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Identification of Houseplants Using Neuro-vision Based Multi-stage Classification System

Narges Ghanei Ghoushkhaneh [1], Abbas Rohani [1*], Mahmood Reza Golzarian [1], Fatemeh Kazemi [2]
[1] Department of Biosystems Engineering, Ferdowsi University of Mashhad, Iran
[2] Department of Horticultural Sciences and Landscape Engineering, Ferdowsi University of Mashhad, Iran

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*Corresponding author's email: arohani@um.ac.ir

Abstract

In this paper, we present a machine vision system that was developed on the basis of neural networks to identify twelve houseplants. Image processing system was used to extract 41 features of color, texture and shape from the images taken from front and back of the leaves. The features were fed into the neural network system as the recognition criteria and inputs. Multilayer perceptron (MLP) neural network with Declining Learning-Rate Factor algorithm (BDLRF) training algorithm was used as a classifier. Classification was done in three stages based on eligibility and strength of characteristics in identifying the plants. Eligibility criteria were assessed at each stage using plants class resolution power. In this classification method, each step requires a small number of attributes and for this reason its speed and accuracy can be very high. The results showed that the accuracy of classification of plants in three steps reaches 100%. Also, the optimal features for classification included three inputting steps of morphological features, HSI color features extracted from back of the leaves, and HSI texture features of the back of the leaves.

Keywords: Artificial neural networks, Houseplants, Identification, Image processing, Multi-stage classification.

INTRODUCTION

Houseplants or apartment plants are a small family of plants that have the ability to grow indoors and are grown for decorative purposes, positive psychological effects and health benefits including indoor air purification. Most of these plants are native to tropical and subtropical areas. In other words, they are adapted to the ecological conditions of these areas and hence, their use in residential and office buildings as houseplants requires conditions that are consistent with their initial ecological needs. Light, temperature, water, soil composition, and humidity are the most important factors that should be considered in the case of houseplants (Sanei Shariat Panahi and Fayaz, 1985). The first step to collect information about growth, thermal, water and light needs of these plants is identifying and knowing the names of these plants. Ability to identify plants requires experience and specialized skills and in some cases is associated with botany, but most enthusiasts do not have this expertise. Therefore, they find the plant identification difficult. Non-expert people have no choice to identify their plants except referring to books, internet resources, and databases. This process is very time-consuming because there are too many species of apartment plants and usually people give up their search.

In addition, many botanical scholars are willing to process the plants information at the time of observation so that they can save their time and continue their study in the field.

Over the past few decades, many research works have been done in the field of image processing to distinguish, classify and identify plants from images. Guyer *et al*. (1986) identified three species of corn, soybeans, and tomatoes and five weed species of cattle, cotton flower, johnson grass (sorghum), jimsonweed, foxtail, and lambs quarters using machine vision and image processing techniques. Two hypotheses were tested to identify plant species: i) difference in reflectance of leaves and soil surface, and ii) differences in the number and shape of leaves. The results showed that the combined use of difference in reflectance curve of soil and vegetation along with an infrared camera can help better soil-plant segmentation. In the next step, four spatial features from digital images were used in a classification algorithm for plant identification purposes.

Other researchers presented color factors according to equations 1 and 2 to separate the weeds from the leaves of sugar beet.

$$L = (R + G + B) / 3 \qquad (1)$$

$$0.371\ B\text{-}0.114G \qquad (2)$$

They tested their algorithm on 300 digital images from sugar beet and seven common weed species. The segmentation results were reported to be 88.5 percent for the images of the weeds, taken under the direct sunshine, and 88.1 percent for the weeds in the shadow. Neto *et al*. (2005) distinguished two species of sunflower (Helianthus pumilus) and young soybean (Glycine max (L.) Merrill.) from two types of weeds, namely, redroot pigweed (Amaranthus retroflexus) and velvetleaf (Abutilon theophrasti Medicus) plants, using image processing techniques. The researchers used elliptical Fourier extracted from the images to identify the form of plants' leaves and reported the accuracy of this method to be 4.88 percent. Although weeds during adolescence or at their third week growth stage were very similar to the crop plants, they were identified 89.4 percent correctly using two methods of Principal Component Analysis (PCA) and Linear Discriminant Models along with elliptical Fourier.

