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Non-Destructive Measurement of Leaf Area in Olive Trees Using the Group Method of Data Handling

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ABSTRACT

Computer skills and mathematical modeling have recently advanced quickly. Their development has gone without a hitch. The developments have accelerated our scientific analyses. Therefore, it is beneficial and necessary to seize these opportunities. One of the most significant characteristics of a tree is its leaf area, which is strongly correlated with its physiological and ecological variables such as growth, evapotranspiration, light interception, photosynthesis, and leaf area index. A sub-model of an artificial neural network is the group method of data handling (GMDH-type NN). Applications of such a self-organizing network are effective across a wide spectrum when used. However, the use of GMDH-type NN is still unusual in several fields, including horticultural science. Research on the individual leaf area of plants, both in horticulture and physiology, requires accurate and nondestructive techniques. Measuring the length (L) and width (W) of leaves is one way to calculate the individual leaf area (LA) of olives (*Olea europaea*). This study examined if an equation could be created to determine the leaf area of various olive genotypes using seventeen olive genotypes in an open-field situation in 2017. In this case, a new approach for designing the whole architecture of the GMDH-type NN uses a genetic algorithm. The purpose of this work was to determine if leaf area (output) could be estimated using GMDH-type NN given certain variables, such as leaf width and length. The findings demonstrate that GMDH-type NN is a useful tool for quickly and accurately identifying patterns in data, producing a performance index based on input investigation, and predicting leaf area depending on leaf width and length.

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1. Introduction

Olive (*Olea europaea* L.) belongs to the family Oleaceae. It is one of the first known cultivated plants and is native to warm temperate and tropical regions of the globe. As a major source for the manufacture of olive oil, the olive tree is crucial to the Mediterranean region's economy (Madureira *et al.*, 2022). The tree is often found along the coasts of the eastern Mediterranean basin, the Arabian Peninsula, India, Asia, and northern Africa, in addition to northern Iran at the southernmost point of the Caspian Sea (Parvaiz *et al.*, 2013).

Leaf area is a crucial agronomic parameter because it is connected to plant growth and photosynthetic capacity, and light interception and consequently of transpiration, and it is often utilized to evaluate the impact of various plant cures. It light interception and consequently of transpiration, photosynthesis and plant productivity (Liu *et al.*, 2021; Zhang *et al.*, 2024; Alam *et al.*, 2021). The importance of this parameter in assessing crop growth, development rate, yield potential, radiation use efficiency, water, and nutrients has been demonstrated by plant physiologists and agronomists (Taube *et al.*, 2020). Using destructive or non-destructive techniques, we calculated the leaf area. There are several destructive or non-destructive measures that can be used to determine leaf areas. Several techniques have been developed to improve leaf area measurement. However, the plants' leaves must be removed in order to use these techniques,

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which include tracing, blueprinting, photographing, and utilizing a traditional planimeter. Therefore, sequentially measuring a leaf is not possible. There is also an impairment to the plant's canopy, which might make additional measures or testing challenging. A portable scan planimeter may be used to measure leaf area rapidly, precisely, and non-destructively (Salehi Sardoei and Fazeli-Nasab, 2021). However, this method is only suitable for small plants with some leaves. The second method of assessing leaf area is using a picture of analysis. By picture evaluation and analysis software. Digital camera photos may be taken quickly, and with the correct software, they can be accurately analyzed (Mueller and Lemke, 2000). However, processing takes time, and the facilities are usually costly. As a result, it provides an inexpensive, quick, dependable, and non-destructive way for agronomists to estimate the amount of leaf area required. If it is feasible to express the mathematical connections between one or more leaf dimensions and leaf area (width and length). GMDH can be used to model complex systems without prior specific knowledge of that system. The main idea of GMDH is to build an analytical function in a feedforward network based on a quadratic node transfer function (Ahmadian-Moghadam, 2012) whose coefficients are obtained from a regression. In recent years however, the use of such self-organizing networks has led to successful application of the GMDH-type algorithm in a broad range of areas such as engineering, science and economics. Thus, by employing GMDH, the problem of having prior knowledge of the mathematical model of the planned procedure has been evaded (Ali and Anjum, 2004). Hence, without requiring specialized system knowledge, GMDH may be employed to represent complex systems. The basic idea underlying GMDH is to create a function of analysis in a feed-forward network based on a quadratic node transfer function, whose coefficients are derived via the regression approach (Nariman-Zadeh *et al*., 2005). In fact, the actual GMDH algorithm—which computes the model coefficients using the least-squares approach—is categorized as imperfect induction, which refers to the multilayered iterative algorithms (MIA) and combinatorial (COMBI) algorithms, respectively (Nariman-Zadeh *et al*., 2003). The GMDH-type algorithm has been successfully applied in a variety of fields, including engineering, science, and economics, due to the benefits of such self-organizing networks (Nariman-Zadeh *et al*., 2002). Hence, the purpose of our research was to extend a pattern for forecasting leaf area from leaf length and breadth i.e. linear measurements of olive types growing in Olive Acclimatization Garden in the Province of Mazandaran.

