International Journal of Tropical Agriculture
Volume 41, Numbers (1-2) • 2023 : pp. 31-47
ISSN: 0254-8755

Advances in Image Processing Applications for Assessing Leafy Materials

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Abstract: Leafy materials are produced from agricultural crops and forestry plants that have important role in human life and environment. Expert-based assessment of leafy materials by humans is time consuming, expensive, and difficult and is sample-destructive task in some cases. Image processing has different applications through simulating vision sense of humans to assess color, textural, and morphological characteristics of objects and can be further enhanced by utilizing spectra beyond human visible range. It is considered as a beneficial and practical tool due to its high speed, accuracy, and repeatability and also it is a low cost and nondestructive technique compared to expert-based assessments. The goal of this paper is to review the advances of image processing applications for assessing the leafy materials including herbs, aromatic, and medicinal plants.

Keywords*:* Herbs, Medicinal plants, Aromatic plants, Leaf, Machine vision, Digital image processing.

1. INTRODUCTION

Leafy materials include herbs, medicinal, and aromatic plants. These products are produced in agricultural fields and forests. These products have high importance because they are used to make many products such as: medicines, foods, soaps, textiles, cosmetic, and furniture in several industries (Husin et al., 2012; Gayatri et al., 2021). In addition, leafy materials are a source of energy and have important role in decreasing global warming (Barbedo, 2013).

Assessment of leafy materials is essential to apply necessary operations correctly and timely to reach high productivity in this sector. Manual assessment and inspection are time consuming and costly processes (Padma et al., 2021), moreover these are difficult, laborious, tedious, expensive, and mistake-prone tasks, and sometimes they include sample-destructive operations. Also, operations based on manual inspection to assess products have low accuracy and high uncertainty probability due to their mental nature. In contrast, image processing technology has attracted high attention in various fields of agriculture, agricultural conversion industries, and other industries due to its consistency of results over long periods, with appropriate software and hardware, high accuracy and speed of analysis and low total cost compared to expert-based assessments (Kheiralipour et al., 2018). Visible image processing has vast applications due to simulating vision sense of human to assess color, textural, and morphological characteristics of objects. In addition, image processing can extend the human vision sense by incorporating spectra from other regions of the spectrum such as ultraviolet, infrared, X-rays, THz etc.

Image processing has used in assessing leafy materials not only in laboratories and industrial settings but also in fields with uncontrolled conditions (Hamuda et al., 2016). Due to the importance of leafy materials and advantages of image processing technology, the goal of this paper is to review different applications of

Article History: Received: 07 February 2023; Revised: 10 March 2023; Accepted: 24 March 2023; Published: 20 June 2023

this technology for assessing leafy materials. This paper briefly describes leafy materials and principles of machine vision which is followed by explanations of many applications of image processing for assessing leafy materials such as identification of plant type and variety, measuring morphological parameters, detecting diseases, assessing shelf life and maturity level, and estimation of water stress and chemical components of leafy materials.

2. LEAFY MATERIALS

Leaves, simple or compound, are fundamental part of forest and agricultural plants because they provide power generation and aerial environmental sensing units (Ellis, 2009; Carvalho et al., 2017). Leafy materials include herbs, medicinal, and aromatic plants. Herbs are plants with green and soft texture that do not produce a woody part above the ground. Also these refer to the fresh or dried leafy greens and flowering parts of plants (Arteca, 2006). Herbs are used in foods, medicines, and fragrances due to their savoring, preserving, garnishing, and therapeutic and health properties (El-Sayed and Youssef, 2019). Herbs can be used as food additives to enhance the organoleptic properties of food and increase food shelf life by their activities against pathogens (Lai and Roy, 2004) and they have beneficial effects on human health due to their anti-oxidative, anti-inflammatory, anti-mutagenic, and immunomodulatory properties (Conn, 1995).

Aromatic plants refer to those leafy materials that have aromatic essential oils and are used in perfumery and aromatherapy. Medicinal plants contain certain amount of medicinal properties to prevent, treat, or cure a certain disease (Putri et al., 2021). Due to nature-based and fewer side effects on human lives, medicinal plants have attracted human attention; however, one should keep in mind that some leafy materials could be allergenic or poisonous so must be used based on thorough knowledge. About 80% of people in the world use products based on medicinal plants in their healthcare(Chan, 2003). Medicinal plants are consumed to protect human body against diseases and free radical damages and sometimes can treat human body against different diseases such as hypertension.

3. MACHINE VISION

Machine vision includes main steps as imaging, image processing, data analysis, and action". (Kheiralipour et al., 2018). These steps are shown in Fig. 1. The main steps are described in the following subsections. One or more algorithms must be coded in a software such as MATLAB, to do these steps, sequentially.

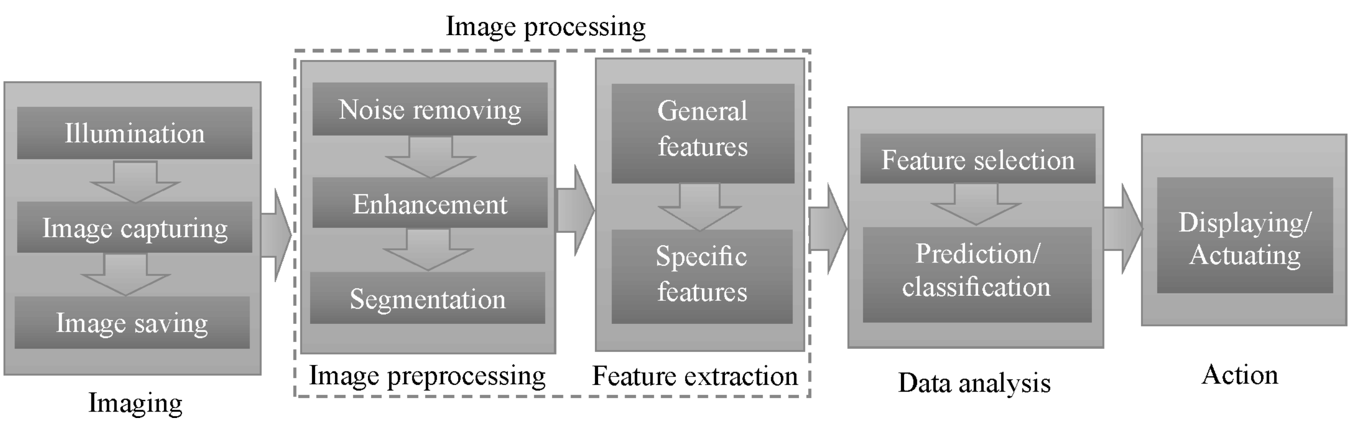


Figure 1: Different steps in machine vision

3.1. Imaging

Imaging is the first step of machine vision systems which involves acquiring images of interests by a camera under a controlled illumination system or in the fields. The cameras receive different spectrum ranges to acquire visible, thermal, hyperspectral, and magnetic resonance, and X-ray images (Vadivambal and *Jayas*, 2016; Kheiralipour et al., 2018). In imaging step, the acquired images are transferred to a computer to be used in image processing step.

3.2. Image processing

Image processing is a branch of signal processing which extracts useful information from images of interests (Gonzalez and Woods, 2002; Kulkarni et al., 2021).

3.2.1. Image preprocessing

Image preprocessing step includes enhancement of images and/or preparing the acquired images to extract features. The first step in image preprocessing is noise removing. To do this, different channels of images are separated and then one or more filtering methods are applied (Kheiralipour, 2012).

After noise removal, segmentation is started. Image segmentation is a step to identify and separate the interested parts of the images from other parts like background. Different techniques have been used to segment plant leaves from the background such as threshold, watershed, clustering, edge-based, and region-based segmentation methods. In this step, different channels of image in one or more color spaces must be obtained and then the object of interest can be separated from the background. The threshold and edge based methods are used for gray scale images whereas watershed, clustering, and region-based methods are used for color images (Lomte and Janwale, 2017). These approaches successfully can segment highly complex plant leaves and can remove distortion of leaf images (Azlah et al., 2019).

3.2.2. Feature extraction

Features extraction step includes calculating a piece of information from the images. There are two types of features: global and local. The global features include morphology, texture, and color information from whole image of interest whereas local features are calculated from a part of image of interest (Thyagharajan and Raji, 2018; Kheiralipour et al., 2018).

Before extracting the features, different color spaces of the images may be obtained in visible images such as I1I2I3, HIS, $C_rC_gC_b$, NRNGNB, $L^*a^*b^*$, and gray level and then these channels are analyzed to extract features from each of them (Kheiralipour and Marzbani, 2016; Azadnia and Kheiralipour, 2022; Hosainpour et al., 2022), but mainly gray channel of other kinds of images such as thermal and hyperspectral images are used for feature extraction (Kheiralipour et al., 2013-2014; Kheiralipour et al., 2015ab).

3.2.2.1. General features

General features include color, textural, and morphological features. The minimum, mean, maximum, standard deviation, coefficient of variation, mode, skewness, kurtosis, median, and covariance are color features (Kheiralipour et al., 2013; Kheiralipour et al., 2021; Khazaee et al., 2022). Other features must be extracted for assessing leafy materials because at least for plant type identification, leaf color alone does not provide enough information for identification of leave types because these vary with different climatic and imaging conditions (Thyagharajan and Raji, 2018). Also a combination of multiple features gives better results for assessing the plant leaves (Suwais et al., 2022).

