GUASNR

Biosystems Engineering and Renewable Energies

Journal homepage: https://bere.gau.ac.ir

ISAMEM

Original Research Paper

Developing a computer vision system for classifying tree leaves

Nadia Saadati[1*], Mohammadreza Ahmadi Teshnizi[2]

[1] *Department of Agricultural Biosystems Engineering, University of Mohaghegh Ardabili, Ardabil, Iran*
[2] *Department of Computer Engineering, Sharif University of Technology, Tehran, Iran*

Biosystems Engineering and Renewable Energies 2025, 1 (2): 101-105

KEYWORDS

Computer vision
Feature extraction
Image processing
Intelligent algorithms
Leaf classification

*** Corresponding author**
nadia.saadati@uma.ac.ir

Article history
Received: 2025-03-24
Revised: 2025-06-27
Accepted: 2025-07-10

ABSTRACT

The identification and classification of tree leaves hold significant importance in botanical and agricultural research. This study focuses on the development of an advanced computer vision system for classifying leaves from five distinct tree species, including pomegranate, fig, almond, raspberry, and hawthorn. The proposed system utilizes a dataset comprising 525 digital images to extract diverse features from the color domain and the gray-level co-occurrence matrix (GLCM). From each image, 126 features are extracted from the color domain and 80 features from the GLCM. The feature selection process is conducted using an advanced method that combines artificial neural networks (ANN) with ant colony optimization (ACO). This approach aids in identifying key features, including the angular second moment, angular contrast, angular maximum probability, the normalized difference index in the CMY and HSV color spaces, and the standard deviation of the first component in the YCbCr color space. Leaf classification is performed using a hybrid ANN and metaphor competition algorithm, achieving a classification accuracy of 93%. This system serves as an effective tool for precise and efficient leaf classification and has the potential to lead to significant advancements in botanical research and agricultural applications. Furthermore, the results of this study indicate that the use of intelligent methods in feature selection can enhance the accuracy and efficiency of classification models. Ultimately, this research emphasizes the importance of developing advanced techniques for leaf identification and classification, representing a crucial step toward improving existing methods in this field.

1. Introduction

Machine vision systems have proven to be highly effective tools for the analysis of tree and plant leaves, which are readily available throughout the growing season and offer a rich array of extractable features (Novotny and Suk, 2013). Consequently, a significant body of research has focused on the classification of diverse leaf types. For instance, (Hamuda et al., 2016) employed a self-organizing artificial neural network (ANN) to classify 15 distinct leaf types, including species such as *Ulmus carpinifolia*, *Acer platanoides*, and *Salix aurita*. This research involved the preparation of 1153 image segments for classification, emphasizing invariant binary two-dimensional image recognition. Two methodologies were proposed: one targeting features invariant to translation, scaling, rotation, and reflection, and another addressing features invariant to general affine transformations, achieving a classification accuracy of 85.71%.

In a study (Mursalin et al., 2013), five types of weed leaves—Capsicum, Burcucumber, Cogongrass, Marsh herb, and *Chenopodium album*—were classified using Bayesian classifiers, support vector machines (SVM), and decision tree methods. The images were captured with a digital camera positioned 40 cm above the ground. This study analyzed 400 image segments (80 per weed type), extracting nine features such as area, perimeter, and convexity. Among the methods tested, the Bayesian classifier exhibited the highest classification accuracy. A few other studies are reviewed in Table 1.

The present study seeks to develop an advanced computer vision system that leverages image processing techniques alongside a hybrid ANN–ant colony optimization (ACO) algorithm to classify leaves from pomegranate, fig, almond, raspberry, and hawthorn trees. The integration of ANN and ACO is motivated by their respective abilities to efficiently handle complex, high-dimensional data and to enhance the learning process.