Leaf angle in elliptic Fourier analysis was very important in the high accuracy achieved. White *et al*. (2006) developed a field guide that was consisted of a database and a machine vision algorithm. The algorithm shows sorted list of the closest matches by comparing the sample with those stored in database collection. The plant was identified by botanists among the presented examples. They developed a prototype of a mobile augmented reality system for accessing and inspecting a large database of virtual species examples side-by-side with physical specimens. Li *et al.* (2006) proposed a new method to extract the leaf veins for identification purposes. They used Independent Component Analysis (ICA) algorithm to create leaf veins map. The results showed that ICA could successfully extract leaf veins, which were then used for automatic identification of plants.

Several researchers used neural networks to classify plants (Wu et al., 2007, Mahmoudi *et* *al.*, 2008). Wu *et al*. (2007) succeeded to classify 32 species of plants with an accuracy of higher than 90%. In this study, from the image of each leaf 12 features were extracted of which five main variables were calculated using PCA. These principal components were used as the inputs of a probabilistic neural network. Wang *et al.* (2008) identified leaves' images with crowded and complex background. They used the features extracted from leaves' shapes and edges. Average classification accuracy was found to be 92.6%. Other researchers sought to achieve a precise color index for image segmentation of the plant regions from soil and plant residue background. They examined three color indices according to equations 3, 4 and 5 for separation of soybean leaves from soil background and plant residue.

$$2G - R - B \qquad (3)$$

$$14R - G \qquad (4)$$

$$(G + R)/ (G - R) \qquad (5)$$

The results of this research showed that two factors of equations 3 and 4 had better performance in segmentation of plant leaves from the background (Meyer and Neto, 2008). Pramanik *et al.* (2010) presented an algorithm for identifying plants on their leaves using Sobel edge detection method. They used morphological features of leaves extracted from the edges. Zheng and Wang (2010) suggested the form of leaf veins as an effective parameter for automatic identification of plants. They presented a new way to extract leaves veins based on mathematical morphology. In this project, two features of tone and brightness were used to separate leaves from the background. Some other researchers examined different combinations of features of morphology, color and texture of plant leaves to optimally identify medicinal plant. The results showed that the highest accuracy of 94.4 and the minimum time for plant identification were obtained by selection of 8 input features. These features included compaction index, eccentricity, aspect ratio and Hu moments, some color features in RGB color space of average, standard deviation, and skewness. The highest accuracy was achieved by selecting all features, but the computational time was longer (Zheng and Wang, 2010). Although many research projects have been conducted in identifying crop plants from images and their associated weeds but there is yet little available literature that focused on identification of houseplants. On the other hand, the specificity of systems for native plants of specific areas in different countries or groups of crops or horticultural plants aimed to identify weeds, limited accuracy and low speed in identification caused these systems to be not generally available yet.

Therefore, the objectives of this project were to develop an image processing system based on neural network, to determine the optimal values of the MLP neural network parameters for identification of houseplant species, to determine the optimal set of features, and to provide a new way for 100% accurate classification of house plants based on the optimal features. Therefore, the ultimate aim of this system is to help researchers to accelerate research and also ordinary users to recognize its surrounding plants.

MATERIALS AND METHODS

The study targeted twelve houseplants commonly found in the urban space including Aglaonema (*Aglaonema* sp.), tradescantia (*Tradescantia zebrina*), peperomia (*Peperomia magnoliifolia*), pedilanthus (*Pedilanthus tithymaloides*), pothos (*Scindapsus* sp.), sansevieria (*Sansevieria trifasciata*), syngonium (*Syngonium podophyllum*), schefflera (*Schefflera actinophylla*),Chinese hibiscus (*Hibiscus rosa-sinensis*), fittonia (*Fittonia argyroneura*), philodendron (*Philodendron pertusum*), rubber fig (*Ficus elastica*), Benjamin's fig (*Ficus benjamina*), jade plant (*Crassula ovata*), asparagus fern (*Asparagus plumosus*), and Yuka (*Yuka* sp.).

