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Artificial Neural Network Model for the Prediction of the Cotton Crop Leaf Area

A. M. Aboukarima[1*], H. A. Elsoury[1] and M. Menyawi[1]

[1]Agricultural Engineering Research Institute, Agricultural Research Centre, Dokki, Giza, Egypt.

Authors' contributions

This work was carried out in collaboration between all authors. Author AMA made artificial neural network analysis, managed the literature searches, and wrote the first draft of the manuscript. Author HAE collected and made measurements on cotton leaves, and managed the literature searches. Author MM managed the experimental process and performed the analysis of the data. All authors read and approved the final manuscript.

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ABSTRACT

Leaf area is an important indicator of crop growth and productivity. There are different instruments besides mathematical empirical models to estimate leaf area of crops, vegetables and fruits. This study investigates an Artificial Neural Network (ANN) model in prediction cotton leaf area. Best fitting results were obtained with 4 input nodes (leaf width, main lobe length, right lobe length and left lobe length), one hidden layer and one output layer (leaf area) as 4-6-1. ANN model performance was tested successfully to describe the relationship between measured and predicted cotton leaf area and coefficient of determination (R^2) was 0.9232. The developed ANN model produced satisfied correlation between measured and predicted value and minimum inspection error. Thus, the model can be used in easy way for agronomists and plant scientists in cotton crop research.

Keywords: Artificial neural network; cotton; leaf area; modeling.

**Corresponding author: E-mail: aboukarima@gmail.com;*

1. INTRODUCTION

Cotton is one of the oldest cultivated plants in Egypt. It is very important cash-crop for small-scale Egyptian farmers. The most important photosynthetic organ of the plant is leaves [1]. Besides, there are several factors affect cotton seed yield such as leaf shape, size, area and number of leaf per plant [2]. However, in the area of physiological and quantitative studies in crops, the accurate prediction of the leaf area from the raw data are playing important role in identifying plant growth [3-6], in estimating plant productivity [7], in analyzing of nutrient take up [8-10] as well as leaf area could be used as a means in analyzing of water use and for management of weeds and other pests for a plant [11-12].

Leaf area is often determined using expensive instruments including hand scanners and laser optic apparatus as well as prediction models. However, they can be very expensive and unnecessarily complex for basic and simple studies [13]. Several leaf area prediction models have been developed for different crops, vegetables and fruits using multiple linear regression technique. Multiple linear regression method is considered as a very powerful technique and is widely used to estimate linear relationship between response variable and predictors [14]. Multiple linear regression method can be used as a rapid and non-destructive method to estimate leaf area that only requires leaf dimensions as inputs. The limitation of modeling using a multiple linear regression technique is that it is useful only when the underlying relation between response and predictor variables is assumed to be linear. However, in a realistic situation, this assumption is rarely satisfied [14]. If there are several predictors, it is impossible to have an idea of the underlying non-linear functional relationship between response and predictor variables. Fortunately, to handle such a situation, an extremely versatile approach of artificial neural networks (ANNs) is developing rapidly [14]. ANNs are computational models based on the behavior of biological neural networks, and can be adjusted (trained) so that a particular input leads to a specified target output [15].

The data analysis using ANN has been increasingly applied worldwide in a range of scientific fields, including biological and agricultural research. Based on ANN, the analysis of results can be obtained in a relatively short time, even when considering lots of data. The method has become an attractive alternative to accepted statistical methods, and provides mean results which fit well the pattern of variable and hard–to-foretell phenomena in biological and agricultural systems [16].

ANNs are applied accurately in crop studies with different purposes [17-22]. However, Zaidi et al. [17] proposed a neural network model for the evaluation of lettuce plant growth. Meanwhile, Liu et al. [18] developed an artificial neural network model for crop yield responding to soil parameters. In addition, Soares et al. [19] utilized the artificial neural network technique in the prediction of the bunches' weight in banana plants. Besides, Dahikar and Rode [20] employed the artificial neural network approach in agricultural crop yield prediction and Guo et al. [21] also used it for crop yield forecasting. Finally, Dunea and Moise [22] applied the artificial neural network approach for leaf area modelling in crop canopies.

Ahmadian-Moghadam [13] employed an ANN model to predict pepper (*Capsicum annuum* L.) leaf area. The neural networks were trained with only 200 sets. After the training process, the predicted values of neural networks were compared with those of actual values not using in training process (10 sets). Comparisons showed behavior patterns of such neural network model in predicting leaf area. These results suggest that the length to width ratio of variables demonstrated strong effects on the leaf area. Results suggest that ANN provided an effective means of efficiently recognizing patterns in data and can be applied for accurate predictions of a performance index based on investigating inputs; it could also be used to optimize leaf area index based on measurements of leaf length and leaf width.

