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# SIGNATURE OF PLANT LEAF
BY

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## ABSTRACT

This research aimed at overcoming some of the limitations encountered in the course of plant leaf shape analysis studies. Mathematical morphology of plant leaf venation was exploited as a shape analysis technique for plant identification purposes. Leaf shape features were extracted from preprocessed leaf color images using a pre-selected set of twenty structuring elements to generate a distinctive leaf signature for individual plants. Prototype leaf signatures were produced from a training set for three plants, namely: Alfalfa (Medicago Sativa), Mint (Mentha Piperita), and Pomegranate (Punica Granatuml) to calculate decision functions for developing a Minimum Distance Classifier. Four factors that could influence the performance of the classifier were considered in forming a testing set of 162 leaf color images. The four factors considered were: plant type, leaf orientation angle, leaf size, and leaf occlusion ratio. The classifier effectively handled the testing set by correctly designating leaves to the plants to which they belong. A perfect performance was achieved in identifying the three plants with correct classification rates of 100%, 96.3%, and 100% for Alfalfa, Mint, and Pomegranate, respectively.

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**Key words:** Precision agriculture, Shape analysis, Leaf venation, Morphological features, Template matching, Leaf signature, Plant identification.

## INTRODUCTION

Information extracted from digital images of plants has become a reliable tool in precision agriculture. Plant digital data used for different studies' objectives have been collected from its: canopy (Shrestha and Steward, 2005; Humburg *et al.*, 2006), stem (El-Faki *et al.*, 2000b; Tang and Tian, 2002), leaves (Franz, 1991; Yonekawa, 1996; Chi *et al.*, 2002), and fruit (Ying *et al.*, 2003, Lu, 2005). Through machine vision techniques, the data collected are used to extract a set of plant features that would enable achieving many purposes, such as: (i) determination of growth stages (Meyer and Davison, 1987; Strolei *et al.*, 1989; Webbecke *et al.*, 1995), (ii) identification of plant species (El-Faki *et al.*, 2000b; Chi *et al.*, 2002) (iii) detection of diseases (Sasaki and Suzuki, 2003; Murakami and Homma, 2005), and (iv) diagnosis of plant nutrient stress (Kwon *et al.*, 2004; Borhan *et al.*, 2004). Leaf shape analysis is gaining more importance in plant identification as a means for weed control systems, monitoring plants for automated greenhouse management, and modeling plant growth in physiological studies (Franz *et al.,* 1991; Chi *et al.,* 2002). Different methods have been employed by researchers to discriminate among various plant species using information obtained from leaf shape. Leaf shape features like length, width, perimeter, area, leaf base and apex are among the most widely used for shape analysis.

Chien and Lin (2002) utilized elliptical Hough Transform to identify occluded leaves, measure leaf area, and count leaf number of four selected vegetable seedlings. They concluded that their algorithm was most suitable for leaf area measurement of seedlings with planar leaves at horizontal orientation. Its accuracy suffers from tilting orientation of leaves, small sizes, and severely occluded leaves. Chi *et al.* (2003) modeled leaf boundary with Bezier curves and developed geometric descriptors from the approximate leaf shape to identify four vegetable seedlings. Lee and Sluaghter, 2004, used leaf area, elongation, and compactness to identify partially occluded tomato plants and weeds. The algorithms performed well in recognizing weeds but not as well for tomato plants due to their long and thin seedlings. Shrestha and Steward, 2005, extracted shape and size features from top projected plant canopies to classify corn and weed plants within corn row sections.

Noble and Brown, 2006, developed a segmentation approach based on simple edge detectors operating on narrow-waveband images from an imaging spectrophotometer to differentiate leaf-leaf boundaries from other interior edges represented by leaf overlap, veins, and blemishes for four species (Soybean and three weeds). Testing resulted in a mean correct leaf segmentation rate of 63%. Shortcomings of the approach were inability to eliminate partial leaves, removal of a significant amount of the leaf area, and dependability on the ability of the band selected to provide leaf-leaf edge contrast while minimizing edges from veins and blemishes. Mathanka *et al.*, 2007, utilized information extracted from leaves in terms of color, texture, and shape features subsequent to eliminating leaf overlapping to differentiate between wheat and weed at three different image resolutions. Shape features used were area, perimeter, equivalent diameter, eccentricity, shape factor, and circularity. Correct classification rate reduced drastically as resolution decreased. The highest correct classification rates obtained were 73% for wheat and 26% for weed at 100% resolution. They concluded that the shape features used were less effective in wheat weed discrimination.