Sample leaves were collected from young and mature plants. According to the experiments, the time from sample collection until they were imaged was short so it didnot injure the appearance or impose physical changes in the samples that could have led to error in identification process. Depending on the type of plant, 40 to 50 leaves per plant type of about ten plant pots were selected and imaged afterwards.

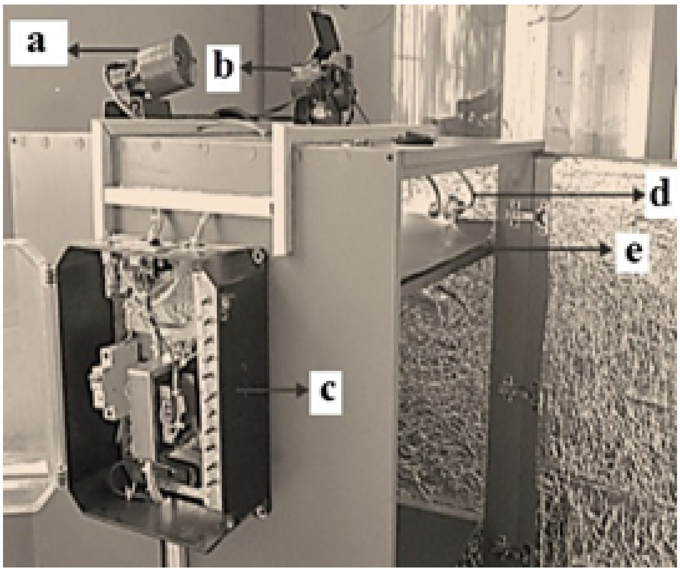

Fig. 1. The designed imaging box: a) electrical motor used for changing the distance of camera to the background plane; b) camera; c) panel for controlling LED lighting and electrical motor; d) LED lighting; e) background plane

The hypothesis of this research was using a set of combined features of color, morphology and texture of the leaves, which all form the input to the neural network, for plant identification purposes. Due to the differences in visual features and especially color and texture features in the front and back of the leaves, both sides of the leaves were imaged. For imaging, an imaging box with a controllable and uniform lighting condition was constructed (Fig. 1). Pixel to mm calibration was required for dimensionless morphological features. This was done in horizontal and vertical direction using a calibration sheet. To avoid errors, especially those caused by marginal distortion, leaves were placed right under the camera lens in order and thus appeared in the middle of images.

The features such as color, morphology, and texture were extracted from the leaves images after image segmentation of leaves from background. The image segmentation was done using the method of thresholding the image histogram, which is one of the most common approaches in image segmentation. The first step before thresholding was to convert a three-channel color image into a grayscale image in that there was a high contrast between the background and plant leaves. Then, the image histogram that is the plot of number of pixels according to intensity of color factors of pixels was provided. Pixels of leaf (green part of plot in Fig. 2) can be extracted from pixels of