Vazquez-Cruz et al. [23] proposed a reliable and accurate model based on ANNs to estimate leaf area of tomato growth under greenhouse conditions. The multi-layer perceptron ANN topology was selected with five and three input variables. These topologies were trained and tested to simulate the response of leaf area with linear measurements leaf length and width. In order to prove the selected topology the ANN was tested with data (leaf length and width) from different experimental growth conditions. Both models had good precision with root mean square errors of 14.86 and 22.56 cm^2, and mean absolute errors of 10.29% and 16.74%, and coefficients of determination of 0.94 and 0.89, respectively. Overall, ANN models are a useful tool in investigating and understanding the relationships between leaf area development and climate factors under greenhouse conditions.

Odabas et al. [24] used an ANN model for the predication of the corn (*Zea mays* L.) leaf area. The results showed that, ANN was potentially an efficient and feasible tool for modeling of corn leaf area and it was much simpler than adopting a high dimensional polynomial regression since no pre-specified parameters, i.e. degree of polynomial and number of terms, are needed.

For both agronomists and plant scientists, inexpensive, rapid, reliable and non-destructive methods are become essential for measuring leaf area [6]. Such methods could save time compare with geometric measurements, and no expensive instruments are needed [25]. Different prediction models have recently been proposed for estimating leaf area of crops. Therefore, in this study, an artificial neural network model has been developed and tested to predict leaf area of cotton crop cultivated in Egypt.

2. MATERIALS AND METHODS

2.1 Basics of Artificial Neural Networks

The benefits of using ANN models are the simplicity of application and the robustness of the results [26]. However, ANNs were invented based on the model of the human brain and a biological neuron is shown in Fig. (1). The biological neuron consists of three main components: 1) dendrites, which channel input signals; 2) a cell body, which processes the input signals; 3) an axon that transmit the output signal to other connected neurons [28]. In the brain, the axon of each neuron transmits its information to other neurons through synapses via electrochemical medium called neurotransmitters. The synapses of a neuron receive information from approximately 10,000 other neurons [29-31].

Similarly to the brain, which consists of a huge number of neurons, ANNs possess lots of elements called artificial neuron (Fig. 2) which aim to process and transmit information. The neurons are associated in structures, the so called networks, by linkages called weights; during the learning process the weight values can be freely changed or else modified. The mode of linking of the neurons in the net, as well as their distribution and incidence, determines the network type and the mode of its action [16].

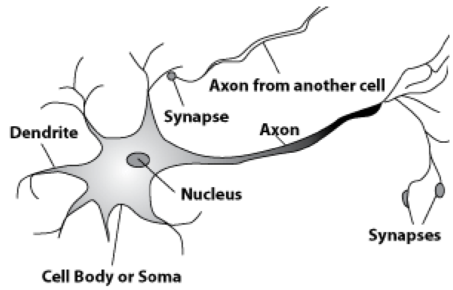

Fig. 1. A simplified model of biological neuron [27]

The sets $x_1,\ldots x_i$ represent input signals (for example leaf width, leaf length and other related variables), the w_{ki} are synaptic weights, b_k is a bias, v_k is an activation potential of the neuron k, $\varphi(.)$ is an activation function, y_k is the output signal of the neuron k and u_k is the net input, which is the sum of all inputs multiplied by all synaptic weights [16]. Each individual constituent of the network receives signals from the one placed in a preceding layer. The connection between the inputs is characterized by the weight coefficient w_{ki} and bias b_k. The signals are multiplied by the so called weighting factors, i.e. synaptic weights and then they are summed up as follows:

$$u_k = \sum_{j=1}^{i} w_{kj} x_j \tag{1}$$

The output is of the form:

$$y_k = \varphi(u_k + b_k) \tag{2}$$

The activation function φ could be sigmoid as shown in equation (3) or hyperbolic tangent (tanh) as shown in equation (4).

$$\varphi(x) = \frac{1}{1+e^{-x}} \tag{3}$$

$$\varphi(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \tag{4}$$

For solution of actual problems, ANN neurons are grouped in layers as shown in Fig. (3); these neural networks are called feed forward multilayer neural networks or multilayer perceptron. The layers between the input layer and output layers are called hidden layers; signals are sent from input layers through hidden layers to output layer [32]. In some networks, the output of neurons is fed back to the same layer or previous layers [33].

