LAUTECH Journal of Engineering and Technology 14 (2) 2020: 65-79

DEVELOPMENT OF A NEURAL NETWORK MODEL FOR AND IDENTIFYING BULK COWPEA SEEDS VARIETY USING ITS ELECTRICAL PROPERTIES

[1]Audu* J., [2]Aremu, A. K. and [3]Ogunlade, C. A.

[1]Department. of Agricultural & Environmental. Engineering, University of Agriculture, Makurdi, Nigeria.

[2]Department of Agricultural & Environmental Engineering, University of Ibadan, Nigeria.

[3] Department of Agricultural Engineering, Adeleke University, Ede, Osun State, Nigeria.

*Corresponding author's Email – audujoh@gmail.com

ABSTRACT

Artificial intelligence using machine leaning algorithms are modern trends in global industrialization. For agriculture to meet the global demand, the need to automate it processes are crucial. The objective of this study was to develop an artificial neural network model; that will be used to detect and identify variety of cowpea seeds in large storage facilities, using its electrical properties. Electrical properties of three variety of cowpea were generated; at five different moisture content, with five different current frequencies. A three-layer model was developed using multi-layer Perceptron method. It was trained and optimized using batch and scaled conjugate gradient methods respectively. Activation functions used were hyperbolic tangent and Softmax for the hidden and output layers; covariates in the input layer were standardized. The developed network model identifies 96, 97 and 93% varieties correctly during training, testing and validation respectively. Receiver Operating Characteristics (ROC) curve plotted for the model performance shows areas under the curve to be above 0.9 for all variety identified. This shows that the model performance was over 90% for predicting all varieties. The cumulative gain and lift charts were plotted to evaluate the model. Inductance was diagnosed to be the most important predictor to the model, while current frequency was the least. Pair t – test analysis at p<0.01, was done to further validate the model. This developed artificial neural network model can be used to program electrical sensors to identify cowpea seeds varieties during bulk storage, handling and processing. Such device can be used for quality control.

Key words: Artificial neural network, model; Cowpea seeds; electrical properties; variety, Artificial intelligence

INTRODUCTION

Cowpea seeds (Vigna unguiculata (L.) Walp) are one of the major sources of protein for most developing countries. Although many authors had reported that it originated from West Africa and spread to other parts of the world. There are not enough archaeological evidences to proof this point beyond reasonable doubt. It belongs to the Resales order, Leguminosae family, Papilionoideae subfamily, *Vigna* genus and *Vigna sinensis* (L) Savi species (Filho et al., 1983; Comlanvi, 2011; Spriggs et al., 2018; Michalis et al., 2019). According to IITA report (2018) the world produces more than 7.4 million tons of dried cowpeas seeds in 2017, with Africa producing nearly 7.1 million. Nigeria the highest producer and consumer of this seeds produces about 48% of African output and 46% of the world output. Nigeria had no recorded evidence of cowpea seeds export. Worldwide consumption of the seed is estimated to more than four million tons. Africa consumed about 387,000 tons alone. Cowpea seed is reported to contain 24% crude protein, 53% carbohydrates, and 2% fat (FAO, 2012; Gerrano et al., 2019). This shows how important cowpeas seeds are to man. So the need to automate its variety identifications to maintain its standard and quality during bulk handling, transportation, marketing and storage processes. To automate, machine learning mathematical algorithms need to be developed. In this study Artificial Neural Network (ANN model was developed for identification of cowpea seed variety.

The ANN is a machine learning mathematical algorithm or model which tries to mimic the behavior of biological neurons. Its leaning process can be either supervised or unsupervised. The ANN algorithm or model is made up of three simple rules. These rules are multiplication, summation and activation. ANN model is divided into three layers which are input, hidden and output layers. The three rules (algorithm) take place in each layer. History of ANN shows that McCulloch and Pitts in 1943 designed the first neural network. Hebb six years later developed the first learning rule in 1949. Rosenblatt then used this learning rule to develop the concept of Perceptron in 1958. In 1960 Widrow and Hoff develop the concept of the ADALINE (ADAptive Linear Element) which is used to calculate classification error in ANN. Then in 1969 Minsky and Papert wrote a book on perceptrons and proved the limitations of single-layer perceptron networks. Then in 1975 the concept of back propagation was developed and introduced by webros. Further more in 1983, Fukushima, Miyake and Ito introduced the neural model of the Neocognitron. This Neocognitron model would recognize hand writing patterns. The ANN is used today in many field of studies. Examples of its application are: text recognition, biology entity identification and classification, e-mail spam filtering, recommendation systems, photo search and many more (Kriesel, 2005; Christopher 2006; Erdi et al., 2016; Harsh et al., 2016; Marzieh and Ehsan, 2016); Halagundegowda and Singh, 2018). Artificial neural network (ANN) had been used by some researchers to classify and identify varieties of agricultural grains and seeds.

