Machine Learning and Artificial Intelligence
J.-L. Kim (Ed.)

doi:10.3233/FAIA230767

A Quantitative Comparison of Classification Methods for Plant Leaf Images

Hai Phong BUI [a,1], Anh Tuan DINH [b], Ngoc Minh NGUYEN [c], Van Khuong PHAM [d]

[a] *Hanoi Architectural University, Hanoi, Vietnam*
[b] *School of Electrical and Electronic Engineering*
Hanoi University of Science and Technology Hanoi, Vietnam
[c] *Hanoi – Amsterdam Highschool for the Gifted, Hanoi, Vietnam*
[d] *BKstar center, Hanoi, Vietnam*

Abstract. In recent years, the automatic classification of leaves has attracted more and more researches. The accurate classification of leaves enables the development of smart solutions in agriculture. The paper analyzes and compares the classification of leaf images using deep neural networks and handcrafted feature extraction methods on public datasets. Both powerful deep neural network models and handcrafted feature extraction methods have been optimized and employed to classify leaf images accurately without using specific domain knowledge. The highest classification accuracies of 94% and 97.78% are achieved on the public (Plant Village) datasets that consist of grayscale and color plant leaf images, respectively. The obtained classification accuracy of apple leaf disease images is 95.53%. Obtained results show the efficiency and robustness of the deep neural networks on the classification of leaf images. The comparison results allow to develop the applications of the automatic classification of leaf imagery in reality.

Keywords. Leaf classification, Deep neural network, Handcrafted feature extraction, Machine learning classifier

1. Introduction

Plants play an important role in human life. Plants provide us sustenance, food, medicines and industrial materials. Each kind of plant has different properties and benefits. For years, the accurate recognition of plants a has become necessary. Botanists are able to recognize based on different parts of plants, such as leaf, flower, seed and root. The leaf classification is considered as one of the most widely approaches [1]. The automatic classification of leaf images aims to predict the correct labels (species of leaves) of input leaf images based on collected data. Figure 1 illustrates different species of leaves.

In recent years, the advances in artificial intelligence (AI) and computer vision techniques have developed the automatic classification of images with high accuracy and ef-

[1]Corresponding Author: Hai Phong BUI, Faculty of Information Technology, Hanoi Architectural University, Hanoi, Vietnam; E-mail: phongbh@hau.edu.vn

ficient execution time [1,2,3]. Traditional methods applied the feature extraction (e.g., color, shape and texture features) and machine learning (e.g., k Nearest Neighbors, Support Vector Machine and Random Forest) to classify leaf images. In recent years, with the advances of convolutional neural networks (CNN), the classification of leaf images has been improved. The paper analyzes and performs the classification of leaves using both handcrafted feature extraction and deep neural networks on large and public datasets. The contributions of the paper can be described as follows:

(1) The paper applies and compares the performance of both handcrafted feature extraction methods and CNN models of the classification of leaf images.

(2) The performance of the methods have been evaluated on four datasets. We evaluate the datasets that consist of grayscale, color and background removal leaf images. The obtained results on the diverse datasets allow to analyze the strengths and weaknesses of classification methods.

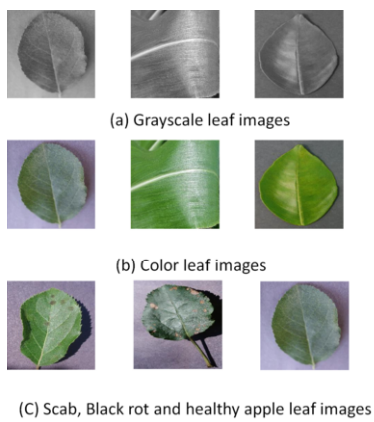


Figure 1. Examples of plant leaf images.

2. Related work

This section analyzes the significant approaches for the classification of leaf images. The work in [4] extracts morphological features and the probabilistic neural network to classify leaf images. The method obtained the classification of 91.41% on the small datasets of 1200 images. The work in [5] proposes the feature extraction based on shape selection to classify leaf images.