He *et al.*, 2003, pointed out that several research groups (Kanuma *et al.*, 1998; Suzuki and Murase, 1998, 2000) had attempted to calculate the leaf area using different image analysis systems. Generally those systems were not adopted, because their analysis accuracy was affected by the inclination of leaves, and changes in leaf color over time. Although plant images acquired by CCD cameras could be processed to measure leaf area non-destructively, yet the results are affected seriously by the object distance, sampling angle, lighting condition and mutual superposition within the leaves (Zhen *et al.*, 2007). Therefore, leaf inclination, occlusion, and variability in size are difficulties facing leaf shape analysis techniques. Despite these difficulties, leaf shape analysis still has its power and a lot to offer whether in plant identification or other applications. Interestingly, several researchers have found leaf shape analysis beneficial in delivering quantitative indicators for qualitative items. Hashimoto *et al.*, 2002, analyzed leaf length and width in the polar coordinate and found them helpful in processing data quantitatively to judge the tree vigor of grapes. Fakagawa *et al.*, 2003, estimated leaf height and number of stems from vegetation cover rate to sense crop status of corn and rice. Ramalingam *et al.*, 2003, investigated leaf blob characteristics such as area, perimeter, and compactness to characterize the spray deposits on leaves.

**Objectives**

This study aimed at overcoming some of the leaf shape analysis limitations by developing a robust method for plant identification depending on the morphology of leaf venation web. The specific objectives were to:

1. Develop preprocessing procedures to get color leaf images ready for extracting accurate morphological features.
2. Get leaf signature by calculating number of matches of a set of twenty selected morphological features.
3. Develop leaf signature prototypes and decision functions to build, train, and test a minimum distance (MD) classifier in identifying plants by classifying leaves: from three different plants (Alfalfa, Mint, and Pomegranate), with two occlusion ratios (0%, 50%), at three axle directions (one horizontal and two diagonals), in other words, at three different directions of leaf orientation angles (0°, 45°, 135°), and of three different sizes (large, medium and small).

## MATERIALS AND METHODS

**Image acquisition**

Leaf images of Alfalfa, Mint, and Pomegranate were captured using a 3-CCD Sony XC-003 RGB color camera fitted with a VCL-25WM lens. Leaves were placed at a distance of 12″ (30.5 cm) away from the camera on an area fiber optic backlight (4.25″x3.37″) (cm) and covered with a transparent glass plate to obtain clear shots of whole leaves. Illumination for training and testing image sets were fixed at 355 FC. Top view images of leaves were acquired and digitized into a 24-bit RGB images with a resolution of 640 x 480 pixels using an Ultra II RGB Industrial Image Capture Board. The imaging system was hosted by a 486 computer, while image processing was performed using a Pentium 4 computer.

A 3x2x3x3 factorial design with three replications was used to test the significance of the differences between correct classification rates (CCR) and misclassification rates (MCR) achieved by the classifier. The CCR is defined as the ratio between the number of leaf images correctly designated to the plant they belong to and the total number of leaf images in the testing set as regard to the factor under question. The MCR is defined as the ratio between the number of leaf images incorrectly designated to the plant they do not belong to and the total number of leaf images in the testing set as regard to the factor under question. ANOVA and multiple comparisons were used for statistical analysis. Factors considers were plant type (three levels), occlusion ratio (two levels), leaf orientation angle (three levels), and leaf size (three levels).

**Training and Testing Sets**

Training set consisted of ninety images, thirty for each plant distributed among large, medium, and small leaf sizes equally. All images of training set were captured at 0° orientation angle, with 0% occlusion ratio. To get 50% leaf occlusion ratio, half of the upper part of the leaf image was erased normal to its axle, manually. Testing set consisted of 162 leaf images covering all treatment combinations with three replications. This was meant to expose the classifier to less complicated situations to receive the least support during training stage, and to address it with more complicated situations during testing stage to assess its scope of capability.