2. Materials and methods

The research was carried out at Iran's Guilan University in Rasht in 2019. The olive cultivars (Carola, Gorgan oily, Mission, Leccino, Dolce agogia, Rudbar local oily, Maari, Frantoio, Moraiolo, Vediqual, Beladi, Kalamon, Ascolano, Arbequina, Simari silar, Rosso) employed in this study were from the Mazandaran province's olive acclimatization garden. As samples for estimating leaf area, leaves of varying sizes were chosen at random from various canopy levels. Following their cutting, the leaves were analyzed for their length (L), width (W), and leaf area (LA). They were then brought directly to the laboratory in plastic bags. The lamina's tip at the intersection of the lamina and petiole was used to determine the length of the leaf. The breadth of the blade was recorded at its longest value. A leaf area meter was used for calculating (LA) (a: Conveyor Belt Unit, Delte-T Device LTD, Burwell, Cambridge England b: Light TBOX, UK c: Camera: iλ_i CV 53200, JAPAN). 3400 data sets (input-output) were used in this study.

Leaf area was the system output, while length and width were the input variables in the data that was gathered. Data were randomly divided into two sets of training (Fig. 1) and testing (Fig. 2) of 2000 and 1400 sets, respectively. We selected 100 data lines (input-output) randomly from 2000 data lines (Training set) and 100 data lines (input-output) from 1400 data lines (testing set). Table 1 shows ranges of data patterns (input-output) (Ahmadian-Moghadam, 2012).

L and W were recorded by the closest 0.01 mm. Leaf area (LA) was measured using 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 collected data sets (input-output data) were randomly selected from the data in order to train and calibrate GMDH-type NN.

2.1. Model development

Numerous references provide a thorough explanation of the terminologies, development, and use of GMDH-type NN (Mueller and Lemke, 2000; Nariman-Zadeh *et al*., 2003). The optimal set of suitable quadratic expression coefficients to illustrate leaf area is obtained using this combination. The variables affecting the leaf area in this multi-input, single-output system are the leaf length and leaf breadth. The GMDH-type NN model was trained using 50 input-output real data lines that were acquired. Only the prediction of such developed neural networks was tested throughout the training phase using testing sets, which had thirty-two unexpected input-output data lines. For every model, two hidden layers were taken into account. Such neural networks were genetically constructed using a population of 50 people with a cross-over frequency of 0.9, a mutation chance of 0.01, and 300 generations. To evaluate the correctness of the model, the mean absolute deviation (MAD) was computed as (Equation 1):

$$\text{MAD} = \frac{\sum_{i=1}^{n}|y_i-\hat{y}_i|}{n} \quad (1)$$

The mean absolute percentage error (MAPE), computed as (Equation 2):

$$\text{MAPE} = \frac{\sum_{i=1}^{n}\left|\frac{y_i-\hat{y}_i}{y_i}\right|}{n} \times 100 \quad (2)$$

The MS error (MSE), computed as (Equation 3):

$$\text{MSE} = \frac{\sum_{i=1}^{n}|y_i-\hat{y}_i|^2}{n} \quad (3)$$

Where: y_i actual value, $\hat{y}_i$ predicted value, and n the number of observations (2000 for training and 1400 for testing).