Guzman et al. (2008), Golpour et al. (2014), Pazoki et al. (2014), Sumaryanti et al. (2015), Cinar and Koklu (2019) and Singh et al. (2020), all developed ANN model for classification of rice varieties. They used either or combination of physical, morphological, colour or image properties of rice as input variables to develop their network. Results of their network models, produces above 90% correctly classified varieties. Dubey (2006), Arefi et al. (2008) and Kayabasi et al. (2018) also developed ANN models for classifying and identifying wheat varieties. They used combination of physical, morphological or image properties as their inputs variables for their neural networks. Their network classification successes range from 84 – 100%. Aye et al. (2018) classified maize varieties with ANN using their image properties. They achieved a classification success of 85%. Bagheri et al. (2019) developed an ANN model for Seed classification of three species of amaranth using its morphological characteristics. Classification results were at range of 80 – 81% success. Artificial neural network models for soya beans and coffee beans were developed by Zhu et al. (2019) and García et al. (2019) respectively. Their networks were developed using image properties for soya beans and physical, morphological and colour properties for coffee beans, with success rate classification of 90 – 98%. Nasirahmadi and Behroozi-Khazaei (2013) developed multilayer perceptron artificial neural network (MLP-ANN) to identify ten varieties of beans (Phaseolus vulgaris L.), using its colour and image properties. Their network successes range from 70 - 100% identification. Barroso et al. (2016) developed ANN to select upright cowpea (Vigna unguiculata) genotypes with high productivity and phenotypic stability, using genetic properties. Their network success was 90%. Among all literatures reviewed, none of the researchers developed an ANN using electrical properties of the grains and seeds.

The objective of this study was to identify (classify) bulk cowpea seeds variety using its electrical properties to develop an artificial neural network model. This model can be used to program electrical sensors to identify cowpea variety for quality control during handling, processing, transportation and storage of bulk cowpea seeds.

MATERIALS AND METHODS

Sample Preparation

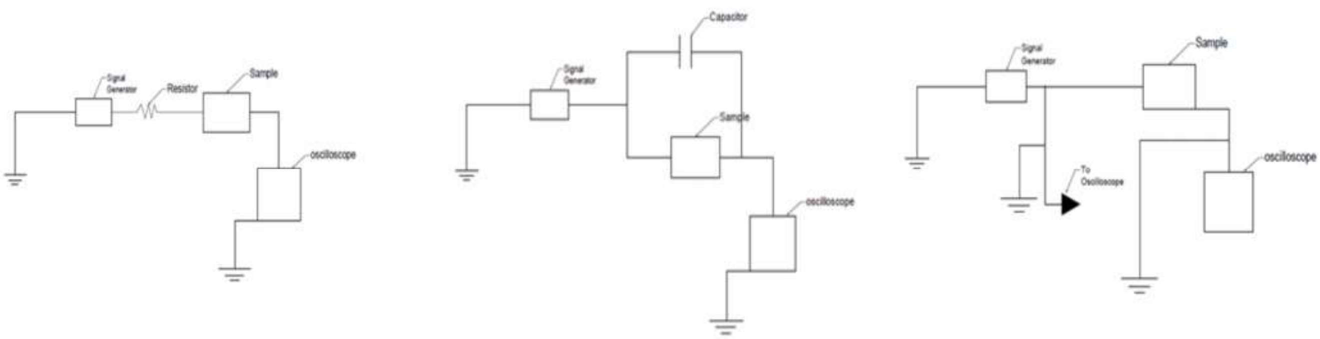
Cowpea seeds varieties were obtained at National Center for Genetic Resources and Biotechnology (NACGRAB), Ibadan, Nigeria. These varieties are NG/AD/11/08/0033, NG/OA/11/08/063 and NGB/OG/0055 (Figure 1). Their moisture contents were determined using ASAE standard (S352.2), at 8, 10, 12, 14 and 16% db.

NG/OA/11/08/063 NGB/OG/0055 NG/AD/11/08/0033

Figure 1: Sample seeds varieties

Determination of Electrical Properties of Bulk Cowpea Seeds Variety

Electrical properties like capacitance, inductance and resistance were determined using circuit connections shown in Figure 2. Components of the circuits are: signal generator, resistor, sample holder, capacitor and oscilloscope. The sample holder was a 60mm Tafton tube with two circular copper ends. Other electrical properties were calculated using equations 1 – 5. Current frequency range used were 1, 500,1000,1500,2000 kHz.



(a) Capacitance (b) Inductance (C) Resistance

Figure 2: Set up circuit for determination of electrical properties of bulk cowpea seeds

$$G = 1/R \text{ ….(1)}, \quad \rho = R\frac{A}{L} \text{ ….(2)}, \quad \sigma = \frac{1}{\rho} \text{ ….(3)}, \quad X_c = \frac{1}{2\pi f C} \text{ ….(4)}, \quad \varepsilon' = \frac{C}{C_o} \text{ ….(5)}$$

Where,
G = Conductance (S), R = Resistance (Ω), ρ = Resistivity (Ωm), A = Area (m^2), L = Length (m), σ = Conductivity (S/m), Xc = Capacitance reactance (Ω), f = frequency current (Hz), C = capacitance of sample (F), Co = capacitance of empty capacitor (F). ε^l = dielectric constant

Developing artificial neural network (ANN) model

The software used for developing the ANN model was SPSS version 23. Multilayer Perceptron procedure was employed to develop the model. The procedure details are (IBM SPSS, 2013; Haykin, 1998; Ripley, 1996):

1. *Assigning variables*

The target or output variable (Variety) was assigned a nominal variable. The independent or predictors' variables were divided into class. Moisture and current frequency were assigned ordinal variables and classified as factors; while conductance, resistance, resistivity, conductivity, capacitance reactance or impudence, capacitance and dielectric constant were assigned scale or continuous variables and classified as covariates.