Textural features include energy, entropy, contrast, correlation, and homogeneity. To do this, firstly the statistical gray-level co-occurrence matrix (GLCM) must be obtained to specify the spatial relationships between image pixels (Mohammadi et al., 2015; Salam et al., 2022; Hosainpour et al., 2022; Kheiralipour et al., 2022).

In addition to textural and color features, analyzing morphological features for agricultural products are very important and are vastly used. Morphological features are size features (width, length, large and small ellipse axes, area, and perimeter), extent, circumference, eccentricity, elongation, roundness, centroid, width, length and Fourier descriptors (Usefi et al., 2016; Kheiralipour and Pormah, 2017; Jahanbakhshi and Kheiralipour, 2020; Kheiralipour and Kazemi, 2020).

3.2.2.2. Leaf specific features

Besides above features, the information from specific characters of the objects are extracted as specific features. For leaf applications, these features include tip, vein, base, venation, margin, and apex of leaves (Thyagharajan and Raji, 2018; Suwais et al., 2022).

3.3. Prediction/classification

For analyzing the extracted features from the images to be used in decisions making, different statistical and artificial intelligence methods are used to predict/classify obtained data from the images. In artificial intelligence methods, machine learning is used for automatic prediction/ classification of image data by training and then fitting training results into models to be applied for untrained data. Machine learning is better than statistical methods but they need large amount of training data (Kheiralipour 2012; Kheiralipour et al., 2018; Kulkarni et al., 2021).

Many classification techniques have been applied in leaf assessing studies including Euclidean classifier, k-nearest neighbor (KNN), decision tree, artificial neural network (ANN), probabilistic neural network (PNN), Bayesian classifier, manifold learning classifiers, linear discriminant analysis (LDA), quadratic discriminant analysis (QDA), radial basis function (RBF), fuzzy neural network, support vector machine, principal component analysis (PCA), random forest (RF), hierarchical clustering, fuzzy c means clustering, and moving center classifier hyper spheres (Kheiralipour, 2012; Gavhale and Gawande, 2014; Vadivambal and Jayas, 2016; Kheiralipour et al., 2018; Thyagharajan and Raji, 2018; Suwais et al., 2022). Also, convolutional neural network, deep belief network, recurrent neural network, and stacked autoencoder have been applied as deep learning analysis tools (Xiong et al., 2021).

Deep learning is a new technique developed in machine learning, its algorithm extracts image features and classifies them continually (Kuswidiyanto et al., 2022; Roy and Lipton, 2022). Deep learning algorithm simplifies feature extraction and classification but supervised learning of it requires a large number of images for training for feature extraction and so this method is time consuming technique and needs a powerful computer with big storage memory. Moreover, training images may be unbalanced or even missing. These are the limitations of deep learning technique that should be considered for solving in future. Also unsupervised learning may assist in removing these limitations (Yu et al., 2013).

3.4. Action

Action is the final step of machine vision systems to display the results of analysis, make a decision, and or do an order such as sorting, grading, separation, and picking by an actuator."

4. PLANT TYPE AND VARIETY

Identification of leafy materials is hard task due to huge number of plant types. As this task is expert-based and time consuming (Shitole et al., 2019), image processing technology is vastly used to identify plant types (Wang et al., 2017; Thyagharajan and Raji, 2018; Suwais et al., 2022).

Researchers classify plants using roots, fruits, seeds, flowers, and leaves (Thyagharajan and Minu, 2013). Leaf is the most important part of the plants to be considered for plant identification because it is visible and always accessible and also it is two-dimensional and its analysis is easy (Waldchen et al., 2018; Manoharan, 2021; Azadnia and Kheiralipour, 2021b).

Manoharan (2021) in the identification of tulsi medicinal plant, applied Canny and Sobel edge detection methods to the images of front and back of 250 leaf samples. The researcher extracted color and morphological features from the images and then classified the features based on convolutional neural networks method and reached the highest identification accuracy of 81.5-92%. Azadnia and Kheiralipour (2021b) developed an image processing algorithm in MATLAB software to identify leaves of six medicinal plants (Fig. 2). They acquired images of the leaves in an illuminated chamber by a Galaxy A8 (SAMSUNG Corporation, South Korea) smart phone camera with 16 MPixel resolution. The algorithm automatically removed the noises and segmented the images. In segmentation step, the algorithm separated R, G, and B channels of the images, used B channel to identify the interesting part of the images from the background. They converted the B channel to binary image, reversed to the B channel, filled the holes in the binary image, removed the background of R, G, and B channels, and finally combined the channels to produce non-background RGB image (Fig. 3).

Then the algorithm extracted textural, color, and morphological features from the non-background image in different color spaces

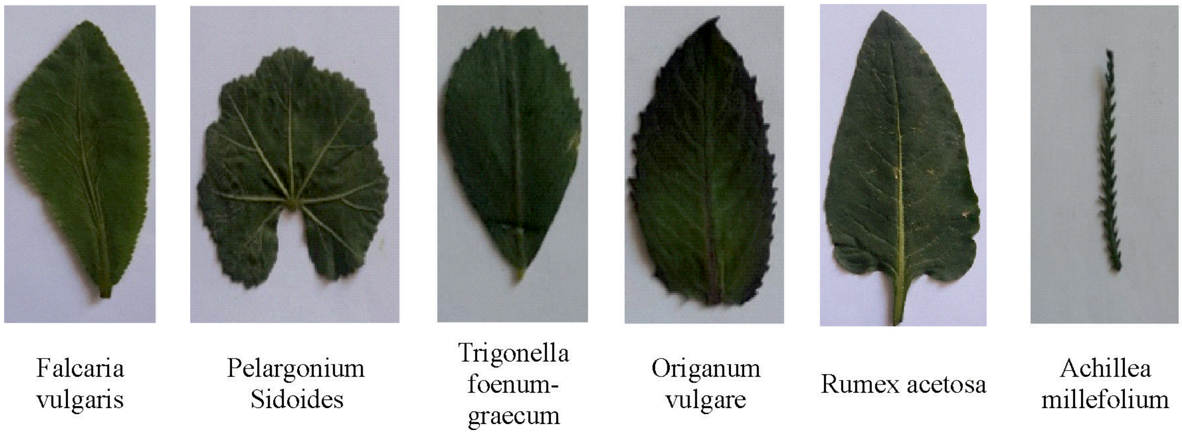


Figure 2: Visible images of different medicinal plants (Azadnia and Kheiralipour, 2021a)