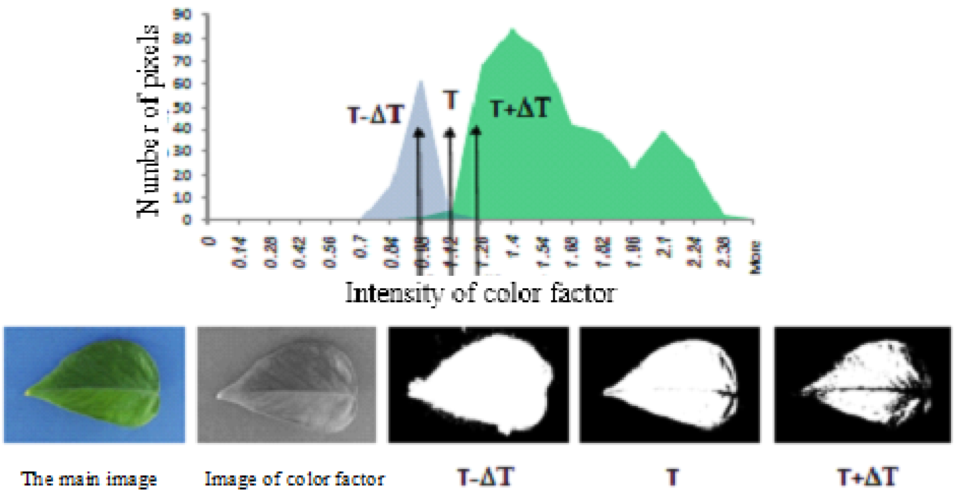

Fig. 2. The impact of choosing an appropriate threshold (T) on the performance of segmentation of leaf region from background (Golzarian *et al.*, 2014).

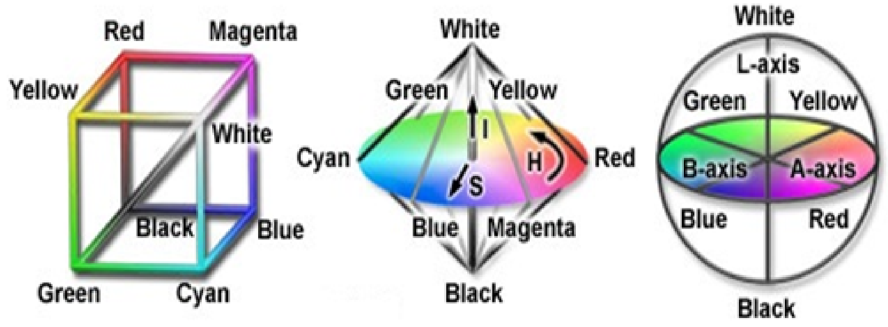

Fig. 3. Three color spaces used in the project, from left to right: RGB space, HSI space, and L*a*b* space (from http://micro.magnet.fsu.edu).

background with threshold value (T). Choosing an optimal threshold value for segmentation was of great importance so that it affected the quality of segmented image considerably and therefore, the output of the following processing steps. Fig. 2 illustrates how important choosing the appropriate threshold value is. If the selected threshold is more than the desired threshold, i.e. T+ΔT (ΔT is the lowest possible value), then a large area of leaves will be lost during segmentation. If the selected threshold is more than the optimal threshold, i.e. T-ΔT, a part of background region will be included as plant region in the segmented image. The gap between leaf and background histograms is controlled by defining a color factor that makes contrast between these two regions. If the gap is higher, which is the result of a good color factor definition, the sensitivity of threshold value selection will be less. In this project, we defined and used color factor of G-B that had optimal performance for segmentation of the green leaves and G/R with performance criteria of 1.5 for separation of red leaves from blue background (Golzarian *et al*., 2014).

Feature extraction is a process by which the prominent features are determined by performing operations on the raw data. The purpose of feature extraction is to convert raw data into a more usable form for following statistical processing. Selection of leaves' features is one of the important steps in image processing. The output of this step can provide an adequate description of the objects and can provide the most separation performance in the classification process. Generally, those features that are measurable and their measurement is easier to make are more appropriate. Features of color, morphology and texture are used for indexing images in image retrieval systems. In agricultural applications, color feature is often used for pests and diseases inspection, product handling, product variety, etc. (Ahmed *et al*., 2012; Jafari *et al*., 2004; Chaudhary *et al*., 2012).

