A phenomic approach of bamboo species identification using deep learning

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Abstract

Plant has high similarity and dense detail information in morphology, color and texture, especially in bamboo species, which consists of ground tissue and vascular bundles, the cross-sectional images of bamboo belong to fine-grained, for this reason, the classification of bamboo species has always required aid from a domain expert. Recently, deep learning and convolutional neural network (CNN) have become a new solution for image recognition and classification, features can be effectively extracted from bamboo images and high accuracy can be outputted. Here, convolutional neural network models were constructed to achieve the rapid classification of bamboo species, meanwhile, to simulate the complex classification of bamboo, identification complexity was artificially added by mixing all images, but the models were still found feasible. These models are trained to identify 45 bamboo types with Top-1 accuracy of 92.14% and Top-5 accuracy of 98.10%, indicating that the models extracted the specific features from the cross-section images efficiently.

1. Introduction

Bamboo, a fast-growing non-wood forest crop\(^1\), which includes more than 1600 species over many tropical and subtropical countries\(^2\). Bamboo has shown its suitability based on a combined low weight, high strength, beauty, and durability. It has been widely used from traditional buildings to innovative architectural projects\(^3\)-\(^5\). A successful application of bamboo in engineering firstly relies on a reliable and accurate bamboo species identification and classification.

Bamboo plants rarely blossom and bear fruit\(^6\), so it is difficult to apply the classification method based on flower and fruit to bamboo plants. At present, the main classification methods of bamboo subfamily plants are basically based on the traits of underground stems and inflorescence as the main research basis, and combined with the characteristics of culms, branches, shoots, sheath and other nutrients to divide genera and groups above genera\(^7\)-\(^9\). At present, researchers at home and abroad make full use of vascular bundles anatomy, biochemical classification, embryological classification, DNA molecular markers and other means to further promote bamboo species classification\(^10\)-\(^13\). However, there is still no unified authoritative classification system. On the one hand, different experts and scholars have inconsistent classification standards for genera; on the other hand, some scholars are more enthusiastic about publishing new bamboo species\(^14\), which leads to the classification of bamboo subfamily at the genus level is more chaotic, and even the attribution position of some common bamboo species often changes, which is of great significance for the classification of bamboo genera.

With the rapid development of computer technology in past decades, artificial intelligence technology has also been applied to the field of plant classification\(^15\)-\(^17\), such as USDA Forest Service built and evaluated models to classify woods at the species and genus levels, with image-level model accuracy ranging from 87.4 to 97.5\%\(^{18,19}\); Chinese Academy of Forestry collected 10,237 images of 15 Dalbergia and 11 Pterocarpus species from the transverse surfaces of 417 wood specimens to construct, trained, and test
models and developed a deep learning-based computer vision recognition system for wood tree species called iWood\textsuperscript{20}. Now methods related to data mining and machine learning are also widely used in woody bamboo species classification. Such as India researchers worked on several machine-learning algorithms to identify bamboo species that were generally found in India\textsuperscript{21}, machine learning combines NIR to produce a rapid approach for the classification of different bamboo shoot species\textsuperscript{22}. The structure of the bamboo culm transverse section is characterized by numerous vascular bundles embedding in parenchyma cells\textsuperscript{23}. The parenchyma cells are more frequent in the inner third of the wall, while the percentage of vascular bundles is higher in the outer part. The spatial distribution of different tissue makes bamboo a nature-designed functionally graded material\textsuperscript{24}, these are important bamboo identification features.

Based on the above research, we know machine learning and computer vision recognition technology could be deployed to extract key features from images of different classes for classification tasks, which brings an alternative approach to bamboo species identification. This chapter proposes a deep learning way by constructing convolutional neural network models to realize bamboo species classification. The main innovation point of this paper is to, first develop the automatic data capture and label method, use the mathematical morphology method of OpenCV, automatically obtain the appropriate size samples from the whole bamboo ring images and keep the balance of the sample. Secondly, various deep learning models were tried and achieved good results.

2. Material And Methods

2.1 Materials

The bamboo rings were supplied by International Center for Bamboo and Rattan, including 45 bamboo species and the detailed information of the bamboo species is listed in Table 1. The bamboo rings with a length of 2 cm were cut from the middle part of the bamboos, then these rings were polished with sandpaper of 320 mesh to expose the vascular bundles and parenchyma for clear observation. The cross-section of the bamboo rings was scanned by a high-resolution scanner (EPSON PERFECTION V850 PRO) in 16 Gy modes with a resolution of 9600 ppi. The images of the cross-section of bamboos obtained from the scanner were used for training and testing the models in the following section.

