International Journal of Engineering and Advanced Technology Studies 11 (1), 19-36, 2023
Print ISSN: 2053-5783(Print)
Online ISSN: 2053-5791(online)
Website: https://www.eajournals.org/
Publication of the European Centre for Research Training and Development -UK

Prediction of Gold associated Mineral worth: An application of mathematically driven artificial neural network technique

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doi: https://doi.org/10.37745/ijeats.13/vol11n11936 Published June 18, 2023

Citation: Gbolagade M.A., Melodi M.M., Amigun J. O., and Alaba O. C. (2023) Prediction of Gold associated Mineral worth: An application of mathematically driven artificial neural network technique, *International Journal of Engineering and Advanced Technology Studies* 11 (1), 19-36

ABSTRACT: *The elemental composition of other associate minerals existing with gold is a significant asset that defines the amount of additional economic contribution that can be obtained from the gold tailings. The elemental composition is a needed factor in increasing the economic value of gold run-off and getting a clear estimation for the quantity of value-added elements in each tonne of gold sand scooped during the separation process. In this study, the artificial neural network (ANN) modeling technique was used to develop an economic worth prediction model for 10 gold-associated minerals. The developed models have a 1:7:10 architecture and were trained using the ANN Bayesian regularization training algorithm. According to the root mean square error values, the results revealed that the predicted values of the associated minerals are closer to the measured values. Also, the developed model prediction performance was found to be appropriate for the estimation of gold-associated mineral economic benefits based on the high coefficient of determination and variance account. The model performance evaluation results show that the developed ANN models are suitable for economic estimation of gold-associated mineral worth.*
KEYWORDS: gold, Nigeria, mining, mineral economics, artificial intelligence, machine learning algorithms

INTRODUCTION

According to Melodi et al., Africa holds around 30% of the world's mineral resources and has the biggest known reserves of strategically vital minerals, including gold [1]. Nigeria has significant quantities of solid minerals, which include, but are not limited to, precious stones, metals, and industrial minerals [2]. Nigeria was a major exporter of tin, columbite, and coal in the early 1970s, given its mineral deposits. However, activity in this sector plummeted as crude oil extraction took front stage and became a key source of foreign exchange for the country. With the return of democracy in 1999, the necessity to diversify the country's financial base became critical. A new national mining emphasis and strategy emerged, and the Nigerian Minerals and Mining Act (the Act) was passed in 2007 to reinvigorate the Nigerian mining industry. Gold, barite, bentonite, limestone, coal, bitumen, iron ore, tantalite/ccolumbite, lead/zinc, barites, gemstones, granite, marble, gypsum, talc, iron ore, lead, lithium, silver, and other minerals are found across the country [3]. However, not all minerals are commercially available, limiting the possibility of investment in the country. The extraction of a mineral such as gold implies the presence of additional gold-associated minerals, which are regarded as useless throughout the processing stage because all emphasis is focused on the gold concentrate. The determination of the quantity or percentage of the mineral existing in the geographical place is explained as mineral evaluation. Because an ore deposit is made up of many elements and minerals, geochemical analysis entails determining the percentage of the desired mineral in a part of the mineral deposit [4]. Gold and silver coins, as well as gold objects dating from the early Bronze Age to antiquity, have been unearthed in European burial sites and hoards [5]. Archaeometallurgists assess the function of these metals in human societies from two perspectives: i) the chain of manufacturing methods from mines to artefacts; and ii) the provenance of ores that supplied the metal needed to create a specific object [6]. Manufacturing, according to Baron et al., is critical to understanding alloying techniques and monetary activity, particularly debasement, while examining the provenance of ores can offer substantial information on ancient sources of wealth and trade routes [8].

Precambrian rocks in and around Nigeria's south-west and northern Schist Belt have gold-bearing quartz veins [9]. The gold reserves were heavily mined during the colonial era, roughly before 1960, and then by artisanal miners after that. There is general descriptive information on gold mineralization in the Maru schist belt [10]. According to Oke et al., Nigerian gold is found mostly in quartz veins and as placers in soil (eluvial) and stream sediments (alluvial). Gold-containing quartz veins are found in combination with metamorphosed rocks ranging in composition from semipelitic to pelitic to mafic [10]. Through weathering processes, primary gold mineralization produced chemical pathfinders in the overburden and adjacent soil. Weathering processes give samples (soils and stream sediments) that yield information on local concealed mineralization or the probable existence of substantial or minor mineralization across a large area [10]. According to Abiola et al., residual soil is a geochemical sample that is frequently used to discover the location of buried mineralization once a zone of economic interest has been identified [11]. Groundwater migration caused a chemical reaction at the surface. This procedure results in an elemental dispersion pattern. The majority of these scattered elements (Cu, Mg, Ag, Zn, Cd, As, Bi, Pb, Sb, Hg, W, Mo, and Se, for example) are good indicators or pathfinders for the presence of gold [12]. The presence of such pathfinder minerals (gold-associated minerals) can provide the gold mining industry with an extra source of financing. When processing gold-bearing sands, these minerals are termed trash or tailings; such additional minerals have some economic value and can be sourced from the market to supplement the economic worth of gold concentrate. The majority of gold resources in Nigeria are placier or alluvial deposits, such as those in Niger State's Kagara region in north-central Nigeria. The mineral title holder corporation investigates alluvial gold deposition along a river channel, dumping the accompanying minerals as garbage. Taiwo et al.

mention that artificial neural networks (ANN) have found continuous application in the development of prediction models in the mining engineering field [12]. According to Shahin et al. [13], ANN modeling techniques are a type of artificial intelligence that attempts to replicate the actions of the human brain and nervous system. [14] Describes such techniques as computer models inspired by biological brain networks that are used to approximate functions that are otherwise unknown. A transfer function, network design, and learning law are the three fundamental components of the technique. The ANN development process is divided into three layers: input, hidden layer(s), and output [15]. These three layers are linked together, and each layer is made up of one or more nodes [16]. Neurons in the input layer send information to the hidden layer, which then sends information to the output layer. ANNs learn from data examples presented to them and use these data to adjust their weights in an attempt to capture the relationship between the historical set of model inputs and corresponding outputs [17]. Artificial neural networks have been the subject of an active field of research that has developed greatly over the past few years. ANN is a computational model based on the structure and functions of biological neural networks; these networks are good at fitting non-linear functions and recognizing patterns [18].