2. Materials and Methods

2.1. Imaging

The imaging process was conducted to capture high-quality images of tree leaves. These images were taken in Kermanshah province under meticulously controlled lighting conditions to ensure uniformity and precision in feature extraction and classification. The imaging setup comprised white LED lights with an intensity of 327 lux, providing consistent illumination. An industrial-grade camera (ImagingSource, model DFK-23GM021) equipped with a 1/3 inch Aptina CMOS MT9M021 sensor, offering a resolution of 1.2 megapixels (1280 x 960), was utilized. The camera was strategically positioned 15 cm above the ground to capture detailed images of the leaves. This setup was selected to maintain high-resolution image quality, which is crucial for accurate analysis. A total of 525 images were collected, distributed among the tree species as follows: pomegranate (108 images), fig (115 images), almond (99 images), raspberry (105 images), and hawthorn (98 images).

https://doi.org/10.22069/bere.2025.23451.1024

Table 1. Summary of research in the field of plant species detection

Study	Feature Type	Number of species	Dataset size & Characteristics	Algorithm Used	Accuracy
Bambil et al., 2020	Color, Shape, Texture	30	40 leaves, 30 species	AdaBoost, Random Forest, SVM, Deep Learning	>93.00%
Kaur and Kaur, 2019	Texture, Color	15	1,125 images, 15 species	Multiclass-SVM	93.26%
Kumar et al., 2012	Shape	184	29,107 images, 184 species	SVM, Nearest Neighbor	96.80% (top 5 accuracy)
Mangaoang and Samaniego, 2023	Shape, Color, Texture	25	31,508 images, 25 species	KNN, SVM, BP networks, CNN	98.50% (CNN)
Naga et al., 2023	Shape, Texture	3	No mention found, 3 species	SVM	99.00-100.00%
Sabzi et al., 2020	Shape, Color, Texture	5	516 images, 5 species	Hybrid ANN-ABC, Hybrid ANN-BBO, LDA	94.04% (ANN-ABC)
Satti, 2013	Color, Shape	33	1,907 images, 33 species	ANN, KNN	93.30% (ANN)
Tan et al., 2020	Vein Morphology	No mention found	No mention found	Pre-trained AlexNet, Fine-tuned AlexNet, D-Leaf (custom CNN)	95.54% (Fine-tuned AlexNet)
Unger et al., 2016	Shape, Vein Morphology	26 (Test set I), 17 (Test set II)	260 (Test set I), 170 (Test set II), 26 & 17 species	SVM	73.21% (Test set I), 84.88% (Test set II)
Çugu et al., 2017	Deep and Hand-crafted Features	57	5,408 images, 57 species	CNN, SVM	No mention found

2.2. Image segmentation

The YCbCr color space was strategically selected for the segmentation of leaf images, effectively isolating the leaf foreground from the background. The YCbCr color space is particularly advantageous due to its ability to distinctly separate chrominance (color information) from luminance (brightness), which is crucial for accurately distinguishing leaves from their backgrounds, especially under varying lighting conditions. The segmentation process involved the application of thresholding techniques on the first (Y) and second (Cb) channels. An optimal threshold value was meticulously determined through comprehensive image analysis to ensure precise segmentation. The thresholding criteria are represented in Eq. (1).

$$Y(i,j) \leq 70 \ or \ Cb(i,j) \geq 50 \quad (1)$$

A pixel is classified as part of the leaf if the luminance component (Y) is less than or equal to 70, or if the chrominance blue component (Cb) is greater than or equal to 50. Pixels not meeting these criteria are categorized as background (Gonzalez et al., 2004). This method ensures robust segmentation, facilitating subsequent feature extraction and classification.

2.3. Feature extraction

Color and texture features extracted to create the dataset. These features were meticulously selected due to their demonstrated efficacy in encapsulating the critical color and texture attributes essential for accurate leaf classification.

The extraction of color features was systematically divided into two categories: statistical features and vegetation index-related features. Statistical features were derived by calculating the mean and standard deviation of each component across multiple color spaces, including RGB, YCbCr, YIQ, CMY, HSV, and HSI. This thorough analysis yielded a total of 42 features, each contributing essential color information that facilitates the differentiation of various leaf types. Furthermore, vegetation index-related features were computed, as outlined in Table 2. Initially extracted for the RGB color space, these indices were subsequently extended to other color spaces, resulting in a comprehensive set of 84 features. These indices are crucial for enhancing the system's ability to discriminate between leaf species by capturing subtle color variations indicative of different species. The gray-level co-occurrence matrix (GLCM) is a statistical method of examining texture that considers the spatial relationship of pixels. It is defined as a matrix where the number of rows and columns is equal to the number of gray levels in the image. The matrix element P(i,j) is the relative frequency with which two pixels, separated by a pixel distance d, occur in the image, one with gray level i and the other with gray level j. The GLCM is defined as Eq. (16).