3. Results

For every input parameter from the learning set, every model built using this data set had a very good response. The GMDH-type NN was found to have two hidden layers and two hidden neurons for the leaf region in its partial descriptions; nevertheless, it was seen to have two secret layers and four hidden neurons for the leaf area. The quantitative relationship between the factors under investigation's output (leaf area) and inputs (leaf length, leaf width, and length-to-width ratio) was disclosed by these equations.

Merely 2000 sets were used to train the neural networks, with 1400 sets being excluded. Following training, the actual values (the remaining 1400 sets) and the predicted values of neural networks were compared. Fig. 1 and 2 present the findings. The quantitative relationship between the input (L, W) and output (LA) variables under research was made clear by equations (Equation 4-7). Such a model's related polynomial equation representations were found to be as follows:

$$\begin{aligned} Y_1 = {} & 0.718510050757413 \\ & + 0.121287983967513L \\ & - 0.023735463929619W \\ & + 0.000206173292108L^2 \\ & + 0.000667999335503W^2 \\ & + 0.003858774037350LW \end{aligned} \quad (4)$$

$$\begin{aligned} Y_2 = {} & 0.038139792323482 \\ & + 1.085811745370992Y_1 \\ & - 0.011850156620582W \\ & + 0.006545234032471{Y_1}^2 \\ & + 0.000295105614010W^2 \\ & - 0.003128618697891WY_1 \end{aligned} \quad (5)$$

$$\begin{aligned} Y_3 = {} & 0.718510051137326 \\ & - 0.023735463936163W \\ & + 0.121287983939317L \\ & + 0.000667999335530W^2 \\ & + 0.000206173292607L^2 \\ & + 0.003858774037589WL \end{aligned} \quad (6)$$

$$\begin{aligned} LA = {} & -1.2225429802073 - 7.7991176920142Y_2 \\ & + 9.1850339426550Y_3 \\ & - 141.2164385877785{Y_2}^2 \\ & + 141.3462482608655{Y_3}^2 \\ & - 282.5919642950296Y_2Y_3 \end{aligned} \quad (7)$$

As previously mentioned, 40 sets of data (validation sets) that were taken out of the database were used to verify the validity of these results (Hassani *et al*., 2019b). Only 20 sets were used to train the neural networks, and 10 sets were left out. After training, a comparison was made between the anticipated values of neural networks and the true values (the remaining 10 sets). The results are shown in Fig. 1. Excellent agreement was observed between the training and validation values of the GMDH-type neural network and the actual and predicted leaf areas.

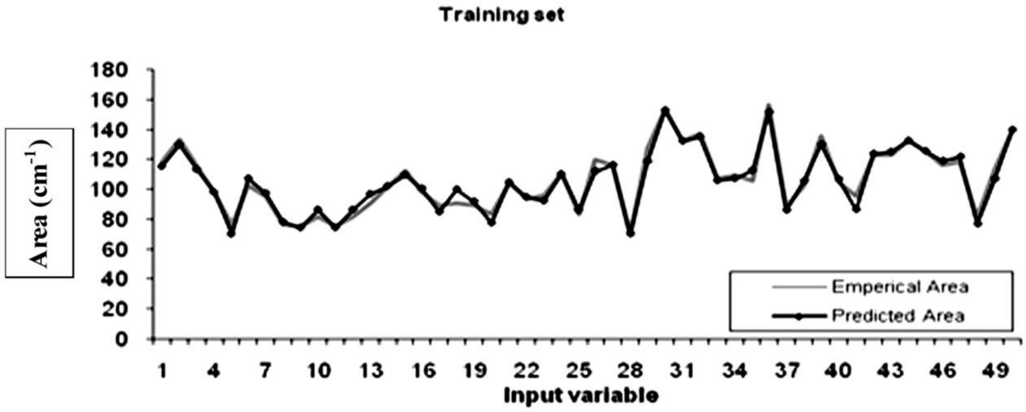

Figure 1. Neural network model-predicted performance in comparison with actual data for the training set (2000 input-output data).

