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Non-destructive Estimation of Leaf Area of *Citrus varieties* of the Kotra Germplasm Bank

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Abstract

Recently, mathematical modeling and computer expertise are advancing hastily. Their progression has been smooth sailing. The advancements have expedited and speeded up our scientific analyses. Hence, it is fruitful and essential to take advantage of the opportunities. Leaf area is among the most important plant properties which are directly related to ecological and physiological variables of a plant including leaf area index, light interception, evapotranspiration, photosynthesis, and growth. Thus, its calculation is extremely important. In this study, leaf area of species typica tress in Citrus and Subtropical Fruits Research Institute of Iran named Kotra Germplasm Bank include Orange (Citrus sinensis), Mandarin (Citrus reticulata), Lime (Citrus aurantifolia), and Lemon (Citrus lemon) were estimated using a non-destructive method Artificial neural network (NN) and by measuring quantitative leaf variables including width, length and a combination of width and length. For this purpose, four genera from each species were chosen and 200 leaves from different parts of their crown were collected. The width and length of the leaves were measured in the lab using a ruler, and their area was measured by a leaf area meter. This disquisition answered if GMDH-type NN was able to be applied to assess the area of the leaf as deferent according to particular variables consisting of a leaf with and leaf length. The average width, length, and area of leaves values significantly differed among the studied species as per the results.GMDH type NN provides a thriving tool for efficient detection of the model in data and precisely anticipating a proceeds indicator based on search input data and it's able to be used to predict leaf area according to width and length.

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Introduction

Citrus cultivation has had a very old history in Iran since 330 BC. The production of citrus fruit as a market crop is almost 303 years old [1]. According to Food and Agriculture Organization, Iran is eighth in the world in citrus production with 2.3 million tons of yield per annum. Leaf area is a crucial agronomic parameter because it is connected to plant growth and photosynthetic capacity [2], and consequently of transpiration and light interception [3], And it is often used to evaluate the impact of various plant cures[2]. It consequently of transpiration and light interception, plant productivity, and photosynthesis [3]. The element's significance in evaluating yield growth, crop potential, development rate, the efficiency of using radiation, water, and nutrients have been indicated by plant physiologists and agronomists [4, 5].

We measured leaf area in both non- and destructive ways. These methods can be used to estimate the value of multiple leaf areas. Numerous ways have been designed to ameliorate the leaf area measurement. Anyhow, these methods, consisting of tracing, photographing, blueprinting, or the use of a conventional planimeter, demanding the removal of leaves from the plants. Thus, making the sequential measurement of leaves impossible. The canopy of the plant is likewise impaired, Which may be the reason for trouble for further measurements or tests. Leaf area can be estimated fast, precisely, and non-wrecking by the use of a transferable to scan planimeter [6], however, its appropriability is for small plants with a small number of leaves. The second method of assessing leaf area is using a picture of analysis. By picture evaluation and analysis software. Taking a photo by digital cameras is fast and with accurate analysis from the correct software [7,8] the only thing being the costly and time-consuming processing. Accordingly, it is a cheap, reliable, fast, and non-destructive way for leaf area estimation needed by agronomists.

The mathematical relations between the area of the leaf and other leaf dimensions (length and breadth) can be explained. Thereby, GMDH was used to use as a way of rounding the problem of mathematical model foreknowledge of the intended procedure [2]. Thus, even without special knowledge of the systems, the modeling of complex systems can be done by GMDH. The construction of a feed-forward analytical function grounded on a quadratic node transfer function principles is the primary opinion of GMDH [6] in which the regression technique is used to get coefficients. The least-squares method that is used for model coefficients calculation in the real GMDH, is classified as complete and incomplete induction, which individually means the combinatorial (COMBI) and multilayered iterative algorithms (MIA) [7]. The benefit of these self-structured networks can lead to the victorious usage of the GMDH algorithm type in various fields like engineering, science, and economics [8]. We were required to apply a suitable sample to assess the area of the leaf in physiological studies of Citrus cultivars. Hence, the purpose of our research was to extend a pattern for forecasting leaf area from leaf length and breath i.e. linear measurements of citrus types was growing in Kotra Germplasm Bank.

Materials and Methods

The examination was carried out in 2019 at Gilan University, Rasht, Iran. The Citrus varieties used for this study were obtained from Kotra Germplasm Bank in province Mazandaran. First, leaves of different sizes were randomly prepared as a sample for leaf area estimation from different canopy levels (Figure 1). Leaves from different Citrus varieties were used for length (L), leaf area (LA), and breadth (W) measurement.

