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Research article

Leaf area estimation based on ANFIS using embedded system and PV panel

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ABSTRACT

Leaf area is one of the important parameters for plant canopy development. It is used as an indicator closely related to plant growth in several studies on plant production. However, most leaf area meters used today are costly and rely on human observations. This situation may be limiting for researchers in terms of having proper leaf area measuring devices. The reliance on human-focused measurements leads to human errors. Digital scanners and cameras, digital image processing-based estimation methods, paper weighing, grid counting, regression equations, width and height correlation models, planimeters, laser optics, and handheld scanners can be used to determine leaf area. However, some of these methods are expensive and unnecessary for simple studies. Therefore, this study aims to design and implement an embedded system with a simpler, cheaper alternative to the currently used methods and devices, minimizing human errors. The proposed embedded system serves as a tool for measuring leaf area using a photovoltaic panel (PV) and an Adaptive Neuro-Fuzzy Inference System (ANFIS). In the study, geometric shapes with known areas are used as the learning data, and real plant leaves with known areas are used in the testing process. As a result, the prediction made by ANFIS is observed to have an accuracy of $R^2 = 0.99$.

1. Introduction

Leaves control various vital mechanisms in plants such as nutrient production, photosynthesis, transpiration, and respiration. Leaves are also an important structural feature of plant canopies and play a fundamental role in clearly displaying certain morphological and physiological characteristics, identifying numerous species and varieties, and measuring the plant's response to various stress environments. The surface of a leaf performs all these vital activities and contributes significantly to the identification of plant species. Therefore, determining leaf area is important for shedding light on methods to be used in various studies [1–3].

Leaf area measurement is an important parameter that provides important information about plant health, development, and productivity [4]. Leaves play a critical role in the processes of photosynthesis, the release of water vapor into the atmosphere, and overall growth [5]. Therefore, leaf area measurement is a widely used technique in research on plant physiology, ecology, and agriculture. Plant yield is related to the photosynthesis rate corresponding to each leaf and the accompanying leaves [6]. The effect of leaf area on plant biomass is an important measure of plant development and yield. Therefore, in most studies in agriculture, leaf area and other parameters were associated, and yield estimates were made [6,7].

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Leaf area (LA) is a parameter that affects the penetration of light into the leaf, the plant's photosynthetic reaction, and consequently, its growth rate [8]. Leaf area can be defined as a measure of leaf size (width, length) and plays an important role in all fields related to plant science, ranging from agriculture to forestry and ecology [9]. It was emphasized in a previous study [10] that leaf area is one of the six characteristics that shape and determine plant form and function, along with plant height, specific density to stem, leaf mass per unit area, nitrogen content per unit leaf mass, and inclusive diaspore mass. The biological and economic yield in plants is largely dependent on leaf area, formation rate, and duration [11]. Many different methods and materials have been used by several researchers to determine leaf area. Studies have attempted to determine leaf area based on length-to-width ratios [12,13], paper weighing and grid counting methods, regression equations [14], width and height correlations [15,16], and planimetry measurements [17,18].

There are various devices and methods used to measure leaf area. Leaf area was measured in four different leaf types with the LAI–2200 Plant Canopy Analyzer, the SS1 SunScan Canopy Analysis System, and Digital Hemispherical Photography (DHP) [19]. The authors classified leaves according to the LAI range of low (0–2 m^2 m^{-2}), medium (2–6 m^2 m^{-2}), and high (6–8 m^2 m^{-2}). As a result, they reported that similar results emerged for all measurement methods for medium-range leaves, whereas LAI-2000 and DHP produced the best results for all leaf measurements. Methods of area measurement by directly tearing off leaves require a lot of physical labor and damage the plant [20]. Indirect measurement methods have been developed to overcome these limiting effects [21]. These measurement methods are faster than direct measurement methods, and they are based on the principle of light capture. The indirect measurement method is effective when obtaining information about the leaf area of plants in large-scale areas (forest areas and forest trees). However, its accuracy must be confirmed with precise data [9].