Table 2. Vegetation index-related features

Feature	Formula	
Normalized RGB Component 1	$R_n = \frac{R}{R+G+B}$	(2)
Normalized RGB Component 2	$G_n = \frac{G}{R+G+B}$	(3)
Normalized RGB Component 3	$B_n = \frac{B}{R+G+B}$	(4)
Gray Channel	$gray = 0.2898 \times R_n + 0.5870 \times G_n + 0.1140 \times B_n$	(5)
Excess Green (EXG)	$EXG = 2 \times G_n - R_n - B_n$	(6)
Excess Red (EXR)	$EXR = 1.4 \times R_n - G_n$	(7)
Color Index for Extracted Vegetation (CIVE)	$CIVE = 0.441 \times R_n - 0.811 \times G_n + 0.385 \times B_n + 18.78$	(8)
Difference of Excess Green and Red (EXGR)	$EXGR = EXG - EXR$	(9)
Normalized Difference Index (NDI)	$NDI = \frac{G_n - B_n}{G_n + B_n}$	(10)
Green Minus Blue Index (GB)	$GB = G_n - B_n$	(11)
Red-Blue Contrast Index (RBI)	$RBI = \frac{G_n - B_n}{G_n + B_n}$	(12)
Red-Green Index (ERI)	$ERI = (R_n - G_n) \times (R_n - B_n)$	(13)
Excess Green Index (EGI)	$EGI = (G_n - R_n) \times (G_n - B_n)$	(14)
Excess Blue Index (EBI)	$EBI = (B_n - G_n) \times (B_n - R_n)$	(15)

$$P(i,j) = \sum_{x=1}^{N} \sum_{y=1}^{M} \begin{cases} 1 & If \ (x,y) = i \ and \ I(x+\Delta x, y+\Delta y) = j \\ 0 & otherwise \end{cases} \quad (16)$$

where $I(x,y)$ is the intensity at pixel (x,y), and $(\Delta x, \Delta y)$ is the offset (Haralick et al., 1973; Petron and Bosdogianni, 2006). Table 3 presents features extracted from four distinct angles: 0, 45, 90, and 135°, resulting in a comprehensive set of 80 features. These features are critical for capturing the texture information necessary for distinguishing between different leaf species.

2.4. Feature selection

The feature selection process utilized a sophisticated hybrid approach combining ANN with ACO. This methodology capitalizes on the ANN's ability to discern intricate patterns and the ACO's strength in optimizing feature subsets, thereby ensuring the identification of the most relevant features for classification tasks. The features selected through this process include variance difference at 0 degrees, dissimilarity at 90 degrees, maximum probability at 45 degrees, the normalized difference index in both CMY and HSV color spaces, and the standard deviation of the first component in the YCbCr color space. This deliberate selection process significantly enhances the system's classification accuracy by concentrating on the most informative features, thus improving the overall performance of the classification model.

Table 3. Texture features extracted from the gray-level co-occurrence matrix (GLCM)

No.	Feature	No.	Feature
1	Homogeneity	11	Entropy
2	Normalized Inverse Difference	12	Normalized Inverse Difference Moment
3	Coefficient of Variation	13	Inverse Difference in Homogeneity
4	Standard Deviation	14	Second Diagonal Moment
5	Cluster Shade	15	Information Measure of Correlation 1
6	Cluster Prominence	16	Information Measure of Correlation 2
7	Sum Entropy	17	Dissimilarity
8	Variance	18	Energy
9	Mean	19	Contrast
10	Diagonal Moment	20	Correlation

2.5. Classification

The classification of the leaf types was executed using a hybrid classifier that integrates ANN with ACO. This hybrid ANN-ACO classifier harnesses the ANN's capacity to learn complex patterns, leading to efficient training processes and significantly improved classification accuracy. The synergy between ANN and ACO ensures that the classifier is both robust and adaptable, capable of delivering high performance across diverse classification scenarios. To facilitate model training and evaluation, 70% of the images were randomly selected and considered for training and validation, while the remaining 30% were reserved for testing the system's performance.

2.6. Performance metrics

The performance of the classification system is evaluated using precision (Eq. 17), recall (Eq. 18), and F1-score (Eq. 19) (Powers, 2011; Jain et al., 2000)

$$\text{Precision} = \frac{TP}{TP+FP} \quad (17)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (18)$$

$$\text{F1} - \text{score} = 2 \cdot \frac{Precision \cdot Recall}{Precision+Recall} \quad (19)$$

where TP is the number of true positives, FP is the number of false positives, and FN is the number of false negatives.