Leaves were placed in plastic bags immediately after cutting then taken to the laboratory. Leaf length

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was measured from the lamina tip to the crossing point of the lamina and the petiole, through with midrib values. L and W were written down to the closest 0.01 mm. Leaf area (LA) was measured to use a leaf area meter (a: Conveyor Belt Unit, Delte-T Device LTD, Burwell, Cambridge England b: Light TBOX, Serial No: 20756112/11/2001 Made In UK c: Camera: iλ_ CV 53200 CE NA P3 21515 MADE IN JAPAN d: The Stand Of Camera A: HFB RBZ 5450 Cerien-RN Made In Germany e: SoftWare Analyzer Windows 2.0).

The data places (input-output data), the collected data includes were around extracted from the data based on training and calibrating the GMDH-type NN (Goudriaan and Van Laar, 1994; Iba et al., 1996).

Figure 1. Leaf shape from (*Citrus* Spp) Twenty-four genotypes.

Table 1. Ranges of data patterns (input-output) that is used from (*Citrus* Spp) Twenty-four genotypes.

Genotype		**Input**		**Input**		**Output**	
		Length (mm)		**Width (mm)**		**leaf area meter (cm^2)**	
		Max	Min	Max	Min	Max	Min
Sweet Orange (*Citrus sinensis*)	Valencia	109.10	54.12	5705	23.27	25.33	5.07
	Thomson Navel	108.43	57.66	89.76	22.75	24.31	5
	Jaffa	178.36	51.1	91.88	20.19	65.43	3.81
	Sanguinello	107.25	49.46	46.07	14.66	17.89	2.58
	Parent novel	12.66	58.15	53.11	23.69	21.37	5.8
	Sanguine	123.17	50.59	52.17	20.92	24.31	4.65
	Washington navel	114.35	30.78	56.33	13.98	24.53	6.26
	Cross sanguine	120.58	27.66	51.08	21.37	39.57	6.07

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	Hamline	132.02	72.59	59.61	29.04	46.92	8.67
	Mars	163.36	56.97	72.3	21.09	42.58	4.86
Mandarin (*Citrus reticulata*)	Tangelo Orlando	88.66	33.77	31.05	15.03	10.97	2.25
	Page	119.37	60.68	47.23	21.41	23	4.97
	Atabaki	104.37	27.36	83.01	11.84	20.76	0.9
	Ponkan	115.79	46.86	49.93	20.4	22.34	3.84
	Cleopatra	84.62	19.89	32.27	8.79	10.16	0.35
	Minulla tangelo	105.02	27.6	48.96	12.14	23.89	1.64
	Unshu	117.2	61.38	46.65	22.51	19.15	3.84
	Clementine	108.22	33.04	35.02	9.67	11.58	1.46
	Dancy	93.33	20.48	45.45	9.09	15.37	0.87
Lime (*Citrus aurantifolia*) and Lemon (*Citrus lemon*)	Lisbon	178.36	76.25	82.98	48.2	54.66	19.55
	Koch Eureka	148.13	67.18	67.69	32.23	35.83	8.5
	Amol pear lemon	117.84	55.46	69.17	36.19	28.4	7.4
	Eureka	140.73	30.98	64.89	20.84	33.03	3.94
	Sweet Lime	120.4	44.53	59.73	20.54	28.71	3.59

Figures 2-9 are describing neural network model-predicted performance compared to actual data.

We selected N data lines (input-output) randomly from X lines of data (training set) and P data lines (input-output) from Y data lines (testing set) for any genotypes.

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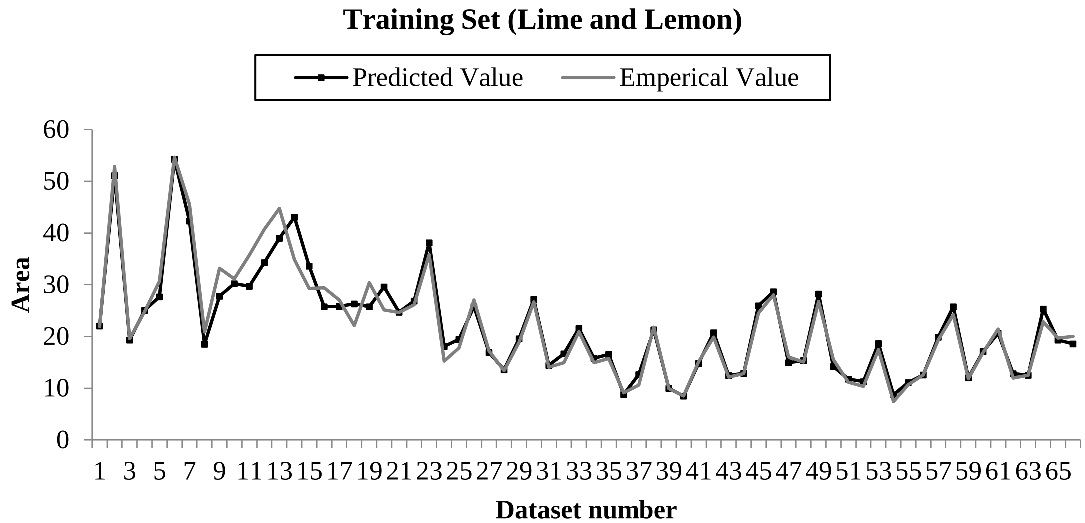

Figure 2. A predicted Neural network model function compared to real data for the training set Lime and Lemon (input-output data).