Table 1 Bamboo species used for classification
<table>
<thead>
<tr>
<th>Bamboo species</th>
<th>Bamboo species</th>
</tr>
</thead>
<tbody>
<tr>
<td>Phyllostachys vivax McClure</td>
<td>Phyllostachys glauca McClure</td>
</tr>
<tr>
<td>Phyllostachys aurea Riviere &amp; C. Rivière</td>
<td>B.multiplex var.shimadai(Hayata)Sasaki</td>
</tr>
<tr>
<td>Phyllostachys sulphurea var. viridis R. A. Young</td>
<td>Phyllostachys nidularia Munro</td>
</tr>
<tr>
<td>Bambusa vulgaris 'Wamin'McClure</td>
<td>Bambusa chungii McClure</td>
</tr>
<tr>
<td>Dendrocalamopsis beecheyana(Munro)Keng var.pubescens(P. F. Li) Keng f.</td>
<td>Phyllostachys nigra (Lodd. ex Lindl.) Munro</td>
</tr>
<tr>
<td>Thyrsostachys oliveri Gamble</td>
<td>Phyllostachys iridescens C. Y. Yao &amp; S. Y. Chen</td>
</tr>
<tr>
<td>Bambusa eutuldoides McClure</td>
<td>Phyllostachys incarnata T. W. Wen</td>
</tr>
<tr>
<td>Phyllostachys parvifolia C. D. Chu &amp; H. Y. Chou</td>
<td>Bambusa oldhamii Munro</td>
</tr>
<tr>
<td>Phyllostachys nigella T. W. Wen</td>
<td>Dendrocalamus minor (McClure) Chia et H. L. Fung var. amoenus (Q. H. Dai et C. F. Huang) Hsueh et D. Z. Li</td>
</tr>
<tr>
<td>Phyllostachys bambusoides Sieb. et Zucc. f. shouzhu Yi</td>
<td>Phyllostachys glabrata S. Y. Chen &amp; C. Y. Yao</td>
</tr>
<tr>
<td>Bambusa multiplex (Lour.) Raeusch. ex Schult. 'Alphonse-Kar' R. A. Young</td>
<td>Bambusa longispiculata Gamble ex Brandis</td>
</tr>
<tr>
<td>Bambusa emeiensis L. C. Chia &amp; H. L. Fung</td>
<td>Phyllostachys sulphurea (Carrière) Riviere &amp; C. Rivière</td>
</tr>
<tr>
<td>Bambusa pervariabilis McClure</td>
<td>Bambusa eutuldoides McClure var. viridivittata (W. T. Lin) L. C. Chia</td>
</tr>
<tr>
<td>Phyllostachys bambusoides Sieb. et Zucc. f. lacrima-deae Keng f. et Wen</td>
<td>Bambusa textilis McClure</td>
</tr>
<tr>
<td>Phyllostachys propinqua McClure</td>
<td>Bambusa tulda Roxb</td>
</tr>
<tr>
<td>Phyllostachys reticulata (Ruprecht) K. Koch</td>
<td>Phyllostachys prominens W. Y. Xiong</td>
</tr>
<tr>
<td>Phyllostachys meyeri McClure</td>
<td>Bambusa giboides W. T. Lin</td>
</tr>
<tr>
<td>Phyllostachys edulis (Carr)H. de Lebaie</td>
<td>Dendrocalamus latiflorus Munro</td>
</tr>
<tr>
<td>Phyllostachys nigra var. henonis (Mitford) Stapf ex Rendle</td>
<td>Phyllostachys aureosulcata McClure</td>
</tr>
<tr>
<td>Phyllostachys heteroclada Oliv.</td>
<td>Bambusa vulgaris Schrader ex Wendland'Vittata'</td>
</tr>
<tr>
<td>Schizostachyum funghomii McClure</td>
<td>Bambusa tuldoides cv.Swolleninternode</td>
</tr>
</tbody>
</table>
2.2 Experimental Dataset

The learning of deep neural networks is often driven by data\(^{25}\), so getting abundant bamboo ring cross-section images is our primary task. Meanwhile, the scanned images we obtained were too high and too wide to input into the defined models (18,000 × 18,000 pixel, Fig. 1(a)), so the procedure of cutting the original images into small size is essential. In the traditional models of training, the way is mostly manual to treat them to generate the dataset\(^{26-28}\). However, such operation is often time-consuming and laborious, so in this paper the morphological method in OpenCV we chose to obtain 512×512 training and testing samples from the original large sample images.

