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Research paper

Prediction of the moisture ratio of Atama (*Heinsia Crinita*) leaves using artificial neural network (ANN)

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Abstract

In this work, an artificial neural network (ANN) model was used to predict the moisture ratio of atama (*Heinsia crinita*) dried under different drying temperatures of 40 ^{0}C, 50 ^{0}C, 60 ^{0}C, and 70 ^{0}C using a laboratory dry oven. The experimental data collected (140 data points in all) which was partitioned into three sets: training (70%), validation (15%), and testing (15%) were modeled using artificial neural network (ANN), an Artificial Intelligence approach. The ANN model architecture of ANN (3 – 4 - 1) used in this work was selected by trial-and-error approach. The input layer had three (3) inputs (drying rate, temperature, time), the hidden layer had four (4) neurons, and the output layer had one (1) output (moisture ratio). Levenberg-Marquardt (LM) algorithm was used for training the network, and TANSIG and Purelin transfer/activation functions were used for the hidden layer and output layer, respectively. The model had a learning rate of 0.7, and the number of epochs was set at 1000. The results obtained showed that the ANN methodology could precisely predict experimental data with high correlation coefficient (R-Squared) value of 0.9995 – 0.9977 and low mean square error (RMSE) of 0.00052568, as the artificial neural network model more accurately predict the drying parameter (moisture ratio). The sensitivity analysis performed shows that temperature has the greatest impact on the moisture ratio of atama. From the finding, the ANN technology which is embedded in the neural toolbox of MATLAB mathematical software is indeed a tool of choice when it comes to the prediction of parameters of non-linear and complex processes like drying. The unique modelling technique and the model it evolved represent a huge step in the trajectory of achieving full automation of moisture ratio estimation which will increase the utilization of atama as well as other vegetables to curb the unending events of food spoilage currently plaguing the global food and agriculture industry.

Keywords: *Prediction; Moisture Ratio; Artificial Neural Network; Atama.*

1. Introduction

Green leafy vegetables play a vital role in the food culture of Nigerians and Africans as a whole [1]. A great variety of nutrients are found in vegetables consumed everyday through leaves, spinach, cabbage, carrot, onions, tomatoes and many others [2]. In fact, vegetables are the cheapest and most available sources of important nutrients and they contributed substantially to protein, mineral salts, vitamins, fibres, essential amino acids and other essential nutrients which are usually inadequately supplied in daily diets [3].

Scarcity of vegetable in the diet is a major cause of vitamin A deficiency, which causes blindness and even death in young children throughout the Arid and semi-Arid areas of Africa [2]. Fresh vegetables contain nutrients like potassium fiber, folate and vitamins A, E and C. Eating a diet rich in vegetables may reduce risk of stroke, cancer, heart disease and type-2 diabetes. More so, eating vegetable can make weight management easier. According to the Centre for disease control and prevention, most produce are low in calories compared to other foods, so filling up on vegetables can aid in weight loss [3].

Atama (*Heinsia crinita*), commonly called Bush Apple is a scrambling perennial shrub with woody stems and branches found in the secondary jungle; usually growing 8 - 13 meters tall in the under storey of high evergreen forests. It is called Atama, tonoposho and tumbwa in Efik, Yoruba, and Igala dialect respectively. It is native to the tropical areas of Africa; from Guinea to West Cameroons and Fernando Po, across the Congo basin up to East and South-Central Africa, most wildly grown in the southern parts of Nigeria [1].

The plant is a common vegetable which belongs in the Rubiaceae family and is cultivated as a source of food and medicine by the indigenous people of West Africa, especially the southern part of Nigeria. It is also said that there are three cultivars of Atama: the aromatic ones, the less aromatic ones, and the slightly bitter ones [4].

Fig. 1: Atama Plant.

Some physical and thermal properties of vegetables and other agricultural products like moisture diffusion, heat and mass transfer, specific energy and activation energy consumption are important factors considered in a proper dryer design [5]. The internal conditions such as moisture content, the temperature and the structure of the product play an important role in its drying rate. It has been accepted wholesomely that the drying phenomenon of biological products is controlled by the mechanism of liquid and/or vapour diffusion [6], [7].

