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Classification of Soils of Central Western Nigeria Using Neural Network Rule Extraction and Decision Table

[1]E.O. Omidiora, [2]G.O. Oyediran, [1]S.O. Olabiyisi and [1]O.T. Arulogun
[1]Department of Computer Science and Engineering, [2]Department of Agronomy,
Ladoke Akintola University of Technology, Ogbomoso, Nigeria

Abstract: This research work explores soil classification using soil of central Western Nigeria as a case study. This study uses Neural Networks and rule extraction and decision table for the classification of the soils. Soil classification was made more accurate, cheaper and easier with the implementation of Neural Network trained model. A well-developed database capable of generating outputs from a non-linear inputs based on its universal approximation properties was employed, thus, reducing the cost, time, mistakes and labour associated with practical fieldwork. However, the method takes into account the topography and parent material (configuration) of a certain soil sample (location). A generalized Neural Network for soil classification was obtained using the Matlab 6.5 Tool box to build, simulate and test the network. The Feed forward back propagation was used. A GUI (Graphical User Interface) was designed to achieve a high predictive accuracy and enables users most especially a lay user to directly experience an interesting and simulated environment via a friendly user interface of the network. A simplified and explanatory representation of the inputs and outputs was employed. The performance goal was met at 28 epochs using Leveberg Marguartt training algorithm. The neural network achieved an accuracy of 98.20%, which suggested quite a stable network.

Key words: Soil, artificial neural networks, topography, rule extraction and decision table

INTRODUCTION

Many factors determine the chemical composition and physical structure of the soil at any given location. The different kinds of rocks, minerals and other geological materials from which the soil originally formed play a role (Anonymous, 2003). Soils are formed as a result of effect of climate and activities of living organisms (fauna and flora) on the parent material as conditioned by topography or local relief over a period of time. Soils are classified generally on the basis of their morphological and physiochemical properties which reflect the influence of the factors of soil formation-parent material, climate, topography, living organisms and time.

In classifying the soils of central Western Nigeria, much importance is placed on differences in the mode of formation of the parent material (Smyth and Montgomery, 1962; Okusanmi and Oyediran, 1985). The main purposed of any soil classification exercise is to provide detailed information for effective land-use planning for Agricultural as well as Engineering projects.

Neural Networks have received a lot of attention because of their Universal approximation property. Neural Networks are computing systems, modelled after the brains mesh like network of interconnected processing elements, called Neurons (Baesens *et al*., 2003). They are a lot simpler in architecture. However, like the brain, the interconnected processors in a neural network operate parallel and interact dynamically with each other. This enables the network to learn from the data it processes, learns to recognize patterns and relationships in the data it processes. The more data examples it receives as input, the better it can learn to duplicate the results of the examples it processes. Thus, the neural network will change the strengths of the interconnections between the processing elements on response to changing patterns in the data it receives and the results that occur (James, 1985).

However, a major drawback associated with the use of neural network for decision-making is their lack of explanation capability. While, they can achieve a high predictive accuracy rate, the reasoning behind how they reach their decisions is not readily available (Baesens *et al*., 2003). In this research work, neural network rule extraction and decision table techniques is employed. Neural Networks are basically used for

Corresponding Author: Dr. E.O. Omidiora, Department of Computer Science and Engineering, Ladoke Akintola University of Technology, Ogbomoso, Nigeria

classification, prediction and control purposes. Neural Network rule extraction and decision table model would be used to classify the soils of the central Western Nigeria.

The problem encountered in soil classification is critical in terms of cost, time, mistakes and labour and predictive accuracy rate. Also, Neural Networks though with their universal approximation properties lack explanation capability. While they can achieve a high predictive accuracy rate, the reasoning behind how they reach their decisions is not readily available. It is becoming increasingly apparent that the absence of an 'explanation' capability in Artificial Neural Networks (ANN) systems limits the realization of the full potential of such systems and it is this precise deficiency that the rule extraction algorithm and decision table process seeks to redress.

Since, the birth of the modern discipline of science roughly a hundred years ago, Scientists in different countries have used many systems to organize the various types of soils into groups (Anonymous, 2003). There is therefore, the need for a better-synthesized method to analyse and classify soils using a better approach.