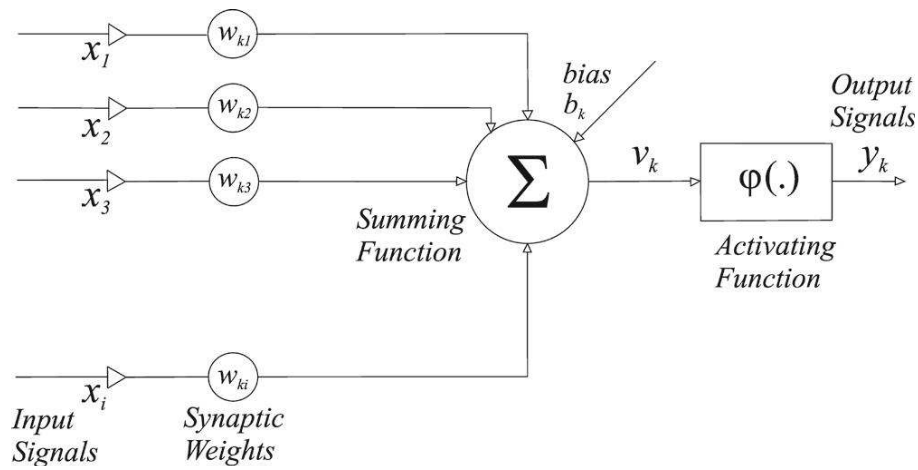

Fig. 2. Artificial neural network with *i* input variables and *k* neurons in its output layer [16]

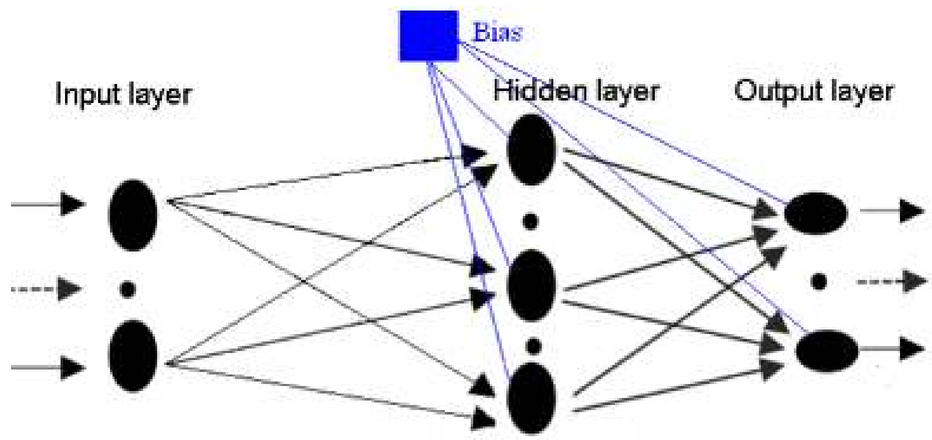

Fig. 3. A simplified three layers fully connected artificial neural network [34]

Each neuron in the net is connected to other neurons in a previous layer and the next layer through adaptable weights that are adjusted during training of a network. The weights are the parameters of the network. The signals from a preceding layer are multiplied by the weights of their corresponding connections. Each neuron in the hidden layers and output layer sums the corresponding weighted inputs and then computes its output according to a transfer function. In the case of a hidden layer, this output is passed on to the next layer; whereas, in the case of the output layer, neuron (s) output is the network output.

During the ANN model design, the most important stages are the assignation and the selection of an appropriate spatial arrangement of the network under construction, i.e. the number of layers and the number of neurons in each of them. This is a very important step, since too few layers or neurons can cause erroneous results, whereas overstatement can lead to biased fitting of the tested data. The next essential step in ANN construction is the process of network learning. However, there are two major learning paradigms, each corresponding to a particular abstract learning task. These are: supervised learning (with the so called "teacher") and unsupervised learning (without "teacher"). The first paradigm is used when there is a possibility to verify the answers given by the network. In this case, for each input vector, the value of the output vector is known as it is the exact solution to a given task. The second learning paradigm is applied when the solution is not known [16]. In most agricultural studies, a feed-forward network trained by a learning method called back propagation is used to develop prediction models [34-36].

2.2 Cotton Leaves Samples Collection

Leaves samples were randomly selected from four different cotton planting sites in Kafer El-Dawar region, El-Behera Governorate, Egypt during August 2014. The leaves were collected from three canopy layers on the cotton plant as shown in Fig. (4). Total 240 leaves were collected and some leaf dimensions like leaf width (distance between left and right lobes tip, W), leaf length (main lobe length [37] or distance between main lobe tip and leaf origin, L), right lobe length (distance between right lobe tip and leaf origin (L1) and left lobe length (distance between left lobe tip and leaf origin (L2) (Fig. 5) were measured and records for use to construct the ANN model. All these dimensions were measured with a graduated rule. Actual leaves were traced on graph papers (Fig. 6) and digital planimeter) Placom, KP-90 N, Koizomi, made in Japan) was calibrated and used to measure the actual area. Table (1) illustrates minimum and maximum values for dependent and independent variables in training data set.

