IDENTIFICATION AND RECOGNIZATION OF BAMBOO BASED ON CROSS-SECTIONAL IMAGES USING COMPUTER VISION

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Abstract. Identification of bamboo is of great importance to its conservation and uses. However, identify bamboo manually is complicated, expensive, and time-consuming. Here, we analyze the most evident and characteristic anatomical elements of cross section images, that's a particularly vital breakthrough point. Meanwhile, we present a novel approach with respect to the automatic identification of bamboo on the basis of the cross-sectional images through computer vision. Two diverse transfer learning strategies were applied for the learning process, namely fine-tuning with fully connected layers and all layers, the results indicated that fine-tuning with all layers being trained with the dataset consisting of cross-sectional images of bamboo is an effective tool to identify and recognize intergeneric bamboo, 100% accuracy on the training dataset was achieved while 98.7% accuracy was output on the testing dataset, suggesting the proposed method is quite effective and feasible, it's beneficial to identify bamboo and protect bamboo in coutilization. More collection of bamboo species in the dataset in the near future might make EfficientNet more promising for identifying bamboo.

Keywords: Bamboo, cross section, images, accuracy, generalization.

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INTRODUCTION

Bamboo, one of the fastest-growing plants in the world, is a complex plant that is difficult to be identified or classified. Considering the ecological and economic importance of bamboo, correct identification is critical to its silviculture and utilization (Clark et al 2015). There are 100 genera and more than 1642 species of bamboo all around the world (Kumar et al 2021). Bamboo is usually classified in accordance with morphology-based taxonomy (Yang and Dezhu 2013), anatomical feature-based taxonomy (Grosser and Liese 1971), molecular biotechnology (Zhao et al 2015), computer-assisted technology, or the combination mentioned above.

The morphology-based taxonomy is established on the morphological and structural characteristics of bamboo reproductive organs (flowers, fruits, and seeds) and vegetative organs (roots, stems, and leaves). Geng et al summarized the morphologic characteristics of more than 500 bamboo species including both domestic species and foreign introduced species in China (Yang and Dezhu 2013). However, there is a remarkable limitation on morphology-based taxonomy due to infrequent and unpredictable flowering events of bamboo (Zhao et al 2015). Researches systematically studied and classified the vascular bundles in bamboo, providing the morphology of vascular bundles represents the evolutionary direction of bamboo, and also an important basis for the identification of different genera and species (Liese 1998; Wen et al 1984, 1985). Numerous vascular bundles are existed in the cross sectional of each individual bamboo ring, which are important identifying information. However, the anatomical characteristics associated with the cross, radial, and longitudinal sections of bamboo were complicated to be prepared and collected. Besides, it usually required a large number of bamboo slices to be prepared for the anatomical characteristic collection, which was time-consuming. The molecular biotechnology used for the classification of bamboo was based on the extraction of genetic information of bamboo with molecular marker and genes testing, Zhao et al found that the majority of the species classified in accordance with DNA information were consistent with their current taxonomic classification, which helped to avoid the homonym and synonym (Zhao et al 2015). However, the molecular biotechnology-based taxonomy demanded high quality of sampling and preservation of bamboo samples. Moreover, the extraction and analysis of genetic information were complicated and expensive.

Recently, as computer technology developed, especially the emergence of computer vision technology and digital image processing technology, machine learning has been used to identify and classify plants intelligently through extracting morphological or anatomical characteristics of plants (Chao et al 2018; Kaya et al 2019; Sun et al 2017; Yusof et al 2013), as well as animals like marine mammals (Shiu et al 2020). Now the method is widely used in wood science fields, Chao et al used the K-means clustering algorithm to make preclassification of wood according to anatomical features, and then the K-Nearest Neighbor classifier identified and classified the wood based on the LBP features that were selected by genetic algorithm. 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% (Ravindran et al 2018, 2019). Kobayashi et al had done a lot of researches in this respect and obtained considerable results, their experimental objects included wood used for sculpture and scripture carving, which is mainly used for cultural relic identification under nondestructive conditions, others are Lauraceae and Fagaceae wood identification for exploring the difference between the genus or species levels according the quantities of computer-based properties (Hwang et al 2018; Kobayashi et al 2017, 2019a, 2019b). These examples proved that artificial intelligence can be combined with Wood science field to help human recognition and classification.