In view of this, classification of soils could be made more accurate, cheaper and easier by the implementation of neural network. This will reduce the cost, time, mistakes and labour associated with practical fieldwork. A well-developed database on a computer system capable of generating outputs from a nonlinear inputs based on its universal approximation properties is employed. It becomes easier and faster to achieve a high predictive accuracy rate and enables the user to directly experience a stimulated environment via a friendly user interface of the neural network proposed model.

The research is intended to predict or delineate soil types based on the underlying rock, parent material and topographic position and then model a neural network with a friendly user interface to determine or classify the soil types at a particularly place in central Western Nigeria based on a previous soil configuration and characteristics data collected which serve as inputs to the system.

MATERIALS AND METHODS

Description of the area: Central western Nigeria lies between longitudes 3°/5[1] and 6°00[1]E and includes 6°35[1] and 8°05[1]N. The soils are underlain by the Pre-Cambrian basement complex metamorphic rocks. The climatic condition of the study area could be described as ranging from humid tropical to fairly hot. Sub humid tropical (towards the northern part of the region). With marked wet and seasons. There is a short period of harmattan in between the two seasons (Okusanmi and Oyediran, 1985).

Artificial neural networks: Artificial neurons may be either discrete or continuous. Discrete neurons send an output signal of 1 if the sum of received signals is above a certain critical value called a threshold value; otherwise they send an output signal of 0. Continuous neurons are not restricted to sending output values of only 1s and 0s; instead they send an output value between 1 and 0 depending on the total amount of input that they receive-the stronger the received signal, the stronger the signal sent out from the node and vice-versa. Continuous neurons are the most commonly used in actual artificial neural networks (Anonymous, 2003).

The Multilayer Perceptron (MLP) and many other neural networks learn using an algorithm called back propagation. With back propagation, the input data is repeatedly presented to the neural network. With each presentation the output of the neural network is compared to the desired output and an error is computed. This error is then fed back (back propagated) to the neural network and used to adjust the weights such that the error decreases with each iteration and the neural model gets closer and closer to producing the desired output. This process is known as "training".

Rule-extraction from trained neural networks: It is becoming increasingly apparent that without some form of explanation capability, the full potential of trained Artificial Neural Networks may not be realized For Artificial Neural Networks to gain a even wider degree of user acceptance and to enhance their overall utility as learning and generalization tools, it is highly desirable if not essential that an `explanation' capability becomes an integral part of the functionality of a trained ANN. Craven and Shavlik (1994) define the rule-extraction from neural networks task as follows: "Given a trained neural network and the examples used to train it, produce a concise and accurate symbolic description of the network" (www.neura-deci-rule\rule-decision\c417lab.html). The following discussion of the importance of rule-extraction algorithms is based on this definition. Rule extraction algorithms significantly enhance the capabilities of ANNs to explore data to the benefit of the user.

Classification factors used for modeling

Parent material: Even though soil type consist of parent material/parent rock(p), topography(t), climate(c), living organism(l), time(t), only 2 factors i.e., the parent material rock type and topography are considered for the computation while other are factors that may also be put into mind are: climate, living organism and time remain constant.

Table 1: Coarse-grained granites and gneisses (Iwo Association)

Topography	Sedentary	Hill-creep	Hill-wash	Iron-pan	Erodent	Poor drainage
	Iwo	Balogun	Oba	Gambari	Nil	Jago Asso.
	Iwo	Asejire	Iregun	Ibule	Nil	Jago Asso
	Iwo	Akure	Apomu	Ijure	Nil	Jago Asso
	Ibadan	Balogun	Oba	Gambari	Nil	Nil
	Ibadan	Asejire	Apomu	Ibule	Nil	Nil
	Ibadan	Akure	Iregun	Ijure	Nil	Nil
	Ekiti	Balogun	Apomu	Gambari	Nil	Nil
	Igbajo/Ife	Akure	Iregun	Ijure	Nil	Nil
	Odeyinka	Asejire	Oba	Ibule	Nil	Nil

Table 2: Medium-grained granites and gneisses (Ondo Association)