Precambrian rocks in and around Nigeria's south-west and northern Schist Belt have gold-bearing quartz veins [9]. The gold reserves were heavily mined during the colonial era, roughly before 1960, and then by artisanal miners after that. There is general descriptive information on gold mineralization in the Maru schist belt [10]. According to Oke et al., Nigerian gold is found mostly in quartz veins and as placers in soil (eluvial) and stream sediments (alluvial). Gold-containing quartz veins are found in combination with metamorphosed rocks ranging in composition from semipelitic to pelitic to mafic [10]. Through weathering processes, primary gold mineralization produced chemical pathfinders in the overburden and adjacent soil. Weathering processes give samples (soils and stream sediments) that yield information on local concealed mineralization or the probable existence of substantial or minor mineralization across a large area [10]. According to Abiola et al., residual soil is a geochemical sample that is frequently used to discover the location of buried mineralization once a zone of economic interest has been identified [11]. Groundwater migration caused a chemical reaction at the surface. This procedure results in an elemental dispersion pattern. The majority of these scattered elements (Cu, Mg, Ag, Zn, Cd, As, Bi, Pb, Sb, Hg, W, Mo, and Se, for example) are good indicators or pathfinders for the presence of gold [12]. The presence of such pathfinder minerals (gold-associated minerals) can provide the gold mining industry with an extra source of financing. When processing gold-bearing sands, these minerals are termed trash or tailings; such additional minerals have some economic value and can be sourced from the market to supplement the economic worth of gold concentrate. The majority of gold resources in Nigeria are placier or alluvial deposits, such as those in Niger State's Kagara region in north-central Nigeria. The mineral title holder company explores the alluvial deposition of gold along a river channel, discarding the associated minerals as waste material. According to Taiwo et al., artificial neural networks (ANN) have found widespread use in the construction of prediction models in the mining engineering sector [12]. According to Shahin et al. [13], ANN modeling techniques are a type of artificial intelligence that attempts to replicate the actions of the human brain and nervous system. [14] defines such techniques as computational models inspired by biological neural networks that are used to approximate functions that are generally unknown. A transfer function, network design, and learning law are the three fundamental components of the technique. The ANN development process is divided into three layers: input, hidden layer(s), and output [15]. These three layers are linked together, and each layer is made up of one or more nodes [16]. Neurons in the input layer send information to the hidden layer, which then sends information to the output layer. ANNs learn from data examples and alter their weights in an attempt to represent the relationship between the historical collection of model inputs and related outputs [17]. Artificial neural networks have been the focus of an active field of research that has grown significantly in recent years. ANN is a computer model based on the structure and functions of biological neural networks, which are good at fitting non-linear functions and identifying patterns [18].

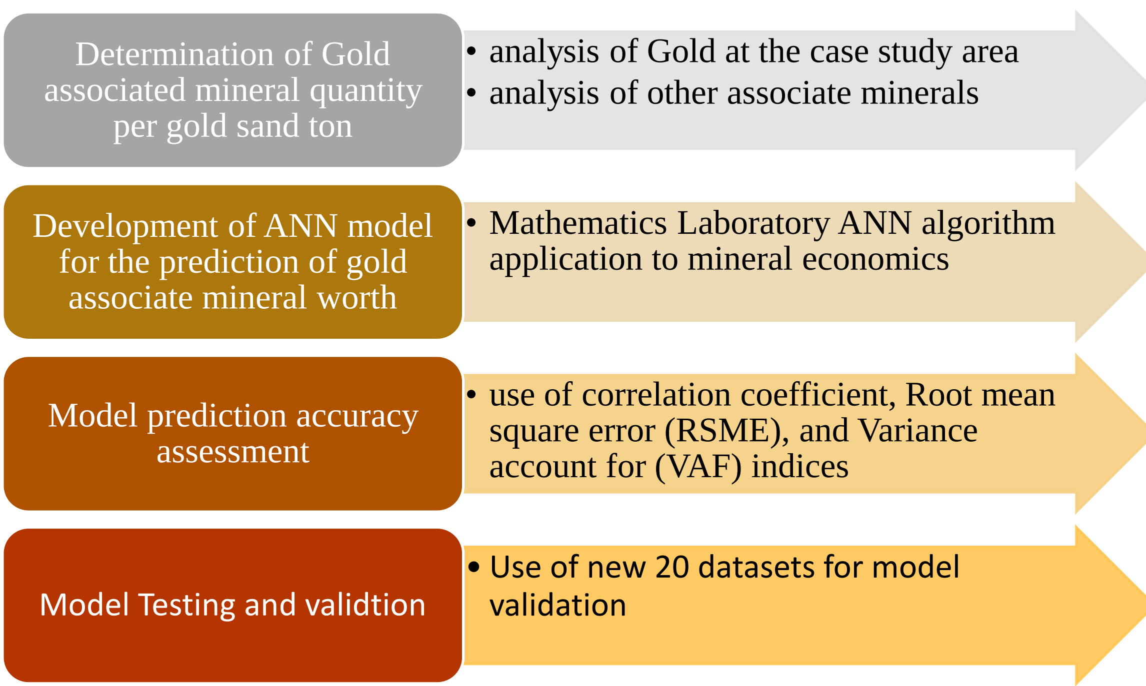

Fig. 1 Study objectives in sequence

MATERIALS AND METHODOLOGY

This section presents the methodology used for sample collection, preparation, and for the chemical composition analysis.

Study area description

The research site is about 13 kilometres north of Kagara and BirniGwari Village in Nigeria. The terrain is mostly undulating, with moderate hills divided by plains with flat soil cover. The

