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A comprehensive comparison on current deep learning approaches for plant image classification

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A comprehensive comparison on current deep learning approaches for plant image classification

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Abstract. Plant identification and classification play a key role in understanding, protecting and conserving biodiversity. Traditional plant taxonomy needs long time intensive training and experience, which limited others to identify plant categories. With the development of automated image-based classification, machine learning (ML) is becoming a popular tool. Image classification, especially plant images taxonomy, has achieved great improvement in these years by deep learning (DL) methods. In this study, we first reviewed current deep learning applications in the field of plant image classification, and then we tested six deep learning methods in four public plant image datasets. In order to test the classification power of DL methods at cultivar level, we prepared a Camellia sasanqua Thunb. dataset, which is called Camellia@clab, for assessing classification performance of the six DL methods. These DL models' classification performance all exceeded 70% in the four public plant image datasets, and LeNet and DenseNet had stable good performance, with median prediction accuracy of the LeNet was over 87.29% and that of DenseNet was over 93.8% in the four public datasets at species level. At cultivar level, the lowest median prediction accuracy of those DL methods decreased to 62%, but LeNet and DenseNet still performed very well. The prediction accuracy of LeNet and DenseNet was 82.3% and 100% in the Camellia@clab dataset, respectively. DenseNet model showed a stable best classification performance among the five datasets. To our knowledge, this is the first study that provides a comprehensive review and comparison on applying current DL methods to plant image classification. This study will provide guidance for DL applications in plant image classification, and point out the protentional DL research direction for modeling improvement.

1. Introduction

Plant identification and classification play an important role in botany, medicine and ecology evolution studies, which is required or interested from professional researcher to general public. In traditional plant taxonomy, some key features of plant organs, for example leaves, flowers and seeds, were used to identify and classify plant, but molecular profile of plant are widely used in modern classification[1]. The training for a professional plant taxonomist demands a long time learning in field work, especially under the threat of constant decrease of plant biodiversity[2, 3]. With the advance of machine learning (ML), new classification technologies bring a bright new aspect for plant identification and classification[4-14].

Nowadays, deep learning (DL) becomes the most popular and efficient way for large dataset classification. The convolutional neural network (CNN) is the major framework in DL, which describes the hidden neural network layers by convolutional kernels. And convolutional kernels are turned out to dropout some irrelevant information and capture more essential details[7]. Singh et al.[15] employed a multi-layer CNN to identify the disease type of infected Mango leaves' images; Bayr et al.[16] adopted a AlexNet type CNN for woody images classification; Nagasubramanian et al.[17] constructed a 3-dimension CNN to classify multi-spectral soybean images situation of disease affected. Wäldchen et al.[18] reviewed current deep learning approaches in plant image classification. All these models achieved classification accuracy over 95% in the spectrum region of plant health. Various of feature descriptors were raised in plant image classification. Lee et al.[19] built a HGO (hybrid generic-organ)-CNN model containing four layers, they are shared layer, organ layer, generic layer and species layer, to classify various organs with all phases. Moreover, they integrated the syllabus that both sole and entire plant organs can be classified and testing on the PlantCLEF2015 dataset, which achieved the classification accuracy with flower was 79.8% and with entire plant was 60.3%[20]. Later the proposed DL models lift the classification accuracy to 88% or over[21-25].

In most review work, they only reviewed current approaches in partial dataset(s), the cos and pos of those classification methods in really datasets are still missing. In this work, we first reviewed current deep learning approaches in plant image classification. Secondly, we picked up six deep learning models and tested on four public plant image datasets at species level and one plant image dataset generated by ourself at cultivar level.

2. Material and Methods

2.1. Traditional ML approaches for plant image classification

Traditional machine leaning methods have a long history in plant image for classification, which include Logistic regression (LR), naive Bayesian (NB), support vector machine (SVM), random forest (RF), neural network (NN), decision tree (DT) and so on[26]. There are two major disadvantages of traditional machine leaning methods in image classification: 1) they need to define features from image for training, which blocks the efficiency of data processing; 2) the classification ability in processing big dataset decrease when the dataset size increasing. To overcome these difficulties, DL was born to deal with big dataset with/without huge number of labels. DL automatically detects features in image, and then trains (learns) these features in different 'deeper' neural networks. In this study, we mainly focus on DLmodels for plant image classification.