2.3 Artificial Neural Networks Cotton Leaf Area Modeling

Commercially available QNET 2000 was employed in this study [38]. This software is a Windows-based package, which supports standard back-propagation algorithm for training purposes. QNET 2000 operates via a graphical user interface (GUI) that enables the user to load the training and test sets, design the network architecture and feed values for the training parameters. It was reported in the literature that one hidden layer is normally adequate to provide an accurate prediction and can be the first choice for any practical feed-forward network design [39-40]. Therefore, a single hidden layer network was employed in this study. So, the ANN used in this study was a standard back-propagation neural network with three layers: An input layer, a hidden layer and an output layer. Before training, a certain pre-processing steps on the network inputs and targets to make more efficient neural network training was performed using the following formula:

$$T = \frac{(t - t_{\min})}{(t_{\max} - t_{\min})} \times (0.85 - 0.15) + 0.15 \qquad (5)$$

Where t is the original values of input and output parameters, T is the normalized value; t_{max} and t_{min} are the maximum and minimum values of the input and the output parameters in training data set, respectively. The training data was used to compute the network parameters. The testing data was used to ensure robustness of the network parameters.

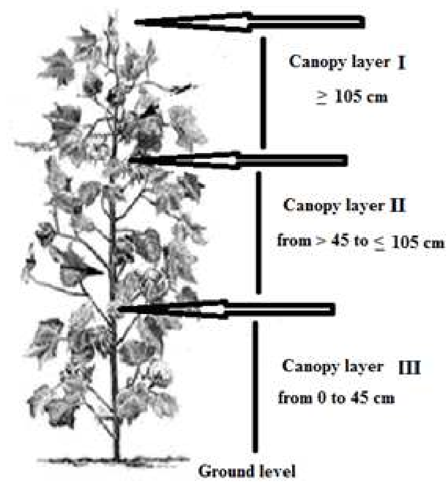

Fig. 4. Diagrammatic representation of canopy layers on a cotton plant

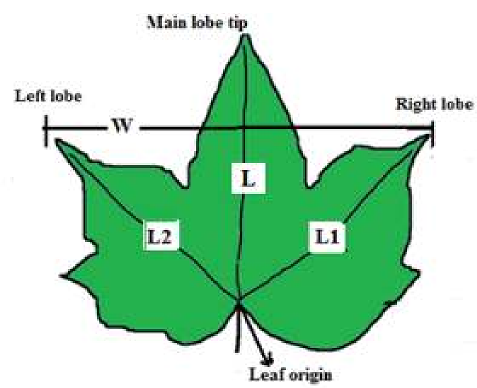

Fig. 5. Diagram of cotton leaf, showing the measured dimensions

The input parameters of the network were leaf width, main lobe length, right lobe length and left lobe length and output parameter was leaf area. Different networks with single hidden layer topology were tried. The most popular approach to finding the optimal number of neurons in hidden layer is by trial and error [41]. In this study, trial and error approach was used to determine the optimum neurons in hidden layer of the network (examined from 2 to 16 neurons). Also, transfer function was varied; however, they were sigmoid and hyperbolic tangent (tanh) in the hidden layer. 220 hundred data lines (training set) and 20 data lines (validation set) were randomly selected by the software from the database to train and test the ANN model. The best ANN model was elected based on highest correlation coefficient and lowest training error. The iteration was fixed to 200000. The learning rate and momentum coefficient was fixed and were to be 0.02 and 0.8, respectively. The transfer function was sigmoid in the hidden layer. The best ANN architecture had 6 neurons in the hidden layer as depicted in Fig. (7), so the trained network structure is 4-6-1. Training error curve of the best ANN configuration is illustrated in Fig. (8), however the training error was 0.023883.The statistical analysis during training and testing ANN model is shown in Table (2).

Fig. 6. Actual leaves traced on graph papers

Table 1. Minimum and maximum for dependent and independent variables in training data set

Statistical criteria	**Independent variables**				**Dependent variable**
	Leaf width	**Main lobe length**	**Right lobe length**	**Left lobe length**	**Actual leaf area**
	(cm)	**(cm)**	**(cm)**	**(cm)**	**(cm^2)**
Minimum	6.80	9.10	6.40	6.20	38.70
Maximum	26.20	22.90	19.00	19.20	321.40

