



PREDICTION OF PHYSICAL PROPERTIES OF AFRICAN LOCUST BEAN SEEDS (PARKIA BIGLOBOSA) THROUGH NEURAL NETWORK

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Abstract

For efficient design of post-harvest processing machines/equipment, knowledge of the physical properties of agricultural materials is required. Individual measurements of respective material's properties are typically used to calculate the equipment/machines design parameters. These properties are important for grading and sorting processes. This study experimentally measured the individual dimensional properties of the seeds and by simulation used artificial neural network to predict some physical properties of African locust bean (*Parkia biglobosa*) seeds. Two artificial neural network structures, the Multilayer Propagation Neural Network (MLP) and the Radial Basis Neural Network (RBF) were employed. The dimensional properties of the seeds were used as the input variables and the derived seeds' properties - volume, surface and projected regions, geometric mean diameter and sphericity - were used as the output variables. The results showed that MLP structures of the artificial neural network could provide a better prediction of the seeds physical properties parameters, making it a viable replacement method for the manual approach.

Keyword: Prediction, physical properties, locust beans, neural network

Introduction

Parkia species are annual tree legumes that are members of the subfamily *Mimosoideae*. Its tree, fruit and seeds could serve the economic, social, nutritional, and medicinal needs of the Africans (Sanya *et al.*, 2013; Agwuwa and Okafor, 2012). The sweet pulp and pod could be fed to cattle, while the seeds could be fermented to make *iru*, a food condiment in the savanna regions of West and Central Africa. About 200,000 tonnes of fermented locust beans was estimated to be produced annually in Northern Nigeria (Ajewole *et al.*, 2018). Fermented locust bean source could provide low-cost protein where protein sources foods are deficient in African countries (Emmanuel *et al.*, 2017). Its seeds are high in protein, carbohydrate, lipids, vitamin A, B2 and lysine contents (Akintan *et al.*, 2013).

Several unit processes (decortication, depulping, steaming, dehulling, washing, and fermenting) are involved in the production of the seed's condiment. The traditional dehulling of the seeds entails foot-pressing, which is laborious, time-consuming, and unsanitary (Sanya *et al.*, 2013). The processing approach applied in any process has been asserted to an essential tool to enhance the process (Okonkwo *et al.*, 2018).

Several unit operations involved in its production required that machines be designed to move its production to a mechanised scale. the traditional locust bean dehulling in Nigeria, for example, had not witnessed any significant mechanisation and as such

the laborious, time-consuming, and inefficient practice approach is still the order (Olaoye, 2010). To achieve this, information about the seeds' engineering properties is needed.

The geometric mean diameter, sphericity, grain trajectory, surface area, grain volumetric and specific weight, density, porosity, and colour of agricultural materials among other physical properties are used in equipment design and for product production, handling, and transportation, sorting and grading, storage, and drying (Tabatabaefar and Rajabipour, 2005). Such properties of the materials are used to determine the final product quality and classifying different agricultural materials (Taner *et al.*, 2015). These qualities allow for the planning, development, and management of a wide range of postharvest devices and machinery. The size and shape of agricultural components should be known to plan sizing, harvesting, separation, planting and handling devices (Sahay and Singh, 2004). Surface and projected area are required for the design of pneumatic separation devices (Bwade and Aliyu, 2012).

The knowledge of physical properties of agricultural seeds plays a major role in machine and structural design and process control engineering. In unit operations of seeds such as dehulling, shelling, grinding, oil extraction, material handling and machine operations modelling, these parameters constitute the essential inputs for appropriate design of equipment (Obetta and Onwualu, 1999; Ezeaku *et al.*, 1998; Ibrahim and Onwualu, 2005; Nwakonobi and Onwualu, 2009).