2. *Rescaling*

Only the covariates or continuous variables were rescaled using the standardized formula:

$$\frac{X\ (value) - Mean}{Standard\ diaviation} \text{ ……..(6)}$$

3. *Data partitioning*

The whole data generated (375) was divided into three partitions:

i. Training sample (sample used to train and develop the network model). 60% of the generated data was assigned to this task.
ii. Testing sample (sample used to track error during training to prevent over training). 10% of the generated data was assigned to this task.
iii. Holdout sample (sample used to validate the developed network model). It gives an honest estimate of the predictive ability of the developed model. 30% of the generated data was assigned to this task.

4. Network architecture

The architectural structure of the network was design to have three layers. The first layer was design for the input variables (factors and covariates). The second layer is the hidden layer with units (perceptions) ranging from 1 – 10 units, depending on the error of predicting. The third layer was the output layer.

5. Activation Function

The activation function (the algorithm used to link the weighted sum of units in one layer to values in another layer) used in the hidden layer was Hyperbolic tangent. This function has the form: $\gamma(a) = tanh(a) = (e^{a} - e^{-a})/(e^{a} + e^{-a})$. It takes real-valued arguments and transforms them to the range (–1, 1). The activation function used in the output layer was Softmax (also refer to as normalized exponential function or softargmax). This function has the form: $\gamma(C_k) = exp(C_k)/\sum_j exp(C_j)$. It takes a vector of real-valued arguments and transforms it to a vector whose elements fall in the range (0, 1) and sum to 1.

6. Training

The batch training method (update network weights by passing it through all training data) was used. The optimization algorithm use to optimize the network was Scaled conjugate gradient. The optimization training was set at Initial Lambda of 0.0000005, Initial Sigma of 0.00005, Interval Center of zero and Interval Offset of ± 0.5. The error function used in the output layer to determine the error of the model was Cross-entropy loss function. This function has the form: $H(y,z) = -\sum_i y_i \log z_i$, where y and z are the experimental and the predicted value respectively.

Evaluation of Model Performance

1. ROC Curve

ROC curve (receiver operating characteristic curve) was plotted to evaluate the performance of the developed model. The graph was plotted using sensitivity (true positive rate) against 1 – specificity (false positive rate) (Fawcett, 2006; Mason and Graham, 2002). Formula used for plotting and evaluating were:

$$Sensitivity\ or\ True\ Positive\ Rate\ (TPR) = \frac{TP}{TP+FN} \quad \ldots\ldots\ldots\ldots\ldots (7)$$

$$False\ Positive\ Rate\ (FPR) = \frac{FP}{FP+TN} = 1 - Specificity \quad \ldots\ldots\ldots (8)$$

$$Specificity\ or\ True\ Negative\ Rate\ (TNR) = \frac{TN}{TN+FP} \quad \ldots\ldots\ldots\ldots (9)$$

$$A = \int_{x=0}^{1} TPR\big(FPR^{-1}(x)\big)\,dx = P(X_1 > X_0) \ldots\ldots\ldots\ldots\ldots (10)$$

Where TP = True positive, FN = False Negative, FP = False Positive, TN = True negative, A = Area under the curve, X_1 is the score for a positive instance and X_0 is the score for a negative instance.

2. Cumulative gain and lift chart

Cumulative gain chart was plotted using sensitivity (True Positive Rate) (TPR) against Support (Predictive Positive Rate) (SUP).

$$Sup = \frac{TP+FN}{N} = \frac{Pridicted\ position}{Total} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (11)$$

Cumulative lift chart was plotted using, Support (Predictive Positive Rate) (SUP) against True Positive over Predicted Positive value $\left(\frac{TP}{PPV}\right)$

$$PPV = \frac{Numbers\ of\ True\ Positives\ (TP)}{Numbers\ of\ True\ positives\ (TP) + numbers\ of\ false\ Positive (FP)} \quad \ldots\ldots\ldots (12)$$

Further Analysis on the developed model

RESULTS AND DISCUSSION

Some electrical properties generated in this study are displayed in Table 1. Total of 375 results were generated for each electrical properties examined. Resistance values generated range from 1.9 - 23Ω, conductance from 0.04 – 0.5S, resistivity from 0.3 – 3.3Ω/m, conductivity from 0.3 – 3.7S/m, capacitance from 1.3 x10^{-11} – 1.5 x10^{-7}F, dielectric constant from 0.5 – 5500, inductance from 6 x10^{-7} – 9 x10^{21}H, impudence from 1033339 - 137184749Ω. Some predicted varieties values generated by the developed

Pair t-test was carried out to compare the generated output and the model predicted output. The test was carried out at a confidence level of 99% ($p < 0.01$).

ANN model was also displayed in Table 1. In order to develop the neural network model 213 data (56.8%) was assign to training of the model (Table 2). This was chosen because of earlier observation during the development where data greater the 60% was used to train, result to over training with high error. To test the model 42 (11.2%) data (case) was used while 120 data (32%) was used to validate the model. The reason for these choices was the same as that explained for training. The information used in building the ANN is shown in Table 3.