In this project, the color features of plants' leaves which were extracted from three color spaces of RGB, HSI and *L *a *b were used. In the RGB color space, each pixel of an image consisted of three values for red, green, and blue channels. Distribution of color intensity for each color component was measured by the standard deviation around the mean value (Gonzalez *et al.*, 2009). In addition to RGB, color components of HSI were used. HSI color space is similar to the human perception of color. The parameter of H is the hue and shades of color that determines the color purity, S is white light interference in color and I is light intensity. L*a*b* color space, like HSI color model, is similar to human visual perception of colors. In this color model, L* describes the brightness component, a* shows the sensitivity of red intensity to blue intensity, which is achieved from red minus green, and b* component indicates the sensitivity of green intensity to blue intensity, which is calculated from the difference of green and blue values. Three color spaces used in this project are shown in Fig. 3.

Morphological features were extracted from the binary image of leaves. Morphological factors are one of the best sets of features to identify leaves. Morphological features, which are expressed in terms of shape parameters, should be dimensionless as much as possible. It means that it should not affect the height of the camera to the desired object. Morphological features, which were used in this research, included area, perimeter, compression ratio, and the ratio of the major

Table 1. Table of class numbers and their corresponding plant species

Class	Name	Number	Class No.	Name	Number
1	*Ficus bejamina*	48	7	*Pedilanthus*	52
2	*Hibiscus*	55	8	*Aglaonema*	50
3	*Fittonia*	50	9	*Yucca spp.*	49
4	*Crassula ovate*	48	10	*Sansevieria*	50
5	*Scindapsus*	47	11	*Zebrina*	49
6	*Peperomia*	57	12	*Coleus*	58

axis to minor axis.

In addition to color and morphological features, texture features were also extracted from the images taken from the back and front of the leaves. In image processing, texture is defined as the intensity change in a region on an image. The parameters extracted from histogram of a color channel represent the distribution of that color intensity over that region and these parameters can be used as features describing texture of that particular region.

The statistical parameters commonly used to describe the texture of a region include mean, standard deviation, softness, third moment, and entropy. Third moment describes symmetrical distribution around the mean value of color intensity in the histogram of a region. This value is zero for a symmetrical histogram, positive for histogram skewed to the right, and negative for the histogram skewed to the left. Entropy measures the random nature of any possible value of a brightness level in an image. Standard deviation and entropy were used in this project to describe the image texture of the back and front of the leaves. In the field of non-morphological features, color and texture extracted features from the back or front of the leaves were used and in the case of morphological features, only shape features extracted from the front of the leaves, which were the same as those extracted from the back of leaves. The extracted features were fed into a neural network system for classification of plant species. For better and uncluttered presentation of classification results, the class number was used instead of the names of plant species. Table 1 shows the used class numbers and their corresponding plant species.

The developed MLP network receives an input feature vector of *Xq* and produces the output vector of *Zq*, which indicates the predicted class for each q (q = 1, ..., Q). The purpose is to make the correct network parameters in order to obtain the actual output of *Zq* that is to be close to their corresponding desired output dq as much as possible. Back-propagation with Declining Learning-Rate Factor algorithm (BDLRF) was used (Rohani *et al.*, 2011; Vakil-Baghmisheh and Pavešic, 2001). The algorithm was written in Matlab programming language.

This training algorithm starts with a relatively constant large step size of learning rate η and momentum term α. Before destabilizing the network or when the convergence slows down, for every T epoch (5≥T≥3) these values decrease monotonically by means of arithmetic progression until they reach x% (e.g. x equals 5) of their initial values.

The cost function used in this algorithm is the total sum-squared error (TSSE) and is calculated using Equation 1:

$$E_q = \sum_k \left(d_k^q - z_k^q\right)^2 \quad \text{for } (q=1,\dots,Q) \qquad (1)$$

where, d_k^q and z_k^q are the k_{th} element of the desired and actual output vector of the q_{th} input, respectively. Network learning occurs in two phases of back-propagation and feed-forward. The weight of each layer is calculated through Equation 2 and 3.

$$u_{jk}(n+1) = u_{jk}(n) - \eta \times \frac{\partial E}{\partial u_{jk}} + \alpha(u_{jk}(n) - u_{jk}(n-1)) \qquad (2)$$

$$w_{ij}(n+1) = w_{ij}(n) - \eta \times \frac{\partial E}{\partial w_{ij}} + \alpha(w_{ij}(n) - w_{ij}(n-1)) \qquad (3)$$

where, w_{ij} is weighted connection between i and, j nodes, u_{jk} is the weighted connection between j and k nodes. The initial values of the weights are selected randomly from the range [-0.25, 0.25]. l_2 and l_3 are the number of neurons in hidden layer and output layer, respectively. n is repetition number of algorithm ($n=1,...,N$).