Some studies have been conducted on the physical and engineering properties; production, nutritional, physicochemical, and biochemical qualities of African locust bean condiment 'dadawa' and its oil (Sobukola and Onwuka, 2011; Bamgboye and Sadiku, 2015; Adewumi *et al.*, 2015; Oluwole and Oluremi 2012; Olaoye, 2011; Ladokun and Adejuwon, 2013; Akintayo, 2004). However, there is a dearth of information on the utilisation of neural networks for the prediction physical properties of the seeds despite several uses of such in agricultural data prediction (Štastný *et al.*, 2011), products classification (Shahin *et al.*, 2002; Khalesi *et al.*, 2012; Dousti *et al.*, 2013; Reshadsedghi *et al.*, 2014), food and crop analysis (El-Sanhoty *et al.*, 2006; Monteiro *et al.*, 2007), drying process (Khazaei *et al.*, 2013), precise weed detection and weed seeds identification (Granitto *et al.*, 2002), yield prediction (Dahikar *et al.*, 2014) and data analysis tool in precision agriculture (Irmak *et al.*, 2006). This study predicts the physical properties of African locust bean (*Parkia biglobosa*) seeds using artificial neural networks.

Materials and Methods

Seed's Measurements

The locust bean seeds used were obtained from a local market in Saki (latitude 8.1239°N, longitude 5.0834°E), Oyo State, Nigeria. Specks of Dirt, broken seeds and any other foreign materials were removed manually from the seeds collection. The sample's moisture content was determined using the air-oven method, which allowed for the samples to be placed in an oven at $103 \pm 1^\circ\text{C}$ for 72 hours (ASAE, S 352.2) and calculated using equation 1

$$Q = \frac{100(m_i - m_f)}{m_f} \quad 1$$

where Q is the moisture content of the seeds (% dry basis); m_i is the initial mass of seed sample (g); m_f is the final mass of the seed sample (g).

The moisture content of the seeds was to be 9.87 % db. The measurements of the seeds' properties were conducted at the same moisture content level.

The axial dimensions (length (L , mm), width (W , mm) and thickness (T , mm)) of 100 randomly selected seeds (Figure 1) were measured with a vernier calliper of ± 0.01 mm accuracy.

The geometric mean diameter, (mm) and sphericity (ϕ) were calculated using equations 2 and 3 respectively (Mohsenin 1986).

Equations 2 and 3 were used to measure the geometric mean diameter, D_g (mm), and sphericity (ϕ) (Mohsenin 1986).

$$D_g = \sqrt[3]{LWT} \quad 2$$

$$\phi = \frac{D_g}{L} \quad 3$$

where L is the length of the seeds (mm); W is the width of the seeds (mm); T is the thickness of the seeds (mm).

The shape index (SI) was calculated using equation 4 (Sayinci *et al.* 2015):

$$SI = \frac{2L}{W+T} \quad 4$$

Using equation 5 the surface area of locust bean seeds was determined in analogous comparison with a sphere of the same geometric means diameter, D_g (Mohsenin 1986).

$$S = \pi D_g^2 \quad 5$$

where S is the surface area of the seeds (mm^2) and D_g is the geometric mean diameter.