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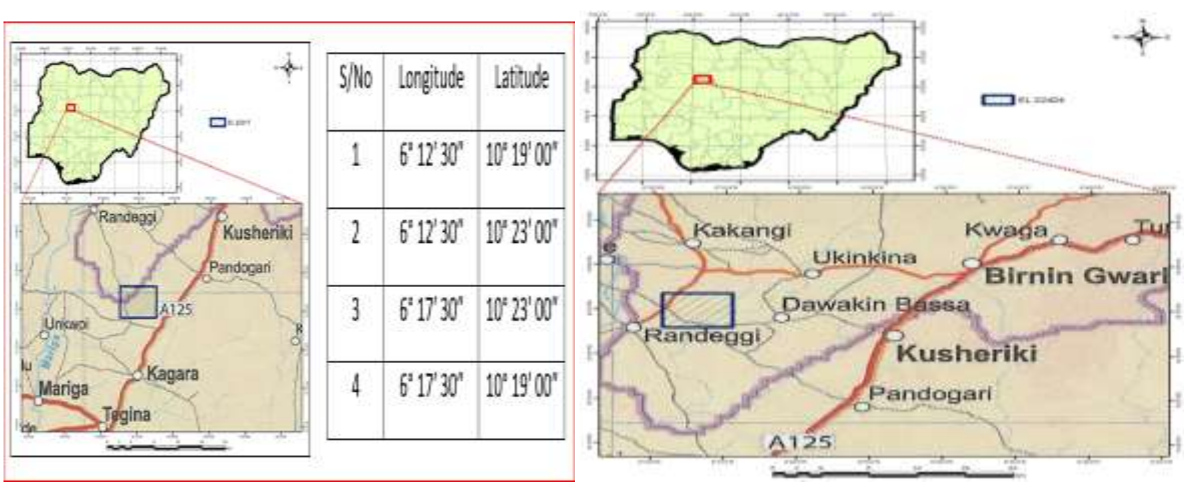
geological area of the case study area is depicted in Fig. 2. Systematic alluvial soil sampling techniques were utilized in this work to collect representative soil parts for geochemical investigation. Each gold-bearing sample's compositional constituents were determined using fire assay (FAA) and multi-element analysis (MEA) procedures developed by Masasire et al. [27] and Harraz et al. [28]. SGS South Africa (PTY) Limited (Randfontein) Laboratory conducted the analysis. X-ray analysis was also employed to generate a diffraction pattern with an appropriate wavelength for sample elemental assessment using the [29] approach. Field samples (soil samples, alluvial deposit samples, and rock samples) were pulverized to 50 m and exposed to an incident beam. A total of 155 questionnaires were issued at random to the workers and management of the various artisanal gold mining sites in BirniGwari and Kagara to collect data on the amount of gold (g/t) mined daily. Cost of blasting pegmatite gold host rock per month, cost of drilling accessories used, cost of explosives used, cost of plant and equipment maintenance, and cost of labour. The information gathered was used to calculate the overall variable cost and the cost of producing one gram of gold. The average selling price of gold concentrate per gram was also gathered.



S/No	Longitude	Latitude
1	6° 12' 30"	10° 19' 00"
2	6° 12' 30"	10° 23' 00"
3	6° 17' 30"	10° 23' 00"
4	6° 17' 30"	10° 19' 00"

a) b)

Fig. 2 Geological Map of the Study Area in a) Kagara and b) BirniGwari

Artificial Neural Network (ANN) for Gold associate Mineral worth prediction

Training ANN networks entails determining the optimal values for the network's various weights and biases [21]. The proposed ANN model in this study was developed using multi-layer perception and the back propagation training approach. Cu, Zn, Pb, Mn, Mg, Ni, Th, U, Li, and Fe were predicted using a single ANN model. This is possible since the elemental compositions have the same size matrix for the targeted outputs. The gold-associated mineral worth models in this work were developed using 111 experimental datasets from the Kagara and BirniGwari studies, as shown in Table 1. The ANN model was created in the MATLAB environment using the integrated neural network toolbox. To increase model accuracy, the dataset was first normalized. Each generated model forecasts the estimated cost worth of the gold associate elements. When training the ANN model, the collected experimental weight datasets were randomly separated into three categories, as indicated by [30]. 80% of the datasets were utilized to train the ANN model, with the remaining 10% used to validate and test it. Following satisfactory data preparation, the MATLAB application was initiated to train, validate, and test the network. Bayesian regularization (trainbr) training algorithms were used to train the model network. The improved model's input and output bias and weight were introduced into Eq. (1) and de-normalized according to Lawal et al. [31] to optimize and minimize the complexity of the model mathematical equation.

$$R_j = f_{sig/purlin}\{P_0 + \sum_{k=1}^{n}[fsig(\mathrm{pnk} + \sum_{i=1}^{m} \mathrm{wik}\Gamma\mathrm{i})\mathrm{w}k \times \ldots]\} \quad (1)$$

where R_j is the output variable, Γ_i is the input variable I, w_{ik} is the weight of the connection between the i^{th} input parameter and the hidden layer, p_0 is the bias in the output layer, w_k is the weight of the connection between the k^{th} of the hidden layer and the single output neuron, p_{nk} is the bias in the k^{th} neuron of the hidden layer, n is the number of neurons in the hidden layer, and f_{purlin} and f_{sig} are the linear and non-linear transfer functions, respectively.

RESULTS AND DISCUSSION

Compositional Mineral Data summary

The summary of the chemical composition analysis is presented in Table 1. The gold (Au), aluminum (Al), copper (Cu), iron (Fe), lithium (Li), magnesium (Mg), nickel (Ni), thorium (Th), uranium (U), and lead (Pb) compositions in the analysis samples range from 0.01-0.19 g/tonne, 0.48-4.91 g/tonne, 5.6-113 g/tonne, 0.51-7.99 g/tonne, 2-30 g/ton, 0.03-0.73g/tonne, 156-3080 g/tonne, 0.25-88.4 g/tonne, 2.6-33.3 g/tonne, 0.53-5.53g/tonne, 0.2-189g/ton, respectively. Skewness is a measure of the symmetry or asymmetry of the data distribution, and kurtosis measures whether the data is heavy-tailed or light-tailed in a normal distribution. The aluminum dataset distribution is peaked and possesses thick tails, as shown by the negative skewness and kurtosis. All other mineral datasets distributions pushed towards the right side, as indicated by the positive skewness and kurtosis (see Fig. 3).

Table 1: Descriptive Statistics of Gold and Associated Minerals in g/ton

Minerals	Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis
Au	0.01	0.19	0.06	0.038	1.61	3.19
Al	0.48	4.91	3.008	1.12	-0.16	-0.88
Cu	5.6	113	29.828	27.927	2.32	4.42
Fe	0.51	7.99	3.133	1.697	1.31	1.79
Li	2	30	8.49	6.307	1.63	2.58
Mg	0.03	0.73	0.135	0.121	3.4	15.19
Mn	156	3080	619.26	588.251	2.45	7.3
Ni	0.25	88.4	18.683	16.659	2.54	8.02
Th	2.6	33.3	12.513	8.441	1.31	0.52
U	0.53	5.53	1.782	1.267	1.38	0.87
Pb	0.2	189	24	29.421	4.92	27.35