In recent years, the CNNs are employed to improve the performance of the leaf classification. Particularly, after several large datasets [2] of leaf images were published, the CNNs are widely investigated for the classification. Compared to traditional methods, the CNNs allow to obtain higher performance. However, CNNs require a large numbers of leaf images to train the models efficiently. The work in [6] applies the transfer learning of CNNs to classify leave images. The work in [7] applies the Mobilenet-v2 to classify bean leaves. The Mobilenet is trained on the dataset consists of 1296 bean leaf images. The method gained the classification accuracy of 97% on the bean leaf dataset.

3. Proposed method

The proposed method is described in Figure 2. Firstly, we apply the image processing for input leaf images (e.g., image normalization, processing grayscale and color images). Then, we compare the performance of the leaf classification using the handcrafted feature extraction and deep neural networks.

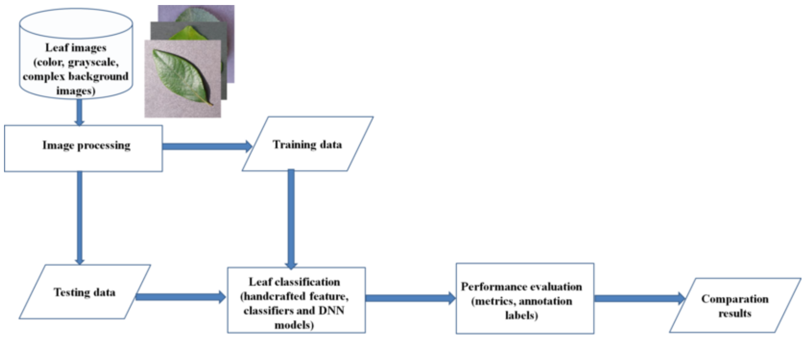


Figure 2. Flowchart of the proposed method.

3.1. The classification of leaf images using handcrafted feature extraction and machine learning classifiers

In the section, several handcrafted feature extraction techniques are applied to extract visual features of leaf images such as: Scale-invariant feature transform (SIFT) [8], Histogram of gradient (HOG) and Discrete Wavelet Transformation (DWT) feature extraction [9]. The techniques extract low-level visual features of plant leaf images.

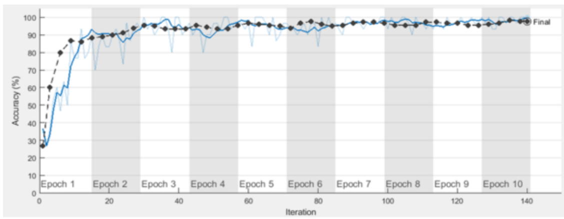
After obtaining visual features, several classifiers are fine-tuned to categorize leaf images into classes: such as Support vector machine (SVM), k Nearest Neighbors (kNN) and Random Forest (RF) [1].

3.2. The classification of leaves using deep neural networks

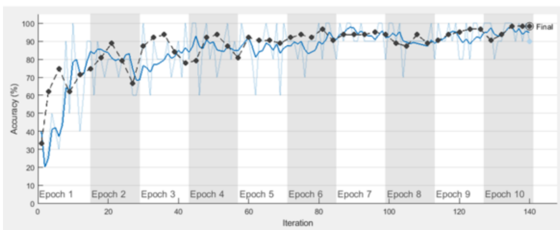
In the paper, several advanced DNNs have been applied and fine-tuned to classify leaf images in an end-to-end way. The feature extraction and classification are performed by using DNNs including Alexnet [10], Resnet-50 [11], Inception-v3 and Densenet-201 [12]. Detail information of the DNNs is described in Table 1. Figure 3 and 4 demonstrate the accuracy and the loss values of the Alexnet and Inception-v3 network during the training process. The gradient descent and stochastic gradient descent (SGD) algorithm [13] is applied to minimize the loss values during the training process of the DNNs. The momentum of the SGD algorithm is set as 0.9. Input leaf images are resized as the requirement of the DNNs. The initial learning rate is set as 0.001. The implementation of the DNNs is supported by the Matlab 2021b environment in a computer with the 8GB RAM and core-i5 processor.

Table 1. Structural information of DNNs

DNNs	Number of layers	Sizes of input images	Number of extracted features
Alexnet [10]	25	227x227x3	4096
Resnet-50 [11]	50	224x224x3	512
Densenet-201 [12]	201	224x224x3	1000
Inception-v3 [14]	48	229x229x3	1000

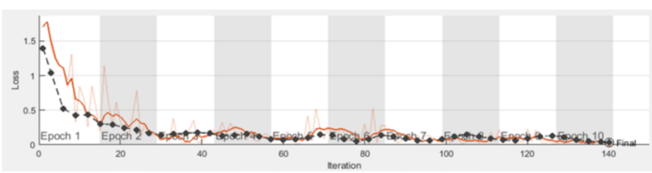


(a) Accuracy of the Alexnet.