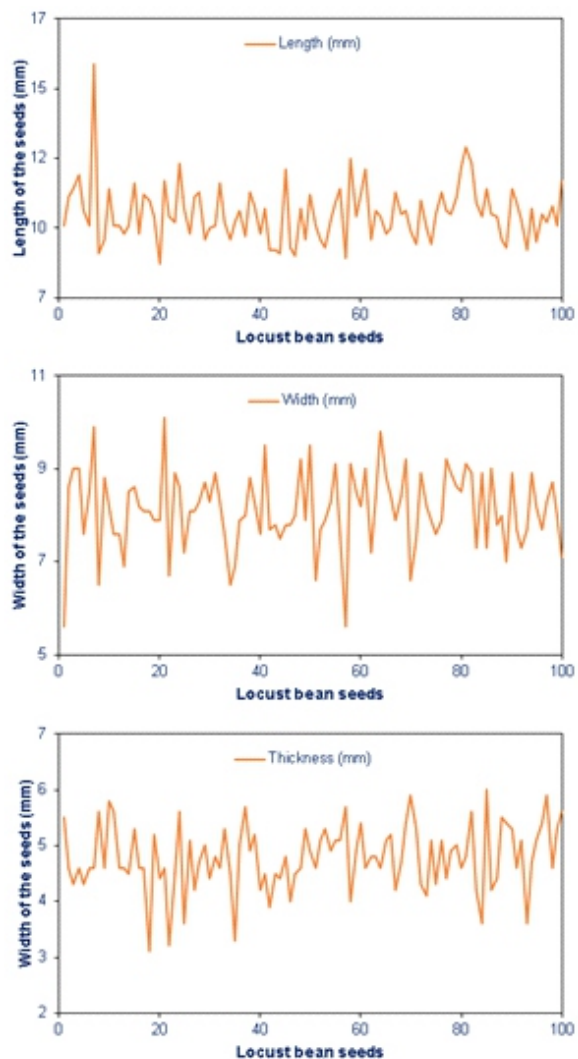


Figure 1. The (a) length, (b) width, (c) thickness main dimensions of the locust bean seeds.

The volume (V , mm^3), projected area (A_p , mm^2) and specific surface area of the seeds, S_{sp} , (m^{-1}) of the seed were calculated using equations 6, 7 and 8 respectively (Khazaei *et al.* 2006; Afonso Junior *et al.*, 2007; Miano *et al.*, 2018).

$$\begin{aligned} V &= \frac{\pi}{6} D_g^3 & 6 \\ A_p &= \frac{\pi}{4} D_g^2 & 7 \\ S_{sp} &= \frac{S}{V} & 8 \end{aligned}$$

Neural Networks

The multilayer perceptron (MLP) network is an input-feed artificial neural network with three layers: input layer, hidden layers and output layer, each with a collection of neurons and activation functions. The neurons measure a single output from different real-value inputs by generating a linear combination of input weights and then subjecting the output to a non-linear function. The output layer weights are changed first in the feed-forward propagation network since each of the outer layer neurons has a good value that could change the desired amount of weight. The amount of the training error was compared to the desired value after the network calculated the error and the learning algorithm optimized the value of the error. The learning process stopped if error learning is less than the determined error. The number of layers, number of neurons in each layer, trigger function (controller output of each neuron), training methods, weights and correction algorithms model the structure of a neural network (Figure 2).

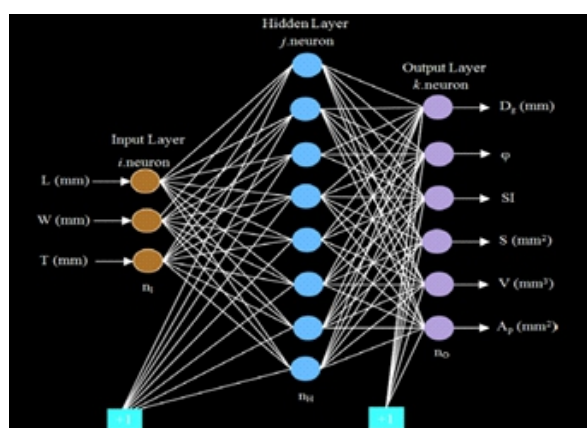


Figure 2: The structure of a neural network

Table 1: The Parameters for the Structures

Network Type	MLP	RBF
Learning rate	0.2	0.2
Momentum term	0.3	0.3
Iteration number	10,000	10,000
Input layer neurons	3	3
Hidden layer neurons	9	9
Output layer neurons	7	7
Transfer function	Sigmoid	sigmoid
RMSE	0.018054	3.376633

The most basic form of the Radial Basis Neural, RBF network is a three-layer neural feedforward network, where the first layer covers the network inputs, the second layer contains a hidden layer of non-linear RBF activation units and the last corresponds to the network's output. The existence of input and output variables determined the number of input and output nodes. Unlike the MLP network, the RBF network's transformation associated with each node of the hidden layer to output traditionally employed the Gaussian distribution function as a transfer function (Figure 2)