Topography	Sedentary	Hill-creep	Hill-wash	Iron-pan	Erodent	Poor drainage
	Ondo	Igunshin	Nil	Gambari	Shunroji	Jago Asso
	Ondo	Igunshin	Nil	Ibule/Itire	Shunroji	Jago Asso
	Fagbo	Igunshin	Nil	Gambari	Shunroji	Jago Asso
	Fagbo	Igunshin	Nil	Ibule/Itire	Shunroji	Jago Asso
	Owo/Odigbo	Igunshin	NIL	Gambari	Shunroji	Jago Asso
	Owo/Odigbo	Igunshin	Nil	Ibule/Itire	Shunroji	Jago Asso

Table 3: Fine-grained biotite gneisses and schists (Egbeda Association)

Topography	Sedentary	Hill-creep	Hill-wash	Iron pan	Eroded	Poor drainage
	Egbeda	Nil	Nil	Gambari	Shanroji	Jago+Origo
	Olorunda	Nil	Nil	Gambari	Shanroji	Jago+Origo
	Mukun	Nil	Nil	Gambari	Shanroji	Jago+Origo

Table 4: Amphiboles (Itagunmodi Association)

Topography	Sedentary	Hill-creep	Hill-wash	Iron pan	Eroded	Poor drainage
	Nil	Araromi	Itagunmodi	Gambari	Nil	Jago+Origo
	Nil	Araromi	Owena	Ibule/Ijure	Nil	Jago+Origo

Table 5: Quartz gneisses and schist (Okemesi Association)

Topography	Sedentary	Hill-creep	Hillwash	Iron pan	Eroded	Poor drainage
	Iwaji	Erinoke	Etion	Gambari	Nil	Jago Asso.
	Iwaji	Okemesi	Etion	Ibule	Nil	Jago Asso.
	Iwaji	Ipele/Irapi	Etion	Ijare	Nil	Jago Asso.
	Omo	Erinoke	Etion	Gambari	Nil	Jago Asso.
	Omo	Okemesi	Etion	Ibule/Ijare	Nil	Jago Asso.
	Omo	Ipele/Irapa	Etion	Gambari	Nil	Jago Asso.

Table 6: Sericite Schists (Mamu Association)

Topography	Sedentary	Hill-creep	Hill-wash	Iron pan	Eroded	Poor drainage
	Mamu	Effon	Nil	Gambari	Nil	Jago Asso.
	Mamu	Effon	Nil	Ibule	Nil	Jago Asso.
	Mamu	Effon	Nil	Ijare	Nil	Jago Asso.

Six association of soil having related morphology can be recognized (Smyth and Montgomery, 1962) which correspond to the following 6 broad parent rock classes (Table 1-6). This translates to six configurations.

- Coarse-grained granites and gneisses (Iwo Association).
- Medium-grained granites and gneisses (Ondo Association).
- Fine-grained biotite gneisses and schists (Egbeda Association).
- Amphiboles (Itagunmodi Association).
- Quartz gneisses and schist (Okemesi Association).
- Sericite Schists (Mamu Association).

Parent material: Four varieties of parent material are recognized:

- Sedentary parent material.
- Drift parent material.
  - Hill creep.
  - Hill wash.

Alluvial parent material: Sedentary parent material of a soil directly overlies the solid rock which it is derived. Drift parent materials is derived from rock and soil material which have been transported from its original site under the influence of gravity (Hill-creep) and erosion process. Alluvial parent material is formed by the redeposition of material carried in suspension by streams and rivers.

Topography-soils relationships: Knowledge of the relationship between the various soil type and topography is very important in mapping. As a result, the sequence of soils from hill top to valley bottom can often be predicted for an area having a certain type of topography and overlying certain type of parent rock.

Hill-creep soils are usually found at a high level in the topography, whereas hill-wash soils are mainly developed at a low level in the topography on relatively gentle slopes immediately above streams. The valley bottom soils are affected by the seasonally high ground water table and the poorly drained (Okusanmi and Oyediran, 1985).

Limitations of the model:

- Soils of the coastal area of the region are excluded from this approach due to the unpredictable nature of their parent materials (Tertiary sediments).
- Variations within a soil series may be difficult to predict because these are usually localized e.g. sandy, red, concretionary, pale and fine gravelly variations of Iwo series.