Moisture often enter into food products in a number of ways; it could come from the production method of the product, the atmospheric moisture in the food production area, the packaging method of the food, or it can be related to the method of food storage, or it could even be a bound component of the food product itself. Drying which is a means of moisture level adjustment and control is a critical practice in the management and storage of many types of food products. As a unit operation, it is one of the most important and commonly used operations in the Food, Agriculture and Processing Industries since it is used in nearly every factory and facility that manufactures or handles food materials [8]. Although, plants respond differently to drying, vegetables, amid other foods when properly dried, are less susceptible to spoilage caused by bacterial growth, mold and insects. The effect of drying on plants will depend on the initial moisture content of the product and this varies with the type of vegetable to be dried [9].

2. Overview of artificial neural network (ANN)

Artificial neural networks (ANNs), usually referred to as neural networks (NNs), are computing systems vaguely inspired by the biological neural networks that constitute human brains. An ANN is an interlinked set of simulated neurons (nodes, inspired by a simplification of neurons in a brain) which are made up of several input signals with synaptic weights. In an ANN model structure, each circular node represents an artificial neuron and an arrow depicts a connection from the output of one artificial neuron to the input of another. An ANN model simply sums the products of inputs and their corresponding connection weights (w) and then it passes it through a transfer or activation function to get the output of that layer and feed it as an input to the next layer. A bias term is often added to the summation function in order to raise or lower the input which is received by the activation function. The activation function does the nonlinear transformation to the input making it capable to learn and perform more complex tasks. The general relationship between input and output in an ANN model can be expressed as shown in Eq. 1 [10].

3. Materials and methodology

3.1. Materials

Mature green and fresh atama leaves was purchased from the Akpan Andem market; a popular market within the Uyo Metropolis area of Akwa Ibom State. Other materials like laboratory dry oven, digital weighing balance, thermometer, stop watch, aluminum foil, and tong were obtained for use from the head technologist of the Chemical Engineering laboratory of the University of Uyo.

3.2. Methods

3.2.1. Drying experiments

Heat is the driving force in drying. If sample drying does not take place, it will not release its moisture (bound or unbound). Hence, heat is the first fundamental drying parameter [11]. The drying experiments were carried out using a laboratory dry oven (model: DHG-9101) in the chemical engineering laboratory of the University of Uyo. To ensure uniform physical characteristics during drying, the atama was gotten from the same plant stock. After being sliced, the atama sample was stored at room temperature ($26 \pm 1\ ^0C$) for 24 hours vacuum following the standard method [12]. After weight measurement, exactly 50g of the atama sample was carefully poured on a pan made from aluminium foil for drying using the available temperature control keys on the oven.

The sample was oven dried at temperatures; 40 ^{0}C, 50 ^{0}C, 60 ^{0}C, and 70 ^{0}C, each at 10 minutes intervals. For each of these temperatures, at every 10 minutes interval, the sample was periodically withdrawn for moisture loss on drying (LOD) measurement on a digital balance (model: PGW 2502e) with an accuracy of ± 0.01g. Drying operation was however, discontinued when the sample reached constant moisture content, after the values given on three separate readings did not change further.

3.2.2. Moisture ratio and drying rate

The Moisture Ratio (MR) of the samples would be calculated according to [13].

$$MR = \frac{M_t - M_e}{M_i - M_e} \quad (1)$$

Where,
MR = moisture ratio (dimensionless)
M_t = moisture content at any given time of drying(kg water/kg dry matter),
M_i = initial moisture content (kg water/kg dry matter), and
M_e = equilibrium moisture content (kg water/kg dry matter).
The value of M_e is relatively small compared with M_t and M_o especially for food materials. Therefore, M_e can be assumed to be zero, hence the equation for MR above can be simplified below [14].

$$MR = \frac{M_t}{M_0} \quad (2)$$

The Drying Rate, DR. of sample is controlled by the rate at which heat is applied to the sample, the rate at which the sample's internal moisture is released from its surface and the rate at which moist air is removed from the area surrounding the sample or product. The drying rate is computed thus [15];

$$DR = \frac{M_{t+dt} - M_t}{dt} \quad (3)$$

Where,
Mt = moisture content at time t.
Mt + dt = moisture content t+dt (kg water/kg dry matter), and
t = drying time in minutes.