The main idea in this project is based on the simulation of human behavior in the separation of the objects from each other. First, humans classify objects into general groups and then, classify objects of each group into smaller groups, and the process continues until all objects are correctly classified. Based on this idea, the first feature is optimal when it can separate more classes completely from others. To achieve this goal, it is required to examine all the features. Of course, a first optimal feature classifies a limited number of classes at each stage. Then, another optimal feature is used in subsequent steps to classify the remaining classes. This procedure is continued until all classes are classified.

RESULTS AND DISCUSSION

First, the optimal value range of the neural network parameters was found by trial and error method. Then, the classification process began based on general morphological criteria and it found the best criterion for classification in the next steps and this process continued until all classes were completely classified.

Results showed that the number of neurons in the hidden layer (network topology) varied from 8 to 18 based on desired number of classes. The increase in the number of neurons caused over-fitting problem and prolonged the network's training time. Also, small topology of the network caused lack of learning in samples. Using momentum factor (α) accelerated the training process of network. The results of applying training algorithm BDLRF showed that the best results were obtained when the parameter α remained constant during the training process. The optimal value of this parameter for all networks was found to be 0.25. The optimal value of the training factor (η) for all networks was found to be 0.95 along with the starting point of BDLRF after 100 or 200 epochs. The final value of η was 0.50 at the end of the training process.

The results of classification for 12 classes based on each of the extracted features are given in Table 2 in training and testing phases. As can be seen, none of these features can classify all

Table 2. Classification results achieved from using each visual feature

	Class	Feature						
		F_RGB	F_HSI	F_LAB	B_RGB	B_HSI	B_LAB	Morpho.
Classification accuracy with respect to each class	1	62.50	77.08	68.75	62.50	68.75	51.17	97.92
	2	56.36	74.55	63.64	94.55	87.27	85.45	89.09
	3	94.00	92.00	100.00	96.00	96.00	96.00	96.00
	4	100.00	97.92	93.75	87.50	91.67	89.58	100.00
	5	76.60	80.85	78.72	89.36	91.49	91.49	100.00
	6	85.96	87.72	89.47	77.19	70.18	82.46	89.47
	7	100.00	100.00	100.00	100.00	100.00	100.00	90.38
	8	100.00	86.00	96.00	90.00	94.00	96.00	100.00
	9	95.92	97.96	95.92	93.88	85.71	97.96	100.00
	10	88.00	80.00	84.00	56.00	78.00	62.00	74.00
	11	100.00	100.00	95.92	100.00	100.00	100.00	97.96
	12	98.28	96.55	100.00	100.00	100.00	100.00	100.00
Total Classification Accuracy in Training phase		87.96	90.82	91.22	88.57	90.61	89.80	94.69
Total Classification Accuracy in Testing phase		88.62	82.93	79.67	82.93	80.49	81.30	93.50

F = Front , B = Back

Table 3. Classification results achieved after using color features

Class	Colour Feature					
	F_RGB (%)	F_HSI (%)	F_LAB (%)	B_RGB (%)	B_HSI (%)	B_LAB (%)
1	68.75	70.83	72.92	72.92	81.25	77.08
2	72.73	81.82	74.55	98.18	100.00	92.73
3	96.00	94.00	98.00	98.00	100.00	100.00
6	87.72	89.47	87.72	87.72	92.98	91.23
7	100.00	100.00	100.00	100.00	100.00	100.00
10	98.00	100.00	98.00	82.00	94.00	94.00
11	95.92	95.92	93.88	100.00	100.00	100.00
Total Classification Accuracy in Training phase	89.62	90.31	89.97	92.73	96.19	95.85
Total Classification Accuracy in Testing phase	83.33	90.28	86.11	86.11	93.06	15.25

