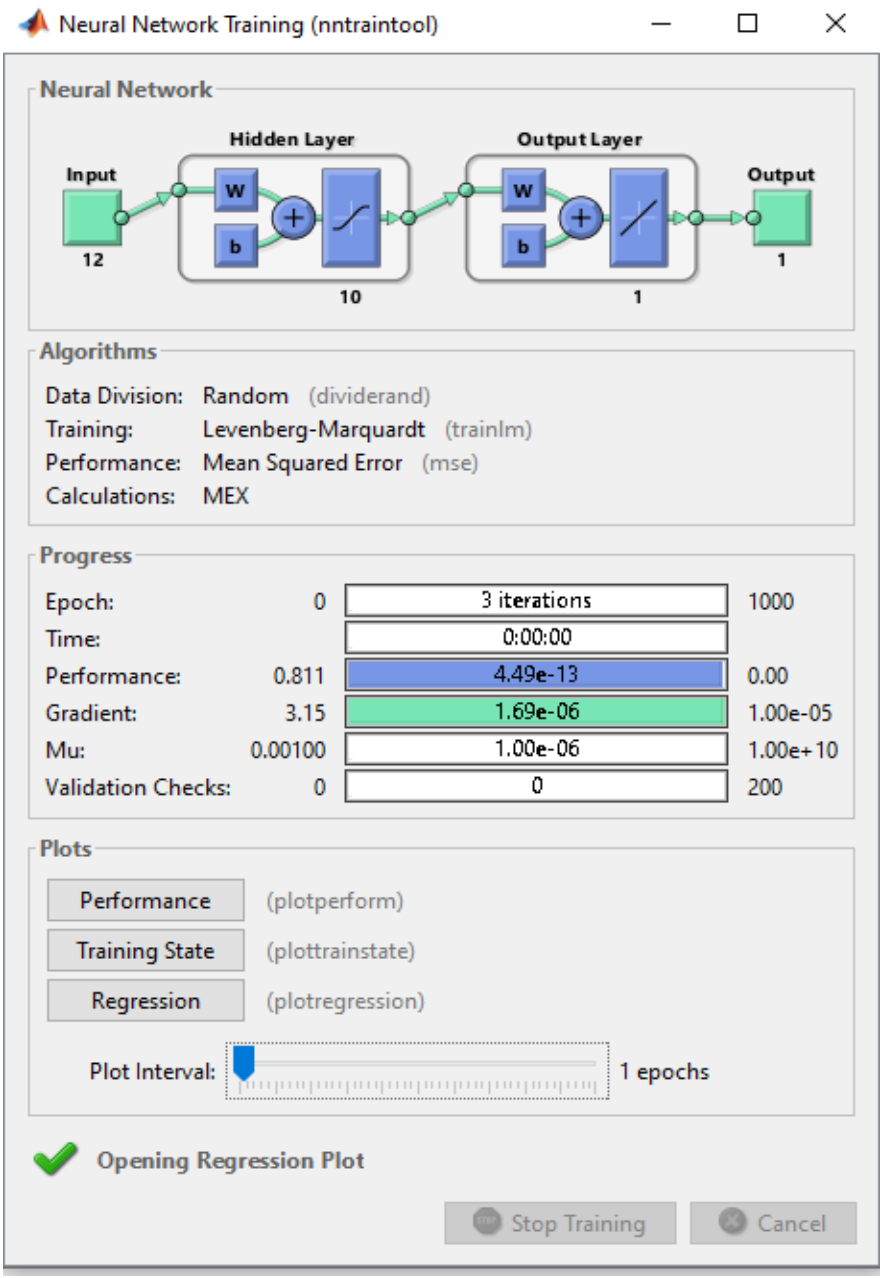


Figure 2: FNN training performance interface (8th run)

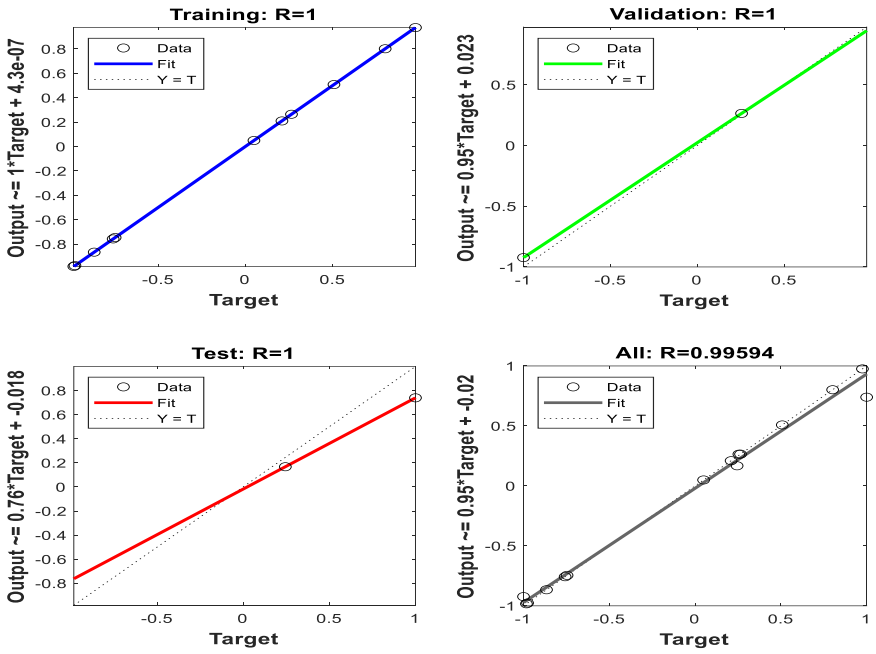


Figure 3: FNN Validation performance interface (8th run)

Source: This research

MSE = 0.6981

RMSE = $\sqrt{MSE} = 0.8355$

R = 0.99594

D = R^2 = 0.99190

Performance of the feed forward Neural Network tool

After the training of the ANN tool the, the input parameters were ran to obtain the predicted water quality index. Table 2 shows the actual WQI and the Predicted WQI:

Results and Discussion

Results of the concentrations of various samples collected are as recorded in table1. All results are average of two values. The table also shows the calculated values of WQI obtained through WAWQI method. All the water quality parameters were expressed in mg/L except pH, and EC (mmhos).