**Preprocessing**

**Step I: Edge Detection**

Each of the RGB color images were subjected to the following processes successively:

1. image mode was converted to grayscale
2. leaf veins were obtained using an edges detection filter.
3. image was inverted
4. image was posterized (the number of gray levels were reduced to three levels {0, 129, 255}, and black lines were drawn on the edges of the image)
5. image was thresholded using a constant threshold value of 128 to obtain a binary image
6. image was saved in a raw format for later processing

The six above processes were performed using Adobe Photoshop version 7.0 ME. All subsequent steps (II-IV) were performed by using programs developed employing Borland C++ 5.02 compiler, and using equations formulated using MS. Excel.

**Step II: Noise Reduction**

The isolated small noise regions were removed using a morphological erosion filter employing a thresholding technique. The algorithm used a 3x3 structuring element to scan the binary image resulted from step I and eliminate central pixels if 3 of their 8-neighbors were non-object. Two iterations of the erosion algorithm were executed.

**Step III: Skeleton Computation**

Mathematical morphology, at its most fundamental level, is a set of principles that define the qualities of a robust transformation (Serra, 1982). The morphological transformations map an image into a more meaningful image (McDonald and Chen, 1990). A thinning algorithm based on mathematical morphology developed by El-Faki, 2000a, was used for deriving the medial axis transform of object regions in the binary image resulted from step II. The output was a unity-thick skeleton of the leaf veins web and boarders. The trials carried out by the researcher confirmed that through this operation it was more likely that the underlying unique characteristics of a leaf would have the potentials to be revealed.

Figure 1 demonstrates an example of the results obtained after implementing steps I, II, and III of the preprocessing stage. Images shown in this example were selected to illustrate image modes and most of the factors considered in the testing set. They illustrate gray-level and binary modes, three orientation angles, two occlusion ratios, and three plant families.
*MD Classifier Development*

**Step IV: Features Selection**

Mathematical morphology is a tool for extracting image components that are useful in the representation and description of region shape (Gonzalez and Woods, 1992). Structuring elements (SE) were developed and formulated into small 5x5 morphological windows; each one corresponded to a feature. An extensive study was carried out on leaf images of training set to come up with the most suitable set of features that would enable correct plant identification. A set of only twenty SEs was formed for each plant to detect different features of leaf venation web. A total of thirty nine different SEs were found most suitable and were applied by this research, one used for all plants, twenty used for both Alfalfa and Pomegranate, and nineteen used for Mint alone. An algorithm was developed based on template matching to analyze leaf images resulted from step III and count the number of occurrences (i.e. number of matches) of each of the twenty SEs. The output was a feature column vector (FCV) of 20 elements. The relative frequency feature vector (RFFV) was calculated for each leaf FCV.

**Step V: Prototyping**

For each plant a sample of thirty leaf images containing three different sizes (10 large, 10 medium, and 10 small) were used as the training set to generate the plant prototype signature. Each leaf image went through steps I through IV mentioned above to obtain the RFFV. The plant prototype signature was obtained through the following:
Plant I-Size I

1. The difference between all possible pairs of the training set was calculated for each of the twenty features of the RFFV separately.
2. For each leaf image of the training set, the outcome would be a group consisting of nine difference-vectors. Then the median-vector of each group was obtained with respect to each feature independently.
3. The sum of the twenty elements for each median-vector was calculated.
4. The size sub-prototype leaf signature was specified as the three RFFVs that produced the median-vectors having the lowest summation.

The previous steps are illustrated mathematically in the following:

1. $Leaf_i = [f_1, f_2, \ldots, f_{20}] \ \forall i = 1,2,\ldots,10$
2. $Sub_{ij} = \left|Leaf_i - Leaf_j\right| = [\left|f_1^i - f_1^j\right| \cdots \left|f_N^i - f_M^j\right|], \ \forall M = N = 20$

Where,

$f_1^i$ : is the first element in $Leaf_i$ feature-vector.

i: is the leaf image number.

3. $$Median = \begin{bmatrix} MEDIAN(Sub_{1,2}, Sub_{1,3}, \ldots Sub_{1,10}) \\ MEDIAN(Sub_{2,1}, Sub_{2,3}, \ldots Sub_{2,10}) \\ \vdots \\ MEDIAN(Sub_{10,1}, Sub_{10,2}, Sub_{10,9}) \end{bmatrix}$$

Where,

MEDIAN: is the statistical median.