There are also plentiful examples of successful research in the field of bamboo. YOLOv3 was trained for recognize vascular bundles to realize the coordinate of the vascular bundles to this location, the number of vascular bundles and calculation of its area (Li et al 2021), this experiment has solved the problem of manual measurement, it’s time and labor consuming. As a major feature and advantage of bamboo, the gradient structure is also used in conjunction with computer technology, the results provide a theoretical basis for the functional improvement of bamboo materials and the development of new bamboo-based smart materials (Xu et al 2021). As an important tissue and research hotspot of bamboo plants, whether the morphology and distribution of organization in cross section can be combined with modern computer vision technology to play its recognition value at this level. For computers, an image is a combination of pixels, different bamboo species have different images of anatomical elements, and the composition of the elements causes distinctions in pixel intensity, arrangement, and distribution. Such differences can be detected learned by convolutional neural network.

In this paper, we propose a practical solution to bamboo recognition, we took the cross-sectional images of bamboo as the research object, experiments were carried out at the level of identification, and computer vision technology was applied to the recognition of bamboo species, EfficientNet (Tan and Le 2019) was exploited as the identification engine. We also studied two diverse transfer learning strategies for the learning process, namely fine-tuning with fully connected layers and all layers. The approaches' performance has been validated on a bamboo dataset with 8000 images for training 2000 images for validation and 2000 images for testing. The experimental results demonstrate that the application of EfficientNet on the dataset considerably improves the overall performance, and thus achieves a better outcome.

MATERIALS AND METHODS

Sample Collection and Processing

Four-year-old bamboo was collected from Fujian province, China. The detailed characteristics was listed in Table 1. The bamboo ring was cut from the bamboo culm with a length of 2 mm at 1.3 m and then these rings were polished with sandpaper of 320 mesh to expose the vascular bundles and parenchyma for clear observation and investigation.

Original Dataset

In the experiment, black flocking cloth was used as the background to avoid the influence of other complex environments, the cross section of the bamboo ring was scanned by a high-resolution scanner (Epson Perfection V850 Pro, Epson, Japan) in 16 Gy modes with a resolution of 9600 ppi and uniformly saved the JPG format. The whole cross section images are shown in Fig 1.

Measurement of Characteristics at the Organizational Level

The number of vascular bundles, the distribution density of vascular bundles, the area of fiber sheath, and the volume fraction of fiber of these 10 genera bamboo were measured by using the bamboo structure analysis software studied in the laboratory (Li et al 2021; Xu et al 2021) (Table 2).

Computer Vision Technology

Transfer learning. Transfer learning refers to the transfer of the weight information in the pre-trained neural network to other neural networks

Table 1. Information of 10 bamboo species.

Bamboo species	Wall thickness (mm)	Outer diameter (mm)	Outer circumference (mm)	Cross section area (mm^2)
Acidosasa edulis	6.18	26.02	81.75	403.79
Bambusa emeiensis	4.60	76.20	239.39	1026.75
Dendrocalamus latiflorus	8.29	84.63	265.87	2395.80
Gigantochloa apus	9.29	82.61	259.54	2169.84
Indosasa sinica	6.81	45.39	142.59	813.93
Oligostachyum sulcatum	4.61	41.62	130.76	473.45
Phyllostachys edulis	5.96	48.78	153.25	2254.54
Schizostachyum funghomii	6.32	34.86	109.52	519.74
Sinobambusa tootsik	4.68	34.47	108.28	388.51
Thyrsostachys siamensis	6.80	25.85	81.22	1104.25