Table 4. Classification results achieved after using texture features

Class	Texture Feature					
	F_RGB (%)	F_HSI (%)	F_LAB (%)	B_RGB (%)	B_HSI (%)	B_LAB (%)
1	83.33	56.25	75.00	68.75	77.08	77.08
2	85.45	94.55	85.45	96.36	94.55	100.00
3	100.00	100.00	100.00	92.00	98.00	88.00
6	78.95	89.47	85.96	61.40	91.23	68.42
7	100.00	80.77	90.38	96.15	82.69	76.92
10	80.00	88.00	70.00	82.00	100.00	98.00
11	85.71	100.00	100.00	91.84	67.35	100.00
Total Classification Accuracy in Training phase	89.62	87.89	87.89	86.51	89.62	87.89
Total Classification Accuracy in Testing phase	79.17	84.72	81.94	73.16	79.17	81.94

T = Texture, F = Front, B = Back

classes completely. In general, morphological features with identification accuracy of 94.69 percent in the training phase and 93.50 percent in testing phase had the best performance for plant identification. However, some of the classes in each of the features completely in both the training and testing of other classes are in separable. For example, classes 4, 7, 8 and 11 are completely (100%) separable based on F_RGB feature. Also, the number of classes that are completely separated from the others is different based on the set of features. Morphological features, RGB from the front of leaves (F_RGB), LAB from the front of the leaves (F_LAB), R, G, B from the back of the leaves (B_RGB), HIS from the back of the leaves (B_HSI), LAB from the back of the leaves (B_LAB), and HSI from the front of the leaves (F_HSI) could fully classify class numbers 5, 4, 3 and 2, respectively. As it can be seen, every plant of class numbers 7, 11 and 12 was classified completely using a minimum of five features. Finally, considering all above discussion, the morphological features were used first in the classification of the plants.

The developed MLP neural network could completely identify the classes 4, 5, 8, 9 and 12 based on morphological features in the first stage. At this stage, we sought another feature to classify the remaining classes using another new neural network system. Results of applying each of color and texture features extracted from the back and front of the leaves, which were used in training and texting phases, are shown in Tables 3 and 4. Network training according to any one of the

Table 5. The results of classification of remaining classes of 1, 6, and 10 based on color and texture features

Class	Colour Feature					
	F_RGB (%)	F_HSI (%)	F_LAB (%)	B_RGB (%)	B_HSI (%)	B_LAB (%)
1	93.75	97.92	97.92	81.25	87.50	70.83
6	98.25	92.98	96.49	89.47	94.74	92.98
10	100.00	100.00	100.00	94.00	94.00	98.00
Total Classification Accuracy in Training phase	97.58	99.19	99.19	88.71	95.16	89.52
Total Classification Accuracy in Testing phase	96.77	87.10	93.55	87.10	80.65	80.65
Class	**Texture Feature**					
	F_RGB (%)	F_HSI (%)	F_LAB (%)	B_RGB (%)	B_HSI (%)	B_LAB (%)
1	91.67	77.08	85.42	87.50	83.33	81.25
6	92.98	96.49	82.46	86.49	100.00	91.23
10	88.00	98.00	92.00	98.00	100.00	100.00
Total Classification Accuracy in Training phase	95.16	91.49	89.52	95.16	96.77	91.49
Total Classification Accuracy in Testing phase	74.19	87.10	74.19	90.32	87.10	87.10

features leads to different classification results. In terms of the overall performance of the network in training and testing phases, color features had better performance as compared with texture features. When HSI color features of the backside of the leaves were used, all classed were classified with the accuracy of 96.19% and 93.06% in training and testing phases, respectively. However, the use of HSI-based texture features extracted from images of backside of the leaves provided 89.62% and 79.17% accurate classification in training and testing phases, respectively. This conclusion also can be applied to other features. However, the number of classes that were completely identified from others was different depending on the color and texture features used. Two classes were fully detected using Lab-based texture features extracted from images of the front of the leaves, while only one class was completely classified when Lab color features were used from the front of the leaves. Therefore, according to these findings, HSI color features of the front of the leaves were selected as optimal classifying criteria, and the MLP neural network that uses these criteria was chosen to be an optimal network at this stage.