2.2. Convolutional neural networks (CNNs)

CNN is a specialized kind of neural network, which uses convolution to replace general matrix multiplication at least in one of the layers, for processing grid-like topology data[7]. For example, time-series data can be treated as a 1-dimension (1-D) grid type samples with regular time intervals; image data can be treated as a 2-dimension (2-D) grid matrix of pixels. With the quick increase of high performance computational power, CNNs have been vastly successfully applied in the past decades. In mathematical functional analysis, convolution is a kind of operation on two functions (f and g) that their product produces a third function($f * g$) where the product function expresses how the shape of f is adjusted by g. The deeper the convolutional layer of CNN is, the more complex the DL model is. These functions require three typical CNN computations are: 1) convolution obtains image features; 2) pooling for redundancy reducing, and 3) non-linear activation function provides the capacity of network. For a feature map with width, height and channels of w, h and c, respectively, the exportation of flatten operation is a one-dimension array with size $w \times h \times c$.

In DL model, convolution layers aim to extract features from image. Usually, low-dimensional convolution layers extract counter features and high-dimensional extracts local details information in the image. How to fuse local details as an entirety as global features by fully connected layers is essential in model detection or classification. In convolution layers, convolutional kernel function acts as a sliding window to resize features. The activation function in CNN is introduced to reduce noise jamming. For different dimensional data, normalization is needed because it operates as mapping function. In the last, the max-pooling step removes redundant of features. A typical workflow of DL model for classification was illustrated in **Figure 1.**

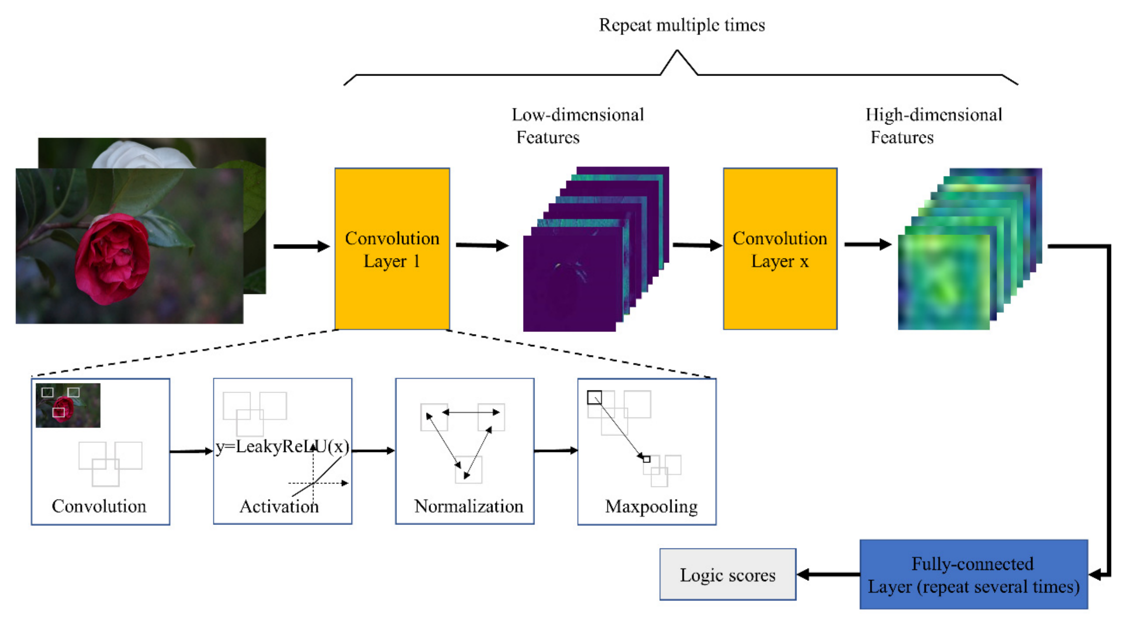

Figure 1. A general workflow of deep learning procedure within CNN. The upper-left acquired Camellia cultivar images are input into models from low to high dimensional layers for feature extraction. And then channel information is fused by fully connected layers, the last of which is trained as a classifier.