Table 1: Multilayer Perceptron (MLP) Network Inputs and Output Values

S/N	Variety	Moisture (%)	frequency (kHz)	Resistance (Ω)	Conductance (S)	Resistivity (Ω/m)	Conductivity (S/m)	Capacitance (F)	Dielectric constant (ε)	Inductance (H)	Impudence (Ω)	MLP Predicted Value
1	1	8	1	23.15	0.04	3.27	0.31	1.3E-07	4642.86	1.1E-06	1224110	1
2	1	8	1	23.15	0.04	3.27	0.31	1.3E-07	4642.86	1.1E-06	1224110	1
3	1	8	1	23.15	0.04	3.27	0.31	1.3E-07	4642.86	1.1E-06	1224110	1
4	1	8	1	23.15	0.04	3.27	0.31	1.3E-07	4642.86	1.1E-06	1224110	1
5	1	8	1	23.15	0.04	3.27	0.31	1.3E-07	4642.86	1.1E-06	1224110	1
6	1	8	500	16.95	0.06	2.4	0.42	2.6E-11	0.9	1.2E-06	12241101	1
7	1	8	500	16.95	0.06	2.4	0.42	2.6E-11	0.9	1.2E-06	12241101	1
8	1	8	500	16.95	0.06	2.4	0.42	2.6E-11	0.9	1.2E-06	12241101	1
9	1	8	500	16.95	0.06	2.4	0.42	2.6E-11	0.9	1.2E-06	12241101	1
10	1	8	500	16.95	0.06	2.4	0.42	2.6E-11	0.9	1.2E-06	12241101	1
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126	2	8	1	6.36	0.16	0.9	1.11	1.5E-09	53.57	1.2E-06	1.06E+08	2
127	2	8	1	6.36	0.16	0.9	1.11	1.5E-09	53.57	1.2E-06	1.06E+08	2
128	2	8	1	6.36	0.16	0.9	1.11	1.5E-09	53.57	1.2E-06	1.06E+08	2
129	2	8	1	6.36	0.16	0.9	1.11	1.5E-09	53.57	1.2E-06	1.06E+08	2
130	2	8	1	6.36	0.16	0.9	1.11	1.5E-09	53.57	1.2E-06	1.06E+08	2
131	2	8	500	4.53	0.22	0.64	1.56	2.0E-11	0.7	1.1E-06	15601403	2
132	2	8	500	4.53	0.22	0.64	1.56	2.0E-11	0.7	1.1E-06	15601403	2
133	2	8	500	4.53	0.22	0.64	1.56	2.0E-11	0.7	1.1E-06	15601403	2
134	2	8	500	4.53	0.22	0.64	1.56	2.0E-11	0.7	1.1E-06	15601403	2
135	2	8	500	4.53	0.22	0.64	1.56	2.0E-11	0.7	1.1E-06	15601403	2
136	2	8	1000	5.32	0.19	0.75	1.33	3.2E-11	0.89	1.2E-06	4972947	2
.	.	.	.	.	.	.	.	.	.	.	.	.
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.	.	.	.	.	.	.	.	.	.	.	.	.
366	3	16	1500	2.54	0.39	0.36	2.78	2.5E-11	1.19	1.1E-06	4243582	3
367	3	16	1500	2.54	0.39	0.36	2.78	2.5E-11	1.19	1.1E-06	4243582	3
368	3	16	1500	2.54	0.39	0.36	2.78	2.5E-11	1.19	1.1E-06	4243582	3
369	3	16	1500	2.54	0.39	0.36	2.78	2.5E-11	1.19	1.1E-06	4243582	3
370	3	16	1500	2.54	0.39	0.36	2.78	2.5E-11	1.19	1.1E-06	4243582	3
371	3	16	2000	2.1	0.48	0.3	3.37	2.3E-11	1.55	5.9E-07	3429619	3
372	3	16	2000	2.1	0.48	0.3	3.37	2.3E-11	1.55	5.9E-07	3429619	3
373	3	16	2000	2.1	0.48	0.3	3.37	2.3E-11	1.55	5.9E-07	3429619	3
374	3	16	2000	2.1	0.48	0.3	3.37	2.3E-11	1.55	5.9E-07	3429619	3
375	3	16	2000	2.1	0.48	0.3	3.37	2.3E-11	1.55	5.9E-07	3429619	3

Variety: 1 = NGB/OG/0055, 2 = NGB/OG/0055, 3 = NG/OA/11/08/063

Table 2: Sample cases used to develop the ANN model for identification of cowpea seeds variety

Cases		Numbers	Percent
Sample	Training	213	56.8%
	Testing	42	11.2%
	Holdout	120	32.0%
Valid		375	100.0%
Excluded		0	
Total		375	

There were three layers in the developed model. One input layer, one hidden layer and one output layer. In the input layer there are two factors and eight covariates. Each factor had five units, so therefore units in the input layer are eighteen. The covariates were rescaled by standardizing their values. The reasoning for standardizing is because we want the means of these covariates to lie within zero and its standard deviation to lie within one. This is to make sure that the covariates with large values and that with lower values have the same weights during training. The hidden layer had one layer with seven units excluding the bias unit. The activation function used in the hidden layer was hyperbolic tangent. The choice of hyperbolic tangent was because we want all output in the hidden layer to lies between 1, 0 and -1. This is because there are three varieties options to predict. The output layer had one dependent variable with three units. The activation function used in the output layer was Softmax. Softmax was chosen because it takes real values and convert it into probability. This is good for predicting categorical output like ours. Cross-entropy algorithm was used to evaluate the error of the model outputs. Cross-entropy is used because it minimizes the distance between two probabilities distribution (i.e predicted and actual). Figure 3 shows the pictorial architectural structure of the developed ANN model.