The detailed procedures were described as follows: firstly\(^{29-31}\), the morphological function is used to search the contours on the bamboo ring images and the minimum boundingRect\(^{32-34}\) was found, which is shown in Fig. 1(b).

In the second step of sampling, according to the total number of samples in each species, the number of samples of each images was calculated to balance the number of the samples. For example, each species need 6000 samples for training and testing, 20 original images of species A and 30 original images of species B were not sufficient, so 300 samples of species A and 200 samples of species B were collected after careful calculations. This study applied two sampling approaches to obtain the samples: step-size sampling and random sampling. The step-size sampling approach is the box moved by 512 step-size (“stride_w=512” and “stride_h=512”) from the upper left corner of the boundingRect (Fig. 1(c) (d)), but it is difficult to obtain enough samples by step-size sampling. Therefore, the random sampling approach was born at the right moment which randomly selected boxes in the boundingRect of the bamboo ring cross-section images. These two approaches are complementary to each other and then the low-quality samples were deleted.

For low-quality samples, the interspecific mean pixel constraint and the interspecific pixel variance constraint were used to filter them, when the samples’ average pixel and pixel variance are below the average of all, it is not eligible to be part of the samples. In addition, an artificial approach is carried out on the generated samples to further obtain high-quality samples data, and about 10% of the low-quality samples are deleted.

At length, 1000 images of each bamboo species were collected, of which 800 were randomly selected for each bamboo species as the training set, 100 as the verification set, and 100 as the test set. The specific dataset is shown in Fig. 2.

2.3 Deep learning models

Contrary to traditional machine learning in which features are marked manually, deep learning models automatically extract higher-level features from dataset. In fact, since 2012 CNN(convolutional neural
network) models have won exclusively the prestigious ILSVRC competition\(^\text{35}\). What's more, CNNs have achieved outstanding accuracies in a plethora of contemporary applications, automatizing its design\(^\text{36}\). For image recognition and classification, CNNs have achieved the state-of-the-art accuracies using different variations of models. In convolutional neural network\(^\text{37-40}\), generally, the input is a series of images, and the permanent weights \(W\) are the filters, the convolution layer alternates with the pooling layer, and finally fully connected layer, each neuron is a fully connected to the previous layer. The layer works like a conventional perceptron, it combines all the input to create the output categories. Better models can be obtained by adjusting the structures of the neural network and the distribution of parameters. In recent years, these structures have evolved by increasing the depth, the width of the networks and decreasing the parameters from the lower layers into the higher layers. Three usual CNNs, ResNet, Inception v3 and EfficientNet were considered, the structure of a typical CNN is shown in Figure. 3.

\subsection*{2.3.1 ResNet}

ResNet\(^\text{41}\), which won the ILSVRC classification task in 2015, address the problem of the vanishing or exploding gradients while increasing the network’s depth to obtain a better accuracy. Several connections between layers are added to fit a residual mapping and these new connections skip various layers and perform an identity, which not adds any new parameters. This network, called a building block, will be repeated in the whole structure.

\subsection*{2.3.2 Inception-V3}

GoogleNet\(^\text{42}\) won the ILSVRC in 2014 and it is based on the repetition of a module called inception. Four convolutions use a 1×1 kernel to increase the width and the depth of the network and to decrease the dimensionality, and 1 × 1 convolutions are performed before the other two convolutions in the module, a 3×3 and a 5×5. Inception-V3\(^\text{43}\) can be considered as a modification of GoogleNet. The building block is changed by removing the 5×5 convolution and introducing two 3×3 convolutions. The resulting network is made up of 10 inception building block. In addition, the base block is modified as the network goes deeper. Five blocks are changed by replacing the n×n convolutions by a 1×7 followed by a 7×1 convolution in order to reduce the computational cost. The last two blocks replace the last two 3×3 convolutions by a 1×3 and a 3×1 convolutions in parallel, what's more, the first 7×7 convolution in GoogLeNet is also changed by three 3×3 convolutions. In total, Inception-V3 model proposes the network can reduce the number of parameters and extract high-dimensional features under the premise of ensuring the quality of the model\(^\text{44}\).