3.2.3. Moisture content

Moisture Content, MC could be calculated using the following formula [15].

$$\text{Moisture content}(\%) = \frac{W_2 - W_3}{W_2 - W_1} X\ 100 \quad (4)$$

Where,
W_1= weight of foil (g);
W_2 = weight of foil and sample before drying (g); and
W_3 = weight of foil and sample (g) after drying.

3.3. ANN modelling process

To train the ANN, the MATLAB software which houses the ANN (as one of its tools) was used. This was done by using the command window to invoke the graphical user interface (GUI). The normalized inputs and target (s) were chosen and fed into network. Command nftool called the ANN tool. Training the network dropped error towards zero. Lower error does always mean a better network. To train the network, the different training algorithms-Levenberg-Marquardt, Bayesian Regularization, or Scaled Conjugate—can be used. Specifically, Levenberg-Marquardt training algorithm was used. Thereafter training dataset was used to adjust the weights on the neural network.
The number of neurons in the input and output layers quite simply determine the number of input and output parameters. ANN model typically consists of three layers: input, hidden, and output layers. Each of these layers consists of neurons (sometimes called nodes). The input layer is the first layer which has neurons that represent the inputs or parameters of a certain problem. The second layer is the hidden layer where the computational process is initiated. The output layer represents the labels or outputs of the problem, and consists of certain number of neurons based on the nature of the problem. In the work proper, well-thought-out choice of number of hidden layer(s) of just 1 with 5 neurons was made.
Validation dataset is a sample of data held back from the model training that is used to give an estimate of model skill while tuning model's hyper-parameters. Validation datasets is used for regularization by early stopping: stop training when the error on the validation dataset increases, as this is a sign of over-fitting to the training dataset. Test dataset is a sample of data equally held back from the training of the model, but is instead used to give an unbiased estimate of the skill of the final tuned model when comparing or selecting between final models. This data set is used only for testing the final solution in order to confirm the actual predictive power of the network.

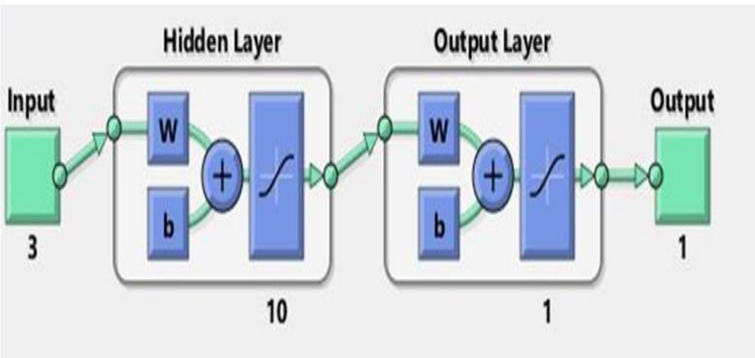

Fig. 2: ANN Configuration.

Also, the network performance was evaluated by correlation coefficient (R^2) and root mean square error (RMSE). These statistical values were computed as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{N} \left(C_{\mathrm{pre},i} - C_{\mathrm{exp},i}\right)^2}{\sum_{i=1}^{N} \left(\overline{C_{\mathrm{pre}}} - C_{\mathrm{exp},i}\right)^2},$$

$$\mathrm{RMSE} = \left[\frac{1}{N}\sum_{i=1}^{N} \left(C_{\mathrm{pre},i} - C_{\mathrm{exp},i}\right)^2\right]^{1/2} \quad (5)$$

Where
$C_{exp,i}$= the ith experimental data,
$C_{pre,i}$ = the ith predicted data by ANN model, and
N = the number of experimental data.