In addition to these measurement methods, leaf area estimation can also be performed using some less commonly tested methods in agriculture. These methods are mostly machine learning-based approaches that provide information about leaf area quickly and without causing damage to the plant. As one such method, an Adaptive Neuro-Fuzzy Inference System (ANFIS) is a machine learning technique that combines the learning capabilities of artificial neural networks and fuzzy logic systems for classification and modeling [22]. It was reported that [23] ANFIS and ANN modeling can be effectively used to predict leaf area in bread wheat species, and ANFIS achieved successful leaf area prediction using specific coefficients related to leaves with an accuracy of $R^2 = 0.997$ [24]. A tool was developed [25] to determine leaf area using a PV panel as a sensor, a wooden enclosure to protect it from the external environment, a flashlight as a light source, and a commercial digital multimeter for voltage measurements. The working principle of the tool was based on the direct variation of the voltage produced by the PV panel depending on the area of the leaf placed inside the enclosure. The obtained leaf area measurement results had an accuracy of $R^2 = 0.9834$. A simple and practical PV-based leaf area meter, which consisted of a silicon solar module composed of 6 interconnected cells in series, a light source, and a parabolic reflector with opal glass was developed. To evaluate the meter's performance, the partial shading effect on the voltage and current of the PV cell was assessed using different geometric shapes (regularly shaped leaves and irregularly shaped leaves), and equations were derived from the measured areas corresponding to the variations in voltage and current. A good correlation was observed in the measured current. The obtained values were $R^2 > 0.99$ for the regular-shaped leaves and $R^2 > 0.95$ for the irregular-shaped leaves. The present study utilized a photovoltaic panel to develop an easy-to-use, simple, and cost-effective leaf area meter, and it employed the ANFIS method for leaf area estimation. The hardware components of the proposed system consisted of a lamp which emitted light with properties close to sunlight, a PV panel, and a simple box surrounding them. A PV panel, which is an optoelectronic material, was used to convert the partial shading effect, which is often considered a disadvantageous situation in panels, into a useful one. As the rays coming from the light source were blocked by the leaf, casting shade on the panel, an inverse relationship between leaf area and the output power of the panel was established. Based on this relationship, it became possible to estimate leaf area using an ohmic load connected to the panel output and the voltage drop across this load. Additionally, the panel temperature has a significant effect on the panel's output power [27,28]. Therefore, both panel temperature and panel output voltage were used in the training and testing processes of ANFIS for leaf area prediction, taking into account all these factors. As the distinguishing and advantageous aspect of our system compared to other leaf area measurement tools, it did not involve mathematical functions, provided instant results independent of personal observations, displayed the results on a user interface (Alphanumeric LCD) quickly, and had the ability to make predictions based on only two input parameters. Unlike our system, other measurement tools often involve multiple input parameters, do not incorporate panel temperature in the prediction process, and do not employ machine learning methods [8,9].

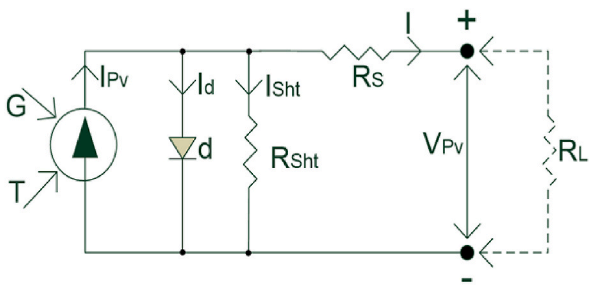

Fig. 1. Electrical equivalent of a PV cell.

2. Material and method

2.1. PV cell model

Solar panels are some of the most significant renewable energy technologies used for electricity generation [29]. PV panels are created by connecting PV cells in series and/or in parallel. In other words, PV cells are the smallest visible structures that make up solar panels. These cells are opto-electronic materials that act as current sources. They are composed of P-type and N-type semiconductor materials. When photons carried by sunlight reach the junction point of the P–N semiconductor material, they generate electron movement. Moving electrons travel through the external circuit and return to the PV cell, creating an electric current. This phenomenon is known as the PV effect. Fig. 1 shows the equivalent circuit of a PV cell with a single diode.