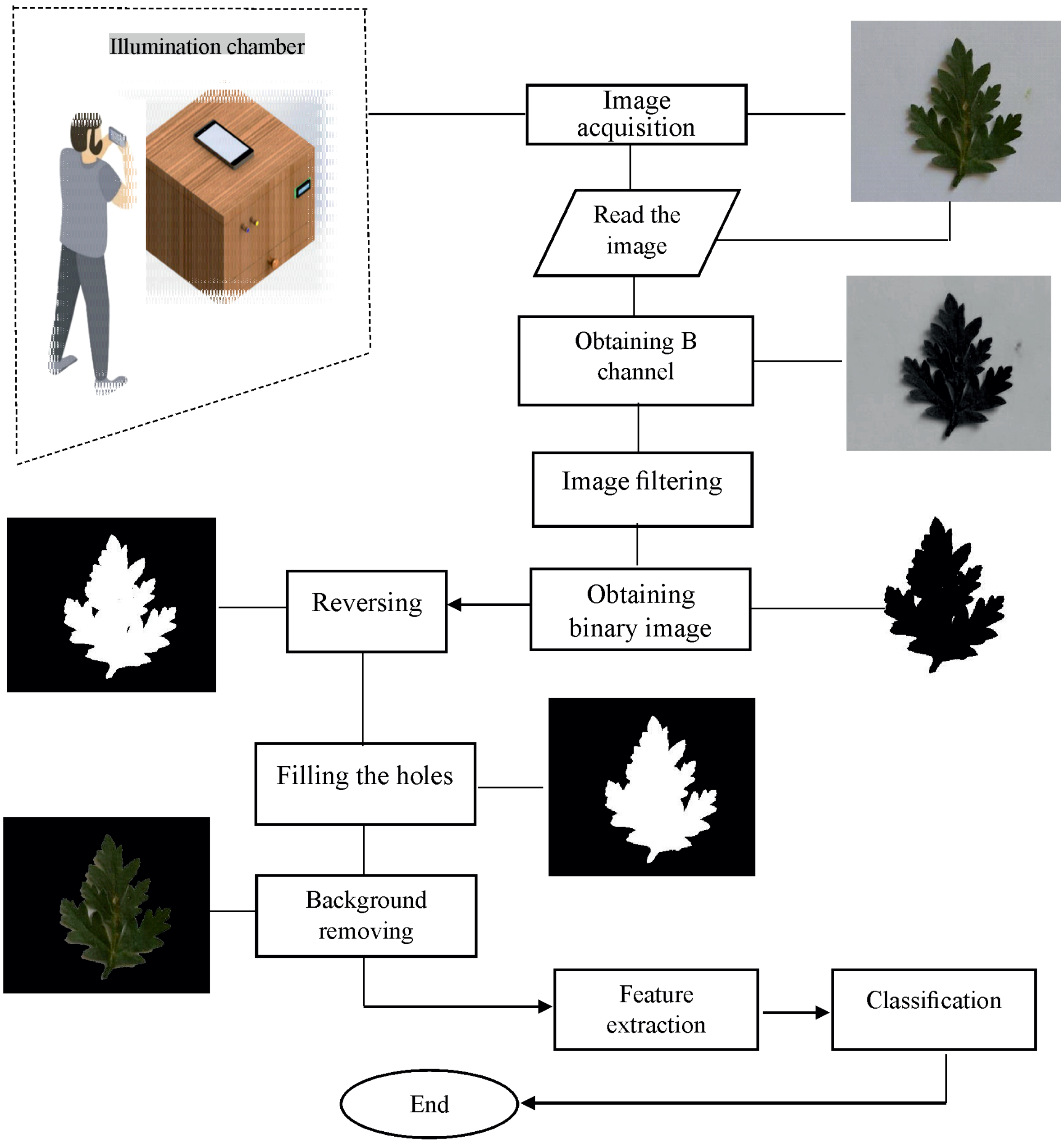


Figure 3: Image processing steps to identify medicinal plants

(totally 296 features). Then 28 features were selected by sequential selection method as efficient features for classification (Table 1). They programed and trained a classification program based on artificial neural networks with 28-10-6 structure and classified the images of different plants with 100% correct classification rate and mean square error of 2.35×10^{-12} (Fig. 4).

Azadnia and Kheiralipour (2021b) classified 28 features from (Table 1) using linear and quadratic discriminant analysis methods and reached accuracies of 97.7 and 100 %, respectively. They selected nine efficient features from the previous features by trial and error and obtained same accuracies and classification errors for the two classification models as100% and 0.0105, respectively. These results showed that each classification method is feature sensitive that can be improved by experience.

Table 1: The efficient features of the medicinal plants (Azadnia and Kheiralipour, 2021b).

No.	*Feature*	*Plant category*					
		A1	*A2*	*A3*	*A4*	*A5*	*A6*
	Color feature						
1	Mean of gray level	0.227	0.229	0.229	0.250	0.205	0.179
2	Entropy of ng channel	0.872	0.937	0.920	0.990	0.974	0.962
3	Kurtosis of nb channel	0.005	0.003	0.004	0.001	0.001	0.001
4	Mean of i1 channel	0.998	0.999	0.998	1.000	1.000	1.000
5	Variance coefficient of i2 channel	0.998	0.999	0.998	1.000	1.000	1.000
6	Median of i3 channel	0.876	0.941	0.923	0.990	0.979	0.970
7	Entropy of cr channel	0.999	0.998	0.998	0.989	0.997	0.998
8	Variance coefficient of cg channel	0.091	0.032	0.407	0.004	0.032	0.040
9	Skewness of cb channel	8328.605	17159.520	226.196	51498.770	17935.750	16871.640
10	Mean of hue channel	0.214	0.212	0.215	0.239	0.189	0.170
11	Variance coefficient of hue channel	0.981	0.978	0.973	0.955	0.981	0.970
12	Variance coefficient of saturation channel	0.872	0.937	0.920	0.990	0.974	0.962
	Textural feature						
13	Contrast of red channel	0.580	0.338	0.342	0.568	0.396	0.429
14	Homogeneity of red channel	0.015	0.021	0.018	0.013	0.022	0.012
15	Energy of gray level	0.004	0.002	0.003	0.001	0.001	0.001
16	Homogeneity of green channel	1.022	1.368	1.213	1.793	0.619	1.598
17	Energy of blue Channe1	0.478	0.475	0.446	0.843	0.348	1.279
18	Correlation of l* channel	-2.792	-1.054	-0.924	-0.783	-1.307	0.116
19	Correlation of i1 channel	0.194	0.191	0.190	0.191	0.218	0.176
20	Energy of i1 channel	0.123	0.137	0.127	0.234	0.127	0.386
21	Contrast of i3 channel	0.876	0.940	0.923	0.991	0.975	0.966
22	Energy of hue channel	0.313	0.177	0.211	0.268	0.168	0.338
23	Energy of saturation channel	0.882	0.937	0.921	0.990	0.974	0.967
	Shape feature						
24	Centroid height	1414.537	1402.590	2575.061	1339.659	1326.652	1278.999
25	Eccentricity	0.884	0.974	0.596	0.996	0.862	0.883
26	Roundness	473046.900	125150.000	232666.700	4442.960	86819.570	153735.800
27	Length	1492.011	1497.276	912.774	1111.205	634.953	804.478
28	Elongation	2.176	4.786	1.270	12.558	1.998	2.173

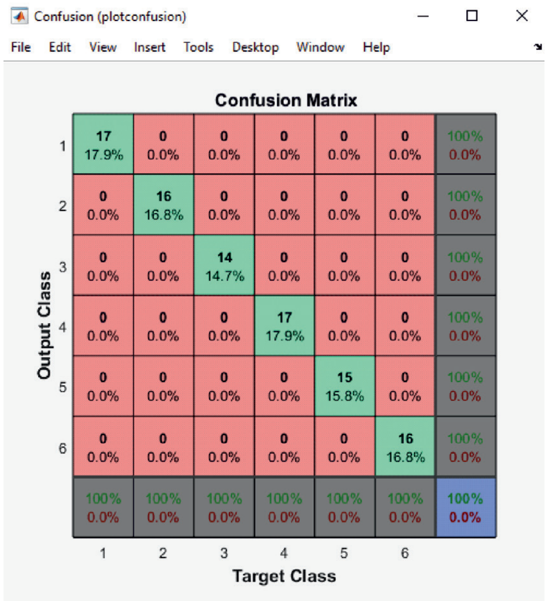


Figure 4: The confusion matrix of classification of medicinal plants (Azadnia and Kheiralipour, 2021b).

Although conventional machine learning is more time consuming due to individually feature extraction and classification steps, but in some cases, it can be more accurate than deep learning. In this regard, Azadnia et al. (2022) applied deep learning to identify five medicinal plants including lemon balm, stevia, peppermint, bael, and tulsi. They used convolutional neural network to classify the extracted data. They obtained highest accuracy of 99.8%.

Haryono et al. (2020) applied convolutional neural network (CNN) in a Raspberry Pi board for authentication of 10 herbal leaves using the artificial intelligence method (Fig. 5) because the method automatically extracts features and does not need an individual feature extraction process. They reached to the highest accuracy of 98%.

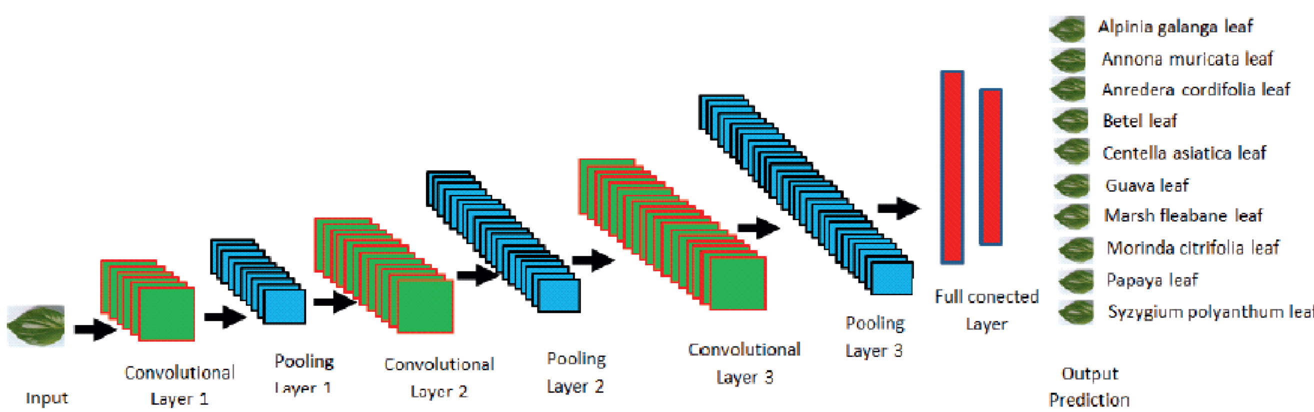


Figure 5: Convolutional neural network used to identify 10 plant leaves (Haryono et al., 2020)**.**

5. MORPHOLOGY PARAMETERS

Morphological parameters of leaves are essential characteristics of physiological and ecological aspects of plants. These parameters include dimensions, area, perimeter, and shape.

The amount of photosynthetic light harvested depends on the area of leaves so measuring leaf area is necessary in studying plant photosynthetic efficiency, light interception, transpiration, growth (Madhavi et al., 2022), productivity, and cultural and technical evaluations such as seedling density, fertilizer, irrigation, and agrochemical application (Carvalho et al., 2017).