Table 2 shows the result the actual WQI determined using WAWQI and that predicted with use of ANN.

Table 1: Analysis of Physicochemical Parameters and Calculated WQI

SAMPLE CODE	pH	TDS	E.C	DO	ALK	TH	BOD	Mg	Cl	NO3	Fe	Zn	WQI
S1	6.73	131.9	219.60	5.38	73.19	91.19	0.73	57.5	74.9	2.55	0.11	0.3	38.54
S2	6.93	123.8	206.00	5.03	125.5	100.9	0.99	59.5	65.9	1.86	0.10	0.63	37.26
S3	6.79	130.3	2.58.00	5.32	130.8	93.48	0.83	58.5	87.6	2.39	0.10	0.13	36.04
S4	6.83	130.9	217.20	5.09	142.4	93.48	0.74	52.5	80.6	1.98	0.11	0.32	38.43
S5	6.91	164.3	273.83	5.26	128.5	74.38	0.85	46.5	112.5	1.83	0.10	0.12	35.87
S6	6.93	163.8	273.00	5.38	127.3	81.38	0.63	53.5	95.3	2.05	0.10	0.16	36.12
S7	7.49	261.4	435.00	3.90	68.3	505.8	1.20	71.0	66.0	2.78	0.15	0.27	49.31
S8	7.40	573.0	955.00	4.80	124.0	246.0	1.00	53.0	74.0	2.64	0.14	0.32	47.13
S9	7.54	483.0	805.00	4.10	227.8	191.2	1.20	48.5	100.6	2.76	0.14	0.26	46.27
S10	7.33	561.0	935.00	4.20	140.8	304.8	0.90	65.5	69.0	3.73	0.14	0.69	48.82
S11	7.33	633.0	973.80	3.8	116.0	233.8	1.20	44.0	122.0	2.97	0.15	0.26	49.21
S12	7.39	573.0	955.00	4.5	130.0	249.8	1.00	53.0	68.5	2.66	0.15	0.26	49.31
S13	7.74	261.1	430.00	3.84	63.8	29.4	1.34	71.8	103.5	4.78	0.18	0.12	56.82
S14	7.63	290.6	447.10	4.14	124	23.4	1.00	66.0	112.8	4.63	0.17	0.10	54.99
S15	7.83	246.8	379.70	3.94	132.2	23.8	0.83	78	105.9	4.81	0.18	0.10	57.10
S16	7.78	243.8	375.10	4.58	134.8	33.6	0.88	61.5	98.5	5.01	0.18	0.08	57.63
S17	7.03	236.3	363.54	3.86	112.0	28.0	1.20	43.5	133.5	3.63	0.18	0.10	57.13

Table 2: Actual and ANN Predicted WQIs

Samples	Actual WQI	FNN Predicted WQI (8th run)
1	38.54	38.5611
2	37.26	37.25752
3	36.06	35.98977
4	38.43	38.43793
5	35.87	36.63504
6	36.05	36.0566
7	49.31	49.55413
8	47.13	47.21388
9	51.78	52.20232
10	48.84	48.95881
11	48.99	48.49691

12	49.21	49.54889
13	56.93	57.28314
14	54.99	55.0945
15	56.99	56.71795
16	57.55	57.54467
17	57.06	56.94749

The study proposed the feedforward neural network tool (FNN) for use in predicting the WQI. In the FNN tool used, the input layer had twelve neurons corresponding to different water quality variables, namely pH, TDS, E.C, D.O, Alk, TH, BOD, Mg, Cl^-, NO^-_3, Fe, and Zn. Secondly, the hidden or "zero" layer, consisting of 10 neurons, (accountable for predictive tasks). Thirdly, the output layer, featuring only one perceptron, is responsible for communicating network outputs using a single-digit WQI score. The first group of neurons (the input layer) in the ANN receives water quality variable readings, while the second cluster of the perceptron (the hidden layer) interprets the hydro-chemistry. Lastly, the third layer (the output neuro-node) formulates a one-digit index rating reflecting the water quality. Various quantitative statistical factors were considered to establish the performance level of the neural networks and distinguish the finest optimal WQI model. These statistics include correlation coefficient (R), coefficient of determination (R2), mean absolute percentage error (MAPE), mean absolute error (MAE), root mean squared error (RMSE), and Nash–Sutcliffe efficiency (NSE) [23].The neural networks (NNs) having the minimal regression error and the leading performance ratio for classification were retained. Figure 2 and below shows the FNN design and the training performance of the neurons. The FNN was ran 8 times before its predictive accurateness was confirmed. Figure 3 shows the validation performance interface indicating the appropriateness of use of this ANN. The results obtained using the FNN neural network was compared with the actual values obtained from WAWQI. The result showed high predictive accuracy of the ANN tool as shown in table 2.

Conclusion

The use of FNN neural network tool designed and used in this research showed high level of accuracy in predicting the water quality index and can be employed for faster and accurate prediction of water quality. The result showed high correlation between the WQI obtained using the WAWQI and use of an ANN. ANNs can therefore be used to accurately predict water quality.

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