The output values of a PV cell can be described using various mathematical equations. The current produced by the cell can be expressed as in Equation (1). Accordingly, the amount of current generated by the cell varies depending on both solar irradiance (G) and the ambient temperature/reference temperature (T_{ref}).

$$I_{PV} = \left[I_{sc} + K_i\left(T_c - T_{ref}\right)\right]\frac{G}{G_{ref}} \tag{1}$$

The cell output current obtained as a result of subtracting the intracellular current losses is calculated using Equation (2).

$$I = [I_{PV} - I_d - I_{sht}] \tag{2}$$

As a result of the voltage drop on the series resistance within the cell, the cell output voltage is calculated using Equation (3).

$$V_{PV} = [V_d - (IR_s)] \tag{3}$$

The variables used in these equations and their explanations are given in Table 1.

2.2. Training and testing of ANFIS

ANFIS is an intelligent technique that combines both a fuzzy inference system (FIS) and an artificial neural network [30]. It is neither a mathematical model nor linear in nature. Due to the non-linearity of the output values of PV panels and their susceptibility to environmental factors, the use of ANFIS produces effective results [31]. In this regard, it is extensively utilized in solving engineering problems [32]. In other words, ANFIS is an approach that learns the relationship between input and output variables in the training dataset and can generate the desired output based on test data. Fig. 2 presents the block diagram illustrating the architectural structure of ANFIS. ANFIS makes estimations by learning the relations between each input parameter and the output parameter. This way, for later states, it can estimate the output parameter based on the relations it has learned by considering only the input parameters. This learning relation takes place via the exemplary rule given below and continues until the last relation.

Rule 1: if x = A1 and y = B1, then f1 = p1 x + q1 y + r1.

Rule 2: if x = A2 and y = B2, then f2 = p2 x + q2 y + r2.

…

Rule n: if x = An and y = Bn, then fn = pn x + qn y + rn.

The rule-based learning relationship described above can be explained better using the block diagram given in Fig. 2.

During the testing phase of ANFIS, the PV panel voltage (V) and panel temperature (T) data are entered as the input variables. ANFIS evaluates the inputs using the relationships established through its network and predicts the leaf area in square centimeters. *The configuration of the input and output parameters of the proposed ANFIS model is presented in* Fig. 3.

Table 1
Variables in equations and their explanations.

Parameter		Statement
I_{PV}	:	PV cell current in Amperes
I_{sc}	:	PC cell short circuit current in Amperes
K_i	:	Temperature factor
T_c	:	PV cell temperature in Kelvin
T_{ref}	:	Reference temperature
G	:	Solar radiation in W/m^2
G_{ref}	:	Reference solar radiation in W/m^2
I_{sht}	:	Shunt resistor current
I_d	:	Diode current in Amperes
I	:	PV cell output current in Amperes
V_d	:	Diode voltage in Volts
V_{PV}	:	PV output voltage in Volts

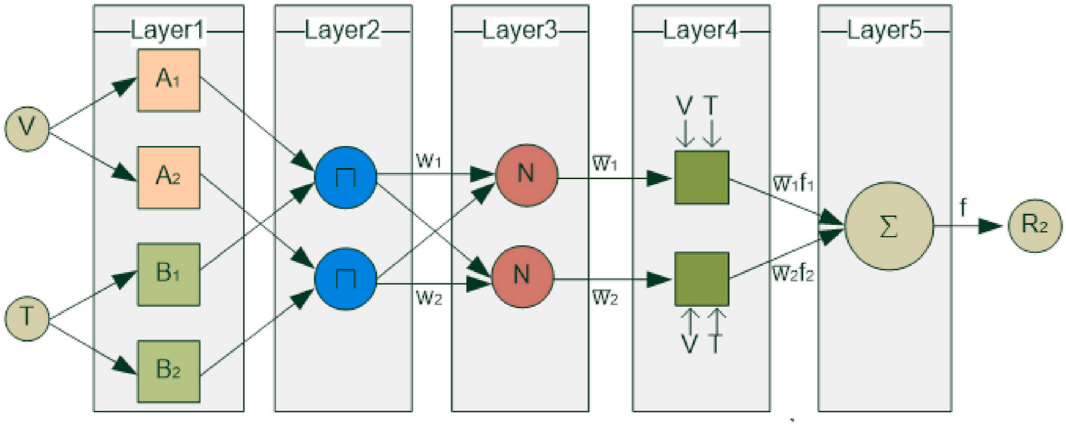

Fig. 2. Rule-based learning relation schema of the ANFIS model.