The conventional method to measure leaves area are square grid, planimeter, gravimetric, and regression equation method that are destructive because the leaves must be separated from the plants. Also, in some research, plant leaf area was measured by destructive image processing system such as Lu et al. (2010) whereas other researchers attempted to develop nondestructive image processing systems for measuring leaf area (Chaudhary et al., 2012).

Madhavi et al. (2022) measured total leaf area of the ice plant leaves using a computer coordinating area curvimeter and image processing technique to calculate overlapping percentage between the total leaf area and canopy area (Fig. 6A). They captured ice plant images using a SONY DSCRX100 vii (Seoul, Korea) digital camera (Fig. 6B) and processed the images in Python Software. The images were converted from RGB to HSV color spaces and segmented (Fig. 6C) using mean value of the grey image as threshold and then the image was converted to black and white image (Fig. 6D). The area of the black and white image was calculated by counting the number of white pixels and then converted to cm^2 using the reference image. Finally, they developed a single-variate linear model to predict total leaves area based on canopy area with R^2=0.99.

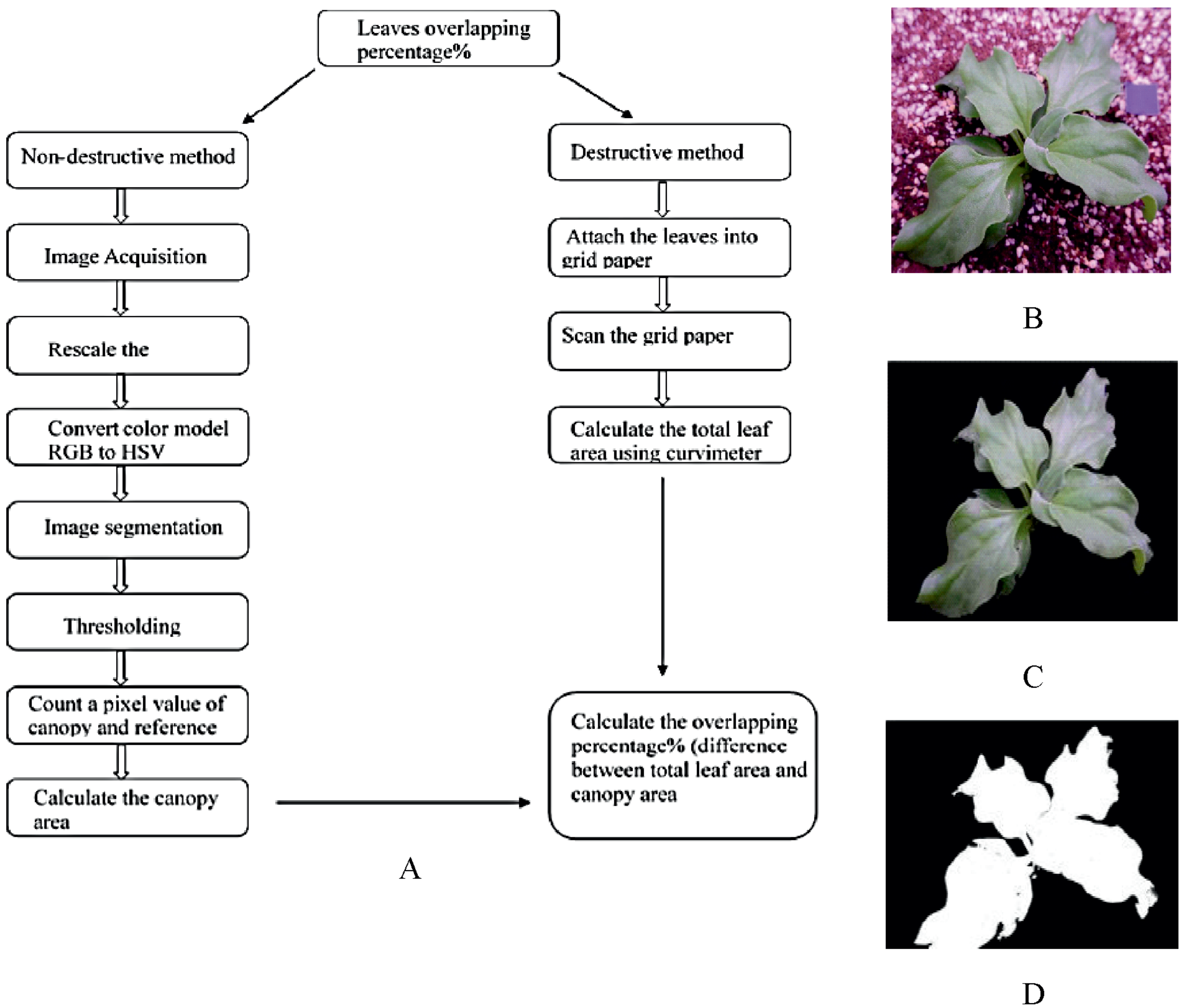


Figure 6: Measurement of overlap percentage (%) of ice plant leaves, A) working steps, B) a sample image of ice plant, C) the segmented image of canopy and D) binary image of canopy (Madhavi *et al.*, 2022)

6. DISEASES

In herbs, disease causes the destruction of plants (Fig. 7). Fungi, bacteria, and viruses are main vectors of plant diseases (Fig. 8). Fungi are mainly identified by their morphology and their reproductive structure is emphasized. Bacteria mainly are single cells and multiplied by dividing into two cells through binary fission. Viruses are very small particles made of protein and genetic material without any associated proteins (Dhaygude and Kumbhar, 2013). Disease causes losses to plants and so it has negative effects from the economic, social, and ecological aspects (Barbedo, 2013; Sinha and Shekhawat, 2020). Moreover, if the diseases are not identified and treated in time, they spread to vast areas (Khan et al., 2021). Detection of diseases in early stage helps to improve the final yield (Bharate and Shirdhonkar, 2017). So detecting leaf diseases, especially early detection, is necessary to avoid production losses and their adverse effects.

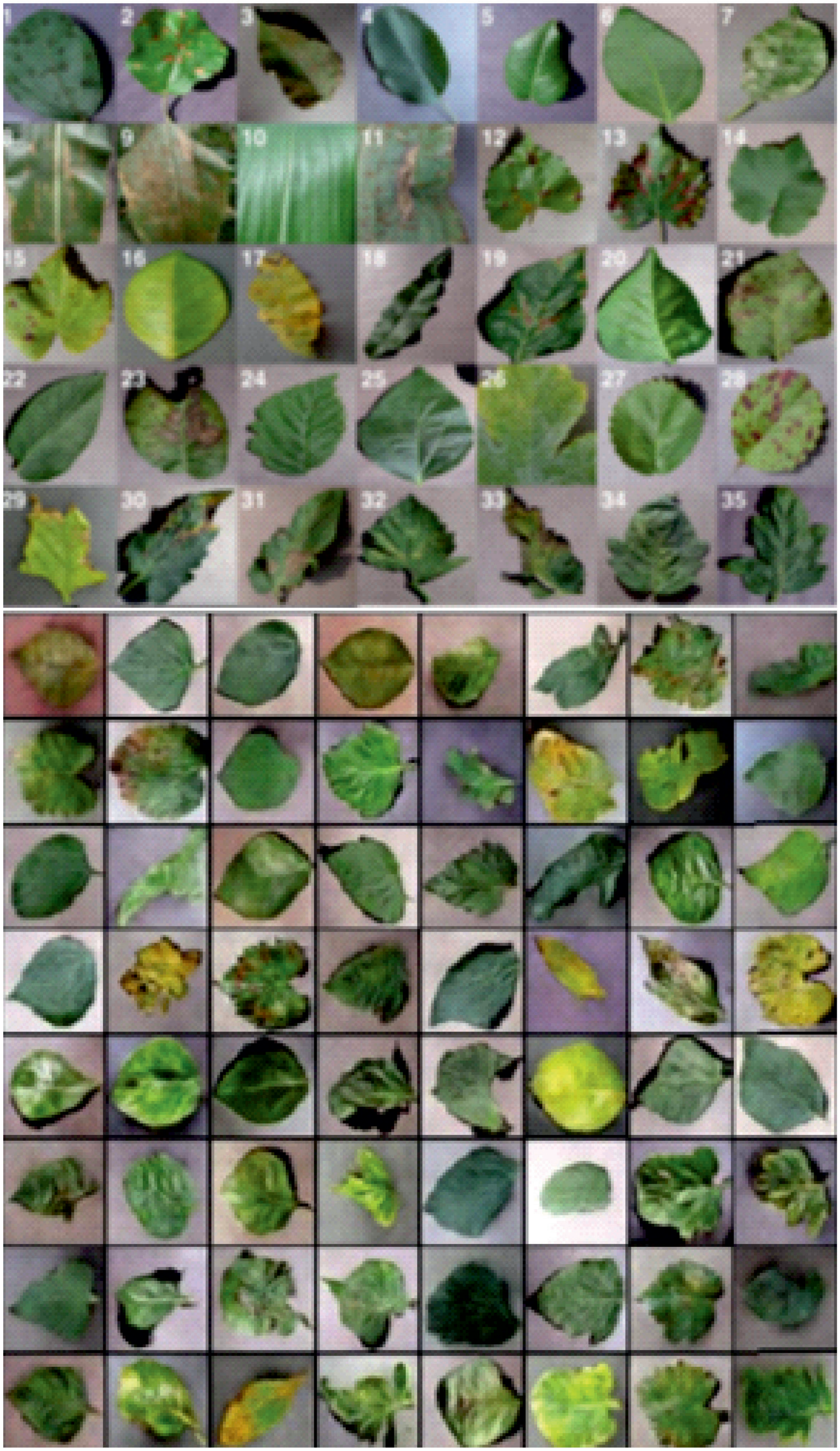


Figure 7: Plant diseases samples (Hughes and Salathe, 2015; Kulkarni et al., 2021).