4. Results and discussion

In this project, the neural network toolbox of MATLAB mathematical software (Version 7.8, MathWorks, USA) was used to predict the moisture ratio of atama. The settings chosen for the ANN model are presented in Table 2. In the MATLAB software, the 140 dataset was partitioned into three sets: the training set (70%), test set (15%) and validation set (15%). The moisture content of the atama leaves at all experimental temperatures of 40 ^{0}C, 50 ^{0}C, 60 ^{0}C, and 70 ^{0}C were successfully reduced from 44.15g to approximately 0.1g (± 0.01g) water/g dry matter. It was clearly seen that the drying times of the leaves reduced significantly to 190 mins, 290 mins, and 380 mins from 480 mins as the temperature of drying increased from 40 ^{0}C to 50 ^{0}C, then to 60 °C, and 70 °C respectively. [17] reported 120 – 490 mins drying time range for microwave oven drying of thyme leaves, which do not vary much when compared with those experimental ranges obtained in this study [17].

4.1. Implementation of the artificial neural network

The predictive capacity of artificial neural network depended heavily on data. Parameter settings for the ANN model used in this work are presented in Table 1. A very good agreement between the experimental results and the ANN model can be identified clearly. For this study, the number of epochs was set at 1000. The input variables in the input layer comprise of drying temperature, drying rate and drying time and the output variable in the output layer is the moisture ratio (MR).

Table 1: Parameter Settings for the ANN Model

PARAMETERS	VALUES
Training data set	98 (70% of dataset)
Testing data set	21 (15% of dataset)
Validation data set	21 (15% of dataset)
Number of hidden layers	1
Number of neurons in hidden layer	5
Activation function (hidden layer)	Tansig
Activation function (output layer)	Purelin
Number of epochs	1000
Learning rate	0.7
Architecture selection method	Trial-and-error
Target goal mean square error	10^{-5}
Minimum performance gradient	10^{-5}

With percentage partition ratio of 70:15:15, the numbers of training, validation and testing data were 98, 21, and 21 respectively. A network (3-4-1) with an input layer of three inputs, one hidden layer of 4 neurons and one output layer of 1 output was used. The chosen network (3-4-1) was found to effectively and efficiently predict the moisture ratio of atama. The well-trained ANN model, having the best performance criteria was used to make the predictions. The performances in training, validation and testing are shown in Fig. 8 for the single hidden-layer (ANN [3-4-1]) model.

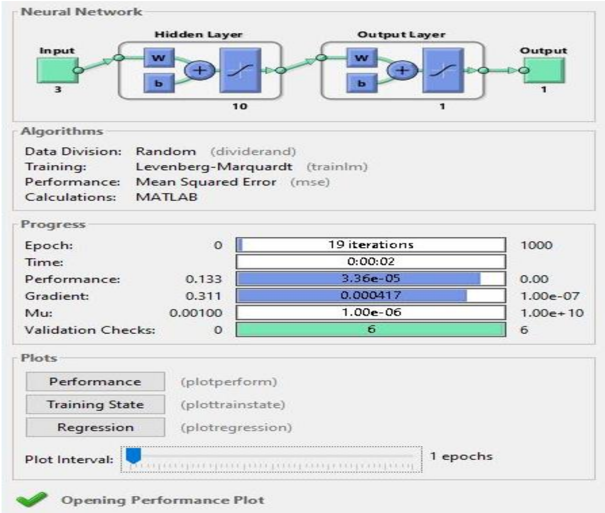

Fig. 3: Network Training Algorithms.

For the stated configuration (ANN [3-4-1]), since the R-square values for Levenberg-Marquardt method were higher compared with those for Bayesian Regularization in the training stages, the Levenberg Marquardt training algorithm was preferred in the modelling of the present experimental data. This algorithm particularly took a small fraction of time and trains faster compared to others. The ‘3’ in the notation refers to the total number of variables in the input layer (i.e. temperature, drying time, and drying rate), while the next ‘4’ refers to the number of neurons in the hidden layer used, while the last ‘1’ denotes the number of parameter in the output layer.