The results of applying the previous neural networks could classify 9 plant classes completely within two stages and only three classes 1, 6, and 10 were not yet classified. This may be due to the proximity of their visual characteristics to each other or those of other classes. In other words, these classes were not completely separable in the presence of other classes. Therefore, new neural networks with new parameters based on additional color and texture features were examined for classifying these samples into their correct classes (Table 5).

The classification process is shown schematically in Fig. 4 based on the selection of the best features at each stage. In the first stage, neural network MLP1 could identify and separate five classes of 4, 5, 8, 9, and 12 completely based on morphological features and then, in the second stage, the developed neural network MLP2 separated the four other classes of 2, 3, 7, and 11 from the other classes with the accuracy of 100%, which were remaining from the previous stage, using HSI color features extracted from the backside of the leaves. Finally, the neural network MLP3 identified 3 classes 1, 6 and 10 based on HSI-based texture features extracted from the backside

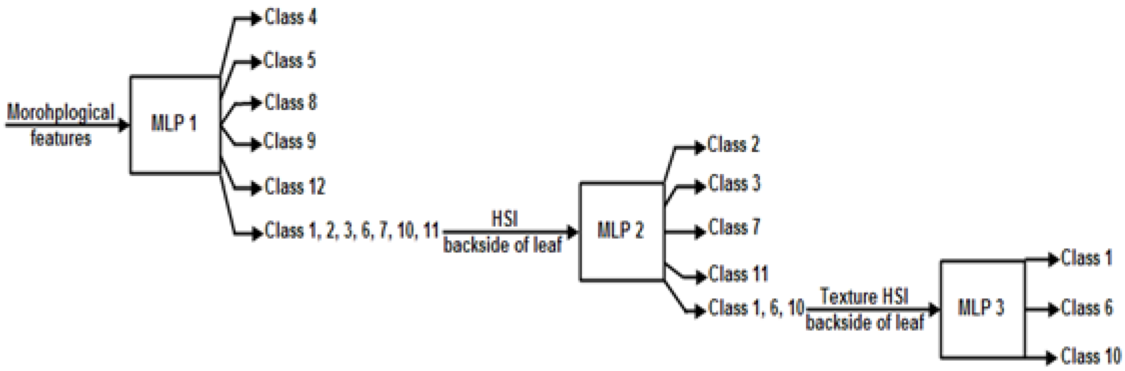

Fig. 4. Classification structure with feature selection method

of the leaves. Overall, three neural networks MLP1, MLP2, and MLP3 identified all 12 classes completely from each other based on morphological features, HSI color features and HSI-based texture features, respectively.

CONCLUSION

In this paper, a computer vision system was developed to extract 18 color features, 18 texture features, and 5 morphological features from the images of the front and back of the leaves. These 41 features were used to group samples within 12 classes of houseplant species. Results of using a set of similar features as the classification criteria in the neural network led to the separation of some classes completely at each stage of training and testing. In other words, the sensitivity of classification in some classes depends on the type of features or criteria used in the process. Optimal features were selected by testing each feature based on the number of classes with 100% classification performance. The results showed that all samples could be successfully classified with three sets of features fed into MLP neural networks: first, morphological features, then HSI color features from the back of the leaves, and finally HSI-based texture features from the back of the leaves. In the real world, human initially uses distinguishing features rather than classifying objects into certain classes with confidence first. They use other features for classifying the remaining objects in consecutive steps. In this paper too, having inspired by this method, plant classification was performed based on optimal features in multi-stage forms, resulting in 100% accuracy for samples of 12 plant species.

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