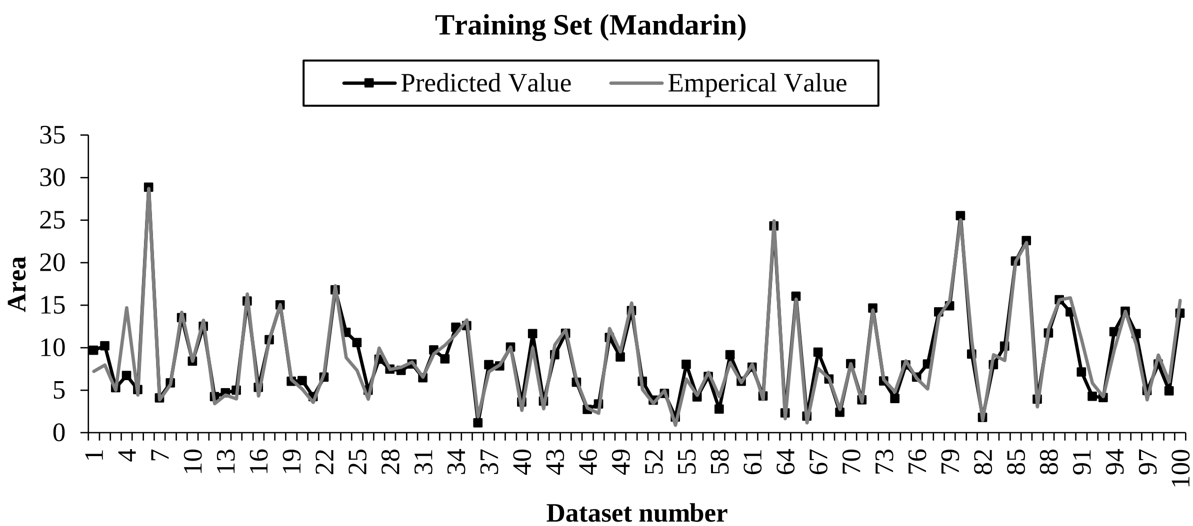

Figure 3. A predicted Neural network model function compared to real data for the testing set Mandarin (input-output data).

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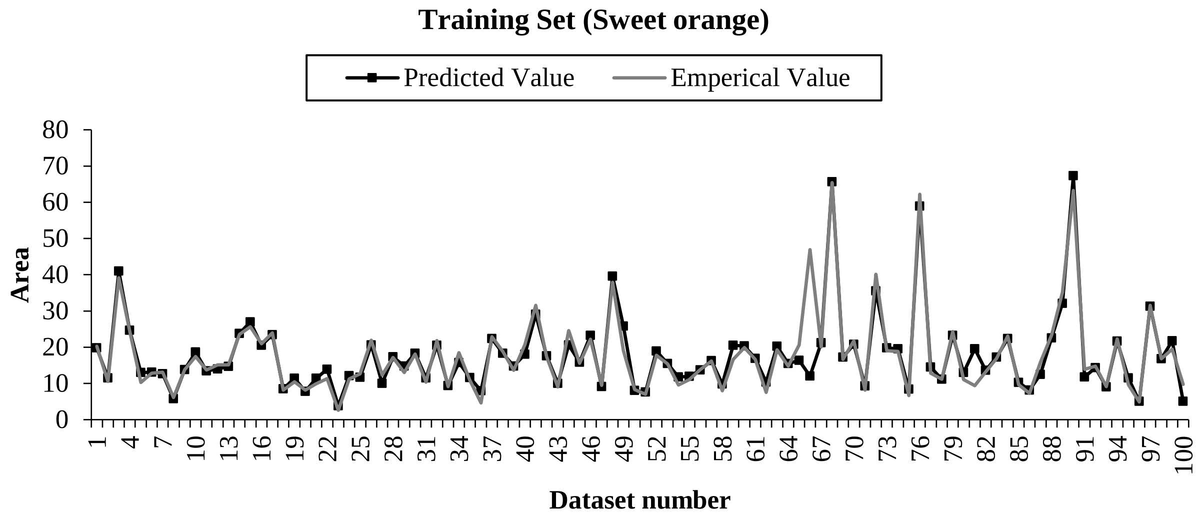

Figure 4. Neural network model-predicted function compared to real data for the training set Sweet orange in (input-output data).