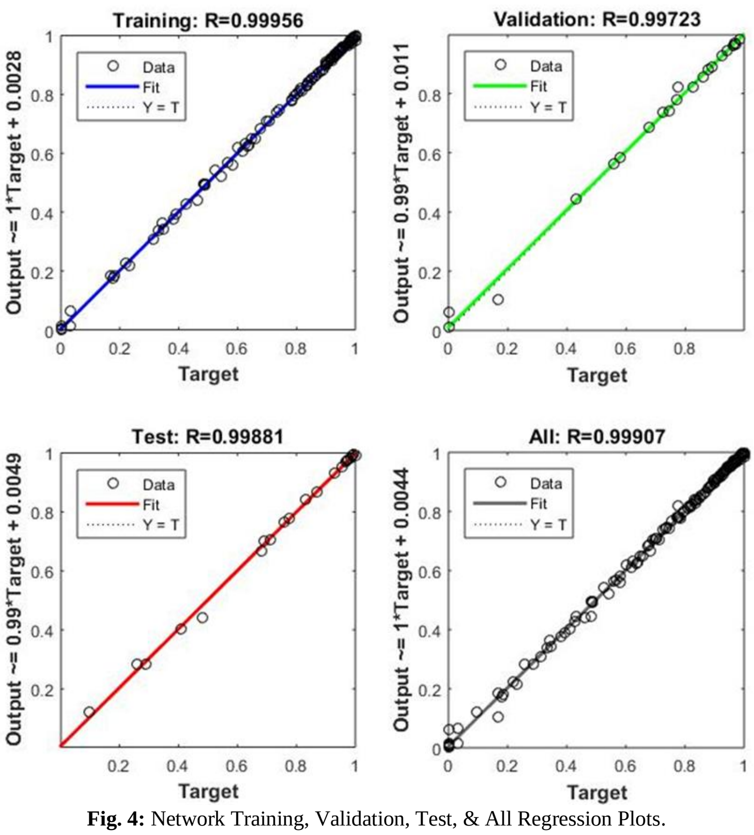

Fig. 4: Network Training, Validation, Test, & All Regression Plots.

The Regression Analysis Plots shows that the linear regression fit to the data points, matching the predicted output to the actual target. With correlation coefficients of 0.99956, 0.9973, 0.99881 for training, validation and testing respectively and an overall coefficient of 0.99907, it can be observed that the ANN model has performed perfectly well. More so, as a way of check, analysis performed using MS Excel also yielded a consistent overall correlation coefficient of 0.998935. This further gives credence to the fact that the ANN model did greatly well.

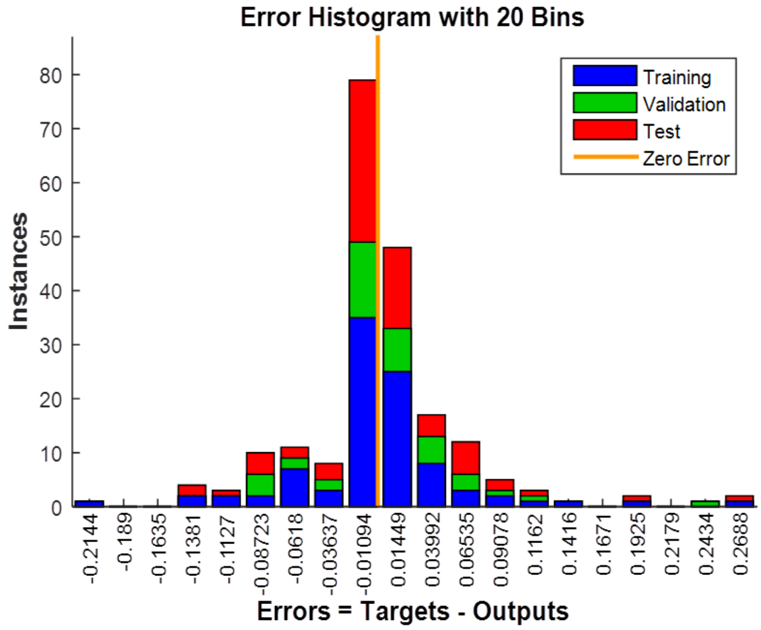

Fig. 5: Network Error Histogram with 20 Bins.

Fig. 5 above shows the distribution of errors for the training, validation and testing of the subsets. Bins are the number of vertical bars observed on the graph. The total error from the neural network ranges from -0.2144 (leftmost bin) to 0.2688 (rightmost bin). This error range is divided into 20 smaller bins; so each bin has a width of 0.02416 [(0.2688-(-0.2144))/20]. Each vertical bar represents the number of samples from the dataset, which lies in a particular bin.