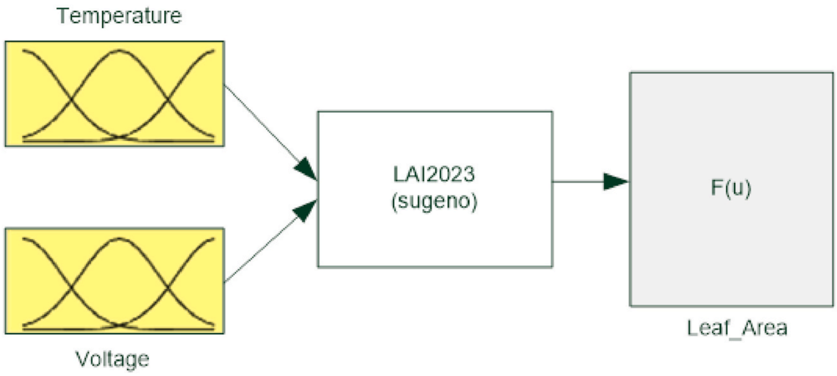

Fig. 3. Input and output variables for proposed ANFIS model.

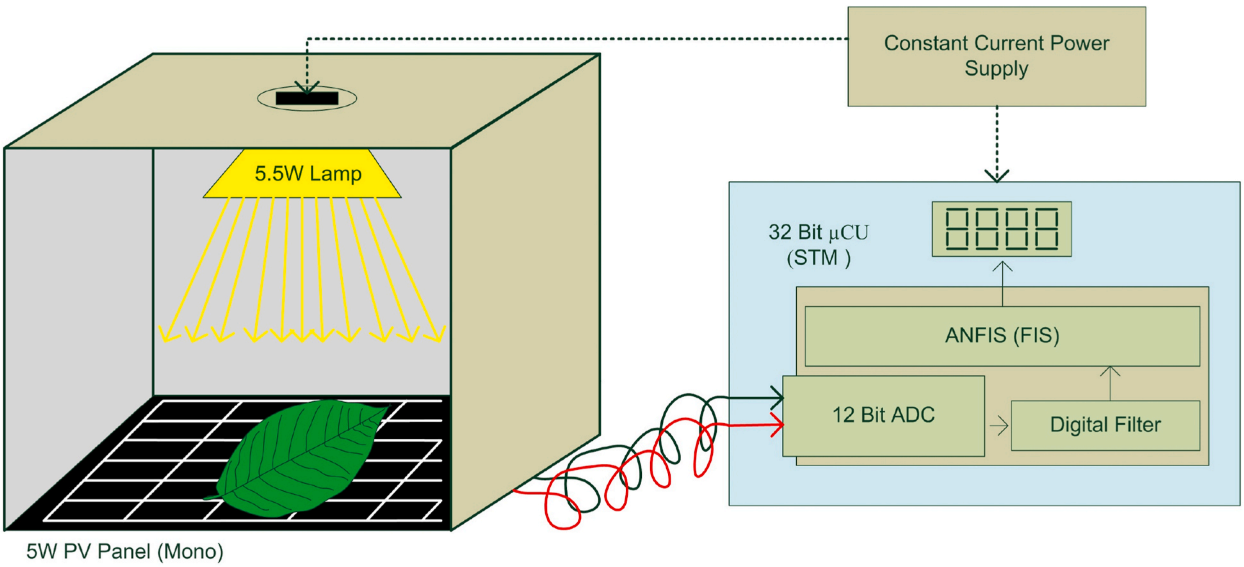

Fig. 4. Block diagram of the leaf area meter.

2.3. Hardware implementation

An embedded system utilizing ANFIS to measure leaf area was established within the scope of the study. For this purpose, software and hardware components were combined.

The user code compiled with Embedded Coder was uploaded to the ARM-based 32-Bit microcontroller (STM32F072) to easily operate the ANFIS model. To reduce the cost and complexity of the system, a very simple design was made, and the number of additional components was kept low. The digital filtering method was used to purify the signal applied to the ADC input from noise.