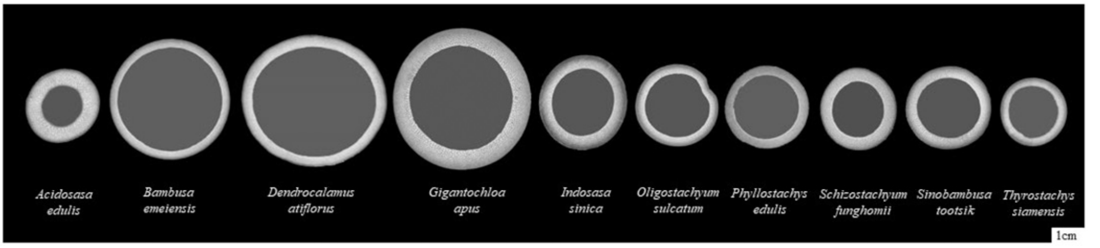


Figure 1. The cross-sectional scanner images of 10 genera bamboo rings.

(Dai et al 2009). At present, the feature distributions of training dataset and test dataset are assumed to be consistent when most machine learning algorithms conduct experiments, but there are differences in real scenes. For example, we are going to classify a new task, but the task of data is not enough, and need a lot of relevant training data, in the actual experiment, the training dataset and the corresponding validation and testing dataset of the experiment do not match the characteristics of distribution, the experimental study using appropriate migration methods can improve classification performance when insufficient samples. In this way, transfer learning allows for the reuse of existing parameters like convolution weights from a model trained on large datasets for training a new model with a relatively less number of labeled images. In this experiment, due to the different diameter of each bamboo ring, the number of images generated by step sampling is also various, and combined with the elimination of invalid images, the whole images of each bamboo are 1200, including training, validation, and testing dataset. In this work, we made use of weights pretrained from the ImageNet dataset as it contains all kinds of images and this is highly useful for classifying the bamboo dataset exploited in our evaluation. In addition, models pretrained on ImageNet has 1000 types of output, the experimental need to change the types of its output layers to 10, we study two different strategies for the learning process, namely fine-tuning with fully connected layers (fine-tuning-FC) and all layers (fine-tuning-AL), the corresponding weights are obtained after training.

Pretreated dataset. For the cross section of single bamboo ring, the experiment used Python sliding window to cut images by step sampling. On the one hand, the step covered all the vascular bundles of a single bamboo species from the outside and inside of the bamboo wall, and on the other hand, the number of images obtained by this method were enriched. The step size is the half size of the images (512×512 pixels), so as to ensure that valid information is not missed and the model can fully learn the organizational characteristics, the final images are shown in Fig 2(b). Since it is necessary to test the configuration of the model and whether the training degree

Table 2. Characteristics at the organizational level of 10 genera.

Bamboo species	Number of vascular bundles	Distribution density of vascular bundles	Area of fiber sheath	Volume fraction of fiber
Acidosasa edulis	1203	2.98	106.47	26.37
Bambusa emeiensis	3575	3.48	446.47	43.48
Dendrocalamus latiflorus	7704	3.22	732.91	30.59
Gigantochloa apus	4308	1.99	887.36	40.90
Indosasa sinica	1916	2.35	336.76	41.37
Oligostachyum sulcatum	1824	3.85	149.17	31.51
Phyllostachys edulis	6168	2.74	481.59	21.36
Schizostachyum funghomii	1230	2.37	181.58	34.94
Sinobambusa tootsik	1511	3.89	121.10	31.17
Thyrsostachys siamensis	3534	3.20	553.43	50.12