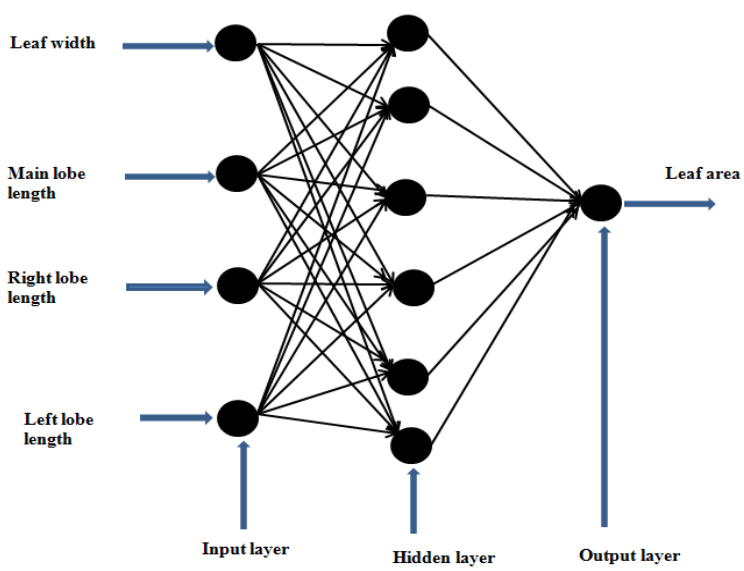

Fig. 7. The best ANN architectures (4-6-1) for prediction cotton leaf area

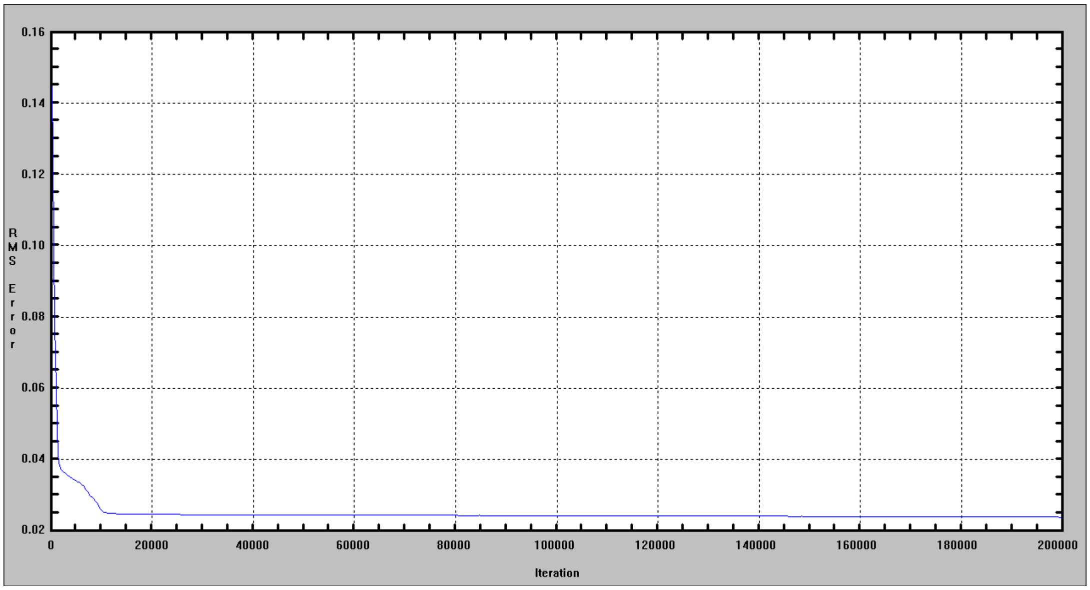

Fig. 8. Root mean square error of the normalized model output (leaf area)

Table 2. Statistical analysis during training and testing ANN model

Data set	Standard deviation (cm^2)	Bias (cm^2)	Maximum error (cm^2)	Correlation coefficient
Training	9.645	-0.0158	28.89	0.9876
Testing	18.811	-6.376	68.76	0.9608

2.4 Evaluation of ANN Model Predictability

In order to perform a supervised training, a way in which the ANN output error between the actual and the predicted output could be evaluated is therefore required. A popular measure is the mean absolute error (MAE), root means square error (RMSE) and mean relative error (MRE) as follows:

$$MAE = \frac{1}{N} \times \sum_{i=1}^{i=N} \left| LA_{viobs} - LA_{vipre} \right| \quad (6)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{i=N} \left(LA_{vi\,obs} - LA_{vi\,pre} \right)^2}{N}} \quad (7)$$

$$MRE = \frac{100}{N} \times \sum_{i=1}^{i=N} \left(\frac{LA_{vipre} - LA_{viobs}}{LA_{iobs}} \right) \quad (8)$$

Where LA_{viobs} and LA_{vipre} are actual and predicted cotton leaf area, respectively, N is number of observations. To measure the correlation between the actual and the predicted leaf area, the coefficient of determination (R^2) was calculated. As R^2 reflects the degree of fit for the mathematical model [42] and the closer the R^2 value is to 1, the better the model fits to the actual data [43].