4. $$Sum_k = \sum_{i=1}^{M} Median_i \quad \forall k = 1,\ldots,10,\ M = 20$$

5. $$Aggregation = \begin{bmatrix} Sum_1 \\ Sum_2 \\ \vdots \\ Sum_{10} \end{bmatrix}$$

Where,

$Sum_1$: is the summation of the elements of median-vector for the first leaf signature.

6. Location = MIN_LOC ($Aggregation_1$, $Aggregation_2$, …., $Aggregation_{10}$)

Where,

MIN_LOC: is a function that gives the values of the indices of the three leaf signatures having the lowest summations of median-vectors within one of the three size categories for a plant.

$Aggregation_1$: is the first element of the aggregation array.

7. Size_Proto = $Leaf_j$ ; $j = 1, \ldots, 3$

Where,

j is the index of the leaf signature within one of the three size categories having one of the three lowest summations of median-vectors for a plant.

The above steps were carried out for each of the three leaf size categories (large, medium, and small) separately. Then the three selected leaf signatures (RFFVs) from each size were gathered to make a set of nine RFFVs. The prototype for the specific plant was then selected from this set following the same procedure. The final outcome was three leaf signatures representing the prototype signatures for the three plants.

**Step VI: Decision Functions Computation**

The three plant prototype signatures resulted from step V were used to compute the three decision functions to form the minimum distance classifier (Gonzalez and Woods, 1992), via equation 1.