3. Results and Discussion

3.1. Optimal configuration of the classifier

The optimal configuration of the ANN classifier was determined using the ACO algorithm, as presented in Table 4. This optimization process is crucial for fine-tuning the network's parameters to achieve enhanced performance and accuracy.The architecture of the MLP classifier consists of three distinct layers, each employing a unique transfer function to optimize learning capabilities. Specifically, the first layer utilizes the radbas function, the second layer incorporates the tribas function, and the third layer applies the tansig function. The training of the network is executed using the trainlm function, which implements the Levenberg-Marquardt backpropagation algorithm, renowned for its effectiveness in ANN training. Furthermore, the learnos function is employed for the online sequential learning of weights and biases, thereby enabling continuous learning and adaptation to new data inputs. This comprehensive configuration ensures that the ANN is well-equipped to handle complex classification with high precision.

3.2. Performance evaluation of the model

Table 5 presents the confusion matrix for the hybrid ANN-ACO classifier, structured as a 5 × 5 matrix. This matrix provides a detailed assessment of the classifier's predictive accuracy and its ability to distinguish among these diverse classes. The confusion matrix is a critical tool for evaluating the classifier's performance, offering insights into both the true positive rates and the misclassification rates for each class. It serves as a foundation for calculating various performance metrics, such as precision, recall, and F1 score, which are essential for a comprehensive understanding of the classifier's effectiveness.

According to the table, the hybrid ANN-ACO classifier achieved an impressive overall accuracy of 93%, reflecting its robust performance in classifying the dataset accurately.The receiver operating characteristic (ROC) curves depicted in Figure 1 further illustrate the classifier's performance by showing the trade-off between sensitivity and specificity for each class. The classes, from 1 to 5, showed pomegranate, fig, almond, raspberry, and hawthorn, respectively. These curves are instrumental in visualizing the classifier's ability to discriminate between the different leaf types, providing a graphical representation of its diagnostic ability across various threshold settings.

The performance of the hybrid classifier was rigorously evaluated using key performance metrics: precision, recall, F1-score, and accuracy (Table 6). These metrics, derived from the confusion matrix, offer a comprehensive assessment of the classifier's proficiency in accurately distinguishing between the different leaf types. The precision metric quantifies the classifier's ability to correctly identify positive instances, while recall measures the ability to capture all relevant instances. The F1-score, a harmonic mean of precision and recall, provides a balanced measure of the classifier's accuracy. These metrics collectively underscore the classifier's robust performance across all classes. According to the feature selection, key features were recognized as the angular second moment, angular contrast, angular maximum probability, the normalized difference index in the CMY and HSV color spaces, and the standard deviation of the first component in the YCbCr color space.

The feature correlation matrix depicted in Figure 3 examines the interrelationships among features. This matrix is instrumental in identifying potential multicollinearity issues and can guide the enhancement of feature selection strategies, thereby improving model performance.

Table 4. Optimized parameter values for the ANN configured by ACO

Parameter	Optimal Value
Number of Neurons	Layer 1: 18, Layer 2: 5, Layer 3: 13
Number of Layers	3
Transfer Function	Layer 1: radbas, Layer 2: tribas, Layer 3: tansig
Training Function	trainlm (Levenberg-Marquardt backpropagation)
Learning Function for Weights/Biases	learnos (Online Sequential Learning)

Table 5. Confusion matrix for the hybrid ANN-ACO classifier on test dataset

Actual Class	Predicted Class					Total Instances
	Pomegranate	Fig	Almond	Raspberry	Hawthorn	
Pomegranate	27	1	1	0	1	29
Fig	1	36	0	2	0	38
Almond	0	1	26	0	2	29
Raspberry	1	0	0	33	0	34
Hawthorn	0	2	1	0	25	28