Fig. 4 illustrates the block diagram of the embedded system. The system consisted of a solar panel, a light source, a temperature sensor positioned on the panel, a non-transparent insulated enclosure containing these components, a constant-current power supply providing energy to the system, a microcontroller running the entire process, and components such as an LCD that provided various pieces of information to the user about the system. The light source and the solar panel were located inside a covered box. This box was designed with insulation to prevent the external light from entering. Additionally, it had a lid that could only be opened during the placement of the leaf. The inner surface of the insulated box was covered with a reflective material to ensure the equal distribution of light on the panel. Accordingly, the light source was positioned on the top of the box, while the panel was located at the bottom. This arrangement ensured that the rays coming from the light source fell directly onto the panel. Thus, by opening the lid and placing the leaf on the panel, the goal was to cast the shadow of the leaf onto the panel.

An analog temperature sensor, specifically an LM35 temperature sensor, was placed below the panel at the center. It measured the temperature of the panel, providing the necessary information about panel temperature for ANFIS. Another analog value was the output voltage of the panel. Table 2 presents the specifications of the panel used in the study.

Both the temperature sensor and the panel output voltage were connected to the microcontroller's analog-to-digital converter module (ADC). This ADC module had a resolution of 12 bits, allowing for precise analog readings. The panel voltage and panel temperature, which were required by the ANFIS module, were taken into the system through analog channels and converted into digital values and then into analog equivalents. The ANFIS model used these two values as input parameters and attempted to predict the leaf area. The embedded system's design also included an alphanumeric LCD for the user to easily obtain information about the leaf's area. All processes were carried out using ST's 32-bit microcontroller, the STM32F072RB. Once the user placed the leaf inside the box and closed the lid, within a few seconds, they could learn the leaf area in square centimeters. Fig. 5 shows the physical implementation of the embedded system capable of estimating leaf area.

In the scope of the study, ANFIS training was carried out using various geometric shapes and plant leaves with known areas. The geometric shapes used in the training included a square, a rectangle, a triangle, and a circle with known areas. The actual areas of the leaves were obtained using a program that can calculate areas based on pixels. In this study, leaf area estimation was performed based on the partial shading effect created by the leaves on the solar panel, along with changes in panel output voltage and panel temperature. The main motivation of this study was to pave the way for the development of an economical leaf area measuring device that can eliminate human errors and eventually become an industrial product.

3. Results and discussion

This study proposed an embedded system design using a PV panel and ANFIS, which enables the practical estimation of leaf area for plants. Various dimensions of Devil's ivy leaves and opaque shapes with known areas, such as circles, triangles, squares, and rectangles, were used in the training of the ANFIS model responsible for leaf area estimations. The total surface area of the PV panel that was used in the system was 187.5 cm^2. Among the geometric shapes with known areas, the largest one (square) had an area of 100 cm^2, while the smallest one (triangle) had an area of 0.43 cm^2. For the leaves, the largest area was $R^2 = 99.09$, and the smallest area was35.09. In this embedded system, two parameters affected the estimation of leaf area: temperature and voltage. An electrical current was converted to voltage through a resistance element connected to the PV panel. Thus, the light falling on the solar panel composed of PV cells was converted to voltage. The intensity of light was directly proportional to the panel output voltage and inversely proportional to the panel temperature. The relationship between the obtained area and voltage values is depicted in Fig. 6.

A number of geometric shapes with known areas were used for the training of ANFIS. During this training, panel voltage and panel temperature data were collected for the geometric shapes. Table 3 presents the corresponding panel voltage and panel temperature values for the area values. Accordingly, as the reference area of the circle and square/rectangle increased, the panel output voltage decreased, and the temperature increased. During the testing process, the temperature of the PV panel increased when it was placed inside a closed box with the light source directly aimed at the panel. Devil's Ivy leaf areas with unknown shapes and geometric shapes

Table 2
Photovoltaic panel specifications (LS005-36 PV panel specification).