2.3. Deep learning approaches for plant image classification

LeNet: In 1998, LeCun et al.[27] developed a light convolutional model, named LeNet, which consists of two convolution layers to identify hand writing in the Modified National Institute of Standards and Technology database (MNIST). The MNMST is the most important handwriting images dataset in machine learning.

AlexNet: In 2012, Krizhevsky et al.[28] constructed a model with more convolutional layers than LeNet for better high-dimensional feature extraction, and then three fully connected layers are used after flatten layer to pool channel information. This model employed rectified linear activation (ReLU) as activation function to speed up training process, which partially solved the vanishing gradient and exploding problem. Features of each layer in AlexNet were depicted in **Figure 2.** Feature visualization of AlexNet layer by layer. The annotations above are defined as Named$@k\times k$, and the annotations below are denominated in form of Operation$d@r\times r$. Where d , k and r is feature depth, convolution kernel and image resolution, respectively..

InceptionNet: In 2014, Szegedy et al.[29] proposed a new architecture with poly depth pathway, which enhances computational resources usage efficiency. The InceptionNet includes four sub-paths for convolution and each pathway has different convolutional kernel and operation layers: 1) convolution path with kernel size 1×1; 2) max-pooling with step 3×3 followed by convolution with kernel 1×1; 3) two convolutions with 1×1 and 3×3, respectively; 4) two convolutions with kernel size 1×1 and 5×5. The network is constructed over 27 layers with ReLU, which speeds up training time significantly and has better batch-normalization.

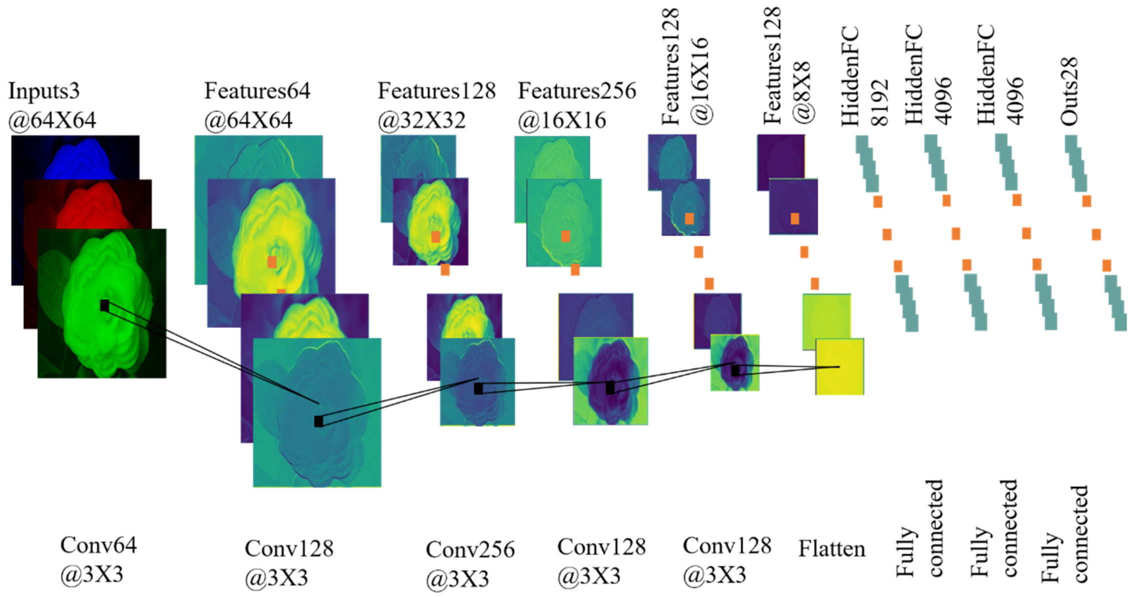

Figure 2. Feature visualization of AlexNet layer by layer. The annotations above are defined as Named$@k\times k$, and the annotations below are denominated in form of Operation$d@r\times r$. Where d , k and r is feature depth, convolution kernel and image resolution, respectively.