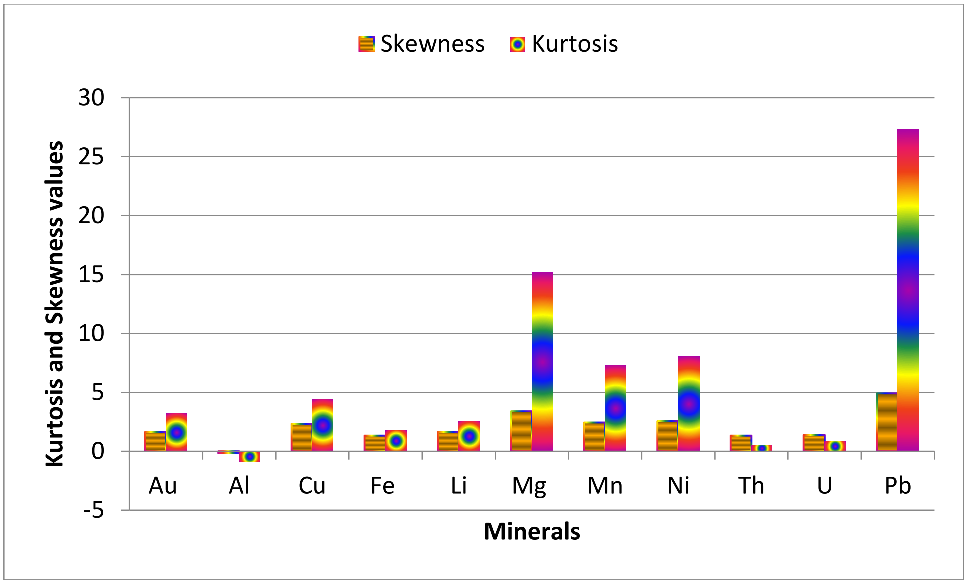
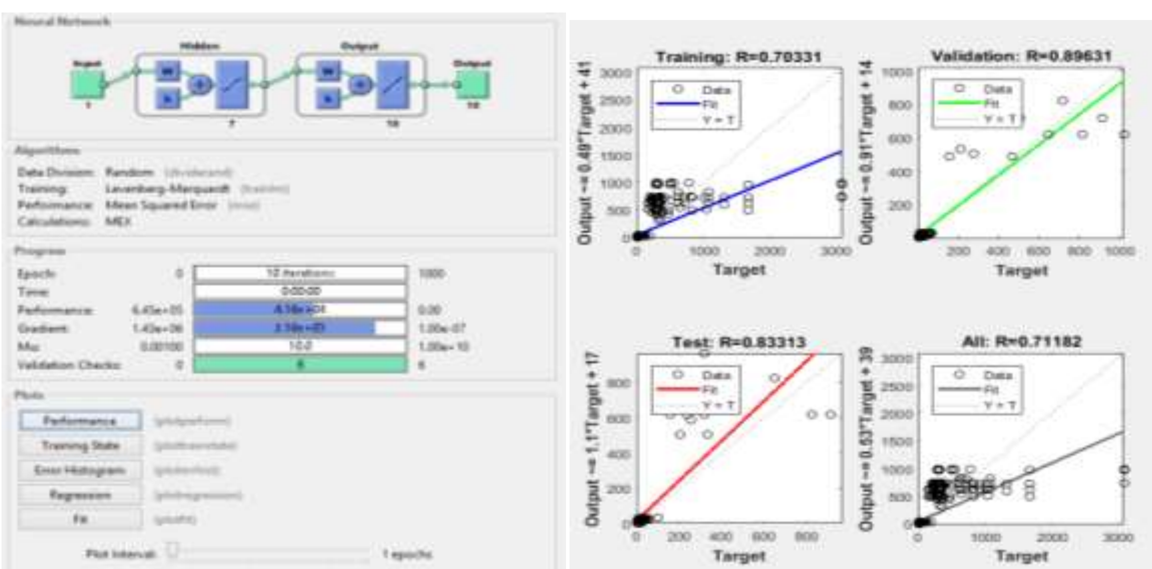


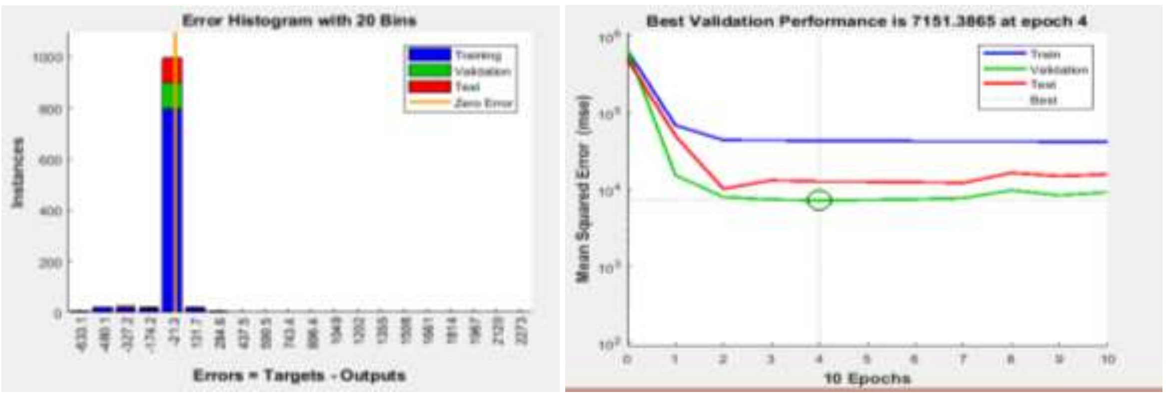
Fig.3. Relationship between each associate mineral data distribution order

Developed ANN model Result

The model with a 1:7:10 architecture was built for the gold-associated mineral prediction using ANN Bayesian regularization training algorithms. The respective performances of the ANN training and testing processes are shown in Fig. 4. The figures show that in each of the cases, the mean squared error decreases up to the points where the best performances were obtained, and their values tend to reach asymptotic values after the best performance. The pattern of the curves for the training, validations, and testing is similar, indicating that the models are successful. The development process has R^2 =0.703 for the training dataset and R^2 =0.83 for the testing dataset.



a. b.



c. d.

Fig.4. ANN model training and testing regression grap; a. ANN model architecture, b. Training and testing regression curve, c. error histogram, d. training performance curve

Development of ANN Cost Model for the Prediction of Associated Zn mineral

The optimum ANN model for all the economic value of the gold associated minerals was extracted into a series of linear mathematical equations after optimum training. The input and output bias and weight of the optimized model were extracted and de-normalized to obtain Eqs. (2-11).