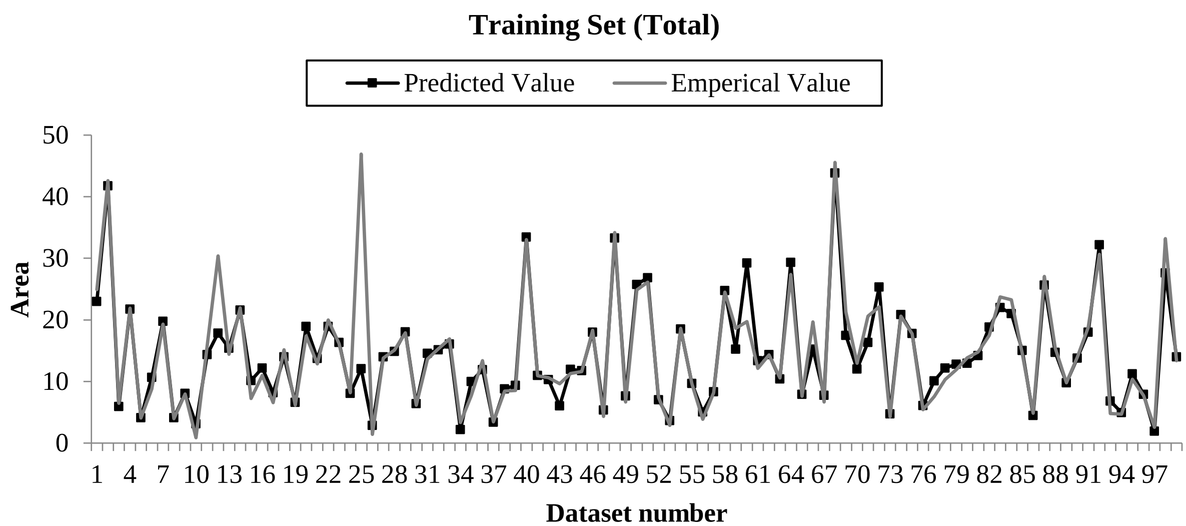

Figure 5. Neural network model-predicted function compared to real data for the testing set Total (input-output data).

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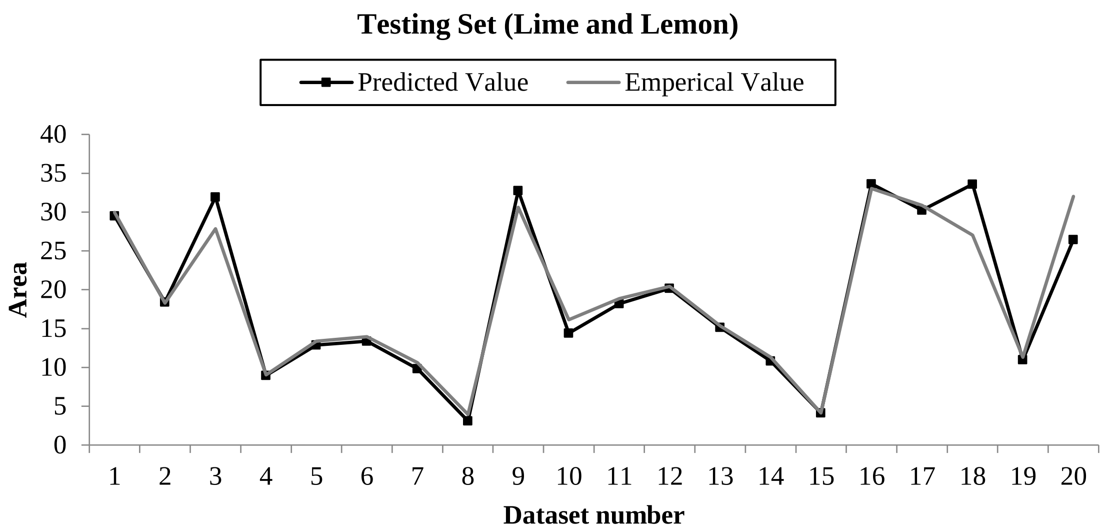

Figure 6. Neural network model-predicted function compared to real data for the training set Lime and Lemon (input-output data).