Data gathering: An appreciable set of data was gathered from a previous research work done at the Department of Agronomy, Faculty of Agric Sciences, LAUTECH, Ogbomoso. In this study, the main characteristics employed in determining the training of the network are:

- Soil configuration (parent material).
- Land topography.

Topography and configuration are used as inputs and coded while the soil series are coded as outputs. In order to achieve simplicity in the presentation of the influential variables to be used in the training of the artificial neural network, the distribution of soil samples under various configurations and topography are as shown in the Table 7.

The desired artificial neural network type used is the popular *feed forward back propagation* artificial neural network. The transfer function of the hidden neuron layer is the *tansigmoid* transfer function and that of the output layer is the *pureln* transfer function. In this case, the output is in the range of (1, 36) and input (1, 6). In the proposed network, the correspondences used in applying the various inputs to the network for training are listed below:

Configurations:

- Coarse-grained granites and gneisses (1).
- Medium-grained granites and gneisses (2).
- Fine-grained biotite gneisses (3).
- Amphiboles (4).
- Quartz gneisses and schists (5).
- Sericite schists (6).

Topography:

- Sedentary (1).
- Hill-creep (2).
- Hill-wash (3).
- Iron-pan (4).
- Eroded t (5).
- Poor-drainage (6).

Furthermore, the training function trianlm was used; this uses the levenberg-marquadart algorithm which ensures a faster convergence though it requires a lot of memory. The performance function employed is the mse, (mean square error) which is set to determine the error difference allowed for a valid and generalized network. The learning function used is learndm. The output of the network was represented as follows in Table 7.

Percentage Accuracy = 100-Average percentage error

$$\text{Average percentage error} = \sum \frac{\text{Percentage error}}{\text{No of unit}}$$

$$= \frac{65.64}{36} = 1.823\%$$

Percentage Accuracy = 100 -1.823 = 98.17 = 98.20%

Simulating the network: Simulating the network using the function sim (net, p); a number of outputs were generated confirming the efficiency of the trained network. The results can be seen in appendix A. Below are some tests carried out on the network:

```
    1. pt= [3; 5];
a=sim (net, pt);
disp (a);
16.9741
    2. ps=[2;3];
a=sim (net, ps);
disp (a);
8.7640
    3. po= [6;5];
a=sim (net, po);
disp (a);
 34.6585
```

From the above tests, it was observed that the network performance was calculated to be 98.20% accurate as indicated:

$$\frac{65.64}{36} = 1.823\%$$

Percentage Accuracy = 100 -1.823 = 98.17 = 98.20%

Table 7: Desired output of the trained network (Target)

Group of soils	Desired output (Target)	Simulated output (Goal)	(Target-Goal)	T-G/T	Percentage error
Iwo, Ibadan, Ekiti, Igbajo/ife, Odeyinka	1	1.4837	-0.4837	-0.4837	-48.4
Balogun, Asejire, Akure	2	2.342	-0.3420	-0.171	-17.1
Oba, Iregun, Apomu	3	3.2227	-0.2227	-0.0742	-7.42
Gambari, Ibule, Ijure	4	4.1253	-0.1253	-0.0313	-3.13
Nil	5	5.0489	-0.0489	-0.0098	-0.98
Jago	6	5.9926	0.0074	0.0012	0.12
Ondo, Fagbo, Owo/odigbo	7	6.7911	0.2089	0.0298	2.98
Igunshin	8	7.769	0.2310	0.0289	2.89
Nil	9	8.7638	0.2362	0.0262	2.62
Gambari, Ibule/ijare	10	9.7742	0.2258	0.0226	2.26
Shunroji	11	10.7989	0.2011	0.0183	1.83
Jago	12	11.8363	0.1637	0.0136	1.36
Egbeda, Olorunda, Makun	13	12.7066	0.2934	0.0226	2.26
Nil	14	13.7631	0.2369	0.0169	1.69
Nil	15	14.8277	0.1723	0.0115	1.15
Gambari	16	15.8986	0.1014	0.0063	0.63
Shunroji	17	16.9739	0.0261	0.0015	0.15
Jago +Origo	18	18.0519	-0.0519	-0.0029	-0.29
Nil	19	18.948	0.0520	0.0027	0.27
Araromi	20	20.026	-0.0260	-0.0013	-0.13
Itagunmodi, Owena	21	21.1014	-0.1014	-0.0048	-0.48
Gambari, Ibule/ijure	22	22.1722	-0.1722	-0.0078	-0.78
Nil	23	23.2368	-0.2368	-0.0103	-1.03
Jago +Origo	24	24.2934	-0.2934	-0.0122	-1.22
Iwaji, Omo	25	25.1636	-0.1636	-0.0065	-0.65
Erinoke, Okemesi, Ipele/irapa	26	26.2011	-0.2011	-0.0077	-0.77
Etioni	27	27.2258	-0.2258	-0.0084	-0.84
Gambari, Ibule, Ijare, Ibule/ijare	28	28.2362	-0.2362	-0.0084	-0.84
Nil	29	29.2311	-0.2311	-0.0080	-0.80
Jago	30	30.2089	-0.2089	-0.0070	-0.70
Mamu	31	31.0074	-0.0074	-0.0002	-0.02
Effon	32	31.9512	-0.9512	-0.0300	-3.00
Nil	33	32.8748	0.1252	0.0038	0.38
Gambari,ibule,ijare	34	33.7774	0.2227	0.0066	0.66
Nil	35	34.6581	0.3419	0.0098	0.98
Jago	36	35.5164	0.4836	0.0134	1.34
Summation Σ					65.64