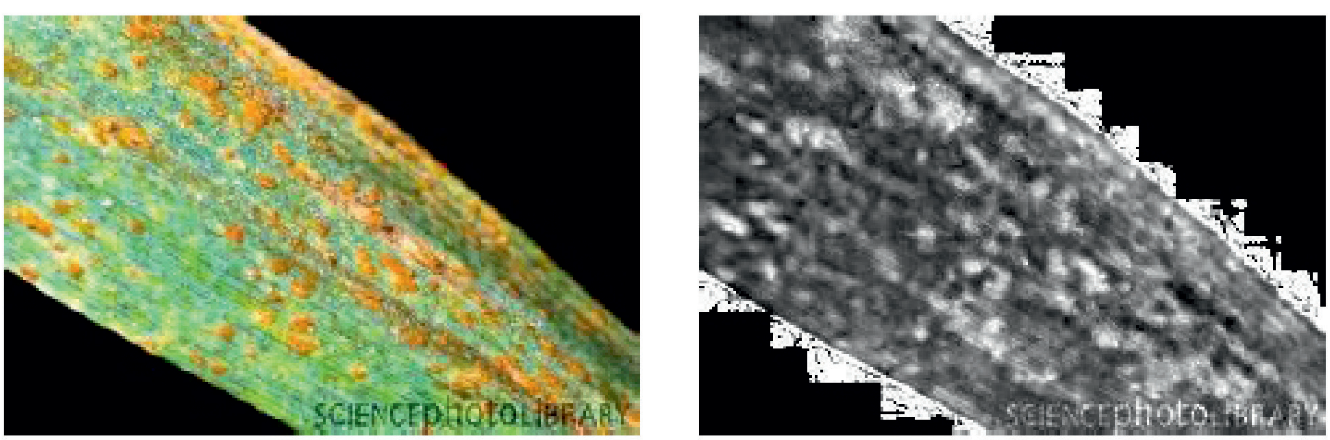
Figure 8: Fungal (A), bacterial (B), and viral (C) disease on leaf (Gavhale and Gawande, 2014).

Conventionally, plant diseases are detected by naked eye observation of experts. This conventional method needs continuous monitoring by people that are well-trained with significant experience, and are tedious, time consuming, and expensive (Al-Hiary et al., 2011). Due to abilities and advantages of visible image processing, it was vastly used to detect leaf diseases (Vishnu and Ram, 2015; Kumar and Kaur, 2015; Sujatha et al., 2017; Singh and Misra, 2017; Dhingra et al., 2018; Khan et al., 2018; Patil et al., 2020; Hasan et al., 2022), classification of disease types (Sinha and Shekhawat, 2020; Sahu et al., 2020;), identification of disease stage (Raut and Ingole, 2017; Halder et al., 2019), and quantification of diseases (Khan et al., 2018) in leaves.

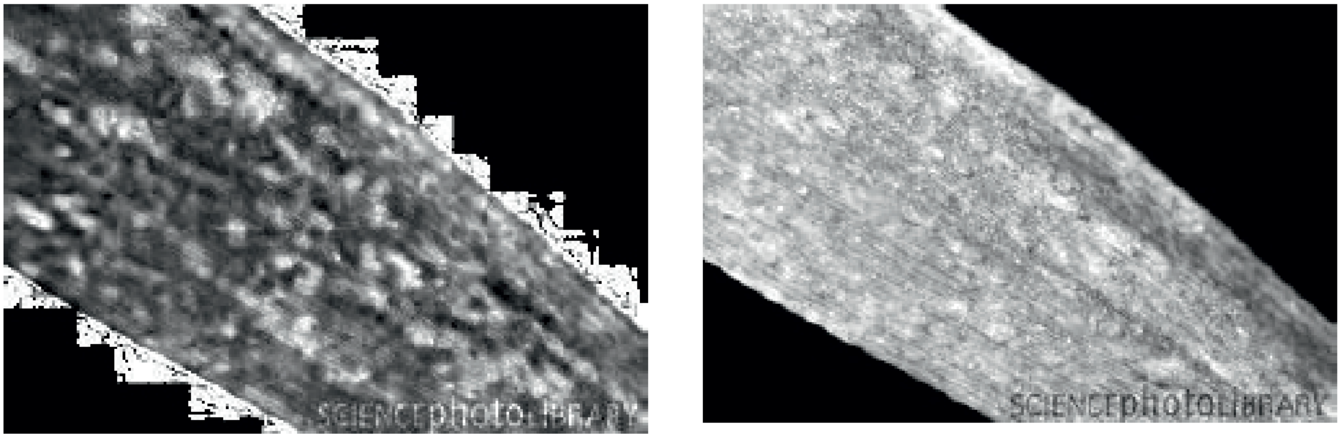
Dhaygude and Kumbhar (2013) developed an algorithm to detect leaf diseases. It converted RGB (red, green, blue) images to HSV (hue, saturation, value) (Fig. 9) because it is an ideal space for color perception and used H channel for processing. The green pixels of the leaves were masked to be zero using a specific threshold value. In segmentation, the infected patches of the leaves were identified. The Spatial Gray-level Dependence Matrices (SGDM) method was applied on hue channel and then textural features including energy, homogeneity, correlation, and contrast were extracted. Finally, they compared the features of infected plants with healthy one without any classification method.

7. SHELF LIFE

Iglesias et al. (2012) processed hyperspectral images (400- 1000 nm) of watercress to specify its shelf life of packed leafy greens in plastic films during 21-day storage period. They processed the images using ad hoc routines and MATLAB software. They applied a radiometric correction to diminish the variation in transmittance of the films (Fig. 10). Their results showed differences between the images during the storage period. Similar research was done by Lara et al. (2013) to assess the shell life of spinach.



A B



C D

Figure 9. RGB image infected by fungus (A), H channel (B) S channel (C) and V channel (D) (Dhaygude and Kumbhar, 2013).

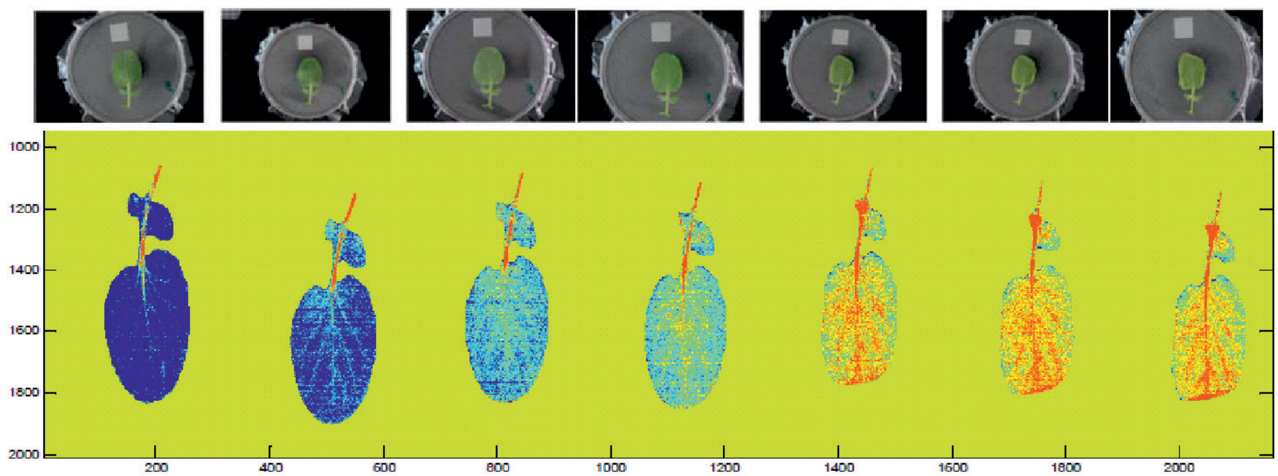


Figure 10. RGB images of a leaf of watercress (and grey reference inside the plate) (top) and Virtual images of scores of PC2 (bottom) along the monitoring period (Iglesias et al., 2012)**.**

8. MATURITY LEVEL

On time maturity detection is an important operation for harvesting and it can improve the product quality and production efficiency and consequently increase productivity. In this regard, image processing can be applied for online monitoring of products by assessing the area, shape, or color of the products.

Shi et al. (2023) used image processing and convolutional neural network to detect maturity of leafy greens. They extracted color, textural, and area features of leafy greens' leaves after segmentation. Their experimental results showed that their system can predict the harvesting time of leafy greens in greenhouse with root mean square error of 2.49 days (Fig. 11).