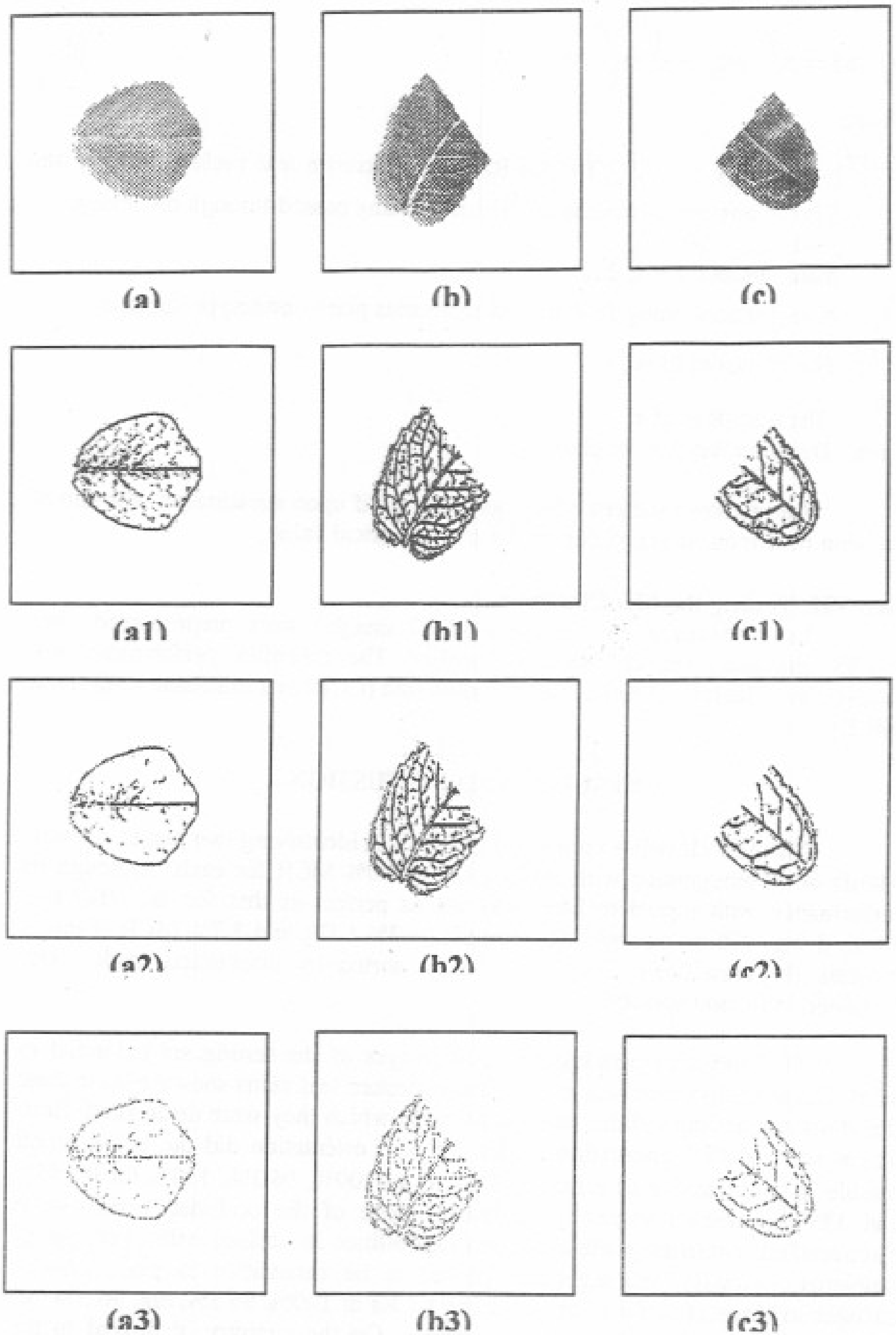


**Figure (1): Leaf images resulted from preprocessing steps for identifying Alfalfa, Mint, and Pomegranate plants, respectively, showing: (a, b, c) gray-level scaling, (a1, b1, c1) edge detection, (a2, b2,**

$$d_i(x) = x^T m_i - \frac{1}{2} m_i^T m_i \qquad (1)$$

Where,

$x = [f_1 \ f_2 \ f_3 \ \cdots \ f_{20}]$ is the RFFV of unknown leaf skeleton image, and

$f_j$ is the number of matches of SE$j$ after being passed through the image, $j = 1, 2, \ldots, 20$

$i$: plant number, $i = 1, 2, 3$

$m_i$ : A vector containing 20 elements represents plant $i$ prototype signature,

$m_i^T$ : The transpose of $m_i$,

$x^T$ : The transpose of $x$,

$d_i(x)$: Decision function of plant $i$,

An unknown pattern $x$ belongs to plant $i$ if upon substitution of $x$ into all decision functions, $d_i(x)$, yields the largest numerical value.

**Step VII: Testing the MD Classifier**

Leaf images of the testing set (162 images) were preprocessed, their RFFVs obtained, and fed to the classifier. The classifier performance was assessed by calculating correct classification rate (CCR) and misclassification rate (MCR).

## RESULTS AND DISCUSSION

The MD classifier performed perfectly in identifying two plants, namely, Alfalfa and Pomegranate with 100% CCR and 0% MCR for each. Although its performance with regard to Mint was not as perfect as that for the other two plants it was still an outstanding one with 96.3% CCR and 3.7% MCR. Table 1 presents the classifier's CCRs and MCRs sorted by orientation angle, size, occlusion ratio, and species.

The only two misclassified leaf images of the testing set belonged to Mint. Classification error was mainly due to broken leaf veins showing up in their skeletons resembling Alfalfa, the plant type to which they were designated. Both leaves were at 45 ° orientation angles, yet leaf orientation did not cause much trouble to the classifier as it achieved CCRs of 100%, 96.3%, 100% for 0°, 45°, and 135° orientation angles, respectively. None of the occluded leaves were misclassified, confirming the algorithm capabilities in dealing with overlapping problems. Likewise, the algorithm proved to be insensitive to plant growth changes in terms of leaf size by achieving CCRs of 100%, 96.3%, and 96.3% for large, medium, and small sizes, respectively. On the contrary, it proved to be greatly sensitive to plant type, a sought attribute. In general, the classifier achieved remarkable results in meeting the main goal of overcoming many of the leaf shape analysis limitations by an overall CCR of 98.9% with only 1.1% MCR (Table 1).