After the training of the data to develop the model, the cross entropy error was found to be 20.1 (Table 4). This is quite a small error done by the model during training. This error accounts for the model predicting 4.2% of the training data wrongly in twenty (20) seconds of training. In testing the model, the cross entropy error was found to be 3.3. This also accounts for the model predicting 4.8% testing data wrongly. This low test result shows that the model was not over trained or under trained. The holdout analysis or the validation analysis shows that the model classified 7.5% of the data given to it wrongly. This validation is the true behavior of the model

Table 3: ANN model information for cowpea seeds identification

Layers	Unit information		
Input Layer	Factors	2	Moisture frequency
	Covariates	8	Resistance Conductance Resistivity Conductivity Capacitance Dielectric constant Inductance Impudence
	Number of Units[a]		18
	Rescaling Method for Covariates		Standardized
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		7
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	Variety
	Number of Units		3
	Activation Function		Softmax
	Error Function		Cross-entropy

a. Excluding the bias unit

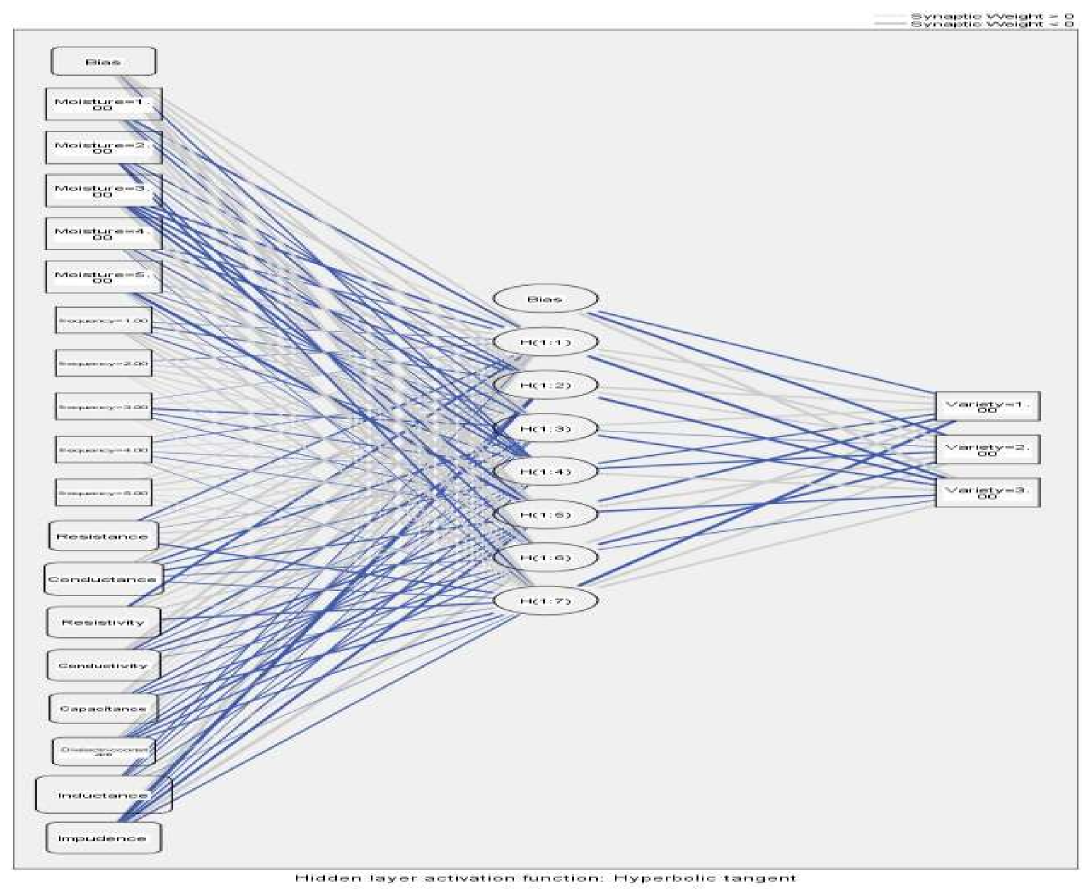


Figure 3: Architectural structure of ANN model for cowpea seeds variety identification.

Table 4: ANN model for cowpea seeds variety identification developmental analysis

Analysis	Activity	Result
Training	Cross Entropy Error	20.107
	Percent Incorrect Predictions	4.2%
	Stopping Rule Used	1 consecutive step(s) with no decrease in error[a]
	Training Time	0:00:00.20
Testing	Cross Entropy Error	3.340
	Percent Incorrect Predictions	4.8%
Holdout	Percent Incorrect Predictions	7.5%

a. Error computations are based on the testing sample.

developed. This is because it gives the honest predicting ability of the ANN model developed. After training, test and validate of the model, we now take a look at the weights developed with the network model. Table 5 shows the weights parameter estimates developed for ANN model used for predicting varieties of cowpea seeds. The ANN model developed is in a form:

$$Y = \left(\sum_{i=1}^{18} \underbrace{(X_i W_{1i} + b_0)}_{Input\ layer} \cdot \underbrace{\frac{(e^{a} - e^{-a})}{(e^{a} + e^{-a})}}_{Hidden\ Layer} \right) + \underbrace{\sum_{i=1}^{7} (H_i W_{2i} + b_1) \cdot \frac{exp(C_k)}{\sum_j exp(C_j)}}_{Output\ Layer} \quad \text{........ (13)}$$

Where Y = output (seed variety), X = predictor (input variables), W_1 = weight in input layer, b_0 = bias weight in input layer, i = number of unit in layer, $\frac{(e^{a}-e^{-a})}{(e^{a}+e^{-a})} = tanh(a)$ = Hyperbolic tangent function, H = input from the hidden layer, W_2 = weight from the hidden layer to the output layer, b_1 = bias weight in hidden layer, $\frac{exp(C_k)}{\sum_j exp(C_j)}$ = Softmax output function. The Hyperbolic tangent and Softmax function are used because the output variables are categorical. These functions render predicted values to lie between -1 and 1 for hyperbolic tangent function, 1 and 0 for softmax function. The performances of the model are displayed in Table 6.