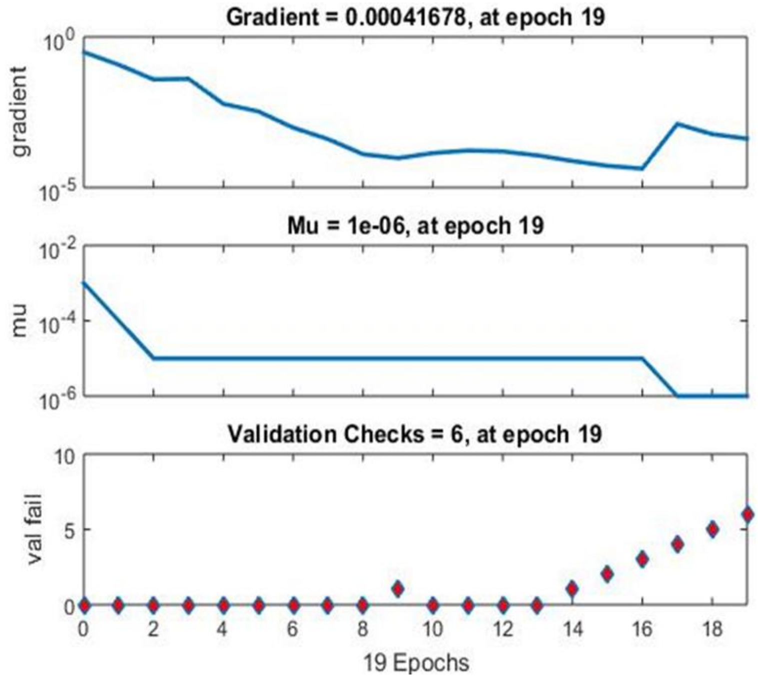

Fig. 6: Gradient Descent, Mu, Validation Checks Plots.

Fig. 6 (top) shows the gradient descent plot. Gradient descent as an optimization algorithm was used to minimize some functions by iteratively moving in the direction of steepest descent as defined by the negative of the gradient. At epoch of 19, the gradient is 0.00041678, as shown in the figure above. Also, it depicts the network Mu plot. Mu means momentum update. It is the approximate training gain which is usually not greater than 1.0. Mu is the control parameter for the algorithm used to train the neural network. Choice of mu directly affects the error convergence. Fig. 6 (bottom) is the validation checks. Validation though, not directly involved in weight estimation, protects the ability to generalize to non-training data. It equally stops training when the non-training validation subset error rate increases continuously for more than 6 (default) epochs. Validation subset error rate is therefore slightly biased.

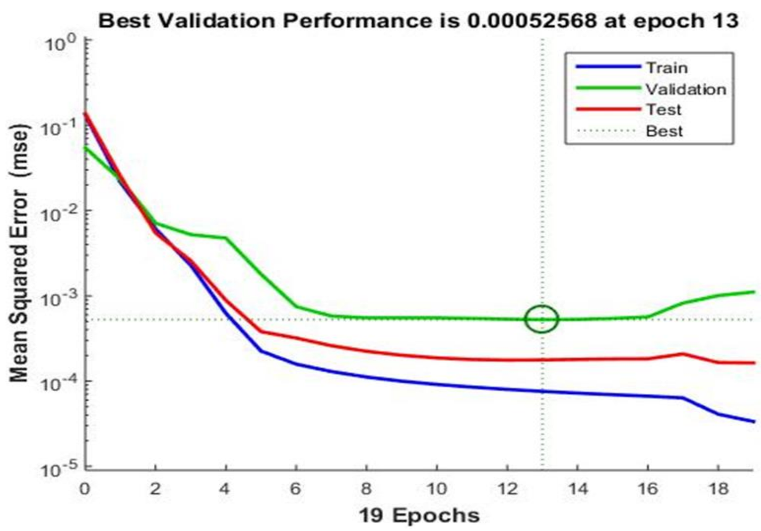

Fig. 7: Network Training Performance.

Fig. 7 above shows how the mean squared error (MSE) decreases, during training, validation and testing, as the number of epoch increases. This eventually culminates in the optimal performance during validation at 13th epoch, having MSE value of 0.00052568 approximately. This behavior shows that the network learns better, as the number of epoch increases.