$ZN = (25.61\tanh(\sum_{i=1}^{4} Xi - 0.1677)+51.68) \times MPT) - (CCT + OCT)$ (2)

$X_1=0.0934\tanh(9.56037AU-10.0367)$
$X_2=0.7566\tanh(-9.41179AU+7.0406)$
$X_3=-0.40301\tanh(10.6842AU-0.3151)$
$X_4=-0.5548\tanh(-8.4788AU+0.35857)$
$X_5=-0.1615\tanh(-10.9327AU+1.8731)$
$X_6=0.0491\tanh(-10.9327AU-6.67209)$
$X_7=0.5802\tanh(-8.9377AU-10.9813)$

Where ZN is the estimated cost of gold associated Zinc benefit in ₦,
MPT is ₦54,000, the market price of zinc today,
CCT is ₦466,226.51, the capital cost of mining today,
OCT is ₦50,958.98, the operating cost of mining today.
AU is the gold per ton from each sample,
X_i is the sum of all the seven neurons' series output (X_1 -X_7).

$U= (0.8375\tanh(\sum_{i=1}^{4} Xi - 0.08685)+5.8625)\times MPT) - (CCT + OCT)$ (3)

$X_1=0.54605\tanh(9.56037AU-10.0367)$
$X_2=-0.1702\tanh(-9.41179AU+7.0406)$
$X_3=-0.5623\tanh(10.6842AU-0.3151)$
$X_4=-0.3615\tanh(-8.4788AU+0.35857)$
$X_5=0.2818\tanh(-10.9327AU+1.8731)$
$X_6=-0.3974\tanh(-10.9327AU-6.67209)$
$X_7=-0.20697\tanh(-8.9377AU-10.9813)$

Where U is the estimated cost of Uranium in ₦,
MPT is ₦25,000, the market price of Uranium today,
CCT is ₦466,226.51, the capital cost of mining today,
OCT is ₦50,958.98, the operating cost of mining today.
AU is the gold per ton from each sample,
X_i is the sum of all the seven neurons' series output (X_1 -X_7).

$$Th = (21.10\tanh (\sum_{i=1}^{4} Xi + 0.51101)+21.50)\ MPT) - (CCT + OCT) \quad (4)$$

X_1=-0.1425tanh (9.56037AU-10.0367)
X_2=-0.7856tanh (-9.41179AU+7.0406)
X_3=0.3356tanh (10.6842AU-0.3151)
X_4=0.4171tanh (-8.4788AU+0.35857)
X_5=0.1217tanh (-10.9327AU+1.8731)
X_6=0.1023tanh (-10.9327AU-6.67209)
X_7=0.2334tanh (-8.9377AU-10.9813)
Where Th is the estimated cost of Thorium in ₦,
MPT is ₦90,000, the market price of Thorium today,
CCT is ₦466,226.51, the capital cost of mining today,
OCT is ₦50,958.98, the operating cost of mining today.
AU is the gold per ton from each sample,
X_i is the sum of all the seven neurons' series output (X_1 -X_7).

$$Pb= (94.40\tanh (\sum_{i=1}^{4} Xi - 0.7069)+94.6) \times MPT) – (CCT+ OCT) \quad (5)$$

X_1=-0.2142tanh (9.56037AU-10.0367)
X_2=0.0869tanh (-9.41179AU+7.0406)
X_3=-0.0318tanh (10.6842AU-0.3151)
X_4=-0.1136tanh (-8.4788AU+0.35857)
X_5=-0.0484tanh (-10.9327AU+1.8731)
X_6=-0.0211tanh (-10.9327AU-6.67209)
X_7=0.3202tanh (-8.9377AU-10.9813)
Where Pb is the estimated cost of Lead in ₦,
MPT is ₦10,000, the market price of Lead today,
CCT is ₦466,226.51, the capital cost of mining today,
OCT is ₦50,958.98, the operating cost of mining today.
AU is the gold per ton from each sample,
X_i is the sum of all the seven neurons' series output (X_1 -X_7).

$$Ni= (44.075\tanh (\sum_{i=1}^{4} Xi - 0.1739)+44.325)\times MPT) – (CCT + OCT) \quad (6)$$

X_1=-0.6729tanh (9.56037AU-10.0367)
X_2=-0.3767tanh (-9.41179AU+7.0406)
X_3=-0.0955tanh (10.6842AU-0.3151)
X_4=0.0355tanh (-8.4788AU+0.35857)
X_5=0.09867tanh (-10.9327AU+1.8731)
X_6=0.05518tanh (-10.9327AU-6.67209)
X_7=0.6651tanh (-8.9377AU-10.9813)

Where Ni is the estimated cost of Nickel in ₦,
MPT is ₦10,000, the market price of Nickel today,
CCT is ₦466,226.51, the capital cost of mining today,
OCT is ₦50,958.98, the operating cost of mining today.
AU is the gold per ton from each sample,
X_i is the sum of all the seven neurons' series output (X_1 -X_7).

$$Mn = (1462\tanh(\sum_{i=1}^{4} Xi - 2.1381)+1618) \times MPT) - (CCT + OCT) \quad (7)$$

X_1=0.29195tanh (9.56037AU-10.0367)
X_2=0.1120tanh (-9.41179AU+7.0406)
X_3=0.2354tanh (10.6842AU-0.3151)
X_4=0.4905tanh (-8.4788AU+0.35857)
X_5=0.2401tanh (-10.9327AU+1.8731)
X_6=0.0949tanh (-10.9327AU-6.67209)
X_7=-1.6112tanh (-8.9377AU-10.9813)
Where Mn is the estimated cost of Manganese in ₦,
MPT is ₦5,000, the market price of Manganese today,
CCT is ₦466,226.51, the capital cost of mining today,
OCT is ₦50,958.98, the operating cost of mining today.
AU is the gold per ton from each sample,
X_i is the sum of all the seven neurons' series output (X_1 -X_7).

$$Mg= (0.39\tanh(\sum_{i=1}^{4} Xi + 0.7507)+0.42) \times MPT) - (CCT + OCT) \quad (8)$$

X_1=-0.5455tanh (9.56037AU-10.0367)
X_2=-0.5826tanh (-9.41179AU+7.0406)
X_3=-0.7707tanh (10.6842AU-0.3151)
X_4=0.62287tanh (-8.4788AU+0.35857)
X_5=0.1025tanh (-10.9327AU+1.8731)
X_6=-0.6629tanh (-10.9327AU-6.67209)
X_7=-0.05809tanh (-8.9377AU-10.9813)
Where Mg is the estimated cost of Magnesium in ₦,
MPT is ₦10,000, the market price of Magnesium today,
CCT is ₦466,226.51, the capital cost of mining today,
OCT is ₦50,958.98, the operating cost of mining today.
AU is the gold per ton from each sample,
X_i is the sum of all the seven neurons' series output (X_1 -X_7).