The table shows that during training of the model; 97% of NGB/OG/0055, 100% of NG/AD/11/08/0033, 90% of NG/OA/11/08/063 was classified (predicted) correctly. The overall correctly Classification (prediction) of the three varieties during training was 95.8%. This shows that the model was not over trained or under trained. It also shows the accuracy of the network to lean and identify to be very high. The testing of the model to a separate set of data after training shows that 100% of NGB/OG/0055, 100% of NG/AD/11/08/0033, 87.5% of NG/OA/11/08/063

Table 5: Weights parameter estimates developed for ANN model

Predictor		H(1:1)	H(1:2)	H(1:3)	H(1:4)	H(1:5)	H(1:6)	H(1:7)	Variety = 1	Variety = 2	Variety = 3
		Parameter Estimates									
		Predicted									
		Hidden Layer 1							Output Layer		
Input Layer	(Bias)	1.589	1.534	1.590	-.575	1.396	2.977	2.092			
	Moisture = 1	-1.682	2.982	-.427	-1.121	2.662	0.647	0.167			
	Moisture = 2	0.451	-1.035	1.691	-0.214	0.149	-0.933	-1.154			
	Moisture = 3	-2.655	-2.728	-1.631	-1.962	-1.699	0.777	2.627			
	Moisture = 4	-1.199	-1.672	2.136	-1.078	3.970	1.677	-0.039			
	Moisture = 5	5.867	3.453	-0.479	3.360	-5.216	-0.151	1.564			
	Frequency = 1	-0.439	-1.609	-0.036	-1.142	1.748	.937	1.797			
	Frequency = 2	-0.390	2.366	1.257	1.364	0.275	0.102	0.244			
	Frequency = 3	-0.053	0.471	-2.344	-1.331	-0.501	0.182	0.115			
	Frequency = 4	1.201	-0.534	0.787	-0.178	-0.491	0.522	-0.037			
	Frequency = 5	0.494	0.427	2.082	0.624	0.221	1.008	0.214			
	Resistance	-1.412	-0.012	1.618	-0.123	1.821	0.308	-2.100			
	Conductance	3.039	2.487	-1.860	-1.000	-2.256	-0.735	-0.956			
	Resistivity	-1.944	0.519	1.564	0.008	2.742	0.744	-2.390			
	Conductivity	2.795	2.091	-1.658	-0.272	-2.258	-1.302	-0.166			
	Capacitance	1.512	0.234	0.050	-0.978	-1.135	-1.509	-1.832			
	Dielectric constant	1.653	0.162	-0.012	-0.693	-1.744	-1.267	-1.383			
	Inductance	-0.363	-0.331	-0.311	0.450	-0.377	0.211	-0.039			
	Impudence	2.581	-4.474	-0.131	-0.573	-2.012	7.834	-0.993			
Hidden Layer 1	(Bias)								-1.812	-3.439	5.109
	H(1:1)								3.130	3.969	-6.909
	H(1:2)								3.423	2.513	-6.014
	H(1:3)								3.185	-0.256	-2.447
	H(1:4)								-1.898	-2.615	4.949
	H(1:5)								-4.330	7.788	-2.684
	H(1:6)								5.326	-4.917	-0.606
	H(1:7)								-6.898	3.365	3.907

Variety: 1 = NGB/OG/0055, 2 = NGB/OG/0055, 3 = NG/OA/11/08/063
Moisture: 1 = 8%, 2 = 10%, 3 = 12%, 4 = 14%, 5 = 16%
Frequency: 1 = 1 kHz, 2 = 500 kHz, 3 = 1000 kHz, 4 = 1500 kHz, 5 = 2000 kHz

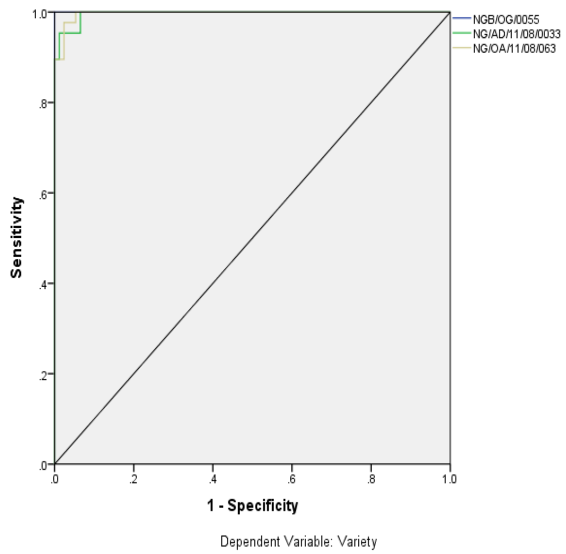
Table 6: ANN classification (prediction) performances during development.