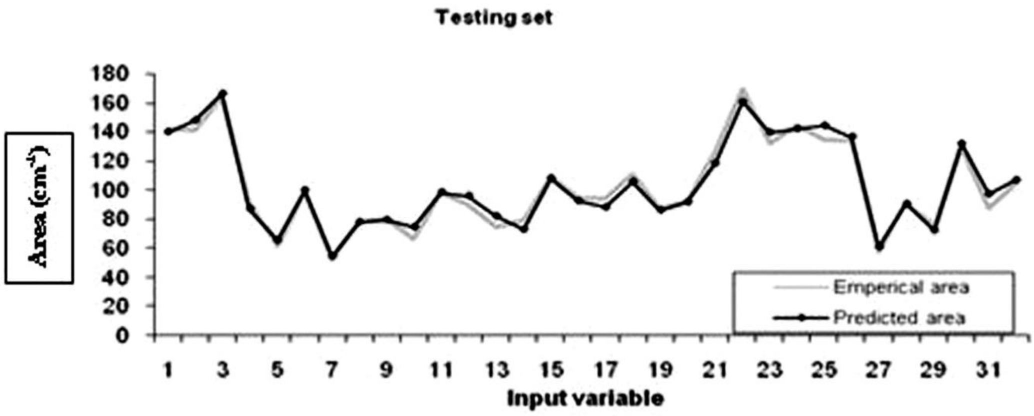

Figure 2. Neural network model-predicted performance in comparison with actual data for the training set (1400 unforeseen input-output data)

Comparisons revealed the neural network models' patterns of behavior in forecasting leaf area. These results, which are consistent with those of previous research, such as (da Silva Ribeiro *et al*., 2023), imply that the length-to-width ratio of factors showed significant impacts on the leaf area. Strong correlations between leaf area and equations utilizing leaf length (L), maximum leaf width (W), or their products were evident in the high coefficients of determination (R2) and low standard error of estimations (Table 2). According to these calculated statistics, GMDH-type NN offers a useful method for quickly identifying patterns in data, and its forecasts for leaf area are predicated on examining inputs (Tables 1 and 2; Fig. 1). To get a polynomial expression for the dependent parameters in the method, the genetic technique might be employed to create networks with the ideal number of neurons, hidden layers, connection arrangement, or both. The statistical outcomes for the training and testing sets of GMDH-type NN models are summarized in Tables 1 and 2. These findings show that predicting error measures depends on how the model and actual data differ.

Table 1. Model statistics and information for the group method of data handling-type neural network model for predicting the Olive leaf area

Statistic[1]	Neural training	Neural testing
R^2	0.985811	0.977558
RMSE	0.5910584	0.610836
MAD	0.4825911	0.403813
MAPE	0.0823313	0.071578
Number of hidden layers	2	
Hidden neurons	3	

MSE[1] = MS error (standard deviation); MAD = mean absolute deviation; MAPE = mean absolute percentage error; hidden neurons = number of hidden neurons suggested by the genetic algorithm to fit the group method of data handling-type neural network models.

Table 2. Ranges of data patterns (input-output) that are Used from Seventeen genotypes.

Genotype	Length (mm) Maximum -Minimum	Width (mm) Maximum - Minimum	Output [leaf area (cm^2)] Maximum - Minimum
Carola	85.38 - 36.1	25.84 - 9.2	13.98 - 3.34
Gorgan oily	85.33 - 33.38	40.47 - 7.9	10.54 - 2.84
Mission	81.28 - 32.55	20.55 - 8.38	13.57 - 2.76
Leccino	73.9 - 43.25	19.91 - 9.89	10.86 - 3.28
Dolce agogia	68.58 - 27.14	18.09 - 6.32	9.13 - 1.83
Rudbar local oily	66.9 - 21.7	32.59 - 6.87	8.39 - 1.71
Maari	97.15 - 43.47	27.43 - 9.85	8.19 - 4.22
Frantoio	77.36 - 38.8	23.87 - 8.67	11.38 - 2.74
Moraiolo	62.92 - 28.81	20.03 - 7.49	8.86 - 2.70
Vediqual	77.85 - 32.53	21.99 - 9.69	11.67 - 3.62
Valonolia	68.68 - 22.25	24.42 - 7.92	10.59 - 1.48
Beladi	63.31 - 27.34	24.63 - 9.14	11.24 - 4.75
Kalamon	77.63 - 27.71	24.38 - 7.62	13.16 - 2.34
Ascolano	81.27 - 39.24	24.24 - 9.67	13.45 - 2.99
Arbequina	66.67 - 32.45	23.16 - 6.95	9.07 - 2.14
Simari silar	99.1 - 43.51	23.97 - 10.4	14.55 - 3.02
Rosso	79.8 - 35.8	18.09 - 6.92	9.25 - 2.22