$$Li= (14.0\tanh(\sum_{i=1}^{4} Xi - 0.6726)+16.0) \times MPT) - (CCT + OCT) \quad (9)$$

X_1=-0.1474tanh (9.56037AU-10.0367)
X_2=-0.0420tanh (-9.41179AU+7.0406)
X_3=0.2271tanh (10.6842AU-0.3151)
X_4=0.0339tanh (-8.4788AU+0.35857)
X_5=0.3543tanh (-10.9327AU+1.8731)
X_6=0.2716tanh (-10.9327AU-6.67209)
X_7=-0.7672tanh (-8.9377AU-10.9813)

Where Li is the estimated cost of Lithium in ₦,
MPT is ₦6,500, the market price of Lithium today,
CCT is ₦466,226.51, the capital cost of mining today,
OCT is ₦50,958.98, the operating cost of mining today.
AU is the gold per ton from each sample,
X_i is the sum of all the seven neurons' series output (X_1 -X_7).

$$Fe= (7.245\tanh (\textstyle\sum_{i=1}^{4} Xi - 0.8752)+7.755) \times MPT) - (CCT + OCT) \quad (10)$$

X_1=-0.6283tanh (9.56037AU-10.0367)
X_2=-0.6104tanh (-9.41179AU+7.0406)
X_3=0.2977tanh (10.6842AU-0.3151)
X_4=0.8274tanh (-8.4788AU+0.35857)
X_5=0.5264tanh (-10.9327AU+1.8731)
X_6=-0.2476tanh (-10.9327AU-6.67209)
X_7=-0.0329tanh (-8.9377AU-10.9813)
Where Fe is the estimated cost of iron ore in ₦,
MPT is ₦40,000, the market price of Iron today,
CCT is ₦466,226.51, the capital cost of mining today,
OCT is ₦50,958.98, the operating cost of mining today.
AU is the gold per ton from each sample,
X_i is the sum of all the seven neurons' series output (X_1 -X_7).

$$Cu= (53.8\tanh (\textstyle\sum_{i=1}^{4} Xi - 0.5177)+59.2) \times MPT) - (CCT + OCT) \quad (11)$$

X_1=-0.5550tanh (9.56037AU-10.0367)
X_2=-0.2384tanh (-9.41179AU+7.0406)
X_3=0.1155tanh (10.6842AU-0.3151)
X_4=0.3059tanh (-8.4788AU+0.35857)
X_5=0.1661tanh (-10.9327AU+1.8731)
X_6=0.0883tanh (-10.9327AU-6.67209)
X_7=-0.4679tanh (-8.9377AU-10.9813)
Where Cu is the estimated cost of Copper in ₦,
MPT is ₦180,000, the market price of Copper today,
CCT is ₦466,226.51, the capital cost of mining today,
OCT is ₦50,958.98, the operating cost of mining today.
AU is the gold per ton from each sample,
X_i is the sum of all the seven neurons' series output (X_1 -X_7).

Model Error Analysis

Validation results of the models were carried out using the coefficient of correlation (R^2), root mean square error (RSME), and variance account for (VAF). (Eq. 12-14). R^2 and VAF show high correlation with low variance between the predicted and measured quantities of all the associate minerals. RSME values show low results, which indicates that the predicted values of the associated minerals are closer to the measured values. The extracted final equation was complemented with both capital and operating expenses. The cost of operation and other capital

Print ISSN: 2053-5783(Print)
Online ISSN: 2053-5791(online)
Website: https://www.eajournals.org/
Publication of the European Centre for Research Training and Development -UK

expenditures were factored into the model. The accuracy of the model was computed using the correlation coefficient (R^2, Eq. 12), root mean square (RSME, Eq. 13), and variance accounted for (VAF, Eq. 14).

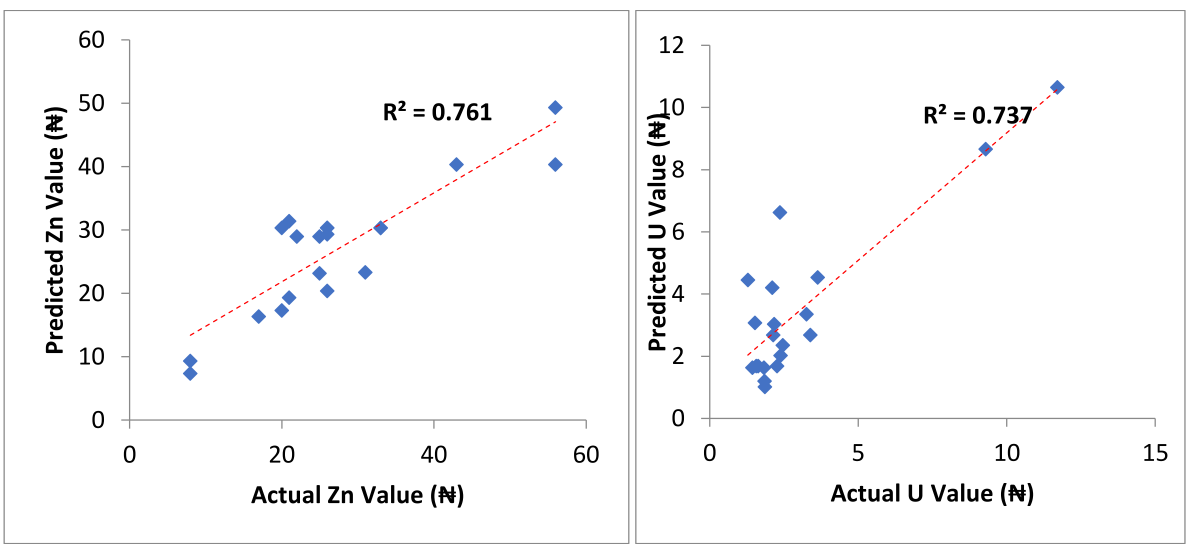
$$R^2 = \frac{\sum_{i=1}^{r}(\alpha-\beta)^2-\sum_{i=1}^{r}(\alpha-\omega)^2}{\sum_{i=1}^{r}(\alpha-\beta)^2} \quad (12)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\alpha-\beta)^2} \quad (13)$$

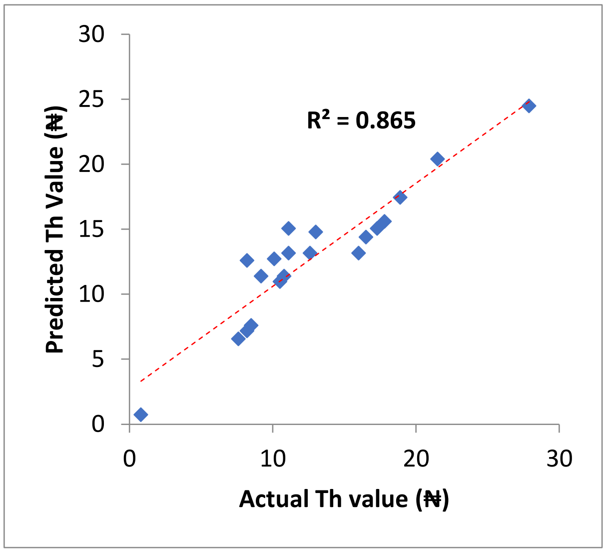
$$VAF = \left(1-\frac{var(\alpha-\omega)}{var(\alpha)}\right) * 100 \quad (14)$$

Where α is the measured associate mineral quantity in g,
ω is the ANN predicted associate mineral quantity in g.

