Available online www.ejaet.com

European Journal of Advances in Engineering and Technology, 2023, 10(9):20-26

Research Article ISSN: 2394 - 658X

Classification of Plant Leaf Images using Deep Neural Networks on Different Hardware Platforms

Phong Bui Hai[1], Lam Tuan Manh[2], Vuong Minh Chau[3] and Pham Van Khuong[4]

[1]Hanoi Architectural University, Hanoi, Vietnam, Email: phongbh@hau.edu.vn
[2]Nguyen Tat Thanh high school, Hanoi, Vietnam
[3]HUS High School for Gifted Students, Hanoi, Vietnam
[4]BK Star center, Hanoi, Vietnam

ABSTRACT

Classification of plant leaf images has attracted many researches in the recent years. There exists several difficulties in the classification of plant leaf images such as the complex background, the overlapped objects and the lack of datasets. The paper applies various deep neural networks to classify leaf images. To overcome the imbalance and the lack of datasets, we have applied the data augmentation of leaf datasets. The proposed method has evaluated on two benchmark datasets. We obtained the classification accuracy of 98% on the Plant Village dataset and 96% on Vietnamese leaf dataset, respectively. Moreover, the method has been deployed on CPU and GPU hardware platforms to compare and analyze the execution time.

Key words: Leaf classification, Deep Neural Network, Imbalanced dataset, Data augmentation

INTRODUCTION

Plants play important role in our life and industry. Plants provide us with food, medicines and industrial materials. There exists more than 50.000 species of plants [1]. Therefore, the accurate and automatic classification of plants becomes necessary. One of the efficient way to classify plants is based on plant leaves [2]. With the advances of computer vision and artificial intelligence, we are able to classify a large number of plant leaves automatically [3]. The automatic classification of plant leaves aims to discriminate the plants based on the collected data using machines without the specific knowledge of human. However, the classification of plants is a challenging task due to the high variation of plant species, leaf shapes, camera-captured conditions of leaves. Fig.1 illustrates some species of plant leaves in real life in different countries. In recent years, the deep neural networks have shown the competitive results for the classification of leaf images. The paper proposes the classification of plant leaf images using various deep neural networks (DNNs). The data augmentation techniques are applied to improve the number of images. The proposed methods are evaluated on two datasets. The first one is the Plant Village dataset and the second one is the Vietnamese leaf dataset. The proposed method is executed on CPU and GPU hardware platforms to compare the performance.

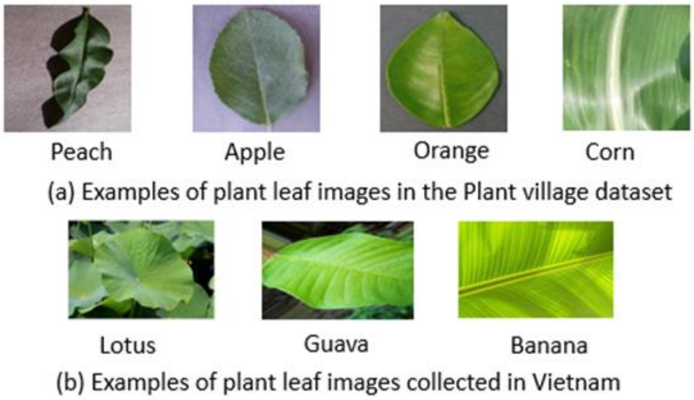


Fig. 1 Examples of various species of plant leaves**.**

RELATED WORK

This section reviews existed approaches for the classification of leaf images. Traditional methods used the extracted features and machine learning classifiers to classify leaf images [4]. Modern methods applied the convolutional neural networks (CNN) [5] to perform the task.