Designing the interface: Since, the major aim of this project work is to classifying soil samples for use by experts especially soil scientists, it is necessary to build a friendly user interface to the neural network to enable users to appreciate and experience a simulated environment.

The interface was designed using the MATLAB GUI (graphical user interface). MATLAB implements GUIs as figure windows containing various uicontrol objects. Each object was programmed to perform the action intended. GUIDE (graphical user interface development environment) primarily; is a set of layout tools. However, GUIDE also generates an M-file that contains code to handle the initialization and launching of the GUI. This M-file provides a framework for the implementation of the callbacks (the functions that execute when users activate components in the GUI).

RESULTS AND DISCUSSION

In this study, neural network rule extraction and decision tables are used to classify the soils of central western Nigeria. This involves: data gathering, coding the data as inputs and output in a form suitable for the model, pre and post processing, building and training the network, simulating the network and designing the interface.

Data gathering: An appreciable set of data was gathered from a previous research work being done at the Department of Agronomy, Faculty of Agriculture, LAUTECH, Ogbomoso. The set of data takes into consideration the Topography and Parent material (configuration) to classify the soils. Topography and configuration are used as inputs and coded while the soil series (Iwo, Ibadan, etc.) are coded as outputs. Coding the data is of paramount importance since all artificial neural network models simulate by only numeric input and produce numeric output. There is duplication of soil samples in the data set because each soil samples were recognized with its identification name wherever it was found. The data set is as shown.

Neural network rule extraction and decision tables: Just like a flowchart, is a tool of programming and system analysis, which is used to define complex program logic.

This was used to arrive at an appropriate data training set for the network. The rule extraction was used to enhance the capabilities of ANN to explore data to the benefit of the user. It describes which actions are to be taken under a specific combination of conditions as fully discussed in Chapter 2. In general, if there are n conditions, there will be 2^n rules.

But in this project, the rules take into consideration all possible combinations of inputs. However, some of the rules are *irrelevant* i.e., *redundant* as in the case of duplication of soil samples and are thus ignored.

As a result, the algorithm/methodology used in getting the maximum number of rules and arriving at the minimum rules for the decision table is described.

Identify conditions and values: The 5 data attributes tested by conditions in this problem are the effect of climate, living organism, time, topography [with 6 values: Sedentary (1), Hill-creep (2), Hill-wash (3), Iron-pan (4), Erodent (5), Poor-drainage (6)] and configuration [with six values: Coarse-grained granites and gneisses (1), Medium-grained granites and gneisses (2), Fine-grained biotite gneisses (3), Amphiboles (4), Quartz gneisses and schists (5), Sericite schists (6)].

Compute maximum number of rules: Multiplying the number of values for each condition data attribute by each other i.e., the maximum number of rules = 5*6*6=180 rules.