A dataset D with N patterns (x_p, y_p) for the RBFN workflow, where x_p is the data set to input and y_p is the actual output. The effects of i th activation function, ϕ_i could be measured in the network's hidden layer using Eq. (9) based on the distance from the x pattern of input to the centre i

$$\phi_i(\|x - c_i\|) = \exp\left(\frac{(\|x - c_i\|)^2}{2\sigma_j^2}\right) \quad 9$$

Here, is the Euclidean norm, c_j and σ_j are the centre and width of the hidden neuron j , respectively. The output of the k -node of the network output layer was calculated using the equation (10).

$$y_k = \sum_{j=1}^n \omega_{jk} \phi_j(x) \quad 10$$

The majority of the traditional techniques in RBF training were carried out in two stages. The first phase used unchecked clustering algorithms to determine the centres and widths and in the second stage, connection weights between the hidden layer and the output layer were found to be minimised via the entire data set by an error criterion like the common mean square error (MSE).

These two learning algorithms were applied to predict parameters of locust bean seeds using Tibco Statistica 14 (Tibco Software Inc.). The derived physical parameters of the locust bean seeds were trained using the process of the multilayer perceptron (MLP) and radial basis function (RBF) NN algorithms.

MLP and RBF Networking Performance

The effectiveness of the MLP and RBF neural networks for predicting the properties of the seeds were evaluated. The coefficient of determination (R^2), the root-mean-square error (RMSE), the efficiency coefficient (NSE) of Nash and Sutcliffe and the uncertainty coefficient (UII) of Theil were the metrics used to evaluate the adequacy and the strength of the networks. The metrics were expressed as:

$$R^2 = \left(\frac{\sum_{i=1}^N (\rho_i - \bar{\rho})(\mu_i - \bar{\mu})}{\sqrt{\sum_{i=1}^N (\rho_i - \bar{\rho})^2 \sum_{i=1}^N (\mu_i - \bar{\mu})^2}} \right)^2 \quad 11$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (\mu_i - \rho_i)^2}{N}} \quad 12$$

$$UII = \sqrt{\frac{\sum_{i=1}^N (\mu_i - \rho_i)^2}{\sum_{i=1}^N (\rho_i)^2}} \quad 13$$

$$NSE = 1 - \frac{\sum_{i=1}^N (\mu_i - \rho_i)^2}{\sum_{i=1}^N (\rho_i - \bar{\rho})^2} \quad 14$$