ResNet: In 2016, He et al.[30] proposed a short connection from low layer to the second higher layer, which increases network layers but avoids degradation at the same time. The residual block idea of ResNet significantly speeds up the learning process between input data and output data space, which makes it easily extended to very deeper learning layers (could be thousands of layers).

DenseNet: In 2017 Huang et al.[31] proposed a scheme to reduce hyper-parameters and guarantee gradient propagate, which aims to release gradient vanishing through feature reuse and bypass. DenseNet has a nice mathematical structure and high classification performance, but it needs a long computational time.

MobileNet: In 2017, Howard et al.[32] proposed an efficient and convenient DL model by magnifying model complexity and depth. MobileNet was easy to transplant on resources limited platform, even on mobile phones. The core idea of this model was to decompose a standard convolution into a depth-wise convolution and a point-wise convolution with kernel 1×1. Furthermore, two hyper-parameters width multiplier and resolution multiplier were designed to adjust model size. MobileNet was a new type of DL model by discarding some adopted parameters according to their weight, which aims to reduce overfitting and keep high classification accuracy in theory.

2.4. Deep learning approaches for plant image classification

In our experiments, the prediction accuracy was evaluated by commonly used mean average (MA) methods[33]. The MA average top-1 accuracy measures the distance between predicting labels and labeled classes. Multiple samples are fed into the test model, and their inference labels according to the highest score are exported as their prediction labels. At last accuracy is calculated by averaging these outcomes. For example, there are n images belong to m classes, and they are fed into a model, the average accuracy in this case can be described as formula:

$$\text{Average}=\frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{m}L(F(x_i)=y_i) \tag{1}$$

Where $L(.)$ is a logic function to verify if argmax index equals to instance label, which means that $L(.)$ is 1 if $F(x_i)=y_i$ otherwise $L(.)$ is 0. Function $F(.)$ means to find the highest score of classify output metrics. The highest score indicates the highest rank in a array which single sample inferred to *n* given classes, and prediction label is the index of the highest score.

Model loss is computed by compound loss which is added by softmax cross-entropy and regularization loss, which expresses the distance between two distributions. Lower cross entropy is, mutual closer are. Regularization loss is inserted to reduce overfitting, which balances model performance and model complexity. On purpose of normalizing losses, softmax is introduced to map true loss value to between zero to one.

2.5. Model training

- To ensure the accuracy of the experimental results and obtain the best classification, the exact parameters and functions as well as classifier built-in the six neural network models are designed as follows:
- The resolution of input data is 224×224 with Red Green Blue (RGB) format, and the inputs are batch normalized before training;
- Batch size is applied which is set to 30 when training, but images are tested one by one;
- An optimized rectified linear activation, Leaky ReLU, was introduced into models after convolution or concatenate layer;
- Learning rate and dropout rate adopt same value 0.001, bias value is 0;
- In MobileNet, width multiplier is 1.2, resolution multiplier is 1;
- For the neural networks with lower depth, the higher training epochs are, the higher probability of over fitting is. Therefor models in which less than 100 layers adhibit raw data 60 epochs, otherwise executed 80 epochs;
- A fully connected layer with softmax activation has 28 nodes, which is regarded as classifier while training but removed when inference.

2.6. Computational resources and environment

In this study, the operation system is CentOS Linux release 7.7.1908 (Core) with 32 CPUs and each CPU has 64 processors. The develop environment built-up is Python(version 3.6.2) packaged by Conda-forge which compiled with GCC (version4.8.2,20140120). Tool packages used in virtual environment are the TensorFlow (version 1.12.0) and the Numpy (version 1.19.2).