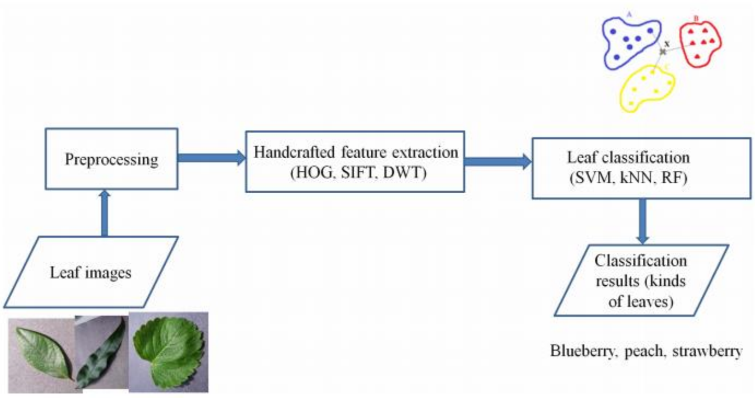


Fig. 2 Classification of leaf images based on the handcrafted feature extraction and machine learning classifiers.

Traditional classification methods of plant leaves attempted to extracted low lever visual features of leaf images. The research in [2] classifies leaf images using the parameters such as length, width of leaf images. The work in [4] extracts a set of morphological features (e.g., eccentricity, perimeter) of leaf images. Then the features are combined with a probabilistic neural network to classify leaf images. The work in [6] used the contour of leaf images and Support Vector Machine (SVM) to classify leaf images. The work in [7] applied the Scale-invariant feature transform (SIFT) feature to classify leaf images. The method in [8] combines several features (e.g., color, texture, shape) of leaf and a neuro-fuzzy classifier to perform the classification. Fig.2. illustrates the process of the classification methods of plant leaves using the handcrafted feature extraction and machine learning classifiers.

Classification of leaf images using deep neural networks.

In recent years, the CNNs are employed to improve the performance of the leaf classification in the end-to-end way. 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 [8] applies the transfer learning of CNNs to classify leave images. The work in [9] proposed a convolutional neural network (CNN) to classify leaf images. The work in [10] 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. In the paper, we evaluate various models of the classification of leaf images to analyse the strengths and weaknesses of the models. Fig.3. illustrates the process of the classification methods of plant leaves using the CNNs

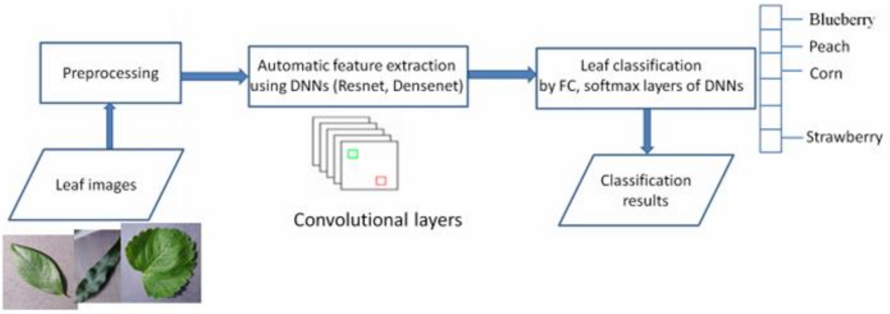


Fig. 3 Classification of leaf images using DNNs.

PROPOSED METHOD

The proposed method is shown in Fig.4. Firstly, we apply the augmentation techniques based on image processing to enlarge numbers of leaf images. Then, we fine-tuned various DNNs to improve the accuracy of the classification of leaf images. After that, the DNN models have been trained and tested on the CPU and GPU hardware platforms to compare the execution time. Finally, the performance of the classification is compared and analyzed to point out the strength and weaknesses of the DNNs on different datasets. Detail steps of the proposed method are described in next sections.