\subsection*{2.3.3 EfficientNet}

The main contribution of EfficientNet is to design a standardized convolutional network extension method, which not only achieves high accuracy but also greatly saves computing resources. That is to balance the three dimensions of resolution, depth, and width to design a better model structure\(^\text{45}\). In terms
of EfficientNet, conventional practice often choose k(3,3), k(5,5), or k(7,7) kernels\textsuperscript{46}. Larger kernels can potentially improve model accuracy and efficiency and help capture high-resolution patterns, while small kernels can extract better complex features from low-resolution patterns.

### 2.4 Experimental Design

Several common deep learning models, such as ResNet, InceptionV3, and EfficientNet, are considered as our training and testing models. In addition, the key hyperparameters, optimizers, and image enhancement operations are kept unchanged, to more scientifically evaluate the performance level of different models for bamboo species classification, the specific configuration is shown in Table 2 below.

Table 2 Hyperparameter and optimizer configuration

<table>
<thead>
<tr>
<th>parameter</th>
<th>parameter meaning</th>
<th>parameter action</th>
</tr>
</thead>
<tbody>
<tr>
<td>Batch_size = 8</td>
<td>sample size for each iteration</td>
<td>The larger batch size is, the more conducive it is to find the gradient direction with the fastest decrease of loss function; however, too large batch_size will consume too much GPU memory to train.</td>
</tr>
<tr>
<td>Epochs = 100</td>
<td>number of training</td>
<td>A sufficient number of training is helpful to find the global or local minimum of the loss function.</td>
</tr>
<tr>
<td>Adam\textsuperscript{47}</td>
<td>optimizer</td>
<td>The adaptive learning rate optimizer, according to the changes in the parameters learned in the past, adapting to the changes of next learning rate, adjusting the gradient descent direction.</td>
</tr>
</tbody>
</table>

### 3. Result

In this subsection ResNet, Inception-V3 and EfficientNet were exhaustively evaluated. To more comprehensively reflect the capability of the models, Top-1 and Top-5 accuracy rates were selected as the main evaluation indicators, and Top-2, Top-3, and Top-4 as auxiliary evaluation indicators. The specific experimental results are shown in Table 3.

Table 3 Test results generated by different models

<table>
<thead>
<tr>
<th>models</th>
<th>Top-1</th>
<th>Top-2</th>
<th>Top-3</th>
<th>Top-4</th>
<th>Top-5</th>
</tr>
</thead>
<tbody>
<tr>
<td>ResNet</td>
<td>0.878</td>
<td>0.920</td>
<td>0.938</td>
<td>0.947</td>
<td>0.955</td>
</tr>
<tr>
<td>Inception-V3</td>
<td>0.828</td>
<td>0.898</td>
<td>0.925</td>
<td>0.944</td>
<td>0.958</td>
</tr>
<tr>
<td>EfficientNet</td>
<td>0.908</td>
<td>0.939</td>
<td>0.951</td>
<td>0.960</td>
<td>0.967</td>
</tr>
</tbody>
</table>

Top-K evaluation of the models of a single bamboo species were obtained, mainly were Top-1 and Top-5 evaluations. The models performed well for most bamboo species, but for a few bamboo species, such as *Bambusa oldhamii Munro*, the classification ability was extremely poor, and even the accuracy was
not as good as the classification ability obtained by random classification. The classification results of Top-1 and Top-5 of single bamboo species are shown in Fig.4.

In the case of Top-1, the classification ability of the model of the three kinds of bamboo was lower than random classification, even referred to the below of 20%. In this regard, there were several hypotheses. First, there were too much dirty data in the bamboo dataset, which leads to the model learn the features of bamboo species invalidly. Second, there were tiny differences between the dataset, and a large number of dataset were misclassified, especially in these three bamboo species.

For these hypotheses, the dataset of the corresponding bamboo species was examined and found that the dataset did not contain dirty data, so hypothesis one could be rejected. Meanwhile, in the case of Top-5 classification, the classification ability of the model is slightly improved. Therefore, we can know that the main reason is that the corresponding bamboo species classification ability is weak and can be easy to be misclassified.

Our main solutions are as follows: one is to increase the model's ability to learn fine-grained differences of samples; the other is to use prior knowledge to increase inter-species differences. Specifically, we augmented the data with MixUp to increase the model's ability to learn fine-grained differences.