Sample		NGB/OG/0055	NG/AD/11/08/0033	NG/OA/11/08/063	Percent Correct
		Predicted			
Training	NGB/OG/0055	67	2	0	97.1%
	NG/AD/11/08/0033	0	74	0	100.0%
	NG/OA/11/08/063	0	7	63	90.0%
	Overall Percent	31.5%	39.0%	29.6%	95.8%
Testing	NGB/OG/0055	14	0	0	100.0%
	NG/AD/11/08/0033	0	12	0	100.0%
	NG/OA/11/08/063	0	2	14	87.5%
	Overall Percent	33.3%	33.3%	33.3%	95.2%
Holdout	NGB/OG/0055	39	3	0	92.9%
	NG/AD/11/08/0033	0	39	0	100.0%
	NG/OA/11/08/063	0	6	33	84.6%
	Overall Percent	32.5%	40.0%	27.5%	92.5%

were classified (predicted) correctly. The overall correctly Classification (prediction) of the three varieties during the test was 95.2%. This confirms that fact that the ANN model is not over fitting (over trained) or under fitting (under trained). The validation (holdout) of the model done
on another separate set of data shows that 92.9% of NGB/OG/0055, 100% of NG/AD/11/08/0033, 84.6% of NG/OA/11/08/063 were classified correctly. The overall correctly Classification of the three varieties during the validation was 92.5%. This now validate the accuracy of the ANN model to be above 90%. Guzman et al. (2008), Golpour et al. (2014), Pazoki et al. (2014), Sumaryanti et al. (2015), Cinar and Koklu (2019) and Singh et al. (2020) obtain similar classification range with their developed neural network for classifying rice varieties. After viewing the performance of the ANN model developed, the need to evaluate its performance becomes necessary.

Evaluation of the performances of the developed model was done using ROC curve, cumulative gains chart and lift chart. The ROC curve (Figure 4) shows that the sensitivities (true positive rate) of the model to classify all three varieties are very high. The sensitivity is greater than 0.9 (90%). This means that more than 90% of correct positive results were predicted (classified) among all positive samples available during the test. This finding also agrees with the classification table (Table 6). The Consistency of the developed network (area between the diagonal and the ROC curve of each variety) is high and spread across the sensitive (true positive) and 1- specificity (false positive). This means that the network model is consistence in its prediction, whether for true or false classification (prediction). The area under curve (Figure 4) shows the probability that an ANN will classify or predict a randomly chosen positive instance higher than a randomly chosen negative one. For our developed network model, areas under curve are: 1.00 (100%) for NGB/OG/0055, 0.996 (99.6%) for NG/AD/11/08/0033 and 0.997 (99.7%) for NG/OA/11/08/063. This means that the network developed is informedness (estimates the probability of an informed decision for a multiclass case). The gain and lift chart measures the effectiveness of the developed network model, as shown in figure 5. The gain chart show the effectiveness of using the developed network model to that of random sampling (experimentation) as the population of the data sample used in training, testing or validation increases. A gain of 30, 60 and 90% was achieved by the developed network model when used for pollution sample of 10, 20 and 30% respectively. The chart also shows that from as population of the sample used exceed 40%, the developed model record no more gain. This is because the developed network model already had acquired enough information to replicate classification or prediction. The lift chart shows that within a sample population of 10 – 30%, the developed network model classification results for all varieties considered were three times more effective than that from the experiment. This effectiveness decreases to as the sample population increases. The decrease could be from the fact that increase sample population will cause over training (over fitting) of the model. It is important to look at how the variables used to develop the model contribute to the accuracy of the model.

Figure 5 shows the importance level of the variables used to develop the ANN model. Inductance was considered the most important variable. This could be because bulk cowpea seeds had tendency to oppose a change in the electric current flowing through it. The other variables in a decrease other of importance are: conductance, moisture, impudence, resistivity, conductivity, resistance, capacitance, dielectric constant and current frequency. Current frequency was the list important because it is almost constant in the inductance of the seeds expect at 2000 kHz. Further analysis was conducted on the developed ANN model.



Area Under the Curve

		Area
Variety	NGB/OG/0055	1.000
	NG/AD/11/08/0033	.996
	NG/OA/11/08/063	.997

Figure 4: ROC (Receiver Operating Characteristic) curve and area under the curve of the developed ANN model.