Parameter	Value
Maximum Power	5W
Maximum Power Current	0.28A
Open Circuit Voltage	21.4V
Short Circuit Current	0.31A
Tolerance	5 %/5W

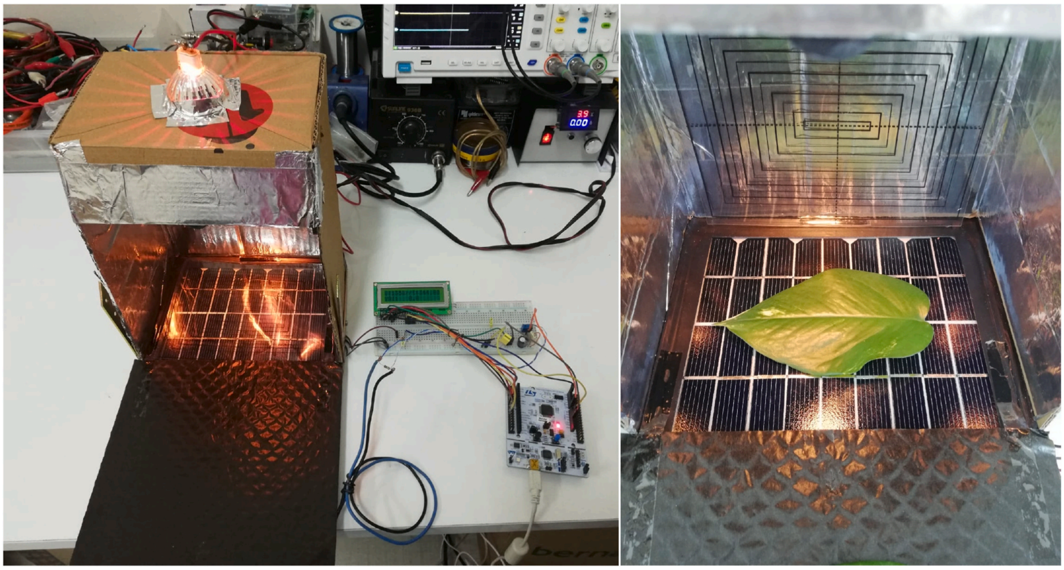

Fig. 5. Temperature and voltage variation in the photovoltaic panel.

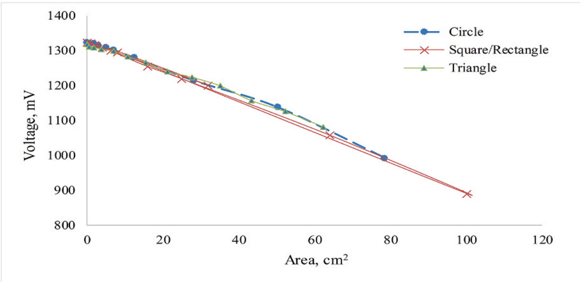

Fig. 6. Temperature and voltage variation in the photovoltaic panel.

Table 3
Reference area, voltage, and temperature of Circle and Square/Rectangle used in the training phase of ANFIS.

Circle		Square		Rectangle	
Ref. Area	$V_{out}(mv)$	Ref. Area	$V_{out}(mv)$	Ref. Area	$V_{out}(mv)$
0	1323	30.6	0	1323	31.3
0.78	1321	30.8	1	1320	31.2
1.76	1320	30.7	2	1317	31
3.14	1315	30.8	2.25	1314	30.8
4.90	1309	30.3	4	1310	31.1
7.06	1303	30.4	6.25	1300	31.1
12.56	1280	30.9	8	1296	31
28.27	1214	31.2	16	1255	31.2
50.26	1138	30.8	25	1220	31.4
78.53	992	30.7	32	1201	31.3
–	–	–	64	1058	31
–	–	–	100	891	31.2

with known areas were used for the ANFIS test data. Devil's Ivy leaves of unknown area were verified using a computer program that calculates pixel-based area. Fig. 7 shows the image of the Devil's Ivy leaves that was uploaded to the pixel-based area calculation program. Table 5 presents the reference areas used in the training and testing processes and the estimated leaf areas produced by ANFIS.

The results obtained in the measurements made with the embedded system were close to the reference area values. More importantly, during the testing of the system with the leaf samples whose areas were known but not included in the training of the

Table 4
Information about the ANFIS model.