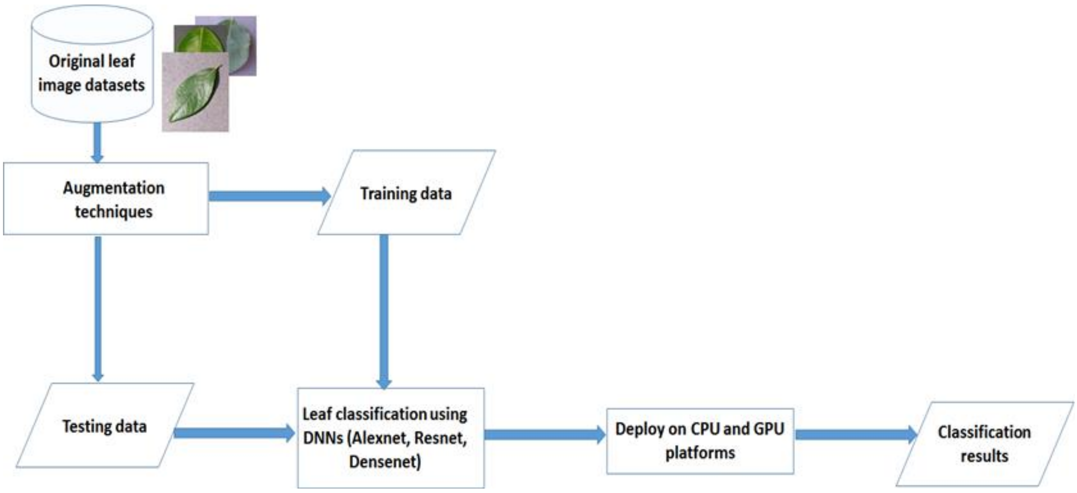


Fig. 4 Proposed method for the classification of leaf images.

Data augmentation based on image processing

The data augmentation is applied using the image processing techniques: image rotation, noise addition and image translation. Figure 5 shows examples of the data augmentation using the image processing techniques. Based on the data augmentation the number of input images are enlarged to avoid the lack of data during the training DNNs. Moreover, we can make the number of leaf images is balance.

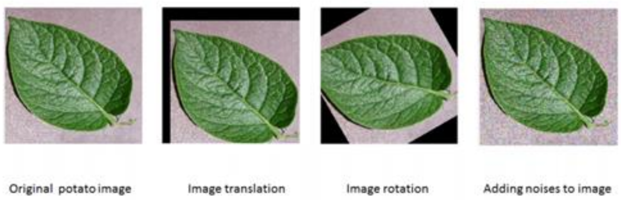
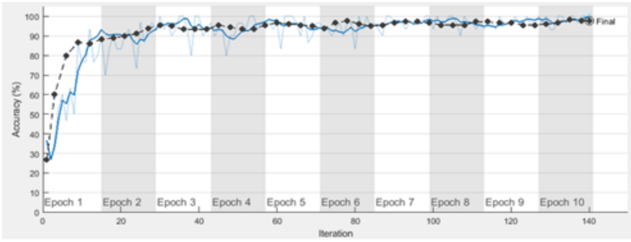
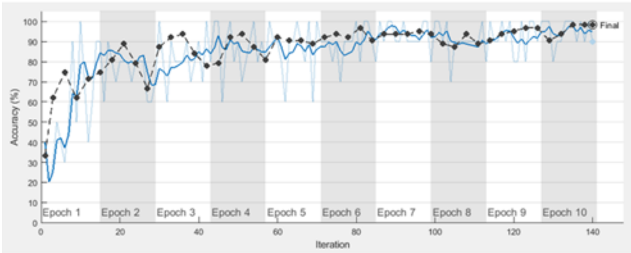


Fig. 5 Examples of image processing applied to an input leaf image



(a) Accuracy of the Alexnet.

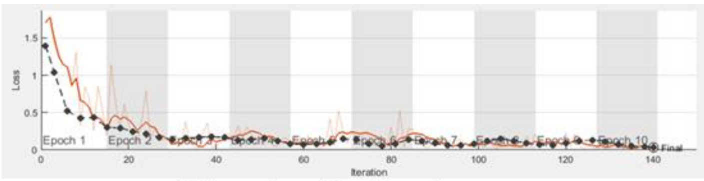


(b) Accuracy of the Resnet-50.

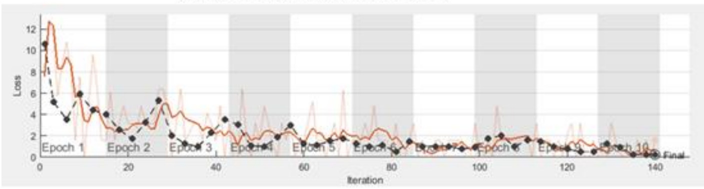
Fig. 6 Accuracy values of Alexnet (a) and Resnet-50 (b) during the training process.