9. WATER STRESS

Farm irrigation must be well managed to ensure enough water for plants. In case of water stress, the yield is reduced whereas water abound causes root rotting and plants diseases. Image processing can assist farmers to manage irrigation operation via detecting water stress or water abound.

As water stress affects leaf water potential, Tung et al. (2018) evaluated leaf water potential by processing hyperspectral images (460-1100 nm) of Fengjing Pakchoi (Fig. 12). They used modified partial least squares regression (MPLSR) to predict the leaf water potential and obtained correlation coefficient of 0.826.

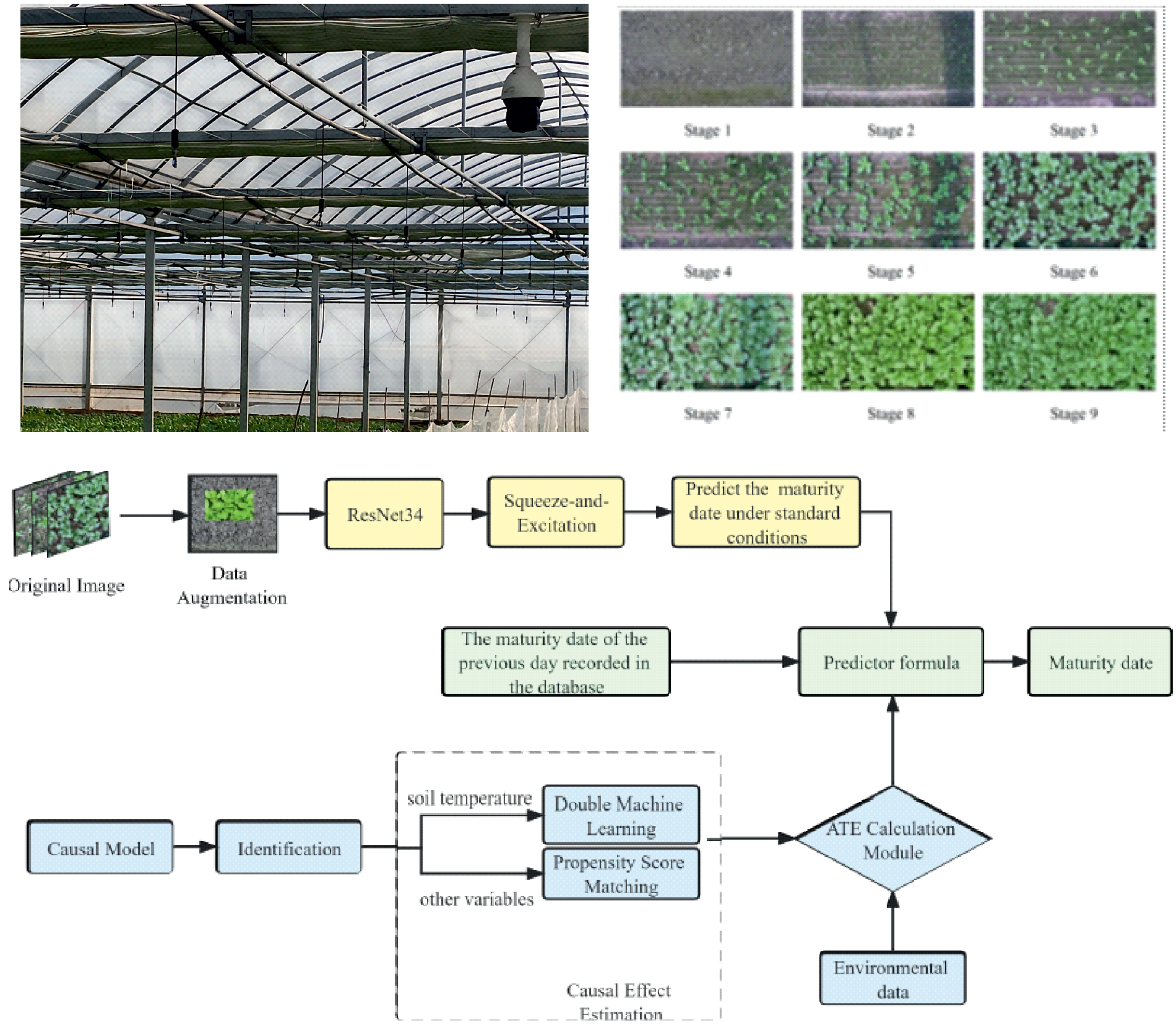


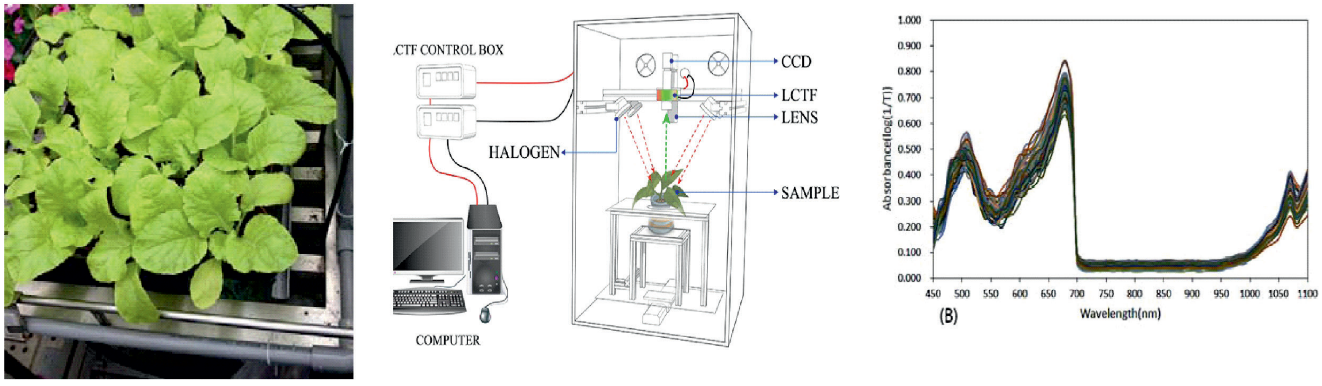
Figure 11: Predicting maturity of leafy greens (Shi et al., 2023)

10. CHEMICAL COMPONENTS

Determining chemical components including nutrients, toxicants, and contaminants, in laboratory is a destructive, time consuming, and expensive. Image processing technique can be applied to estimate the components in a fast and nondestructive manner.

Souza et al. (2022) determined cadmium contamination of kale (*Brassica oleracea*) and basil (*Ocimum basilicum*) leafy vegetables using hyperspectral imaging (400-998 nm). They used ReliefF algorithm and principal component analysis to analyze the features to generate data for artificial neural network, ensemble learning (EL), and support vector machine methods. They reported that 519-574, 692, and 732 nm were the best spectra to predict cadmium contamination and ANN model had higher accuracy (100%) than other methods (Fig. 13).

Suhartono et al. (2019) used visible imaging to predict antioxidant activity of gomer (*Nothaphoebe sp*.) leaf. They extracted image features and developed a nonlinear model as Antioxidant activity= -54.9592 + 1.0295 R + 0.3757 G + 2,006 B -0,0004 R*G - 0.0012 R*B + 0.004 G*B with r = 0.76 to predict antioxidant activity of the leaf.



A B C

Fig. 12. Fengjing Pakchoi plant (a), acquiring hyperspectral images of leaves (b), and spectral absorption spectra of the leaves (c).
Source: composed from Tung et al. (2018).

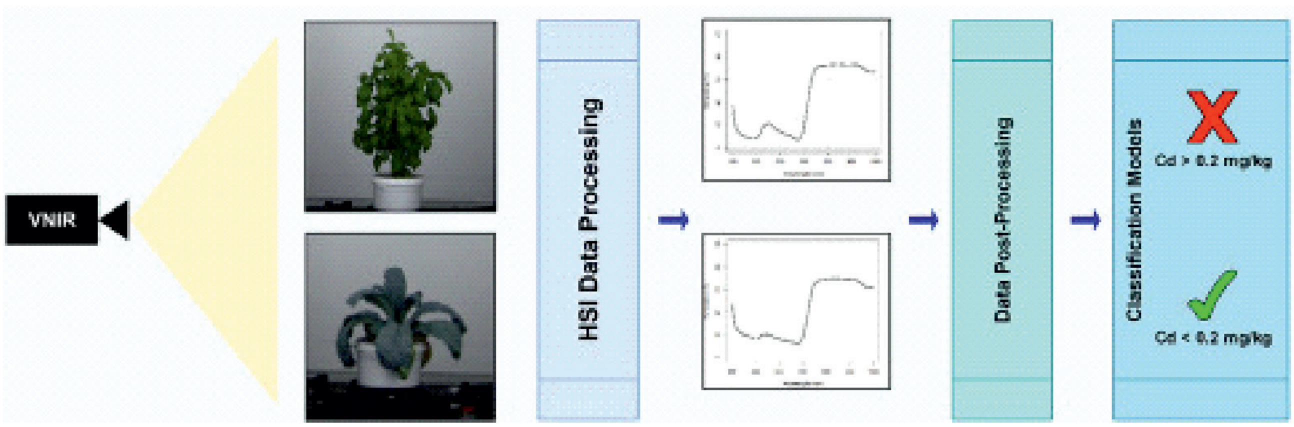


Figure 13: Determining cadmium contamination (Souza et al., 2022).