3. RESULTS AND DISCUSSION

3.1 Frequency Distributions of Cotton Leaf Area Measurements

Frequency distribution for cotton main lobe length, for cotton leaf width, for right lob length of cotton leaf, for left lob length of cotton leaf and for measured cotton leaf area is shown in Figs. (9-13), respectively. Distributions for these dimensions were approximately normal. The range of the cotton main lobe length was between 9.1 to 22.9 cm, the rang of the cotton leaf width was 6.8 to 26.2 cm, the range of the right lob length of cotton was 6.4 to 19 cm, the rang of the left lob length of cotton leaf was 6.2 to 19.2 cm and the range of the measured cotton leaf area was 38.7 to 321.4 cm^2.

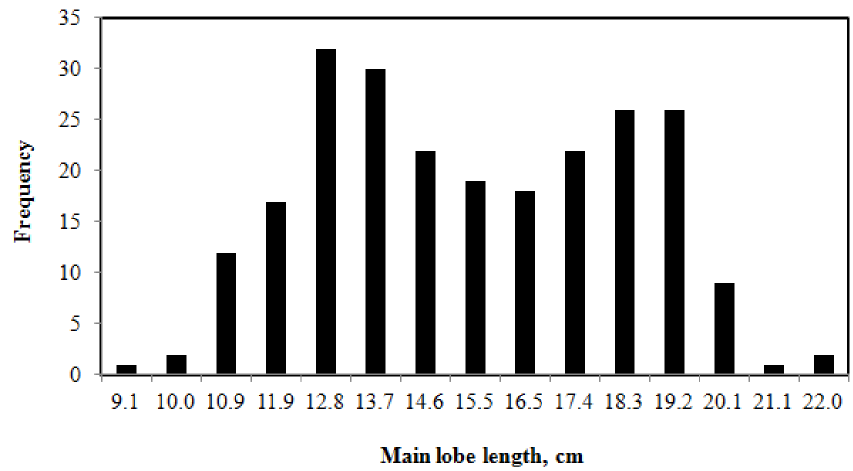

Fig. 9. Frequency distribution for main lobe length of cotton leaf

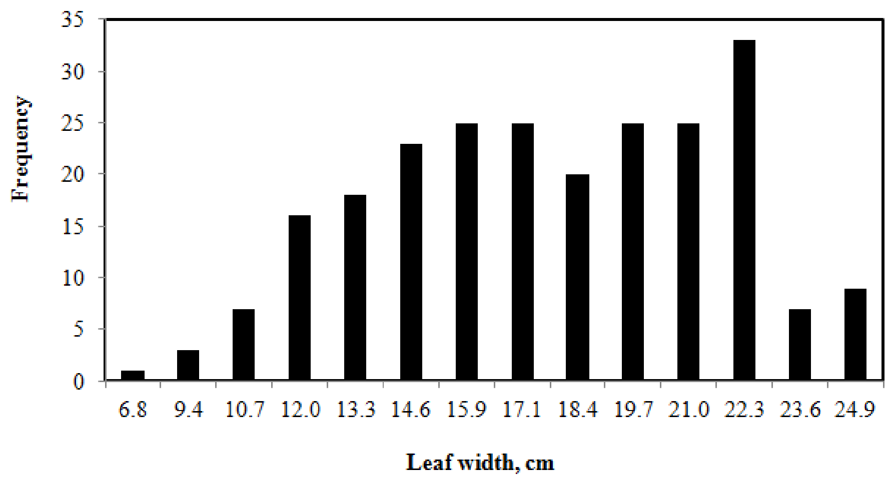

Fig. 10. Frequency distribution for cotton leaf width

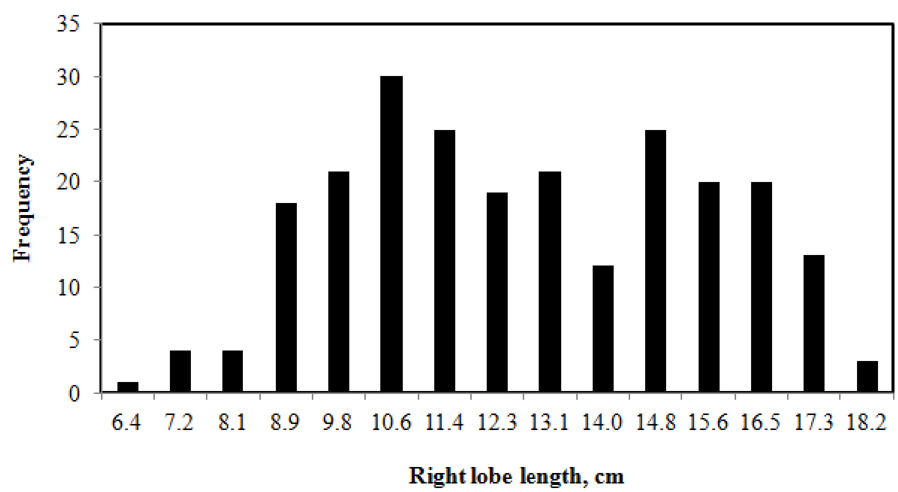

Fig. 11. Frequency distribution for right lob length of cotton leaf

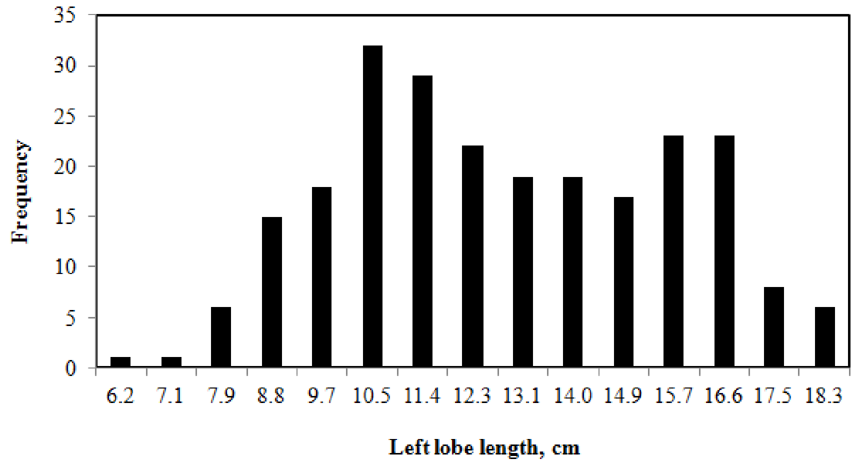

Fig. 12. Frequency distribution for left lob length of cotton leaf

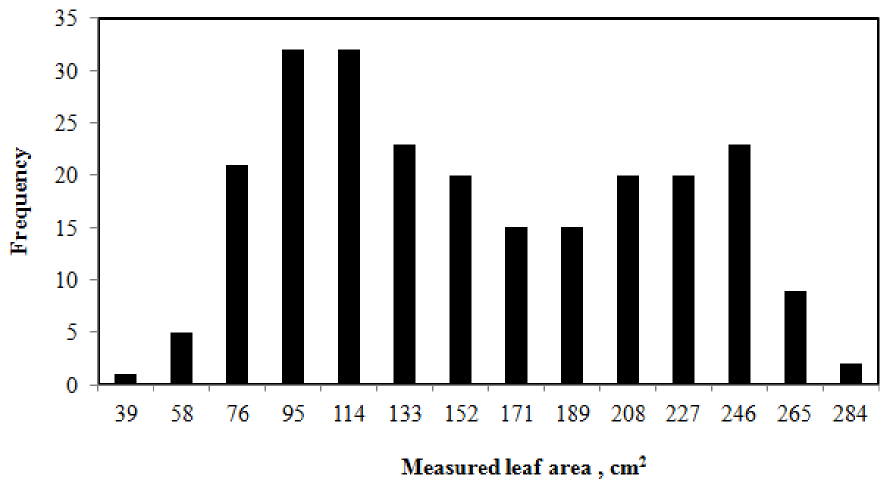

Fig. 13. Frequency distribution for measured cotton leaf area

3.2 Evaluation Performance of the Developed ANN Model

Results showed that feed-forward neural networks trained by back propagation algorithm had a good ability for creating of nonlinear mapping between input (leaf width, main lobe length, right lobe length and left lobe length), and output (leaf area) parameter. Among the various structures, model of good performance was produced by the 4-6-1 structure with sigmoid transfer function. Before arriving at this ANN configuration, several tests were carried out with different configurations of the neural network. The progress of the training was checked by plotting the measured (actual) leaf area and predicted leaf area by ANN model as shown in Fig. (14). Meanwhile, the plotting of the measured (actual) leaf area and predicted leaf area by ANN model during testing process is shown in Fig. (15). Mean absolute error, root means square error and mean relative error between cotton leaf area estimated by ANN model and actual values are presented in Table (3) during training and testing processes. RMSE between measured (actual) leaf area and predicted leaf area were 9.65 cm^2 and 18.81 cm^2 during training and testing phases, respectively as illustrated in Table (3). The obtained results demonstrated a very good agreement between measured cotton leaf area and predicted cotton leaf area using the ANN model. Also, the fit of the ANN model was evaluated by using coefficients of determination which are 0.9754 for training stage and 0.9232 for testing stage as illustrated in Fig. (14) and Fig. (15), respectively.