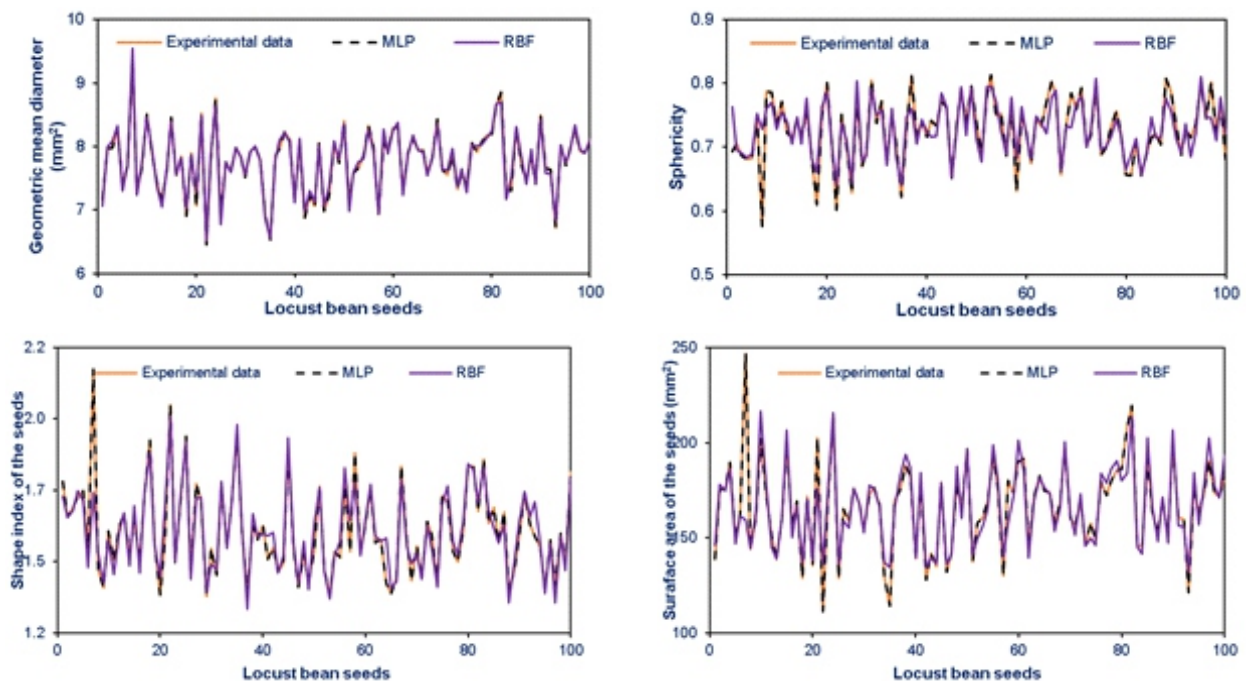
Where μ_i are the predicted values, P_i is the observed value of N is the number of observations of physical properties datasets. The evaluation of the computing model was based on the ranges of RMSE.

The accuracy performance analysis of each model is expressed as excellent prediction accuracy if the range of RMSE falls below 0.009; good prediction accuracy if the value ranges between 0.009 and 0.09; Reasonable prediction, if the value ranges between 0.09 and 0.5; and inaccurate prediction if the value is greater than 0.5.

Results and Discussion

The measured axial dimensions of locust bean seeds - length, width and thickness were used to determine some physical parameters - projected area, geometric mean diameter, sphericity, arithmetic mean diameter, shape index, surface area, aspect ratio, specific surface and volume. The derived data were trained in the MLP and the RBF structures.

Figure 3 presents the forecast outcomes of the predicted geometric mean diameter, sphericity, shape index, surface area, aspect ratio, volume, and specific surface of the locust bean seeds using the RBF and MLP structures. The prediction results of the parameter using the two algorithms were considered good. The MLP algorithm predictions presented a better description of the physical parameter than the RBF.