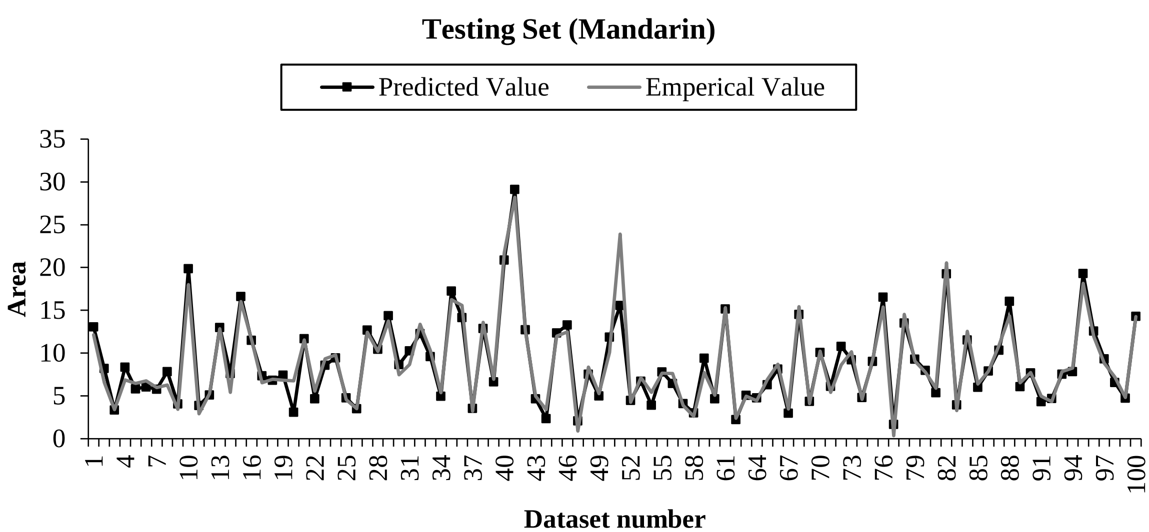

Figure 7. Neural network model-predicted function compared to real data for the training set Mandarin in (input-output data).

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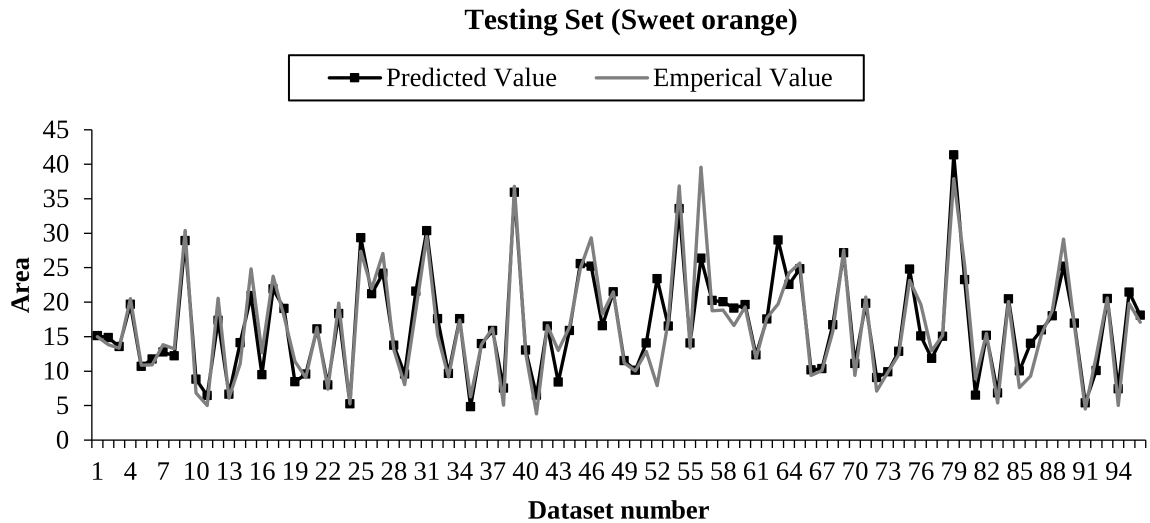

Figure 8. Neural network model-predicted function compared to real data for the training set Sweet orange (input-output data)