Table 2: Summary of the Results

	SAMPLES	MSE	RMSE
Training	98	5.418e-4	9.99e-1
Validation	21	5.256e-4	9.997e-1
Testing	21	5.671e-4	9.998e-1

4.2. Performance of the ANN model

With prediction capability being the primary objective of a trained ANN, it is expected that the performance of a particular ANN during testing with test data should be the factor for selecting the best ANN architecture. The number of neurons in the hidden layer influences the generalization ability of the ANN model. Hence, in order to determine the optimal architecture for the network, a trial-and-error approach was used to select the optimum number of neurons in the hidden layer. In this direction, a series of topologies were examined (as listed in table 1), in which the number of neurons was varied from 10 to 20. The mean square error (MSE) was used as the error function. Decision on the optimum topology was based on the minimum error of testing. Each topology was repeated 15 times to avoid random correlation due to the random initialization of the weights. After repeated trials, it was found that a network with four (4) hidden neurons in the hidden layer produced the best performance for the ANN model with a validation MSE value of 5.2×10^{-4}. The optimal architecture of the ANN network and the drawn architecture/topology of the ANN result are shown in Fig. 7 and Fig. 8, respectively.

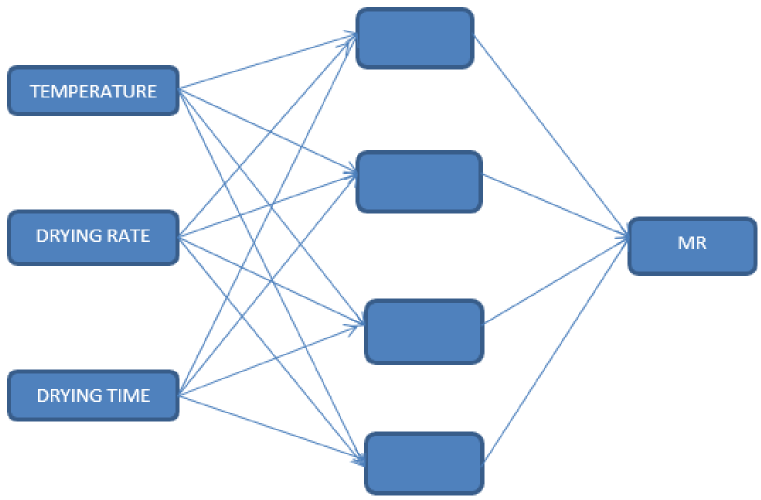

Fig. 8: Architecture (topology) of the ANN Network (3-4-1).

Table 3: Process Input and Output Parameters of Atama

PARAMETER	MINIMUM	MAXIMUM	AVERAGE	STANDARD DEVIATION
Drying Time (min)	0	480	185.6835	125.2941
Temperature (ºC)	40	70	51.51079	10.62630514
Drying rate (ºC/min)	0	1.484716	0.254100719	0.294648

Sequel to the normalization of input variables, the assignments of weights and biases to the normalized variables were performed. ‘W’ and ‘b’ denote weights (W) and biases (b) and were automatically generated by the network. The crucial and relevant relationship is linearly developed using equation 4.1 carefully outlined below:

$$E_{1,i,n} = \sum_{i=1}^{j}(W_{1,i,t} * t_{(norm)n} + W_{1,i,T} * T_{(norm)n} + W_{1,i,DR} * DR_{(norm)n}) + b_{1,i} \quad (6)$$

Where $W_{1,i,t}$, $W_{1,i,T}$, and $W_{1,i,R}$ refer to the weights assigned respectively to the drying time (t), drying temperature (T), and drying rate (DR); '$b_{l,i}$' is the bias at the particular hidden layer (l) assigned to the neuron (i). $t_{(norm)n}$, $T_{(norm)n}$, and $R_{(norm)n}$ are the nth values of normalized t, T, and DR respectively. '$E_{l,i,n}$' refers to the nth sum of the weighted normalized variables, based on the weight assignment in association with ith neuron at the hidden layer (l); j is the last count of neuron in the network.
List of aggregate weights and bias for the normalized input variables used in determining E1,i,n for ANN configuration (ANN[3-4-1]) is as shown in Table 4.