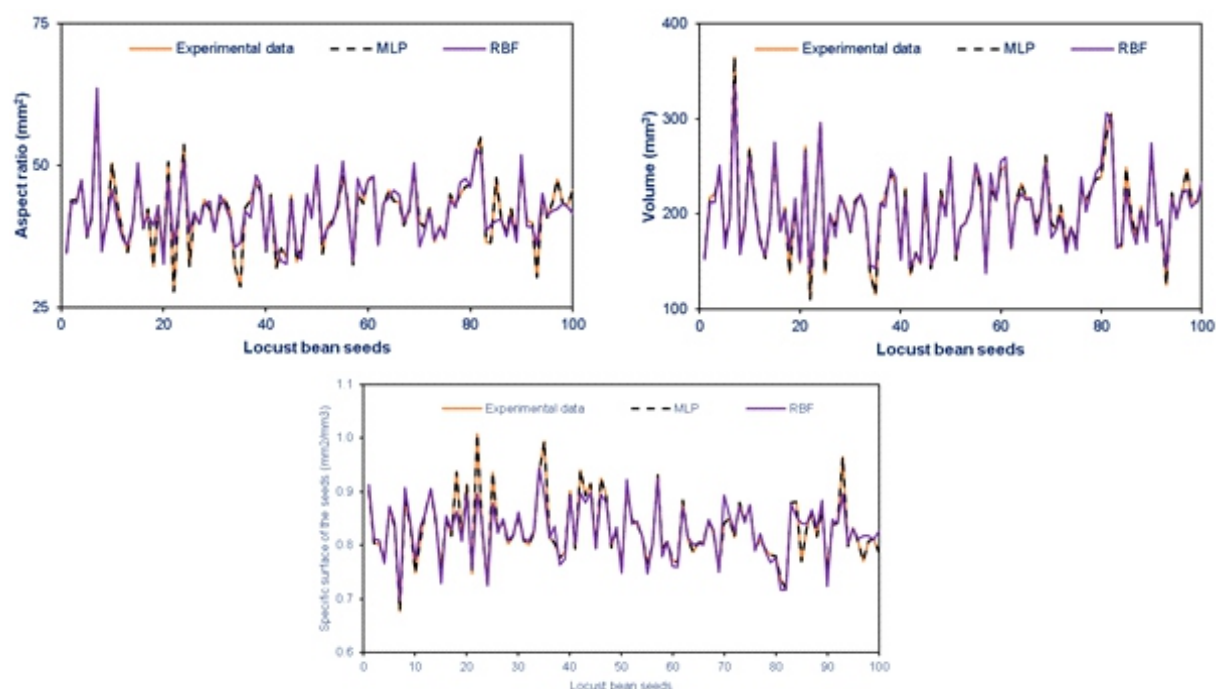


Figure 9. The experimental and prediction outcomes of geometric mean diameter, sphericity, shape index, surface area, aspect ratio, volume, and specific surface of locust bean seeds parameter using the MLP and RBF structures

From the simulation results, the MLP structure presented better predictions of related physical parameters than the RBF structure. The computing

model's evaluation was explained based on ranges of R^2 , RMSE, UII and NSE are summarised in Table 2.

Table 2: The Models' Performance Evaluation

Properties	MLP				RBF			
	RSQ	RMSE	UII	NSE	RSQ	RMSE	UII	NSE
Geom. mean dia.	0.99999	0.00180	0.00025	1.00000	0.97754	0.07704	0.01058	0.99989
Sphericity	0.99999	0.00013	0.00018	0.99999	0.73983	0.02576	0.03533	0.61024
Shape Index	1.00000	0.00031	0.00020	1.00000	0.85017	0.06123	0.03908	0.82345
Surface Area	1.00000	0.04489	0.00027	1.00000	0.76083	11.45705	0.06809	0.71402
Aspect ratio	1.00000	0.01237	0.00029	1.00000	0.83322	2.38566	0.05671	0.79280
Specific surface	0.99998	0.00028	0.00034	0.99998	0.82918	0.02492	0.02995	0.76689
Volume	1.00000	0.06660	0.00032	1.00000	0.94982	9.60477	0.04613	0.94432

The RMSE performance observed for locust seeds was 0.01805 and 3.37663 for MLPN and RBFN respectively. Demir *et al.* (2017) although obtained a similar RMSE performance trend for pumpkin seeds with 0.0025 and 0.06875 for BPNN and RBFN respectively. They reported that RBFN presented better predictions of the properties.

The generated pattern to describe the weight of the seeds by the MLP structure gave a very close shape and description as the experimental data. From the results, the MLP network presented a superior predictive performance in the estimation of the physical properties of the seeds compared to the RBN network. However, Eski *et al.* (2019) reported, superior performance of the RBF network compared to a modular neural network (MNN) in estimating the weight of different almond varieties.

Conclusions

This study determined the physical parameters of locust bean seeds. A neural network approach, using RBF and MLP structures, was used to predict the physical properties, as an alternative for the conventional calculation approach. The physical parameters evaluated were geometric mean diameter, projected area, sphericity, surface area, shape index, aspect ratio, specific surface and volume. From the experimental and simulation results, the MLP predictor presented better predictions compared to its counterpart, RBF. Therefore, the MLPN predictor can be used as an alternative method in the prediction of the physical parameters of the physical properties of African locust bean seeds.

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