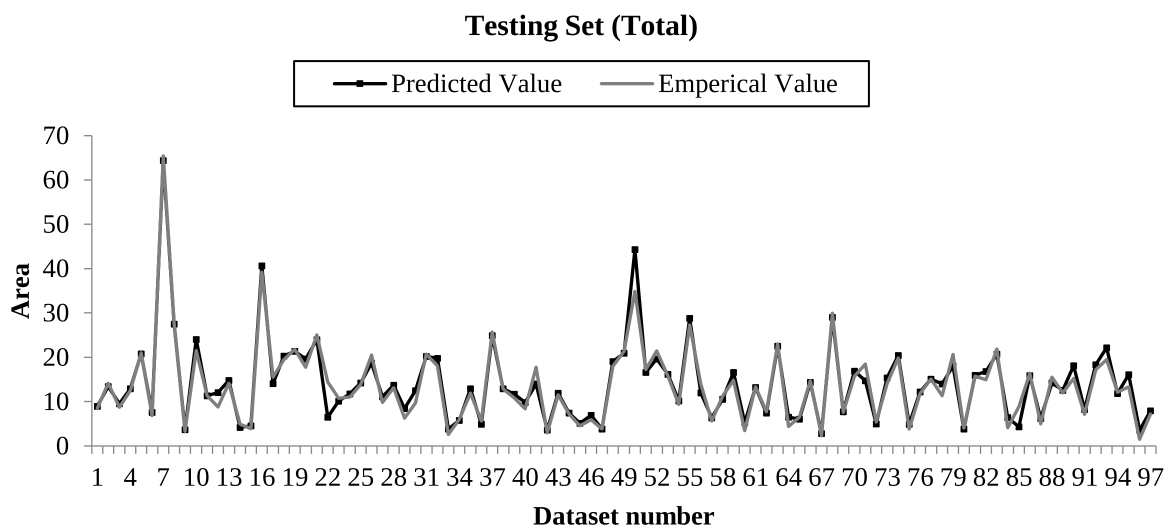

Figure 9. Neural network model-predicted function compared to real data for the training set Total in (input-output data)

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Model development

Model Development: An exhaustive explanation of the terms, advancement and application of the GMDH type is beyond the domain of this article [9-11]. This neural network recognition procedure, in turn, requires a nonlinear technique of optimization to discover the best architectural network. Thus, for the design of the entire architecture of GMDH-type NN, i.e., the configuration of connections of neurons and in their number in each hidden layer, in amalgamation by a single value, a combination to discover the best collection of proper coefficients of quadratic expressions for leaf area modeling, a Genetic Algorithm (GA) is used. Interested factors in this multi-input and single-output approach that impact the surface of the leaf are length (mm) and breath (mm). [(67 for lime and lemon), (215 for Mandarin), (200 for Sweet Orange), (600 for Total)]. The training of NN GMDH models was done by the obtained real input-output data lines.

The Mean absolute deviation (MAD), calculated by

$$MAD = \frac{\sum_{i=1}^{JL} |y_i - \dot{y}_i|}{n}$$

The mean absolute percentage error (MAPE), calculated by

$$MAPE = \frac{\sum_{i=1}^{JL} \left| \frac{y_i - \dot{y}_i}{y_i} \right|}{n} \times 100$$

The MS error (MSE), calculated by

$$MSE = \frac{\sum_{i=1}^{JL} |y_i - \dot{y}_i|^2}{n}$$

The corroboration of the models precision was by 1) Mean absolute deviation (MAD 2) The mean absolute percentage error (MAPE), 3) The MS error (MSE), Where yi is the real value, ŷi equals the estimated value, and n equals the number of the observations [(67 for lime and lemon), (215 for Mandarin), (200 for Sweet Orange), (600 for Total)] for training, and [(20 for lime and lemon), (100 for Mandarin), (96 for Sweet Orange), (97 for Total)] for testing.

Results

An excellent reply to all input parameters from the learning set was used the data set for all models. The limited explanation of GMDH-type NN for the leaf area was detected with two hidden layers and neurons

The testing set, that Included [(20 for lime and lemon), (100 for Mandarin), (96 for Sweet Orange), (97 for Total)] Input-output data lines were used in the test process solely to test the ability to predict such neural networks evolved whilst in the training process. Normally in each model two hidden layers were assumed. Neural networks creation, needed a population of 50 by a probability of crossover of 0.9, a probability of mutation of 0.01, and 300 generations were utilized.

Artificial neural network (NN) is a useful instrument as a modeling system, depending on the internal structure of the existing data set instead of understanding the modeled processes between inputs and outputs. One sub-model of the mock neural network is the group methods of data handling-type neural network (GMDH-type NN), Used in a wide spectrum of fields for the mining of data and discovery of knowledge, predicting, and optimization of modeling technique and the recognition of sequences. Induction GMDH algorithms allow automatic interrelation of data, select the prime structure of a network or model, whilst increasing the precision of existing algorithms. Using a self-structuring network directs to efficient use in a wide range. Nevertheless, in some domains, like horticultural science, the use of GMDH-type NN is routine. And non-destructive methods for selecting the individual leaf area of plants are beneficial in physiological and horticultural studies. To establish the area of every leaf (LA) Includes the measurement of leaf elements such as breadth (W) and length (L). Thus, a genetic algorithm is used in a new way to model the whole design of the GMDH-type NN.

but it has appeared by four hidden neurons and two hidden layers for the area of the leaf. These equations showed a measurable relationship between the research variables input (leaf length, breadth, and their ratio) and output (area of the leaf).