11. FUTURE TRENDS

Image processing technology was vastly used for assessing leafy materials. In future, it can be used for different purposes such as quality control, detection of unwanted leaves, and detection of adulteration in leafy materials.

Although image processing was mostly used in research with controlled illumination conditions, it can also be used in the field with different light intensities. This technology can be applied to develop machine vision systems to be used for real time and online applications such as monitoring, sorting, and grading. Moreover, machine vision systems can be applied to monitor leafy materials combined with internet of thing under web portals.

12. CONCLUSION

In this paper different applications of image processing in recent years to assess leafy materials were reviewed. Image processing has wide applications for leafy materials because of high degree of uniformity, accuracy, and speed and low cost. However, applications of image processing in leafy materials are too specific because these depend on plant type, plant growing stage, imaging condition, and image processing and analyzing method. This methodology can be used in factory and fields under various lighting intensities.

Applied image segmentation and data analyzing techniques successfully gave acceptable results even for highly complex leaves with image distortion. It is mentionable that for a particular plant, a specific prediction/ classification method may provide better results than other classification methods. Also, for each prediction/classification method, only a certain combination of features may give a better result. Therefore, in assessing a specific plant leaf it is necessary to test different prediction/ classification methods to analyze different combination of features.

REFERENCES

Al-Hiary, H., Bani-Ahmad, S., Reyalat, M., Braik M., AlRahamneh, Z. 2011. Fast and accurate detection and classification of plant diseases. International Journal of Computer Applications, 17(1), 31-38.

Arteca, R.N. 2006. Introduction to Horticultural Science. Thomson Delmar Learning. New York, US.

Asadi-Samani, M., Moradi, M.-T., Mahmoodnia, L., Alaei, S., Asadi-Samani, F., Luther, T., 2017. Traditional uses of medicinal plants to prevent and treat diabetes; an updated review of ethnobotanical studies in Iran. Journal of Nephropathology 6, 118.

Azadnia, R., Kheiralipour, K. 2022. Evaluation of hawthorns maturity level by developing an automated machine learning-based algorithm. Ecological Informatics, 71, 101804.

Azadnia R, Kheiralipour K (2021a) Implementation of a machine vision system to process the images of medicinal plants and those classification by linear and quadratic discriminant analysis method. Journal of Researches in Mechanics of Agricultural Machinery, 10(4): 1-15.

Azadnia R, Kheiralipour K (2021b) Recognition of leaves of different medicinal plant species using a robust image processing algorithm and artificial neural networks classifier. Journal of Applied Research on Medicinal and Aromatic Plants, 25: 100327.

Azadnia, R., Al-Amidi, M.M., Mohammadi, H., Cifci, M.A., Daryab, A., Cavallo, E. 2022. An AI based approach for medicinal plant identification using deep CNN based on global average pooling. Agronomy, 12, 2723.

Azlah, M.A.F., Chua, L.S., Rahmad, F.R., Abdullah, F.I., Alwi, S.R.W. 2019. Review on techniques for plant leaf classification and recognition. Computers, 8, 77.

Barbedo, J.G.A. 2013. Digital image processing techniques for detecting, quantifying and classifying plant diseases. Barbedo SpringerPlus, 2, 660.

Patil, A.R.B., Sharma, L., Aochar, N., Gaidhane, R., Sawarkar, V., Fulzele, P., Mishra, G. 2020. A literature review on detection of plant diseases. European Journal of Molecular & Clinical Medicine, 7(7), 1605-1614.

Bharate, A.A., Shirdhonkar, M.S. 2017. A review on plant disease detection using image processing. International Conference on Intelligent Sustainable Systems. IEEE Xplore Compliant - Part Number: CFP17M19-ART.

Carvalho, J.O.; Toebe, M.; Tartaglia, F.L.; Bandeira, C.T.; Tambara, A.L. 2017. Leaf area estimation from linear measurements in different ages of *Crotalaria juncea* plants. Anais da Academia Brasileira de Ciencias, 89, 1851-1868.

Chan, K. 2003. Some aspects of toxic contaminants in herbal medicines. Chemosphere, 52, p. 1361-1371.

Chaudhary, P., Godara, S., Cheeran, A.N., Chaudhari, A.K. 2012. Fast and accurate method for leaf area measurement. International Journal of Computer Applications, 49, 22–25.

Conn, E.E. 1995. The world of phytochemicals. In: Gustine, D.L., Flores, H.E. (Eds.), Phytochemicals and Health. American Society of Plant Physiologists, Rockville, MD, 1-14.

Dhaygude, S.B., Kumbhar, N.P. 2013. Agricultural plant leaf disease detection. International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering. 2(1), 599-602.

Dhingra, G., Kumar, V., Joshi, H.D. 2018. Study of digital image processing techniques for leaf disease detection and classification. Multimedia Tools and Applications, 77, 19951-20000.

El-Sayed, S.M., Youssef, A.M. 2019. Potential application of herbs and spices and their effects in functional dairy products. Heliyon, 5(6), e01989.

Ellis, B. 2009. Manual of leaf architecture. CABI, Wallingford, Oxfordshire, UK.

Gavhale, K.R., Gawande, U. 2014. An overview of the research on plant leaves disease detection using image processing techniques. IOSR Journal of Computer Engineering, 16(1), 10-16.

Gayatri, K., Kanti, D.R. Rayavarapu, S.R.V.C., Sridhar, B., Bobbili, R.G.V. 2021. Image processing and pattern recognition based plant leaf diseases identification and classification. Journal of Physics: Conference Series. 1804, 012160.

Gonzalez, R. C., & Woods, R. E. (2002). Digital Image Processing (2nd ed). Prentice Hall Inc., Hoboken, New Jersey, US.

Halder, M., Sarkar, A., Bahar, H. 2019. Plant diseases detection by image processing, A literature review.

SDRP Journal of Food Science & Technology, 3(6), 534-538.

Hamuda, E., Glavin, M., Jones, E. 2016. A survey of image processing techniques for plant extraction and segmentation in the field. Computers and Electronics in Agriculture, 125, 184-199.

Haryono, A., Anam, K., Sujanarko, B. 2020. Herbal leaf authentication using convolutional neural network on Raspberry Pi 3. AIP Conference Proceedings 2278, 020047.

Hasan, N., Mustavi, M., Jubaer, A., Shahriar, T., Ahmed, T. 2022. Plant leaf disease detection using image processing: A comprehensive review. Malaysian Journal of Science and Advanced Technology, 2(4), 174-182.

Hosainpour, A., Kheiralipour, K., Nadimi, M., Paliwal, J. 2022. Quality assessment of dried white mulberry (*Morus alba L.)* using machine vision. Horticulturae, 8(11), 1011.

Hughes, D.P., Salathe, M. 2015. An open access repository of images on plant health to enable the development of mobile disease diagnostics through machine learning and crowdsourcing. https://doi.org/10.48550/arXiv.1511.08060.

Husin, Z., Shakaff, A.Y.M., Aziz, A.H.A., Farook, R.S.M., Jaafar, M.N., Hashim, U., Harun, A. 2012. Embedded portable device for herb leaves recognition using image processing techniques and neural network algorithm. Computers and Electronics in Agriculture, 89, 18-29.

Iglesias, D., Lara, M.A. Molina, M., Lleo, L., Ruiz-Altisent, M., Artes-Hernandez, F., Roger, J.M. 2012. *Monitoring leafy vegetables through packaging films with hyperspectral images*. International Conference of Agricultural Engineering, CIGR-Ageng2012, 8-12 July, Valencia, Espana.

Jahanbakhshi A, Kheiralipour K (2020) Evaluation of image processing technique and discriminant analysis methods in postharvest processing of carrot fruit. Food Science and Nutrition, 8(7): 3346-335.

Kaur, G., Din, S., Brar, A.S., Singh, D. 2014. Scanner image analysis to estimate leaf area. International Journal of Computer Applications, 107(3), 5-10.

Madhavi, B.G.K., Bhujel, A., Kim, N.E., Kim, H.T. 2022. Measurement of overlapping leaf area of ice plants using digital image processing technique. Agriculture, 12, 1321.

Khan, R.U., Khan, K., Albattah, W., Qamar, A.M. 2021. Image-based detection of plant diseases: from classical machine learning to deep learning journey. Wireless Communications and Mobile Computing, 5541859.

Khazaee Y, Kheiralipour K, Hosainpour A, Javadikia H, Paliwal J (2022) Development of a novel image analysis and classification algorithms to separate tubers from clods and stones. Potato Research, 65(1): 1-22.

Kheiralipour K (2012) Implementation and construction of a system for detecting fungal infection of pistachio kernel based on thermal imaging (TI) and image processing technology, Ph.D. Dissertation, University of Tehran, Iran.