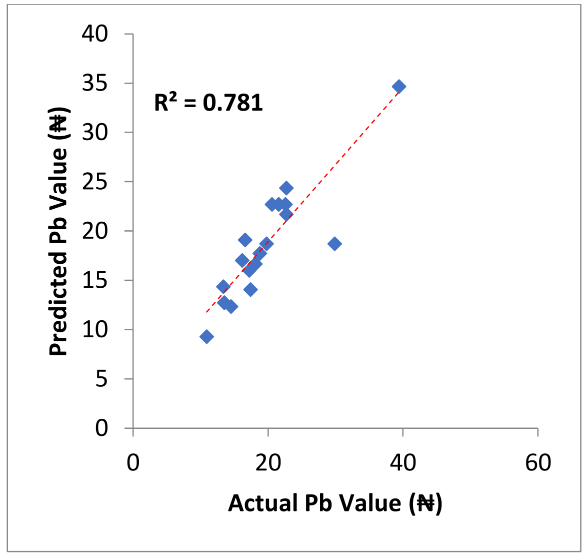
The prediction accuracy of the extracted equations was evaluated with 20 testing datasets. The coefficient of correlation of the zinc model ($R^2 = 0.761$), the uranium model ($R^2 = 0.737$), thorium ($R^2 = 0.865$), lead ($R^2 = 0.781$), nickel ($R^2 = 0.839$), manganese ($R^2 = 0.764$), magnesium ($R^2 = 0.62$), lithium ($R^2 = 0.808$), iron ($R^2 = 0.817$), and copper ($R^2 = 0.878$), respectively. The visualized relationship between the predicted economic worth and the calculated values are presented in Fig. 5. The results show that the extracted ANN equations are replicates of their respective ANN soft computing models and are suitable for economic estimation of gold's prominent associated mineral worth.



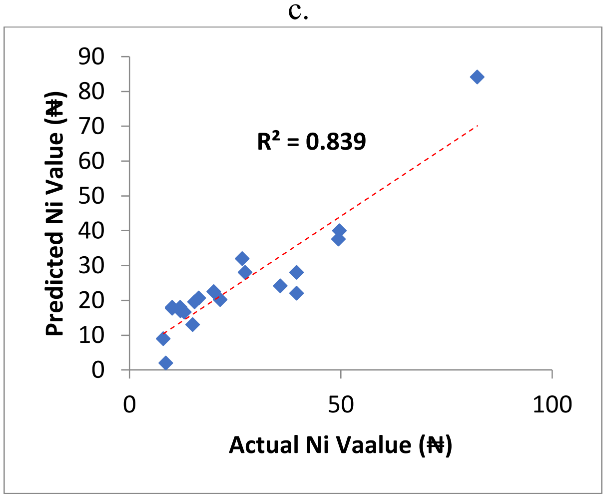
a. b.


Predicted Th Value (₦)
Actual Th value (₦)
$R^2 = 0.865$
0
5
10
15
20
25
30

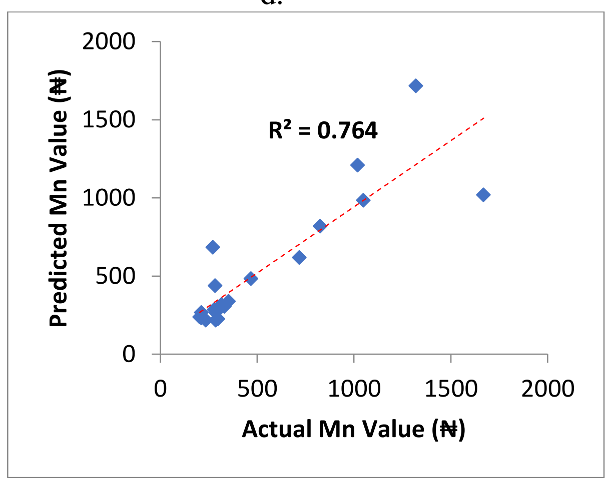
c.


Predicted Pb Value (₦)
Actual Pb Value (₦)
$R^2 = 0.781$
0
5
10
15
20
25
30
35
40
60

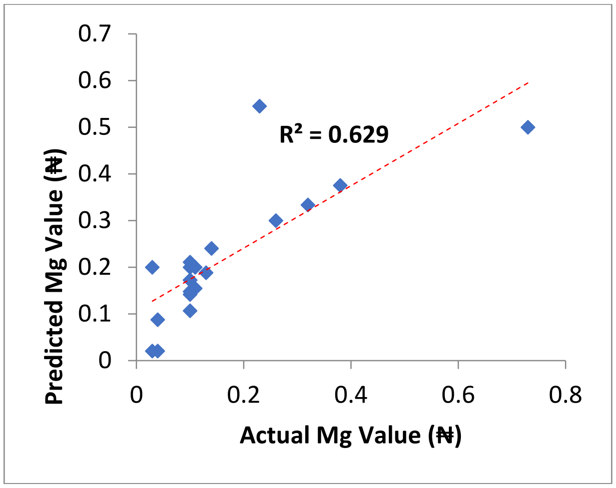
d.

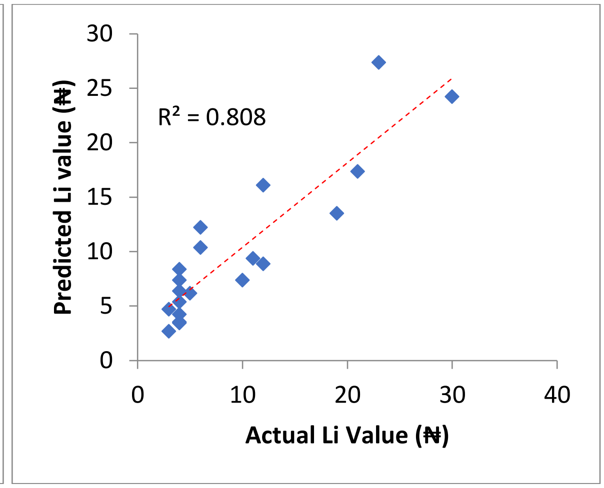

Predicted Ni Value (₦)
Actual Ni Vaalue (₦)
$R^2 = 0.839$
0
10
20
30
40
50
60
70
80
90
100

e.