2.7. Plant image datasets

In order to test the classification performance of the six selected DL models, we picked up four public published datasets of plant images at species level with flowers or leaves. Meanwhile, we generated a plant image dataset at cultivar level, which called **Camellia@clab**. A summary of these datasets were described in **Table 1. *Details information of five plant image datasets.***. And there are detailed descriptions of five datasets.

Flavia was generated by Wu et al.[34], include total 1907 leaf images with 32 species, and the raw data is photographed against white plane background from various perspective that are blade front and back. Each specie's images ranges from 50 to 77.

Swedish leaf was generated by Söderkvist O.[35], include total 1125 leaf images of 15 tree species, and each species contains 75 image files with tiff format what is taken aganist a white plain background.

Oxford Flower is a combination of the Oxford Flower17 and the Oxford Flower 102 which includes 8174 images of 102 flower species. Most images of these two datasets are flower images from different websites, and only a small part generated by the Oxford Flower[36].

D-leaf was generated by Tang and Chang[24], which include total 1290 leaf images with 43 species, and the images are pure color background to reduce noise. This dataset has a special focus on local plants in Malaysia.

Camellia@clab was generated by ourselves, include 12602 images of 28 C. sasanqua cultivars, which

Table 1. Details information of five plant image datasets.

Datasets	Species	Images	Organ	Reference/Website
Flavia	32	1907	Leaf	http://flavia.sourceforge.net
D-leaf	43	1290	Leaf	https://figshare.com/articles/D-Leaf_Dataset/5732955
Swedish Leaf	15	1125	Leaf	http://www.cvl.isy.liu.se/en/research/datasets/swedish-leaf
Oxford Flower102	102	8174	Flower	http://www.robots.ox.ac.uk/vgg/data/flowers
Camellia@clab	28	12602	Leaf+Flower	——

were taken with natural background in the florescence of C. sasanqua at 2019 and 2020 from the Kunming Botanical Garden (KBG). Each cultivar's image number ranged from 192 to 623. All the 28 C. sasanqua cultivars were indexed and sorted according to Camellia classification book[37], and detail information was given in the supplement Table 1. ***Details information of five plant image datasets.*.**

3. Results and Discussions

3.1. Classification performance of the six DL models in plant image datasets
In this study, we evaluated the classification performance of six DL models in five plant image datasets. 10-fold cross-validation (CV) was employed 10 times to evaluate the prediction performance of each method[26]. All images in each dataset were normalized without preprocessing before model training. The 10-fold CV technology random split each set into 10 folds, which 9 folds were taken as training datasets and the rest one fold acted as testing dataset. Each round of the CV process produced the average top-1 classification accuracy value of each model, and this CV repeated 10 times. Meanwhile, the classification loss of each method was also estimated in the 10 time 10-folds CV. The boxplot of the 10 times 10-fold CV prediction accuracy and loss of each DL classification model in five plant image datasets were showed in **Figure 3.** *The boxplot of the 10 times 10-fold CV prediction accuracy and loss of each DL classification model in five plant image datasets. A) The boxplot of the 10 times 10-fold CV prediction accuracy of each DL classification model in five plant image datasets. B) The boxplot of the 10 times 10-fold CV prediction loss of each DL classification model in five plant image datasets. Black points in boxplots are actual outcomes. All models maintain the same parameters and training strategies.*.

In all these six DL classification models, most of the models achieved median classification accuracy over 62.16% and loss rate lower than 10%. In all these models, DenseNet and LeNet achieved stable good prediction accuracies and low lose in all datasets. DenseNet showed a stable best prediction performance in all datasets with median accuracy value over 90% in D-leaf dataset, 98.33% in Swedish leaf, and 100% in the rest three datasets. LeNet showed a stable good prediction performance in all datasets with median accuracy over 82.3%. The median classification accuracy of the 10 times 10-fold CV and loss of each DL model in five plant image datasets were showed in **Table 2.** Median classification accuracy of six models on five plant image datasetsa.