Parameter	Value
Number of epochs	320
Number of member functions	3
Number of fuzzy rules	9
Train RMSE	0.775691
Train MSE	0.601697
Test RMSE	0.80814
Test MSE	0.65309

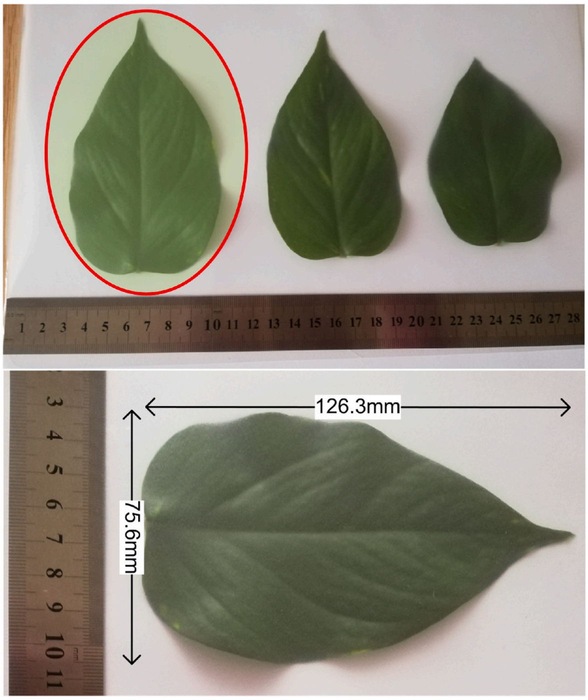

Fig. 7. Reference measurements of Devil's Ivy leaves whose images were uploaded to the pixel-bases area calculation program.

Table 5
Reference and ANFIS estimation values for circle, square/rectangle shapes, and Devil's ivy leaves.

Circle		Square/Rectangle		Devil's ivy	
Reference Area cm^2	Estimated Area cm^2	Reference Area cm^2	Estimated Area cm^2	Reference Area cm^2	Estimated Area cm^2
0	1323	30.6	0	1323	31.3
3.14	3.1	16	16.6	60.77	61.7
7.0	7.5	64	65.3	75.81	77.6
28.27	28.8	100	100.6	99.09	100.6
–	–	–	–	62.4	63.4
–	–	–	–	78.9	82
–	–	–	–	35.9	37.3
–	–	–	–	74.9	73.9
–	–	–	–	88.9	91.5
–	–	–	–	54.4	54.9
–	–	–	–	95.3	89.7
–	–	–	–	72.3	68.5

ANFIS model, the estimated areas were very close to the actual measured areas. The measurements conducted with regular-shaped samples including circles, squares, and rectangles provided more accurate results compared to the measurements conducted with the Devil's ivy leaves. This was because leaf surface areas were more curved and irregular compared to the tested geometric shapes. As a result, the estimated areas produced by the embedded system were very close to the areas used in the training process, indicating that this system could be used as a tool for leaf area measurement. A high level of accuracy, at a rate of $R^2 = 0.99$, was found for the relationship between the reference and estimated area results (Fig. 8), indicating that the estimated measurements were very close to the reference measurements, further confirming the reliability of the estimation process. The design parameters of the created ANFIS model are given in Table 4.

In a previous study [26], the researchers calculated the leaf areas of various species using PV panels. As they mentioned in their study, the output power of the PV panel is dependent on solar irradiance and panel temperature. In the study, the authors selected a light source that would not affect the panel temperature. However, the temperature of the room/area where their system was installed could vary, which in turn would affect the panel temperature. If they could not maintain a constant temperature in the area where the system was installed, the measurements taken at different times of the day or in environments with different temperatures could introduce errors. In another study [25], mathematical methods were used for leaf area calculations. The panel temperature data, which would be expected to affect the output power of the PV panel, was not considered significant. Therefore, repeated measurements taken at different temperature values in their study would produce incorrect results. In our proposed system, the panel temperature was included in the training data and used as an input for the system. Temperature variations affect the operation of PV panels, so they should be considered in leaf area calculations.