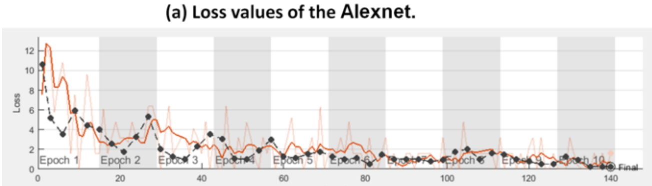


(b) Accuracy of the Inception-v3.

Figure 3. Accuracy of the classification of leaf images during the training process of the Alexnet (a) and Inception-v3 (b).



(a) Loss values of the Alexnet.



(b) Loss values of the Inception-v3.

Figure 4. Loss values of the classification of leaf images during the training process of the Alexnet (a) and Inception-v3 (b).

4. Experimental results

4.1. Dataset and evaluation metric

In the paper, the proposed method has been evaluated on four sub-datasets of the Plant village dataset [15]. The dataset 1 consists of 1500 leaf color and complex background

Table 2. Statistic information of four leaf datasets.

Dataset	Number of classes of leaves	Training (Number images)	Testing (Number images)
Dataset 1 [15]	12	1000 / type	500 / type
Dataset 2 [15]	12	1000 / type	500 / type
Dataset 3 [15]	4	500 / type	150 / type
Dataset 4 [15]	12	1000 / type	500 / type

images. The dataset 2 consists of 1500 leaf grayscale leaf images. The dataset 3 consists of 600 apple leaf disease images. The classes of apple leaves in the dataset 3 are: healthy, scab, black rot and cedar rust [15]. The dataset 4 consists of 1500 leaf color and background removal images. The information of the four datasets is shown in Table 2. Figure 5 illustrate examples of grayscale, color and complex background leaf images in the datasets.

(a) Grayscale blueberry leaf (b) Color and complex background blueberry leaf (c) Color and background removal blueberry leaf

Figure 5. Examples of grayscale, color and complex background leaf images in the datasets.

To obtain the clear evaluation, the precision (P), recall (R) and F1 score metrics are widely applied for the classification task. Mathematically, F1 score is the harmonic mean of precision and recall. The score can be calculated as follows:

$$F1 - score = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{1}$$

Moreover, the Matthews correlation coefficient (MCC) [16] is also applied in the work to evaluate the performance of the classification methods of leaves.

4.2. *Performance evaluation*

Performance comparison of the classification methods of leaf images is shown in Table 3, 4, 5 and 6. The results show that the CNNs obtain higher classification accuracies compared to the handcrafted feature extraction methods. The classification using the Densenet-201 network obtains the highest accuracy on the leaf image datasets because the network extracts more visual features than other methods. The classification results on dataset 2 and 3 are lower than those on the dataset 1 and 4 because the datasets are more challenging. The classification of leaves on grayscale images is harder compared to that on color ones. The apple leaf disease images are similar, therefore, the misclassification is caused. Figure 6 illustrates the efficient feature extraction of Alexnet. As shown in the Figure, the classes of leaf images are possibly separated. It shows that the Alexnet is able to discriminate leaf images with high accuracy. In this study, the t-distributed stochastic neighbor embedding (t-SNE) dimensional reduction [17] is applied to visualize the distribution of features extracted by the Alexnet. Figure 7 illustrates some examples of the classification of plant leaf images.

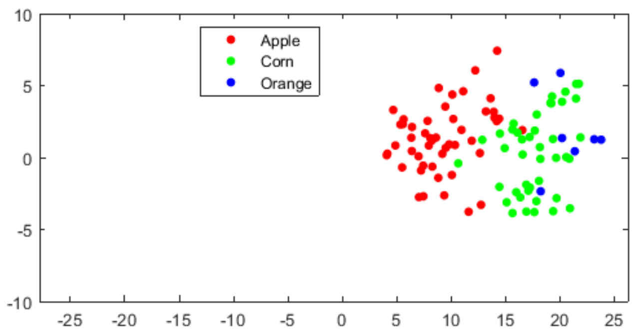


Figure 6. Illustration of feature distribution of leaf images extracted by Alexnet. Extracted features of apple, corn and orange leaves are represented in red, green and blue circles, respectively.