3.2. Label imbalance influence the classification performance
Usually, image type and the image number of each species would influence the model's training results. In this part, we only considered the model prediction performance in four public plant image datasets at species level. Let's first check the image type, clean background (like **Flavia**, **D-leaf** and **Swedish leaf)** or natural mass background would not influence the model's classification results significant, where showed in the **Table 2.** *Median classification accuracy of six models on five plant image datasetsa*. The

average image number of each species in **Flavia**, **D-leaf**, **Swedish** and **Oxford Flower102** is 59.59, 43, 75, 80 with average classification accuracy of 81.24, 80.66, 85.7, 86.79 respectively. This indicates that the increase of image number will improve the classification performances.

Table 2. Median classification accuracy of six models on five plant image datasets[a]

Models	**Datasets**				
	Flavia	**D-leaf**	**Swedish leaf**	**Oxford Flower102**	**Camellia@clab**
LeNet	87.29	88.55	92.67	**94.78**	82.30
AlexNet	70.10	73.64	80.30	**84.45**	66.65
ResNet	**76.01**	72.11	81.71	75.38	65.45
InceptionNet	78.18	74.58	82.93	**84.47**	62.16
DenseNet	**100**	**98.33**	**93.80**	**100**	**100**
MobileNet	75.83	76.76	82.80	**81.68**	73.60
Mean	81.24	80.66	85.70	86.79	75.03

[a.] Best performance of each model is bold, all figures are percentage.

3.3. DenseNet performance best at stain level

In order to test the classification ability of deep learning models at cultivar level, we generated a dataset of 12,602 images (flower and leaf) with 28 **C. sasanqua** cultivar, called **Camellia@clab** for testing. Like in other dataset, we performed 10 times 10-fold CV for the six DL models. The boxplot of the 10 times 10-fold CV prediction accuracy and loss of each DL classification model in **Camellia@clab** were showed in Figure 3. DenseNet performed best among all six methods with accuracy 100%, LeNet ranked second with accuracy 82.3%, and the rest models' accuracy also over 62% level. All those DL models' loss value were below 5, which showed in **Figure 3.** The boxplot of the 10 times 10-fold CV prediction accuracy and loss of each DL classification model in five plant image datasets. A) The boxplot of the 10 times 10-fold CV prediction accuracy of each DL classification model in five plant image datasets. B) The boxplot of the 10 times 10-fold CV prediction loss of each DL classification model in five plant image datasets. Black points in boxplots are actual outcomes. All models maintain the same parameters and training strategies. . This result gave an important clue for plant classification at cultivar levels. Liu et al.[38] reviewed that by using DNA barcoding or genome for plant classification in Pedicularis (Orobanchaceae), and classification accuracy could only achieve around 65%. With limited computational resource, the classical LeNet could be an efficient and economy option for plant image classification at cultivar level.