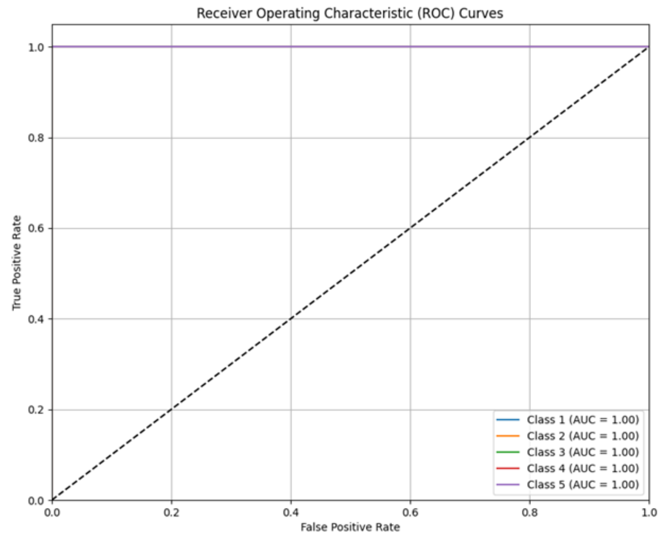

Figure 1. Receiver operating characteristic (ROC) curves for each class

Table 6. Performance Metrics for the Hybrid ANN-ACO Classifier

Class	Precision	Recall	F1-Score
Pomegranate	0.90	0.93	0.92
Fig	0.92	0.95	0.94
Almond	0.90	0.90	0.90
Raspberry	0.97	0.97	0.97
Hawthorn	0.89	0.89	0.89

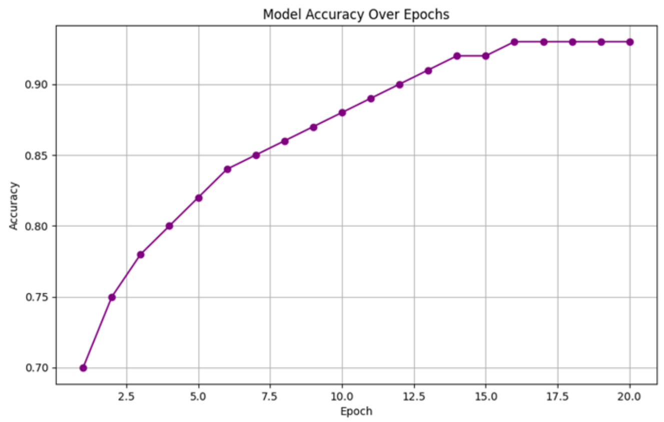

Figure 2. Model accuracy across training epochs

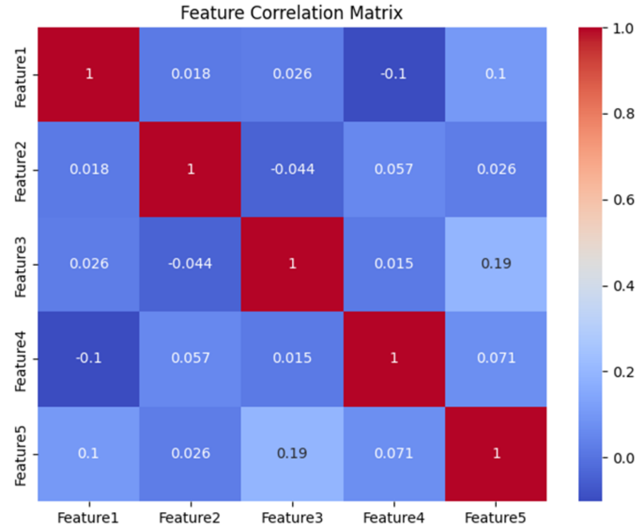

Figure 3. Feature correlation matrix

4. Conclusion

The YCbCr color space has emerged as the most effective for segmentation tasks, particularly under controlled lighting conditions, significantly enhancing the precision and reliability of image processing in various computer vision applications. Despite advancements, the detection and classification of diseased leaves remain a formidable challenge, necessitating the development of advanced classification techniques for accurate identification and categorization, crucial for agriculture and plant pathology. The application of intelligent feature selection methods has proven superior to traditional statistical approaches, enhancing model accuracy and efficiency by reducing dimensionality and focusing on the most relevant features. The hybrid ACO classifier has demonstrated a remarkable accuracy rate of 93%, underscoring its robustness and effectiveness in managing complex classification tasks and highlighting its potential for broader applications in machine learning and data analysis. Future research should focus on integrating these findings into real-world applications, exploring the scalability of the hybrid ANN-ACO classifier, and refining feature selection techniques to adapt to diverse datasets and evolving challenges in computer vision.