Identify possible actions: The possible actions are configuration (6) and Topography (6) which gives 36 possible actions.

Enter all possible rules: All possible rules are as stated in Table 8.

Define actions for each rule: The defined actions are as stated in Table 8.

Verify the policy: This is achieved by the output (goal) generated from the trained network.

Simplify the table: The table is simplified as shown in Table 8 showing the desired output code for each group of soil as output.

Pre and Post processing: This enabled the data to be scaled into the appropriate range suitable for the network to learn. This was achieved using *the feed forward* back propagation neural network with the transfer function of the hidden neuron layer as *tansigmoid* and that of the output layer as *pureln* transfer function.

Table 8: Data coding: The data was coded as inputs and outputs as shown in the Table 8

Inputs		Outputs
Configuration	Topography	Group of soils
1	1	1 (Iwo,Ibadan,Ekiti, Igbajo/Ife Odeyinka)
1	2	2 (Balogun,Asejire,Akure)
1	3	3 (Oba,Iregun,Apomu)
1	4	4 (Gambari,Ibule,Ijure)
1	5	5 (Nil)
1	6	6 (Jago)
2	1	7 (Ondo,Fagbo,Owo/Odigbo)
2	2	8 (Igunshin)
2	3	9 (Nil)
2	4	10 (Gambari,Ibule/Ijare)
2	5	11 (Shunroji)
2	6	12 (Jago)
3	1	13 (Egbeda,Olorunda,Makun)
3	2	14 (Nil)
3	3	15 (Nil)
3	4	16 (Gambari)
3	5	17 (Shanroji)
3	6	18 (Jago+Origo)
4	1	19 (Nil)
4	2	20 (Aerodrome)
4	3	21 (Itagunmodi,Owena)
4	4	22 (Gambari,Ibule/Ijare)
4	5	23 (Nil)
4	6	24 (Jago+Origo)
5	1	25 (Iwaji, Omo)
5	2	26 (Erinoke,Okemesi,Ipele/Irapa)
5	3	27 (Etioni)
5	4	28 (Gambari,Ibule,Ijare)
5	5	29 (Nil)
5	6	30 (Nil)
6	1	31 (Mamu)
6	2	32 (Effon)
6	3	33 (Nil)
6	4	34 (Gambari,Ibule,Ijare)
6	5	35 (Nil)
6	6	36 (Jago)

Building the Network: The MATLAB Neural Network 6.5 toolbox was used. The Neural Network Toolbox (NNT) is a multi-purpose neural network package that has an environment to train and simulate the model. A high level network creation function *neff* was used to create a trainable feed forward back propagation.

Training the network: The batch mode where all inputs are applied to the network before the weights and biases are updated was used with the *train* function. The training function *trianlm* (Levenberg-marquadart) ensures a faster convergence. The performance function *mse* (mean square error) was employed to determine the error difference allowed for a generalized network and the *learndm* learning function was used.

Simulating the network: The network was simulated using the function *sim(net,p);* the output of each simulated combination of inputs (goal) was compared with the desires output of the network (target) with the difference and percentage error rate calculated as shown in Table 9.