When considered in terms of system limitations, using more data in ANFIS training would be beneficial in producing more accurate predictions. The proposed system is a desktop type in its current form and a preliminary prototype. When the system is transformed into a more compact structure, that is, when the electronic components are transferred to the PCB, and the cabling is more stationary, the leaf area meter will be more user-friendly. Additionally, in its current form, it is more sensitive to the disruptive effects originating from the environment, and by transforming it into a compact structure, it will be more resistant to the disruptive effects originating from the environment. Currently, halogen lamps are used as the light source of the system. This means spending extra energy to produce the desired light value. Additionally, a large part of the energy spent turns into heat energy. If the light source is replaced with LED, the temperature effect will decrease, and it will become a more efficient structure. A more uniform light distribution can be achieved by optimally placing LEDs at the top of the leaf area meter.

The leaf area meters that are actively used in agriculture are laboratory-type or portable (handheld) devices. The leaf area meter used in this study had fewer components as it used machine learning (ANFIS), and it had almost no moving components. As a result of this design, it had a very simple structure. On the other hand, having multiple moving components makes laboratory-type leaf area meters that are used prevalently in the market expensive. Converting the prototype system presented in this article into a product with optical sensors -as in currently available laboratory-type devices, conveyor belts, and large parts would make it an inexpensive device. Moreover, handheld meters can lead to errors in reading values as they can tear plant leaves during measurement. Furthermore, some handheld leaf area meters pose challenges to the user during measurement as they include a measurement probe and a console component, resulting in a total weight value of approximately 3000 g. Although such leaf area meters allow the user to make measurements in the field, they have limitations in terms of ergonomics. Nevertheless, the leaf area meter presented in this article cannot make area measurements for leaves with dimensions greater than 12x15 cm. In particular, it is easier to measure the areas of pepper, strawberry, peach, bay, peanut, soybean, and other plant leaves, while the measurement capacity of the system is limited for plant leaves that are narrow and long, such as the leaves of maize and sorghum plants. Table 6 presents the comparison of some properties of the proposed system and other leaf area meters.

4. Conclusion

This study introduced the design and implementation of an easy-to-use and human error-reducing embedded system based on PV panels and ANFIS for leaf area measurements. The estimated results of this embedded system were very close to the known reference areas used in the study. Additionally, when leaf samples not included in the ANFIS training set were used as test data, the estimated data produced very close results to the reference leaf data. A high accuracy of $R^2 = 0.99$ was observed between the ANFIS prediction results and the reference areas. Accordingly, the embedded system produced estimated areas very close to the areas used in the training process, indicating that this system can be used as a tool for leaf area measurements. To further improve the accuracy of leaf area measurements, it is suggested to use light sources such as LEDs that do generate little to no heat instead of incandescent lamps in the proposed system. Additionally, using poly-crystalline or thin-film PV panels instead of mono-crystalline ones in the system can increase

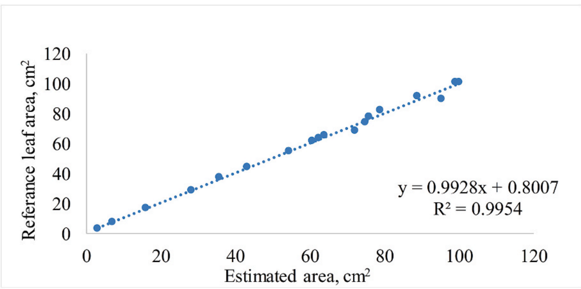

Fig. 8. The relationship between reference and estimated leaf areas.

Table 6
Comparison of the proposed product and some prevalently used leaf area meters in the market.

Product type	Cost	Maintenance requirement	Measurement speed	Size and weight	Leaf size limit for measurement	Working principle	Moving parts
Proposed product	Low (<500USD)	Almost none	Fast (under 1 s)	Medium/ light	Up to 225 cm2	Machine learning	None except for the lid
Prevalently used (lab-type)	>2500USD	Yes	Moderate (>2 s)	Large/ heavy	All leaf sizes	Mathematical model/static code	Yes (conveyor belt, optical sensor, caddy)
Prevalently used (handheld)	>1500USD	Little	User-dependent	Small/light	Narrow and long	Mathematical model/static code	Few (probe-type)

measurement accuracy.

Data availability statement

Data will be made available on request.

CRediT authorship contribution statement

Goksel Gokkus: Writing – original draft, Software, Project administration, Methodology, Investigation, Data curation, Conceptualization. **Mualla Keten Gokkus:** Writing – original draft, Validation, Methodology, Investigation, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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