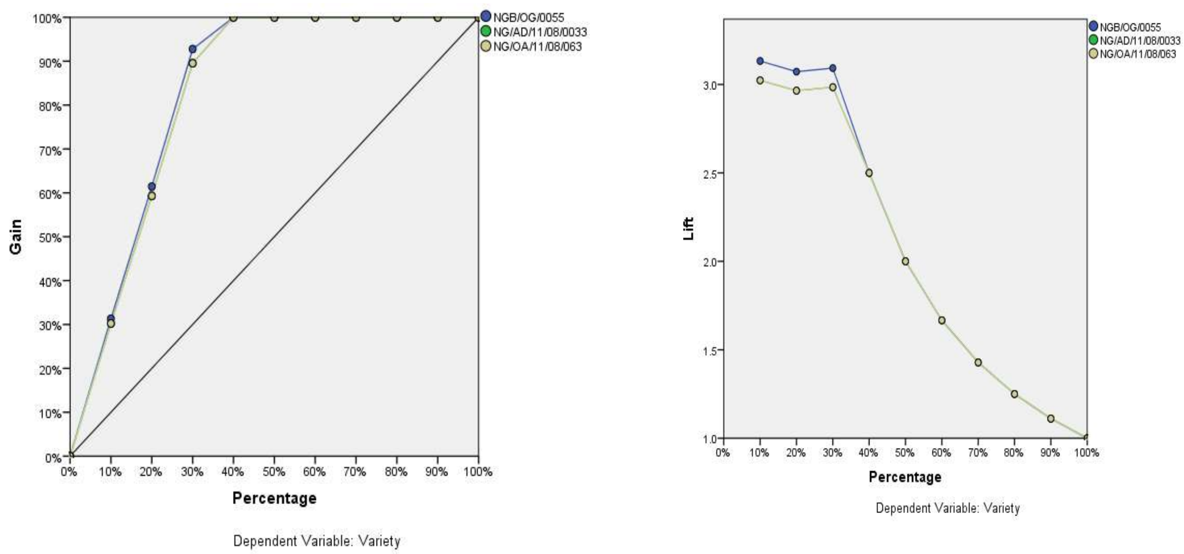


Figure 5: Cumulative gains and lift chart of the developed ANN model.

Independent Variable Importance		
	Importance	Normalized Importance
Moisture	0.107	68.10%
frequency	0.059	37.40%
Resistance	0.091	57.80%
Conductance	0.115	72.70%
Resistivity	0.101	64.10%
Conductivity	0.1	63.50%
Capacitance	0.089	56.50%
Dielectric constant	0.076	48.30%
Inductance	0.158	100.00%
Impudence	0.104	65.90%

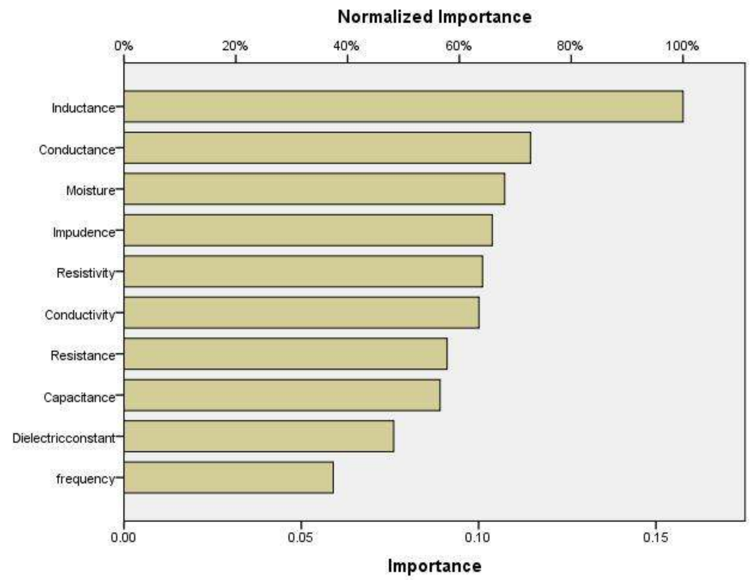


Figure 6: Independent variable (predictors) importance of the developed ANN model

A pair t – test was conducted between the predicted results from the network model developed and the experimental results generated at P<0.01. Table 7 shows the compared results obtain after the test (2 tail test). The standard errors of their mean results were both 0.04. This means that the accuracy their results are the same. The Paired Correlation between predicted results and the actual results was 0.96 (96%). This shows that both results are nearly perfectly related. The significant of this correlation was 9.36 x 10^{-208} at P<0.01. The pair significant for the comparison of 2 tail test was 0.025 at P<0.01. This significant indicate that there was no significant different between the means, of the predicted network model results and the experimental results at 99% confident level (i.e P<0.001).

Table 7: Paired t- test (at P < 0.01) between Variety and Predicted values for variety

Statistic	Variety	Predicted Value for Variety
Number of sample	375	375
Mean	2.0000	1.9733
Std. Deviation	0.81759	0.78375
Std. Error Mean	0.04222	0.04047
Paired Correlation	0.960	
Correction Significant	9.3616E-208	
Paired Mean	0.02667	
Paired Std. Deviation	0.22970	
Paired Std. Error Mean	0.01186	
T	2.248	
Degree of Freedom	374	
Paired Significant (2-tailed)	0.025	

CONCLUSION

Data was generated for electrical properties (resistance, conductance, resistivity, conductivity, capacitance, dielectric constant, inductance, impudence) at five different moisture content levels using five different current frequency ranges. Generated data was used to develop a multi-layer Perceptron artificial neural network model for classification (predicting) of bulk cowpea seeds variety. The developed network model performance was evaluated using ROC curve, gain and lift chart. The developed artificial neural network model, classified (predicted) more than 90% of all data given to it, whether during training, testing or validation correctly. A further analysis of 2 tailed paired t – test at p<0.01 was carried out for the model predicted and experimental results. The results show 96% (0.96) correlation between the results, with a paired significant of 0.025. Showing that there is no significant difference between the model predicted results and the experimental results at 99% confident level (P<0.001). This developed artificial neural network model can be used to program electrical sensors to identify cowpea seeds varieties during storage, handling and bulk transportation. Such device can be used to maintain standard and quality of cowpea seeds during bulk handling, processing, transportation, marketing and storage.

ACKNOWLEDGMENT
I want to thank the staffs of the electrical and electronic laboratory at the University of Ibadan; for the assistance and guidance given to me during data collection.

FUNDING
This work was supported by the Tertiary Education Trust Fund (TETFund) Nigeria.

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