The neural networks were trained by only [(67 for lime and lemon), (215 for Mandarin), (200 for Sweet Orange), (600 for Total)] Sets, and [(20 for lime and lemon), (100 for Mandarin), (96 for Sweet Orange), (97 for Total)] collections were deleted. After the training process, the forecasted values of neural networks were compared by those of real values (the remaining [(20 for lime and lemon), (100 for Mandarin), (96 for Sweet Orange), (97 for Total)] sets). The results are shown in Figures 2-3. The results (test and training values) indicated a very comprehensive agreement with the predicted and real.

Depending on the internal structure of the existing data set instead of understanding the modeled processes between inputs and outputs of the artificial neural network happen to be a classified technique neural network of data management type (GMDH-type NN). The sets were deleted. After the test procedures, the foreseen denominations of the neural networks were contrasted with the real (residual) quantities.

Comparisons revealed manners like neural network models in prediction. Showed a quantitative relationship between input (L, W) and output (LA) variables under the study. The related polynomial equation representations like a model were obtained as follows:

Lime and Lemon

(1): $y = -1.74087577959889 - 0.07037995763483x_1 + 0.21423144103783x_2 + 0.00154143605596x^2_1 + 0.00364850867100x^2_2 - 0.00148049642896x_1x_2$

(2): $y_2 = -0.02264862393381 + 0.04148612768257x2 + 0.90635001723062y1 - 0.00176113190358\ x22 - 0.00508884996458y12 + 0.00629186020507\ x2y1$

(3): $AREA = 2.24876152350328 + 1.19742925361528y_2 - 0.09038299504881x_1 + 0.00374095802899y^2_2 + 0.00084853546954\ x^2_1 - 0.00360640120644y_2x_1$

Sweet Orange

(1): $y_1 = 14.37251555597781 - 0.40252897703186x_1 + .30143363776517x_2 + 0.00109352683259x_1^2 - 0.00574563374623x_2^2 + 0.00665833815000x_1x_2$

(2): $y_2 = 0.61391333795404 - 0.23650065902606x_1 + 2.15566731422036y_1 + 0.00356926837072\ x_1^2 + 0.03302544337939y_1^2 - 0.02448103036776x_1y_1$

(3): $y_3 = 14.37251555759699 + 0.30143363777425x_2 + 0.40252897706825x_1 - 0.00574563374623x_2^2 + 0.00109352683278x_1^2 + 0.00665833814993x_1x_2$

(4): $AREA = .13671625128682 + 0.97552799842355y_2 + 0.00509468604010y_3 + 0.07912434613140y^2_2 + 0.09054392215437y^2_3 - 0.16938248655308y_2y_3$

Mandarin

(1): $y_1 = 2.55821533338069 - 0.10231921996697x_1 + 0.05237231567034x_2 - 0.00016851218940x^1_2 - 0.00513494983228x^2_2 + 0.00776184494433x_1x_2$

(2): $y_2 = -0.47886501707714 + 0.15818304578634x_2 + .43489624808822y_1 - 0.00527146777707x^2_2 - 0.02218623278275y^1_2 + 0.02640756535164x_2y_1$

(3): $AREA = -0.02431367538199 + 0.95397382097888y_2 + 0.01121642125478x_2 - 0.00165987036205y^2_2 + 0.00035277969688x^2_2 + 0.00196638952909x_2y_2$

Total

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(1): $y_1 = 0.652420657147466 - 0.208037488058355x_1 + 0.023852225565556x_2 + 0.013789304030918x_1^2 + 0.000395922650935x^2{}_2 + 0.007880522547553x_1x_2$

(2): $y_2 = 8.614282421383512 - 7.373703439346921x_1 + 0.311114375115556x_2 + 1.579894301265659x_1^2 - 0.005167967635005x_2^2 - 0.083156685671300x_1x_2$

(3): $y_3 = 3.1022401568978190 - 0.142473867248759y_1 - 3.936611929447119x_1 + 0.001555068792016y_1^2 - 1.253023197872120x_1^2 + 0.148619549113522x_1x_2$

(4): $y_4 = 4.377521609546449 + 1.849992253269352y_2 - 3.481336997966936x_2 - 1.481484233677111y_2^2 + .681868440198004x_2^2 - 0.005037364500511x_1x_2$

(5): $AREA = 0.012060757755492 - 0.229907599926492y_2 + 0.964613455667388y_4 + .618467463130229y_2^3 + 0.089284818621712y_4^2 - 0.105278833351005y_3y_4$

Table 2 outlines the arithmetical outcomes for the sets of training and testing of the GMDH-type NN models. These results demonstrate the what-if error measurement according to the discrepancy between the actual and model quantities.

Table 2. Statistics and information model for group method of data handling-type neural network model for predicting the *Citrus spp* leaf area.