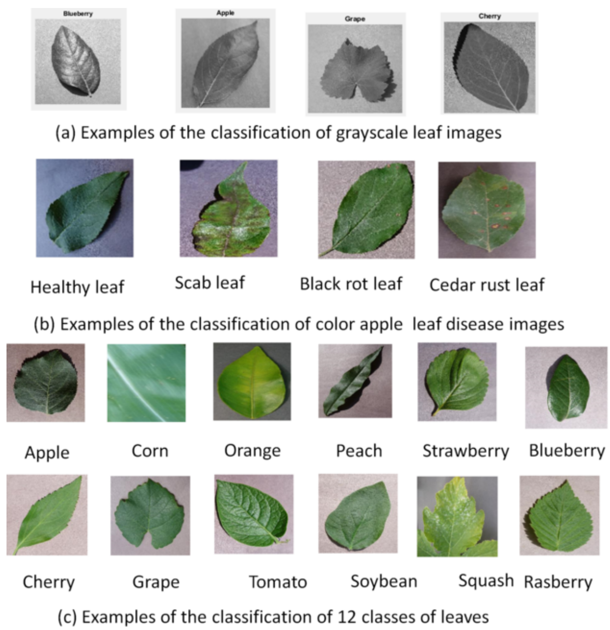


Figure 7. Examples of the classification of plant leaf images.

5. Conclusions and future works

The paper has presented a quantitative comparisons of the classification methods of leaf images. Both handcrafted feature extraction and deep neural network methods are analysed and compared for the classification of leaves. The use of DNNs allows to obtain higher accuracy of the classification than those of handcrafted feature extraction methods. The classification of color plant images using the Densenet-201 network obtains the highest scores. For the classification of grayscale leaf images, the handcrafted feature extraction methods gain the competitive results compared with the DNN models. In the future, the study can be extended and evaluated on other species of leaves.

Table 3. Performance comparison of the classification of leaves on the dataset 1 that consists of color and complex background images of 12 classes of leaves.

Methods	P	R	F1	MCC
HOG and SVM [9]	89%	87%	87.99%	86.45%
DWT and kNN [9]	85%	83%	83.99%	82.49%
SIFT and RF [9]	90%	88%	88.99%	87.50%
Alexnet [10]	91%	89%	89.99%	88.40%
Inception-v3 [14]	93%	92%	92.50%	90.96%
HGANet [16]	95.50%	93.80%	94.64%	93.11%
Resnet-50 [11]	95%	93%	93.99%	92.45%
Densenet-201 [12]	96%	94%	94.99%	93.45%

Table 4. Performance comparison of the classification of leaves on the dataset 2 that consists of grayscale images of 12 classes of leaves.

Methods	P	R	F1	MCC
HOG and SVM [9]	84%	81%	82.47%	80.55%
DWT and kNN [9]	82%	80%	80.99%	79.08%
SIFT and RF [9]	85%	83%	83.99%	82.09%
Alexnet [10]	89%	86%	87.47%	85.58%
Inception-v3 [14]	90.5%	88.5%	89.49%	87.57%
Resnet-50 [11]	93%	91%	91.99%	89.30%
Densenet-201 [12]	94%	91.5%	92.73%	90.84%

Table 5. Performance comparison of the classification of leaves on the dataset 3 consists of apple leaf disease images.

Methods	P	R	F1	MCC
HOG and SVM [9]	87.4%	85.4%	86.44%	85.54%
DWT and kNN [9]	84.4%	82%	83.18%	82.30%
SIFT and RF [9]	88.2%	86%	87.09%	86.19%
Alexnet [10]	92%	89%	80.45%	89.58%
Inception-v3 [14]	93%	91%	91.99%	91.09%
CSLNet [18]	93.60%	92.40%	93.00%	92.09%
Resnet-50 [11]	94%	92%	92.99%	92.09%
Densenet-201 [12]	95.53%	94%	94.76%	93.86%

Table 6. Performance comparison of the classification of leaves on the dataset 4 that consists of color and background removal images of 12 classes of leaves.