Table 9: Comparison of the target and goal output

Group of soils	Desired output of the network (Target)	Simulated output of the network (Goal)	(Target-Goal)
Iwo, Ibadan, Ekiti, Igbajo/ife, Odeyinka	1	1.4837	-0.4837
Balogun, Asejire, Akure	2	2.342	-0.3420
Oba, Iregun, Apomu	3	3.2227	-0.2227
Gambari, Ibule, Ijure	4	4.1253	-0.1253
Nil	5	5.0489	-0.0489
Jago	6	5.9926	0.0074
Ondo, Fagbo, Owo/odigbo	7	6.7911	0.2089
Igunshin	8	7.769	0.2310
Nil	9	8.7638	0.2362
Gambari, Ibule/ijare	10	9.7742	0.2258
Shunroji	11	10.7989	0.2011
Jago	12	11.8363	0.1637
Egbeda, Olorunda, Makun	13	12.7066	0.2934
Nil	14	13.7631	0.2369
Nil	15	14.8277	0.1723
Gambari	16	15.8986	0.1014
Shunroji	17	16.9739	0.0261
Jago +Origo	18	18.0519	-0.0519
Nil	19	18.948	0.0520
Araromi (20)	20	20.026	-0.0260
Itagunmodi, Owena	21	21.1014	-0.1014
Gambari, Ibule/ijure	22	22.1722	-0.1722
Nil	23	23.2368	-0.2368
Jago +Origo	24	24.2934	-0.2934
Iwaji, Omo	25	25.1636	-0.1636
Erinoke, Okemesi, Ipele/irapa	26	26.2011	-0.2011
Etioni (27)	27	27.2258	-0.2258
Gambari, Ibule, Ijare, Ibule/ijare	28	28.2362	-0.2362
Nil	29	29.2311	-0.2311
Jago	30	30.2089	-0.2089
Mamu	31	31.0074	-0.0074
Effon	32	32.9512	-0.9512
Nil	33	32.8748	0.1252
Gambari, Ibule, Ijare	34	33.7774	0.2227
Nil	35	34.6581	0.3419
Jago	36	35.5164	0.4836

Network simulated output:

```
1. > pt=[1;1]
 pt =
    1
>> a=sim(net, pt);
>> disp (a);
    1.4837
2. >> pt=[1;6]
 pt =
    1
    6
>> a=sim(net, pt);
>> disp (a);
    5.9926
3. >> pt=[2;2]
 pt =
    2
    2
>> a=sim(net, pt);
>> disp (a);
    7.7690
```

From the previous discussion, the Neural Network was trained and it met performance goal at 28 Epochs with an average accuracy of 98.976%. This suggests a quite stable network, which can be used reliably for further soil classification.

This implies that when a certain topography and configuration are selected as inputs, it gives an output of a group of possible soil types (classification) which corresponds to the input values.

The GUI helps in providing users of the network with the six basic configuration and topography used. Using the pop-up menu, the interface avoids the possibilities of users going out of range of the input values to the network, since the network was built to only classify soils of central western Nigeria.

The supervised mode of training was employed using the *levenberg-marquadart* algorithm, a very fast gradient algorithm which on application with the correct parameter settings; a satisfactory result for the problem was obtained after 28 epochs with a learning rate of 0.001 the final network values yielded a mean square error of 0.0485586. The training of the network is illustrated as follows:

```
Net = newff ([16; 16], [2, 1], {'tansig','purelin'},'trainlm');
 net.trainParam.epochs=10000;
 net.trainParam.lr=0.001;
 net.trainParam.goal=0.055;
 net.trainParam.show=100;
 net= train(net,p,t);
TRAINLM, Epoch 0/10000, MSE 521.92/0.055, Gradient 2302.6/1e-010
TRAINLM, Epoch 28/10000, MSE 0.0485586/0.055, Gradient 22.1658/1e-010
TRAINLM, Performance goal met.
```

As shown in the graph, the maximum epochs was set to 10000 and the goal set to 0.055. The function net = train (p, t) was executed where p and t are the inputs and targets outputs respectively.

CONCLUSION AND RECOMMENDATIONS

This research work was successfully implemented with the approximation property of neural network for classification of the central western Nigeria soils. The art of neural computing requires a lot of rigorous work as data is fed into the network system. It involves the selection of learning rules, transfer functions, summation functions and connection of neurons within the network. However a major drawback associated with the use of neural network for decision-making is their lack of explanation capabilities, while they can achieve a high predictive accuracy rate. The reasoning behind how they reach their final decisions is not readily available but with a GUI, explanation capability was provided.

During the course of training, performances are monitored, connection and neurons adjusted, standards are modified and goals improved until the network achieves a satisfactory desired result. The performance goal was met at 28 epochs using the Levenberg Marquardt training algorithm. The neural network achieved an accuracy of 98.976%, which suggested quite a stable network.

The successful application of a neural network usually demands experimentation. The result of this work is recommended for use as it has been tested and found to have a very low percentage error.

Subsequently, since an effective neural network is determined by the volume of the data trained with, it is recommended that further research work should be done in this field especially in further classification of central western Nigeria soils in more specific and detailed classes. Also the implementation of a GUI with better explanation capabilities should be greatly encouraged.

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