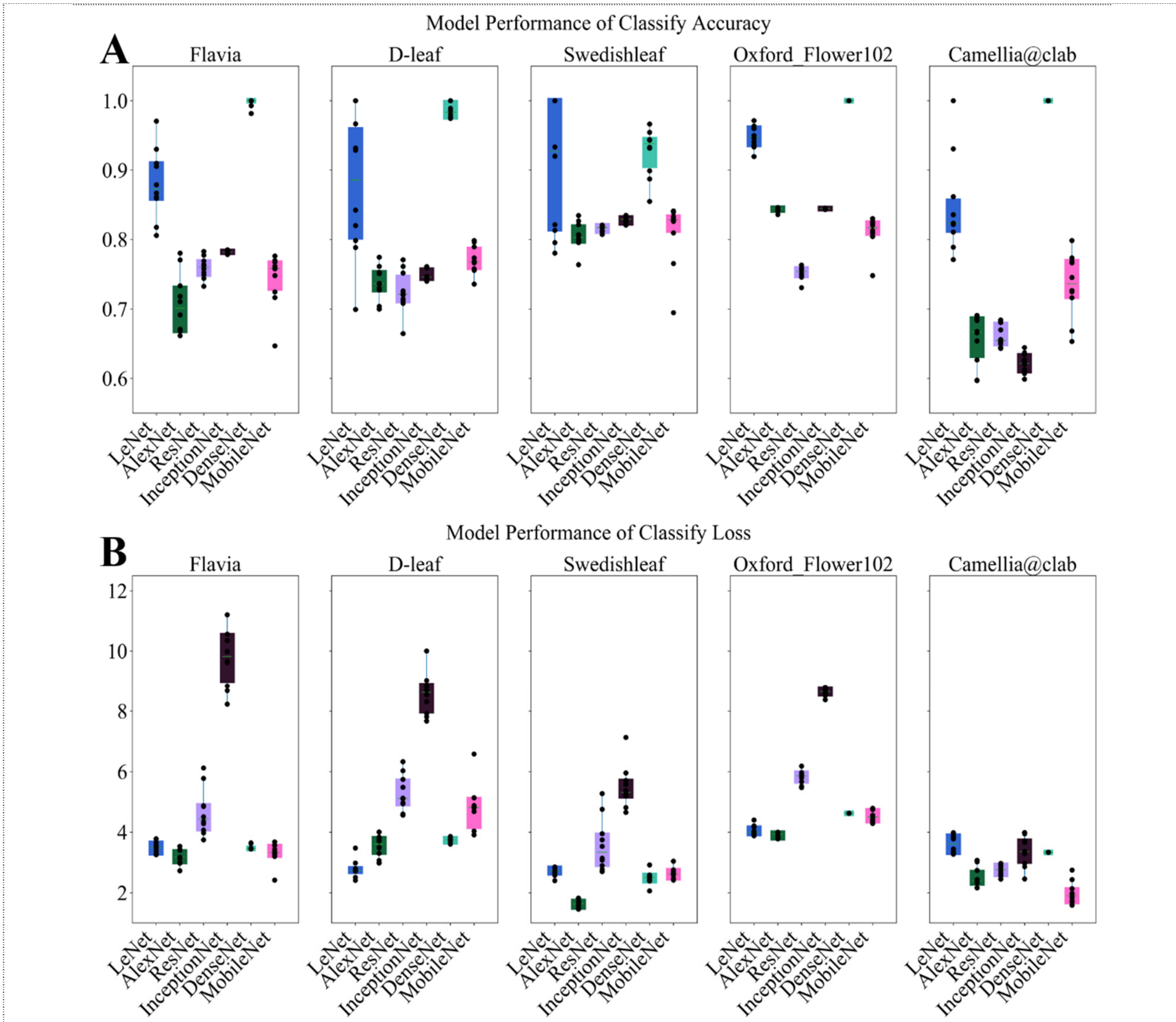

Figure 3. The boxplot of the 10 times 10-fold CV prediction accuracy and loss of each DL classification model in five plant image datasets. A) The boxplot of the 10 times 10-fold CV prediction accuracy of each DL classification model in five plant image datasets. B) The boxplot of the 10 times 10-fold CV prediction loss of each DL classification model in five plant image datasets. Black points in boxplots are actual outcomes. All models maintain the same parameters and training strategies.

4. Conclusion

In this work, we reviewed major deep learning models for plant image classification. Then we picked up deep learning methods and comprehensively evaluated their classification performance in five plant image datasets, including one generated by ourselves, to test the DL models classification ability at plant cultivar levels. Through the study, we found that DenseNet performed best in the five datasets with accuracy almost around 100%. Besides, LeNet, as a classical method, also achieved relatively competitive performance. All other DL models could achieve classification accuracy over 70% at species level and over 62% at cultivar level. Species with more images would help to lift the classification accuracy of DL models.

This work was a preliminary study on how to apply DL models to plant image classification, we need to take more biological feature and data into count and more robust DL models for integrating plant data, not only image.

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