References

Bambil, D., Pistori, H., Bao, F., Weber, V., Alves, F. M., Gonçalves, E. G., & Bortolotto, I. M. 2020. Plant species identification using color learning resources, shape, texture, through machine learning and artificial neural networks. *Environment Systems and Decisions*, *40*(4), 480-484.

Çuğu, İ., Şener, E., Erciyes, Ç., Balcı, B., Akın, E., Önal, I., & Akyüz, A. O. 2017. Treelogy: A novel tree classifier utilizing deep and hand-crafted representations. *arXiv preprint arXiv:1701.08291*.

Gonzalez, R. C., Woods, R. E., & Eddins, S. L. 2010. *Digital image processing using MATLAB*. Tata McGraw Hill Education.

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. https://doi.org/10.1016/j.compag.2016.04.024

Haralick, R. M., Shanmugam, K., & Dinstein, I. H. 1973. Textural features for image classification. *IEEE Transactions on systems, man, and cybernetics*, 6, 610-621. https://doi.org/10.1109/TSMC.1973.4309314

Jain, A. K., Duin, R. P. W., & Mao, J. 2000. Statistical pattern recognition: A review. *IEEE Transactions on pattern analysis and machine intelligence*, *22*(1), 4-37. https://doi.org/10.1109/34.824819

Kaur, S., & Kaur, P. 2019. Plant species identification based on plant leaf using computer vision and machine learning techniques. *Journal of Multimedia Information System*, *6*(2), 49-60. https://doi.org/10.33851/JMIS.2019.6.2.49

Kumar, N., Belhumeur, P. N., Biswas, A., Jacobs, D. W., Kress, W. J., Lopez, I. C., & Soares, J. V. 2012. Leafsnap: A computer vision system for automatic plant species identification. In *Computer Vision–ECCV 2012: 12th European Conference on Computer Vision, Florence, Italy, October 7-13, 2012, Proceedings, Part II 12* (pp. 502-516). Springer Berlin Heidelberg.

Mangaoang, E. V. D., & Samaniego, J. M. 2023. Leaf-based Classification of Important Indigenous Tree Species by Different Feature Extraction Techniques and Selected Classification Algorithms. *International Journal of Advanced Computer Science and Applications*, *14*(1). https://doi.org/10.14569/IJACSA.2023.0140104

Mursalin, M., Hossain, M. M., Noman, M. K., & Azam, M. S. 2013. Performance analysis among different classifier including naive bayes, support vector machine and C4. 5 for automatic weeds classification. *Global Journal of Computer Science and Technology Graphics & Vision*, *13*(3).

Novotný, P., & Suk, T. 2013. Leaf recognition of woody species in Central Europe. *biosystems engineering*, *115*(4), 444-452. https://doi.org/10.1016/j.biosystemseng.2013.04.007

Petrou, M. M., & Petrou, C. 2010. *Image processing: the fundamentals*. John Wiley & Sons.

Powers, D. M. 2020. Evaluation: from precision, recall and F-measure to ROC, informedness, markedness and correlation. *arXiv preprint arXiv:2010.16061*. https://doi.org/10.48550/arXiv.2010.16061

Sabzi, S., Pourdarbani, R., & Arribas, J. I. 2020. A computer vision system for the automatic classification of five varieties of tree leaf images. *Computers*, *9*, 6. https://doi.org/10.3390/computers9010006

Satti, V., Satya, A., & Sharma, S. 2013. An automatic leaf recognition system for plant identification using machine vision technology. *International journal of engineering science and technology*, *5*(4), 874.

Unger, J., Merhof, D., & Renner, S. 2016. Computer vision applied to herbarium specimens of German trees: testing the future utility of the millions of herbarium specimen images for automated identification. *BMC Evolutionary Biology*, *16*, 1-7.

Wei Tan, J., Chang, S. W., Abdul-Kareem, S., Yap, H. J., & Yong, K. T. 2018. Deep learning for plant species classification using leaf vein morphometric. *IEEE/ACM Transactions on computational biology and bioinformatics*, *17*, 82-90. https://doi.org/10.1109/TCBB.2018.2848653

Yaswanth, T. N. S., Lakshmi, K. V., Vamsi, K. G., Supraja, D., & Vani, K. S. 2023, July. Classification of Medicinal Leaves using SVM. In *2023 World Conference on Communication & Computing (WCONF)* (pp. 1-7). https://doi.org/10.1109/WCONF58270.2023.10235087