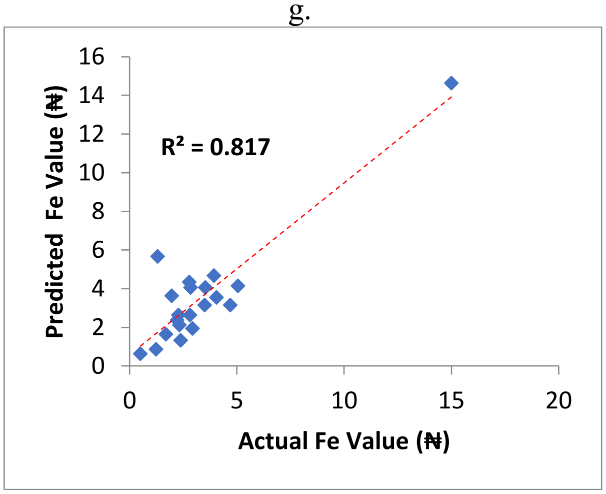

Predicted Mn Value (₦)
Actual Mn Value (₦)
$R^2 = 0.764$
0
500
1000
1500
2000

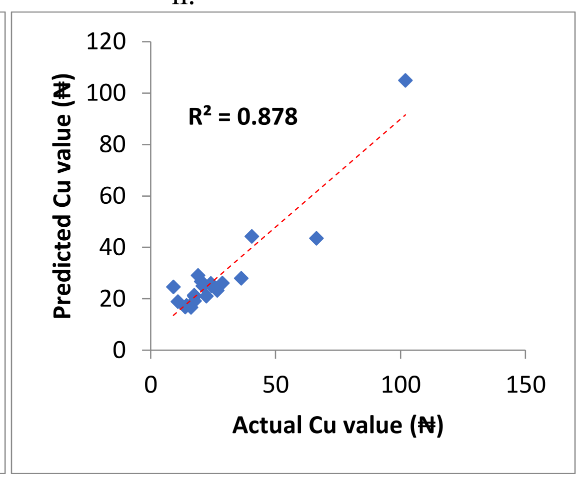
f.





g. h.

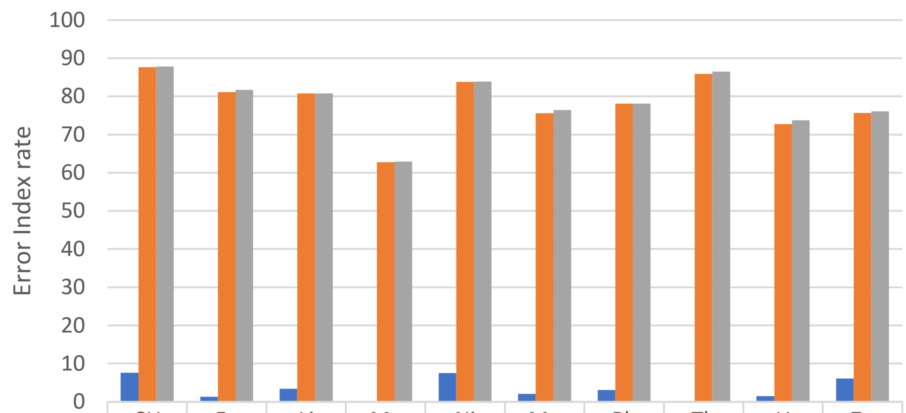




i. j.

Fig.5 Relationship between the actual and predicted associate mineral economic value a)Zinc, b) Uranium, c)Thorium, d)Lead, e)Nickel, f) Manganese, g) Magnesium, h)Lithium, i) Iron, j) Copper

Fig. 6 presents the validation results of the 10 models using the coefficient of correlation (R^2), root mean square error (RSME), and variance account for (VAF). In terms of R2 and VAF, the model shows a high correlation with low variance between the predicted and measured quantities of all the associate minerals. According to the root mean square error values, the low results revealed that the predicted values of the associated minerals are closer to the measured values. As a result, the developed model's prediction performance is appropriate for the estimation of gold-associated mineral economic benefits.



	CU	Fe	Li	Mg	Ni	Mn	Pb	Th	U	Zn
RSME	7.6	1.28	3.41	0.11	7.51	2.05	3.09	0	1.43	6.1
VAF	87.62	81.1	80.75	62.76	83.78	75.56	78.12	85.92	72.77	75.68
R2	87.8	81.7	80.8	62.9	83.9	76.4	78.10	86.5	73.7	76.1

Fig.6 ANN predicted Value Validation Graph

CONCLUSION AND RECOMMENDATION

The availability of a gold-associated mineral prediction model will assist the gold mining industry in focusing on extracting other valuable mineral constituents from gold sand. Less consideration is given to other associate minerals that can be found with gold during the processing stage. This is because gold is the major mineral of interest and is sometimes given a full extraction target. This study proposed the application of artificial intelligence modeling techniques for the prediction of gold's associated mineral economic worth. The geochemical exploration study carried out revealed that in the case study area, gold consists of aluminum, copper, iron, lithium, magnesium, nickel, thorium, uranium, and lead in economic quantity, with content ranging from 0.01-0.19 g/tonne, 0.48-4.91 g/tonne, 5.6-113 g/tonne, 0.51-7.99 g/tonne, 2-30 g/ton, 0.03-0.73g/tonne, 156-3080 g/tonne, 0.25-88.4g/tonne, 2.6-33.3 g/tonne, 0.53-5.53g/tonne, 0.2-189 g/ton, respectively. The prediction results show that the ANN models created in this study are suitable for the economic estimation of gold's prominent associated mineral worth.

Availability of data and materials
The data used in the study are available from the corresponding author on reasonable request.

Competing interests
The authors declare that they have no competing interests.

Funding
No funding was received for conducting this study.

Authors' contributions
All sections of the manuscript including data collection, analysis and interpretation were carried out by the author.

Acknowledgement
The authors' acknowledged the support of Taiwo Blessing Olamide in ANN model development and for the support offered in analyzing the data.

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