Table 4: Network Weights and Biases for Normalized Input Variables

Hidden layer 1	$W_{1,I,t}$	$W_{1,I,T}$	$W_{1,I,DR}$	Bias
1	1.7576	-1.4136	1.4395	3.2851
2	4.1975	1.9739	-0.85576	-2.486
3	-1.8104	1.9017	1.7116	1.5474
4	2.5558	1.2732	0.89907	-1.6959
5	2.1715	2.1031	0.32552	-0.062494
6	-2.5383	-1.07	0.19553	-0.97021
7	-2.8213	0.075674	0.49278	-2.3894
8	0.071363	2.4678	-1.1002	1.9251
9	1.8736	2.3361	0.55061	2.7212
10	1.6048	2.127	-1.7879	2.7361

Eq.10 expresses the assignments of weights and bias to the normalized variables at the hidden layer of the network. The listed weights and biases in Table 4 are simplified aggregates for each of the input variables, based on the 1 hidden layer in ANN [3-4-1]. The arrangement in the table simplifies the mathematical operations occurring between Equation 6 and the normalized input variables. Individual normalized variables are already expressed in Equation 6 to 9. The weights and bias indicated in Table 4 are aggregates of the results obtained after the simplification. Thus, '$E_{1,i,n}$' value can be readily determined by multiplying the appropriate weights (in Table 4) with values of the independent variables in Equation 6. The next step in developing the ANN-based model requires mathematical operation on the $E_{1,i,n}$ so obtained using Sigmoid transfer function. The function is mathematically expressed below:

$$\text{Sigmoid}\left(E_{1,i,n}\right) = M_{1,i,n} = \frac{L}{1 + e^{-k(E1,i,n-E1,i,n(0))}} \quad (7)$$

Where L = curve's maximum value, K = steepness of the curve, and $E_{1,i,n(0)}$ = mid-point value. Constraining the function such that K = 1, $E_{1,i,n(0)}$ = 0, and L = 1, equation 4.3 is obtained:

$$\text{Sigmoid}\left(E_{1,i,n}\right) = M_{1,i,n} = \frac{1}{1 + e^{-E1,i,n}} \quad (8)$$

It is pertinent to state that the description is limited to the single-hidden layer model used and it is solely for the sake of simplicity. The normalized final output is given here:

$$P_0 = (W_{o,i} * M_{1,i,n}) + b_o \quad (9)$$

Where Wo,i = 0.7690003 and b_o = -0.0390887, being the weight and bias at the output layer (o) respectively. $M_{1,i,n}$ is the previously defined value of the Sigmoid transformed variable, associated with the sum of the nth normalized input variable at the last hidden layer (l).
For this ANN model, the training process was truncated at 130 epochs for a 3-4-1 network architecture with a validation MSE of 5.2×10^{-4}. Therefore, the 3-4-1 architecture is considered the best neural network for the present problem due to its superior prediction capability. The predicted model fits so well to the actual values for both training, testing and validation sets as can be seen in their correlation coefficients (R) of 0.99956, 0.99881 and 0.99773 for the training, testing and validation data, respectively. The model generated by applying the Levenberg–Marquardt (LM) algorithm is given in Fig. 3.
More so, as a way of check, analysis performed using MS Excel also yielded a consistent overall correlation coefficient of 0.998935. This further gives credence to the fact that the ANN model did greatly well.

5. Conclusion and recommendation

In this work, it is shown that it is possible to predict the moisture ratio of atama using artificial neural network model. The ANN model predicted the moisture ratio with a high degree of precision, giving an optimized network R of 0.99907 for prediction of moisture ratio of atama. Successful application of the ANN tool as has been demonstrated in this work has the potential of increasing farmer's income by value addition as it represents a huge step in the trajectory of achieving full automation of moisture ratio estimation. And this will go a long way in reducing the quantity of atama lost yearly to spoilage as a result of insufficient storage facilities, which will ultimately increase the shelf-life of food products. The authors of this work therefore, recommend that future researchers should try using other drying methods like microwave drying, freeze drying, fluidized bed drying, etc. and other AI techniques like ANFIS, Fuzzy logic systems, Also, using genetic algorithms of the required threshold weights and biases provided in this research to see if they can replicate a similar result or trend as observed in this work.

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