**Table (1): The CCRs and MCRs achieved by the MD classifier in identifying three plants.**

| Species | *Alfalfa* | | | *Mint* | | | *Pomegranate* | | |
|---|---|---|---|---|---|---|---|---|---|
| CCR of species by Orientation Angle | $0^o$ | $45^o$ | $135^o$ | $0^o$ | $45^o$ | $135^o$ | $0^o$ | $45^o$ | $135^o$ |
| | 100.0 | 100.0 | 100.0 | 100.0 | 88.9 | 100.0 | 100.0 | 100.0 | 100.0 |
| CCR of species by Size | *Large* | *Medium* | *Small* | *Large* | *Medium* | *Small* | *Large* | *Medium* | *Small* |
| | 100.0 | 100.0 | 100.0 | 100.0 | 94.5 | 94.5 | 100.0 | 100.0 | 100.0 |
| CCR of species by Occlusion Ratio | *0% Occlusion (Whole leaf)* | *50% Occlusion (Half leaf)* | | *0% Occlusion (Whole leaf)* | *50% Occlusion (Half leaf)* | | *0% Occlusion (Whole leaf)* | *50% Occlusion (Half leaf)* | |
| | 100.0 | 100.0 | | 92.6 | 100.0 | | 100.0 | 100.0 | |
| CCR by Species | 100.0 | | | 96.3 | | | 100.0 | | |
| Overall CCR | 98.8 | | | | | | | | |

The statistical analysis revealed that there were no significant differences neither between CCRs nor between MCRs with no interactions between factors. Despite being trained using leaf images that considered levels of only two factors, namely, plant type and leaf size, the classifier effectively handled the testing set that considered all levels of all experiment factors.

## CONCLUSIONS

Preprocessing of leaf color images was performed by detecting edges, eliminating noise, and computing skeletons, successively. Morphological features were extracted from preprocessed images employing a pre-selected twenty SEs. Subsequently, leaf signature was obtained by searching skeleton of leaf image for matches of the twenty SEs, through template matching. Prototypes of leaf signatures for three different plants were developed from a training set consisting ninety leaf images. Decision functions were generated utilizing prototypes of plant leaf signature and were used to develop the MD classifier. The MD classifier was tested in identifying three different plants, namely, Alfalfa, Mint, and Pomegranate with reference to their leaves' features (signature). The three plants were successfully identified by the classifier with an overall CCR of 98.8% and a MCR of only 1.2%.

The outstanding performance of the classifier substantiates the effectiveness of the algorithm developed in detecting distinctive signatures of plant leaves facilitating discrimination between plants. Thus the technique of exploiting leaf morphology for plant identification was efficient and operative in overcoming many of the limitations of leaf shape analysis. In brief, the extent of success accomplished by this technique in plant identification makes its scope of relevance well extendable to other applications.

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## بصمة ورقة النبات

**محمد صالح الفقيه**

قسم الهندسة الزراعية ــ كلية الزراعة ــ جامعة صنعاء ــ الجمهورية اليمنية.

يهدف البحث إلى التخلص من بعض جوانب القصور التي تواجه دراسات تحليل شكل ورقة النبات ضمن مجال معالجة الصور الرقمية. إستخدمت تقنية المورفولوجي الرياضية لتحليل الشكل الخاص بشبكة تعرق الورقة وذلك للتعرف على النبات. إستخلصت معالم شكل الورقة من الصور الرقمية الملونة للأوراق بعد إخضاعها لمعالجة تحضيرية ثم تمرير عشرين عنصر بناء (نافذه) تكويني منها عبرها للحصول على بصمات منفردة لكل نبات على حده.

أنتجت النماذج المرجعية لبصمات الورق من مجموعة التدريب لثلاثة نباتات هى البرسيم، النعناع، والرمان، ومن ثم إستغلت تلك النماذج لاحتساب دوال التمييز، والتى بدورها أدمجت لإنشاء مصنف أقل إنحراف. تم التركيز على أربعة عوامل يمكن أن تؤثر على أداء المصنف وأخذت فى الإعتبار عند تشكيل مجموعة الإختبار المشتملة على ١٥٢ صورة رقمية ملونة لأمراق النباتات. العوامل الأربعة المعنية هى: نوع النبات، زاوية إتجاه الورقة، حجم الورقة، ونسبة إحتباس الورقة عن الرؤية.

تمكن المصنف من التعامل مع مجموعة الإختبار بفاعلية عن طريق تصنيف الأوراق إلى النباتات التى تنتمى إليها بنجاح. وبذلك فقد تم تحقيق أداء مثالى للتعرف على النباتات الثلاثة بواسطة بصمات أوراقها بنسب ١٠٠%، ٩٦,٣%، ١٠٠%لكل من البرسيم، النعناع، والرمان على التوالى:

**كلمات داله:** الزراعة الدقيقة، تحليل اشكل، شبكة تعرق ورقة النبات، معالم البنية، مطابقة النموذج، بصمة ورقة النبات، التعرف على النبات.