This result means that ANN model was able to explain 97.54% of variability in cotton leaf area in calibration (training) data and 92.32% of variability in validation (testing) data, when leaf width, leaf length, second right lobe length and second left lobe length were used as the input variables.

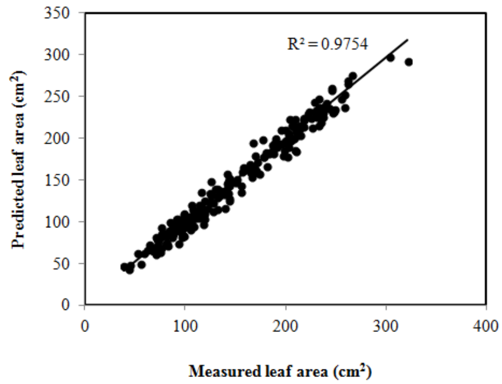

Fig. 14. Relationship between measured cotton leaf area and predicted cotton leaf area using the developed ANN model in training phase

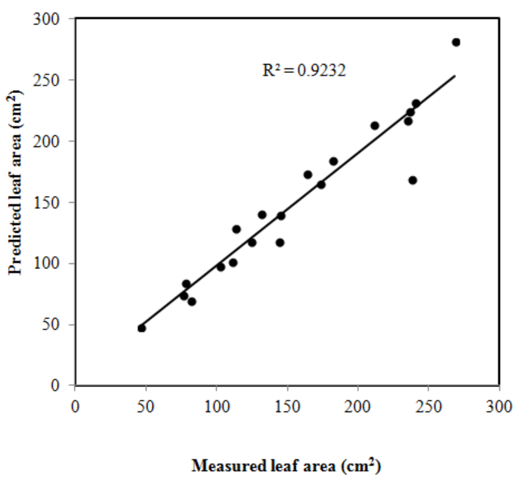

Fig. 15. Relationship between measured cotton leaf area and predicted cotton leaf area using the developed ANN model in testing phase

Table 3. Mean Absolute Error (MAE), Root Means Square Error (RMSE) and Mean Relative Error (MRE) of leaf area predictions

Data set	MAE (cm^2)	RMSE (cm^2)	MRE (%)
Training	7.41	9.65	-0.54
Testing	12.26	18.81	3.38

3.3 The Relative Importance of Input Variables

A sensitivity analysis was performed after the ANN model was trained, in which the relative contribution of each input variable to the output was examined. Sensitivities are determined in training set by cycling each input for all training patterns (cases) in the final network solution and computing the effect on the network's output response [44]. This analysis helps to identify the most important factors to leaf area. It was determined by the input node interrogator of the software (Qnet2000). Fig. (16) depicts contribution percent of input factors for prediction of cotton leaf area. The leaf width contributed with 29.03% to the networks output, meanwhile the main lobe length contributed with 13.21%, right lobe length contributed with 25.18% and left lobe length contributed with 32.58% to cotton leaf area.

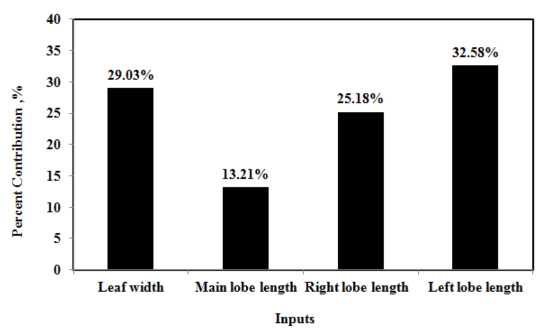

Fig. 16. The relative importance of the four input nodes to the network response

4. CONCLUSION

For crop growth and productivity studies, leaf area is become an important indicator in identifying plant growth, in estimating plant productivity, in analyzing of nutrient take up as well as leaf area could be used as a means in analyzing of water use and for management of weeds and other pests for a plant. Thus, different instruments and prediction models have been used and developed to estimate leaf area of different crops, vegetables and fruits. In the study, an artificial neural network (ANN) model for predicting leaf area was developed for cotton. The ANN model was able to explain 97.54% of variability in cotton leaf area in calibration (training) data and 92.32% of variability in validation (testing) data, when leaf width, leaf length, second right lobe length and second left lobe length were used as the input variables. Although leaf width, leaf length, second right lobe length and second left lobe length contributed significantly to the prediction of cotton leaf area with the ANN model, left lobe length was slightly superior, contributing 32.58% of the predictive capability. Overall, the neural network approach is promising for rapid collection of cotton leaf area information in effective manner without cost.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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