Classification of leaf images using various DNNs

In the section, we applied and fine-tuned various DNNs to improve the accuracy of the classification of leaf iamges: Alexnet [11], Resnet-50 [12] and Densenet-201 [13]. The Alexnet consists of 25 layers and the input images are normalized at the size of 227x227x3. The Resnet-50 consists of 50 layers and the input images are normalized at the size of 224x224x3. The Densenet-201 consists of 201 layers and the input images are normalized at the size of 224x224x3. The learning rate of the DNNs is set at 0.0001 and the stochastic gradient descent (SGD) algorithm [14, 15] is selected to minimize the loss values during the training the DNNs. The momentum is set as 0.9 for the SGD algorithm. The accuracy and loss values during the training process of the DNNs is shown in Fig.6 and 7, respectively. The Figures shows that the accuracy values increase and the loss values descrease during the training process of DNNs.



(a) Loss values of the Alexnet.



(b) Loss values of the Resnet-50.

Fig. 7 Loss values of Alexnet (a) and Resnet-50 (b) during the training process.

Training and testing the method on CPU and GPU hardware platforms

In recent years, different hardware platforms are improved to support the execution of DNNs. In the paper, we have deployed the training and testing of the DNNs on the CPU core i5 of 4.4 GHz and the GPU NVIDIA GTX 980 in a computer with memory of 8 GB RAM. The method was implemented in the Matlab 2021 environment. The programming supports training DNNs in both CPU and GPU with the Parallel computing toolbox.

EXPERIMENTAL RESULTS

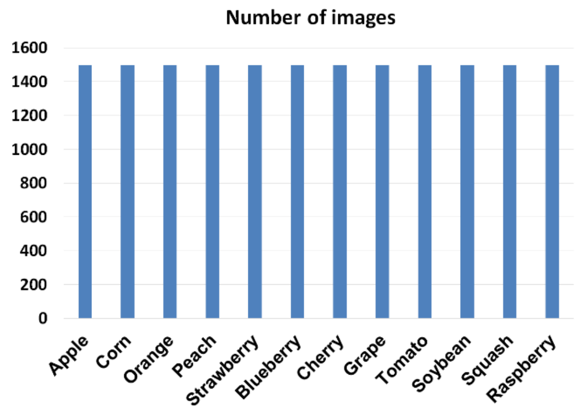
Datasets and evaluation metrics

The proposed method has been evaluated on two datasets. The first dataset is the Plant Village [16] that consists of 12 species of leaf images. The second dataset is the leaf dataset that is collected in Vietnam. The dataset

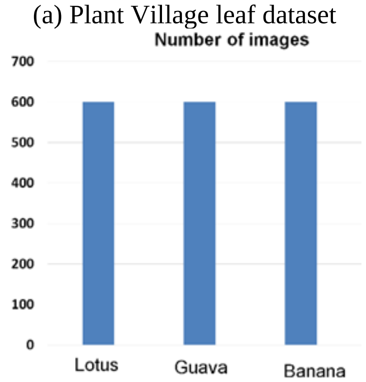
consists of 3 species of leaf image. Information of the datasets is described in Table1. Fig.8. illustrates the number of each kind of leaf images in the Plant Village and Vietnamese leaf dataset, respectively.
To obtain the clear performance evaluation of the proposed method, we applied the Precision, Recall and F1 score metrics [15]. The metrics are widely adopted for the classification task.

Table 1: Information of Plant Village and Vietnamese dataset

Dataset	Number of classes of leaf image	Number of training images	Number of testing images
Plant Village leaf dataset	12	1000	500
Vietnamese leaf dataset	3	400	200



(a) Plant Village leaf dataset



(b) Vietnames leaf dataset

Fig. 8 Number of each kind of leaf images in the Plant Village leaf (a) and Vietnamese (b) datasets.