Methods	P	R	F1	MCC
HOG and SVM [9]	89%	87%	87.99%	87.24%
DWT and kNN [9]	85%	83%	83.99%	83.24%
SIFT and RF [9]	90%	88%	88.99%	88.24%
Alexnet [10]	92.5%	89.5%	90.98%	90.23%
Inception-v3 [14]	94%	92.5%	93.24%	92.49%
Resnet-50 [11]	94.5%	93%	93.74%	92.99%
Densenet-201 [12]	97.78%	95.5%	96.36%	95.88%

Acknowledgement

This study is partially supported by the NextX AI company (https://nextx.ai), Hanoi, Vietnam.

References

[1] Muhammad AFA, Lee SC, Fakhrul RR, Farah IA, Sharifah RA. Review on techniques for plant leaf classification and recognition. Computers. 2019, 8(4): 77.
[2] Wu SG, Bao FS, Xu EY, Wang YX, Chang YF, Xiang QL. A leaf recognition algorithm for plant classification using probabilistic neural network. In: IEEE 7th International Symposium on Signal Processing and Information Technology. 15-18 December 2007, Giza, Egypt.
[3] Beikmohammadi A, Faez K. Leaf Classification for plant recognition with deep transfer learning. In: 4th Iranian Conference on Signal Processing and Intelligent Systems (ICSPIS). 25-27 December 2018, Tehran, Iran.
[4] Hossain J, Ashraful Amin M. Leaf shape identification-based plant biometrics. In: Proceedings of the 13th International Conference on Computer and Information Technology (ICCIT). 23-25 December 2010, Dhaka, Bangladesh.
[5] Chaki J, Parekh R, Bhattacharya S. Plant leaf classification using multiple descriptors: A hierarchical approach. Journal of King Saud University – Computer and Information Sciences, January 2018;32(10).
[6] Wagle SA, Harikrishnan R, Md Ali SH, Faseehuddin M. Classification of plant leaves using new compact convolutional neural network models. Plants. December 2021, 11(1).
[7] Elfatimi E, Eryigit R, Elfatimi L. Beans leaf diseases classification using mobilenet models. IEEE Access. January 2022;10: 9471-9482.
[8] Hussin C, Jamil N, Nordin S, Awang K. Plant species identification by using Scale Invariant Feature Transform (SIFT) and Grid Based Colour Moment (GBCM). In: 2013 IEEE Conference on Open Systems, 2013, Kuching, Malaysia.
[9] Suwais K, Alheeti K, Duaa A. A review on classification methods for plants leaves recognition. International Journal of Advanced Computer Science and Applications, 2022;13(2).
[10] Alex K, Sutskever I, Hinton GE. ImageNet classification with deep convolutional neural networks. In: Advances in Neural Information Processing Systems, 2012;p.1106-1114.
[11] He KM, Zhang XY, Ren SQ, Sun J. Deep residual learning for image recognition. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2016;p.770-778, 2016.
[12] Gao H, Liu Z, Maaten LVD, Weinberger KQ. Densely connected convolutional networks. In: 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2017;2261-2269.
[13] Iqbal I, Odesanmi GA, Wang JX, Liu L. Comparative investigation of learning algorithms for image classification with small dataset. Applied Artificial Intelligence, 2021;35(10): 697-716.
[14] Szegedy C, Liu W, Jia YQ, Sermanet P, Reed S, Anguelov D, Erhan D, Vanhoucke V, Rabinovich A. Going deeper with convolutions. arXiv:1409.4842, 2014.
[15] Hughes DP, Salath M. An open access repository of images on plant health to enable the development of mobile disease diagnostics. arXiv:1511.08060, 2015.
[16] Iqbal I, Walayat K, Kakar MU, Ma JW. Automated identification of human gastrointestinal tract abnormalities based on deep convolutional neural network with endoscopic images. Intelligent Systems with Applications, November 2022;vol.16.
[17] Maaten LVD, Hinton G. Visualizing data using t-SNE. Journal of Machine Learning Research. 2008; 9:2579–2605.
[18] Iqbal I, Younus M, Walayat K, Kakar MU, Ma JW. Automated multi-class classification of skin lesions through deep convolutional neural network with dermoscopic images. Computerized Medical Imaging and Graphics. 2021;88:101843.