4. 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 (Blanco and Folegatti, 2005). 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 (Williams and Martinson, 2003). 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 (Blanco and Folegatti, 2005; Demirsoy, 2009). 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 (Großkinsky *et al*., 2015). Also, ecologists use the leaf area variable to determine the competition status among different species (Markov, 2021; Twyford, 2017; Narango *et al*., 2018). 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, photosynthesis, and transpiration are investigated (Ahmadian-Moghadam, 2012; Cho *et al*., 2007). This study generated a straightforward, precise, non-destructive and time-saving, GMDH-type NN for accurate prediction of plant leaf area has been a long-time matter of the plant. Evaluations for leaf area are used in experiments on fruit physiology and other routine experiments investigating horticultural crops where some physiological phenomena such as light, photosynthesis, respiration, plant water consumption and transpiration are studied (Cho *et al*., 2007; Ahmadian-Moghadam, 2012; Hassani *et al*., 2019a; Hassani *et al*., 2019b) and this research develops a simple, accurate, non-destructive and time saving, GMDH-type NN for leaf area estimation in Olive.

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 (Demirsoy, 2009). However, for this method to work small-sized plants with a few leaves need to be used (Nyakwende *et al*., 1997). 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 (Bhatla *et al*., 2012). 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 (Posse *et al*., 2009). Therefore, utilization of non-destructive sampling methods that 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 (Cristofori *et al*., 2007; Serdar and Demirsoy, 2006).

Modeling of leaf area is regarded among the non-destructive methods that 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 follow previous reports on finding non-destructive and linear indices for calculation of leaf area (Mendoza-de Gyves *et al*., 2007; Rivera *et al*., 2007; Rouphael *et al*., 2007).

The conduction of this study will provide the first steps for future research regarding the leaf area of trees. Modeling of leaf area for Olive trees in Iran is new and does not possess a significant history. This study attempted to model the leaf area of 17 species of typical trees in the Olive Acclimatization Garden in the Province of Mazandaran; 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 the effective detection of sequences in the data and prediction of the area of the leaf based on examining input (Kasaeian *et al*., 2017). 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). Results (training and validation values) showed very good agreement with actual and predicted leaf areas from the GMDH-type neural network. Comparisons showed behavior patterns of such neural network models in predicting leaf area. These results suggest that the length-to-width ratio of variables demonstrated strong effects on the leaf area, results similar to those of other studies, for example, (Ahmadian-Moghadam, 2012). Equations using leaf length (L), maximum leaf width (W) or their products had strong relationships with leaf area, manifested in high coefficients of determination (R2) of equations and low standard error of estimates (Table 2). Table 2 summarizes statistical results for the training and validation sets of GMDH-type NN models. These results indicate forecasting error measurements based on differences between the model and actual values. By considering these training data, the lowest records for MSE, MAD, and MAPE, and the highest R2 were calculated for leaf area. For validation data, however, the lowest records for MSE, MAD, and MAPE, and the highest R2 were observed for leaf area.

5. Conclusion and further research

According to computed statistics, GMDH-type NN offers a useful way to quickly identify trends in data and forecast a leaf area by looking at inputs. To generate a polynomial expression for the process's dependent variables, the genetic technique might be employed to create networks with the ideal number of neurons, hidden layers, connection configurations, or both. Using the polynomials that were developed, leaf area (LA), depending on length (L) and width (W), may be optimized. With GMDH-type NN, the findings (training and testing values) demonstrated extremely excellent agreement with real and projected LA. Comparisons demonstrated how these neural network models behaved when forecasting LA. The equation makes it simple to get leaf area (LA) from measured leaf length (L) and width (W). This procedure is non-destructive and efficient. Furthermore, the technique would allow measurements to be taken on the same leaves at different times during the growing season.

Conflict of interests

There are none to declare.

Ethics approval and consent to participate

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

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.

Authors' contributions

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

Informed consent

The authors declare not to use any patients in this research.

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