4. Discussion

Through former experiments, it is found that the existing models were not capable for learning fine-grained differences of samples, mixing samples of different types was a way we chosen which can simulate complex situations in real life and increase the challenge of recognizing in a certain extent. The models learn the finer textures to distinguish such mixed difficult samples, thereby the models' ability of distinguish specific bamboo species can be promoted. The specific formula for generating new samples is below:

\[ new\_sample = \alpha * \text{rand\_sample} + (1 - \alpha) * \text{sample(type = sample)} \]

Formula(1)

\(new\_sample\): the newly generated sample;

\(\text{rand\_sample}\): the randomly introduced mixed image;

\(\text{sample}\): the mixed image;

\(\alpha\): mixing coefficient.

The type of composite sample was determined by the image being mixed. Generally, the mixing coefficient was set as 0.2 and 0.3. When the mixing coefficient is too large, the characteristics of the sample category are not obvious, which can be considered as a generalized wrong sample, which will
lead to deviation of the gradient descent direction of the models, and thus fail to converge to the global optimal solution. When the mix coefficients $\alpha=0.2$, 400 samples as the training set and 300 original images as the test set were collected. An example of a newly generated sample is shown in Fig. 5 below.

On the basis of keeping the models configuration completely unchanged, the extended MixUp dataset was retrained and experimented, and the experimental model was EfficientNet model. The overall effect of the test set is shown in Table 4 below.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Top-1</th>
<th>Top-2</th>
<th>Top-3</th>
<th>Top-4</th>
<th>Top-5</th>
</tr>
</thead>
<tbody>
<tr>
<td>original dataset</td>
<td>0.908</td>
<td>0.939</td>
<td>0.951</td>
<td>0.960</td>
<td>0.967</td>
</tr>
<tr>
<td>MixUp dataset</td>
<td>0.921</td>
<td>0.957</td>
<td>0.970</td>
<td>0.977</td>
<td>0.981</td>
</tr>
</tbody>
</table>

From Table 4, it can be found the overall Top-K indicator has been improved in a way, but the model should be applied to the whole bamboo species, not just one. Therefore, we evaluated the classification ability of each bamboo species by Top-K indicator. The classification results of Top-1 and Top-5 of single bamboo species are shown in Fig. 6 below.

From the results, it can be seen the model be retrained with MixUp datasets, Top-K indicator of the model generally increased by about 2%, and the imbalance of accuracy between species is alleviated. Subsequently, various genus relationships of bamboo can be introduced to conduct MixUp operation on bamboo species with close relatives, which can theoretically further learn fine-grained features to obtain better classification ability.

In addition, VGG16$^{48}$ and VGG19$^{48}$ were also experimented, which were relatively basic deep learning models, fail to learn bamboo features well after sufficient training, and the overall result was equal to random classification. This finding also suggests that if the model's ability to classify bamboo species is to be further improved in the future, the model needs to strengthen the learning ability of fine-grained distinctions.

5. Conclusions

Identification and classification of bamboo plays an significant role in the bamboo industry. Automatically classification of bamboo is possible as deep learning developed in recent years. This study demonstrated the reliability and effectiveness of deep learning to be performed for bamboo classification by identifying the vascular bundles in the cross-section of the bamboo culm. These models were trained by 45 bamboo species. The results indicated that these trained models can classify bamboo correctly and fast for bamboo species in the dataset. Deep learning is a promising technology to classify bamboo
according to the identification of vascular bundles in cross-section of bamboo. In the future, the dataset will be expanded by including more bamboo species.

Declarations

Author contributions

Z. W wrote the main manuscript, J. L, H. W, and W. Y conducted the experiments, G. T, H. C and X. Y designed and financed the research. All authors reviewed the manuscript.

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Competing interests

The authors declare no competing interests.

Data availability

The datasets used during the current study are available from the corresponding author on reasonable request.

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**Figures**

![Figure 1](image)

**(a)** Cross-section of bamboo ring **(b)** Minimum boundingRect of bamboo ring **(c)** Image including the whole bamboo ring **(d)** Sampling process
Figure 2

Schematic diagram of sample dataset

Figure 3

The structure of a convolutional network
Figure 4

Top-1 and Top-5 classification ability of the EfficientNet model for individual bamboo species

Figure 5

Legend of mixed sample with mixing coefficient=0.2
Figure 6

The ability of the EfficientNet model to classify Top-1 and Top-5 of the original and MixUp bamboo species datasets