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Statistic	Neural training		Neural testing
		Lime and lemon	
R^2	0.9902		0.9884
RMSE	2.407239		2.259203
MSE	5.7948		5.104
MAD	1.59		1.33114
Number of hidden layers		2	
Hidden neurons		3	
		Sweet orange	
R^2	0.97		0.98
RMSE	3.499962		2.887055
MSE	12.24974		8.335088
MAD	1.842849		0.010045
Number of hidden layers		2	
Hidden neurons		3	
		Mandarin	
R^2	0.9802		0.985
RMSE	1.410674		1.237457
MSE	1.99		1.5313
MAD	0.9		0.775571
Number of hidden layers		2	
Hidden neurons		3	
		Total	
R^2	0.97		0.99
RMSE	2.81104		1.905141
MSE	7.901945		3.629561
MAD	1.384321		1.269762
Number of hidden layers		2	
Hidden neurons		3	

Discussion

Leaf area is the most important factor in physiological studies including the growth of plants, light capture, evapotranspiration, photosynthesis efficacy, and plant response to irrigation and fertilizers [15]. Agronomists and Plant physiologists have expressed the significance of this indicator in calculating growth and rate of development of the crop, and light, radiation, and water use efficiency [16].

Leaf area is among the most important structural properties of forest ecosystems and may be regarded as a major Eco physiological variable, which is related to light interception, evapotranspiration, response to precipitation, and plant growth and development [9, 15]. Accurate and exact estimation of the area of the leaf has been a long-time interest of plant researchers and plant physiologists always require precise measurement of leaf area for production-related studies in plants [17, 18]. Also, ecologists use the leaf area variable to determine the competition status among different species [19-21].

Leaf area assessment is used in experiments on the physiology of fruits and other regular tests looking into horticultural products, in which some physiological events like plant water consumption, respiration light,

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photosynthesis, and transpiration are investigated [2, 6, 8]. and this study generated a straight forward, precise, non-destructive and time-saving, GMDH-type NN for accurate prediction of plant leaf area has been a long time a matter of the plant.

Calculation of the leaf area of the trees is possible via different methods. Leaf area may be measured rapidly with precision using a portable planimeter [6]. However, for this method to work small-sized plants with a few leaves need to be used [12]. Although using digital cameras for taking photos and their analysis via software is a precise, rapid and suitable method, its proceeding is time-consuming and equipment is costly [13]. Another method involves the usage of leaf area meter apparatus which needs the leaves to be collected and transferred to the lab. An important note about the mentioned methods is that they usually require the collecting of leaves from the tree crown and are considered destructive sampling. Furthermore, these methods are costly and time consuming [14]. Therefore, utilization of non-destructive sampling methods which do not impose a serious injury to the tree crown is always considered by foresters and ecologists. A desirable, inexpensive, and feasible method to calculate the area of the leaves of trees which is widely used in numerous countries is the application of regression models. In this method, an acceptable estimation of leaf area is provided using simple quantitative leaf variables such as leaf width and length and modeling [15, 16].

Modeling of leaf area is regarded among the non-destructive methods which require a single sampling of leaves. These models may be used for the same or the other studied tree species in the future without further sampling from the tree crown. These results are following previous reports on finding non-destructive and linear indices for calculation of leaf area [8, 17, 18].

Conduction of this study will provide the first steps for future research regarding the leaf area of trees. Modeling of leaf area for citrus trees in Iran is new and does not possess a significant history. This study attempted to model the leaf area of four genus typica trees in the Kotra Germplasm Bank of Ramsar; the results of which may be used in related fields. The results received show that the establishment of simple regression models in leaf area prediction of the studied species using quantitative variables of leaf breadth, length, and a combination of leaf width and length is feasible easily.

The estimated statistics show that GMDH-type NN is an efficient instrument for effective detection of sequences in the data and prediction of the area of the leaf based on examining input.

The genetic approach was able to be utilized to give optimal networks in terms of latent layers, and configuration of their connections, number of neurons, or both to achieve a polynomial expression for process-dependent variables. The resulting polynomials can be used to optimize leaf area (LA), based on length (L) and width (W).

Conclusion

The findings (test values and training) indicated a compelling agreement by the real and estimated LA with GMDH-type NN. Comparisons indicated the neural network's performance models in predicted LA. Using Equation, one can easily calculate leaf area (LA), according to measured leaf length (L) and breadth (W). This technique also enables one to make measurements on the same leaves during the season of growing.

Authors' Contribution

All authors shared the responsibilities in the design work analysis and design of the manuscript.

Conflict of interest

There are none to declare.

Consent for publications

Approval of the final manuscript is granted by all authors.

Availability of data and material

Data are available on request from the authors.

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Ethics approval and consent to participate

In the research, no harm was realized to animals or other persons.

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