Kheiralipour, K., Ahmadi, H., Rajabipour, A., Rafiee, 2018. Thermal Imaging, Principles, Methods and Applications, 1st Edition. Ilam University Publication, Ilam, Iran.

Kheiralipour K, Ahmadi H, Rajabipour A, Rafiee S, Javan-Nikkhah M (2015a) Classifying healthy and fungal infected-pistachio kernel by thermal imaging technology. International Journal of Food Properties, 18: 93-99.

Kheiralipour K, Ahmadi H, Rajabipour A., Rafiee, S., Javan-Nikkhah M, Jayas DS (2014) Detection of healthy and fungal-infected pistachios based on hyperspectral image processing. 8th Iranian National Congress of Agricultural Machinery Engineering (Biosystems) and Mechanization. 29-31 January, Mashahd, Iran.

Kheiralipour K, Ahmadi H, Rajabipour A, Rafiee S, Javan-Nikkhah M, Jayas DS (2013) Development of a new threshold based classification model for analyzing thermal imaging data to detect fungal infection of pistachio kernel. Agricultural Research, 2(2): 127-131.

Kheiralipour K, Ahmadi H, Rajabipour A, Rafiee S, Javan-Nikkhah M, Jayas DS, Siliveru K (2015b) Detection of fungal infection in pistachio kernel by long-wave near-infrared hyperspectral imaging technique. Quality Assurance and Safety of Crops & Foods, 8(1): 129-135.

Kheiralipour K, Ahmadi H, Rajabipour A, Rafiee S, Javan-Nikkhah M, Jayas DS, Siliveru K, Malihipour, A (2021). Processing the hyperspectral images for detecting infection of pistachio kernel by R5 and KK11 isolates of *Aspergillus flavus* fungus. Iranian Journal of Biosystems Engineering, 52(1): 13-25.

Kheiralipour K, Kazemi A (2020) A new method to determine morphological properties of fruits and vegetables by image processing technique and nonlinear multivariate modeling. International Journal of Food Properties, 23(1): 368-374.

Kheiralipour, K., Marzbani, F. (2016). Pomegranate quality sorting by image processing and artificial neural network. 10th Iranian National Congress on Agricultural Machinery Engineering (Biosystems) and Mechanizasion. 30-31 August, Mashhad, Iran.

Kheiralipour, K., Nadimi, M., Paliwal, J. 2022. Development of an intelligent imaging system for ripeness determination of wild pistachios. Sensors, 22(19), 7134.

Kheiralipour, K., Pormah, A. (2017). Introducing new shape features for classification of cucumber fruit based on image processing technique and artificial neural networks. Journal of Food Process Engineering, 40(6), e12558.

Kulkarni, P., Karwande, A., Kolhe, T., Kamble, S., Joshi, A., Wyawahare, M. 2021. Plant disease detection using image processing and machine learning. arXiv:2106.10698.

Kumar, S., Kaur, R. 2015. Plant disease detection using image processing- A review. International Journal of Computer Applications, 124(16), 6-9.

Kuswidiyanto, L.W., Hyun-Ho Noh, H.-H., Han, X. 2022. Plant disease diagnosis using deep learning based on aerial hyperspectral images: A review. Remote Sensing, 14, 6031.

Lai, P.K., Roy, J. 2004. Antimicrobial and chemopreventive properties of herbs and spices. Current Medicinal Chemistry, 11, 1451-1460.

Lara, M.A., Lleo, L., Diezma-Iglesias, B., Roger, J.M., Ruiz-Altisent, M. 2013. Monitoring spinach shelf-life with hyperspectral image through packaging films. Journal of Food Engineering, 119(2), 353-361.

Lomte, S.S., Janwale, A.P. 2017. Plant leaves image segmentation techniques: A review. International Journal of Computer Sciences and Engineering. 5(5), 147-150.

Lu, C., Ren, H., Zhang, Y., Shen, Y. 2010. Leaf area measurement based on image processing. International Conference on Measuring Technology and Mechatronics Automation. IEEE Congress, 13-14 March 2010, Changsha, China..

Manoharan, S.J. 2021. Flawless detection of herbal plant leaf by machine learning classifier through two stage authentication procedure. Journal of Artificial Intelligence and Capsule Networks, 3(2), 125-139.

Mohammadi, V., Kheiralipour, K., & Ghasemi-Varnamkhasti, M. (2015). Detecting maturity of persimmon fruit based on image processing technique. Scientia Horticulturae, 184, 123-128.

Nimah, F.S., Sutojo, T., Setiadi, D.R.I.M. 2018. Identifikasi tumbuhan obat herbal berdasarkan citra daun menggunakan algoritma gray level co-occurence matrix dan K nearest neighbor. Jurnal Teknologi dan Sistem Komputer, 6(2), 51.

Padma, U., Jagadish, S., Singh, M.K. 2021. Recognition of plant's leaf infection by image processing approach. Materials Today: Proceedings, 51(1), 914-917.

Putri, Y.A., Djamal, E.C., Ilyas, R. 2021. Identification of medicinal plant leaves using convolutional neural network. Journal of Physics: Conference Series, 1845, 012026.

Raut, S., Ingole, K. 2017. Review on leaf disease detection using image processing techniques. International Research Journal of Engineering and Technology, 4(4), 2044-2047.

Roy, A., Lipton, M. 2022. A review paper on plant disease detection and recognition by using deep learning. International Journal for Research in Applied Science & Engineering Technology, 10, 1150-1154.

Sahu, K., Tiwari, S., Mandal, S. 2020. Review on leaf disease detection using image processing. International Research Journal of Engineering and Technology, 7(5), 5427-5431.

Salam, S., Kheiralipour, K., Jian, F. 2022. Detection of unripe kernels and foreign materials in chickpea mixtures using image processing. Agriculture, 12(7), 995.

Shi, J., Shi, F., Huang, X. 2023. Prediction of maturity date of leafy greens based on causal inference and convolutional neural network. Agriculture, 13, 403.

Shitole, D., Tamboli, F., Motghare, K., Raj, R.K. 2019. Ayurvedic herb detection using image processing. International Journal of Trend in Scientific Research and Development, 3(4), 491-494.

Sinha, A., Shekhawat, R.S. 2020. Review of image processing approaches for detecting plant diseases. IET Image Process., 2020, 14(8), 1427-1439.

Singh, V., Misra, A.K. 2017. Detection of plant leaf diseases using image segmentation and soft computing techniques. Information Processing in Agriculture. 4(1), 41-49.

Souza, A., Rojas, M.Z., Yang, Y., Lee, L., Hoagland, L. 2022. Classifying cadmium contaminated leafy vegetables using hyperspectral imaging and machine learning. Heliyon, 8(12), e12256.

Suhartono, E., Setiawan, B., Santosa, P.B, Idroes, R., Indrawan, M.S. 2019. Antioxidant activity using image processing. Journal of Physics: Conference Series. 1374, 012057.

Sujatha, R., Kumar, S.Y., Uma Akhil, G. 2017. Leaf disease detection using image processing. Journal of Chemical and Pharmaceutical Sciences, 10(1), 670-672.

Suwais, K., Alheeti, K., Al-Dosary, D. 2022. A review on classification methods for plants leaves recognition. International Journal of Advanced Computer Science and Applications, 13(2), 92-100.

Thyagharajan, K.K., Raji, I.K. 2018. A review of visual descriptors and classification techniques used in leaf species identification. Archives of Computational Methods in Engineering, 4, 933-960.

Thyagharajan, K.K., Minu, R.I. 2013. Prevalent color extraction and indexing. International Journal of Engineering and Technology, 5(6), 4841-4849.

Tung, K.-C., Tsai, C.Y., Hsu, H.-C., Chang, Y.-H., Chang, C.-H., Chen, S. 2018. Evaluation of water potentials of leafy vegetables using hyperspectral imaging. IFAC-Papers On Line, 51(17), 5-9.

Usefi, S., Farsi, H., Kheiralipour, K. 2016. Drop test of pear fruit: experimental measurement and finite element modelling. Biosystems Engineering, 147, 17-25.

Vadivambal, R., *Jayas*, *D*.S. 2016. Bio-Imaging: Principles, Techniques, and Applications. 1st Ed. CRC Press, Taylor and Francis Group, New York, US.

Vishnu, S., Ram, A.R. 2015. Plant disease detection using leaf pattern: A review. International Journal of Innovative Science, Engineering & Technology, 2(6), 774-780.

Waldchen, J., Rzanny, M., Seeland, M., Mader, P. 2018. Automated plant species identification-trends and future directions. PLOS Computational Biology., 14, e1005993.

Wang, Z., Li, H., Zhu, Y., Xu, T.F. 2017. Review of plant identification based on image processing. Archives of Computational Methods in Engineering, 24(3), 637-654.

Xiong, J.; Yu, D.; Liu, S.; Shu, L.;Wang, X.; Liu, Z. 2021. A review of plant phenotypic image recognition technology based on deep learning. Electronics, 10, 81.

Yu, K.; Jia, L.; Chen, Y.Q.; Xu,W. Salakhutdinov, R.R. 2013. Deep learning: Yesterday, today, and tomorrow. Journal of Computer Research and Development, 50, 1799-1804.