Table 2: Performance comparison of the classification of plant leaf images using DNNs on Plant Village dataset

Methods	P	R	F1 score
Alexnet	91%	89%	89.99%
Inceptionnet-v3 [10]	94%	92.5%	93.24%
Resnet-50	95%	93%	93.99%
Densenet-201	98%	96%	96.99%

Table 3: Performance comparison of the classification of plant leaf images using DNNs on Vietnamese leaf dataset

Methods	P	R	F1 score
Alexnet	90%	88%	88.99%
Resnet-50	94%	92%	92.99%
Densenet-201	96%	94%	94.99%

Performance evaluation

Performance comparison of the classification of leaf images on the two datasets is shown in Table 2 and 3, respectively. The table shows that the Densenet-201 obtains the highest scores for the classification of leaf images. Compared to Alexnet and Resnet-50, the Denset-201 consists more layers and the feature extraction is

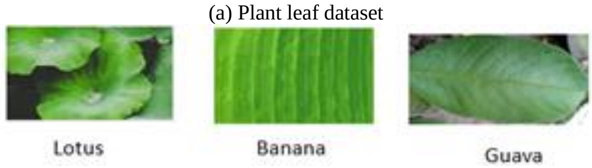
better. Compared to the existed method in [10], our proposed method using the Densenet-201 allows to obtain higher accuracy of 4%. The method in [10] used the Inception v-3 network to classify leaf images.
The accuracy of the classification of leaf images in Plant Village and Vietnamese leaf datasets is 98% and 96%, respectively. Fig.9 illustrates examples of the classification of leaf images in Plant Village and Vietnamese datasets. The classification accuracy in Plant Village is higher than that in Vietnamese leaf dataset because of the large number of leaf images. Moreover, in the Plant Village dataset, images were captured in higher quality.

Table 4: Execution time of the testing phase of the classification of leaf images in Plant Village dataset using DNNs on CPU and GPU hardware platforms (in minutes)

Methods	Execution time with CPU	Execution time with GPU
Alexnet	30	15
Resnet-50	45	18
Densenet-201	50	20

Table 4 demonstrates the comparison of the execution time of the testing phase of the classification of leaf images in Plant Village dataset using DNNs on CPU and GPU hardware. The Table shows that the Alexnet obtains the best execution time on both CPU and GPU because of the structure of Alexnet is not as complicated as other neural networks. The GPU allows to save much execution time compared to CPU. Actually, the GPU consists of 2018 CUDA cores and 128 texture units, therefore, the computing ability of the GPU is higher than that of CPU [17].

(a) Plant leaf dataset



(b) Vietnamese leaf dataset

Fig. 9 Examples of the classification of leaf images in Plant Village (a) and Vietnamese leaf (b) datasets.

CONCLUSION

The paper has presented the application of various deep neural network to classify plant leaf datasets efficiently. The Densenet-201 obtains the highest accuracy compared to Alexnet and Resnet. However, the execution time of the Desenet-201 on CPU and GPU is longer than that of Alexnet and Resnet. The data augmentation allows to enlarge the number of input leaf images dataset. Based on the data augmentation, the DNNs have been trained efficiently. The proposed method has been evaluated on Plant Village and Vietnamese leaf datasets with the obtained accuracy of 96% and 98%, respectively. In the future, more advanced deep neural networks will be applied to improve the classification accuracy. Moreover, we will extend the method to classify more species of plants.

ACKNOWLEDGMENT

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]. Sakai, N., Yonekawa, S., Matsuzaki, A., 1996. Two dimensional image analysis of the shape of rice and its applications to separating varieties. J. Food Eng, 1996, 27, 397–407.

[3]. 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).
[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]. 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.
[6]. V. Srivastava and A. Khunteta. Comparative analysis of leaf classification and recognition by different SVM classifiers. International conference on inventive research in computing applications, 2018, pp. 626–631,
[7]. 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.
[8]. 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).
[9]. 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).
[10]. Elfatimi E, Eryigit R, Elfatimi L. Beans leaf diseases classification using mobilenet models. IEEE Access. January 2022;10: 9471-9482.
[11]. Alex K, Sutskever I, Hinton GE. ImageNet classification with deep convolutional neural networks. In: Advances in Neural Information Processing Systems, 2012, p.1106-1114.
[12]. 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.
[13]. 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.
[14]. 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.
[15]. 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.
[16]. 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.
[17]. Sayali S Pangre, Aditya K Sinha, Milind Bhandare. A study of Machine Learning Workloads on different hardware and Benchmarks for deep learning. International Journal of Engineering and Tec*hnical Research (IJETR)*, September-**2020**, Volume 10 Issue 9, 2454-4698.