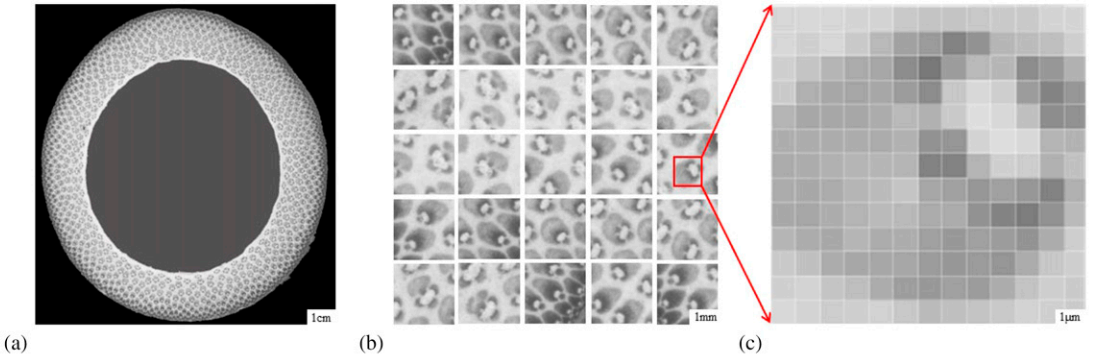


Figure 2. Schematic diagram of the images processing flow (a) the scanner image of *Schizostachyum funghomii* (b) the result images of step sampling (c) partial magnification of the cross-sectional image.

is overfitting or underfitting in the process of model construction, the dataset was divided into three parts: the training and validation dataset for training model, and the other is the testing dataset. The training and validation dataset is used to train the pretrained model, and then the test dataset is used to verify the effectiveness of the model and select the model with the best effect. In this experiment, the 12,000 images are divided into training, validation, and testing dataset by a ratio of 4:1:1.

Evaluation metrics. From the manually labeled dataset, we know exactly which category each image belongs to, and we are interested in how well the prediction label match with the true label. Thus, accuracy, precision, recall, and F1 score are utilized to measure the model performance.

Accuracy: The metric is defined as the ratio of correctly identified images to the total number of bamboo images in the dataset:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \times 100\% \tag{1}$$

Precision and Recall: The metric is to measure how accurate the results for each label are, with respect to the corresponding true label.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \times 100\% \tag{2}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100\% \tag{3}$$

F1 score: The metric is computed as the harmonic average of precision and recall by means of the following formula:

$$\text{F1} = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \times 100\% \tag{4}$$

TP: The true label of positive that the model considers to be positive.
FN: The true label of positive that the model considers to be negative.
FP: The true label of negative that the model considers to be positive.
TN: The true label of negative that the model considers to be negative.

In addition, for a more intuitive view of the detailed recognition results, we derive the confusion matrix, where each genus of labels can be observed, which can help us to pursue deeper recognition mechanism.

RESULTS AND DISCUSSION

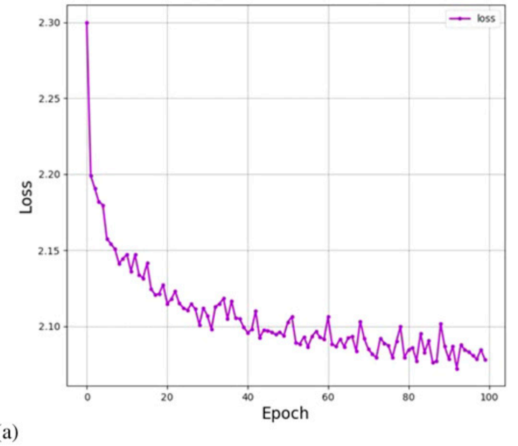
Characteristics at the Organizational Level

The progress of bamboo system classification needs multidisciplinary penetration, it is not only to the study of the external morphology of bamboo nutrients and reproductive bodies, but also to cooperate with anatomy, pollen morphology, starch morphology, chromosome, biochemistry, quantitative classification, and other means. The morphology and distribution of bamboo vascular bundle are also an important means. The vascular bundles are a complex of the conductive tissue and strong tissue of bamboo, vessels, and sieve tubes in the vascular bundles connect the tip and the root, even branches and leaves, communicate of the whole plant body, to transport nutrient solution. Bamboo individual is relatively tall, to protect the smooth conduction tissue, there must be a relatively tough strong tissue in the outer edge of the conduction tissue to protect bamboo's growing, so the fiber sheath of bamboo is usually more developed, and the whole vascular bundle tissue usually accounts for 40-60% of the volume and 70-80% of the weight of bamboo (Liese 1998). To identify bamboo, computer vision is used to extract features of vascular bundles and fiber sheath, as well as their size and arrangement from bamboo sections, such as points, blobs, corners, and edges from images, and these are determined by the pixels (Fig 2[c]).

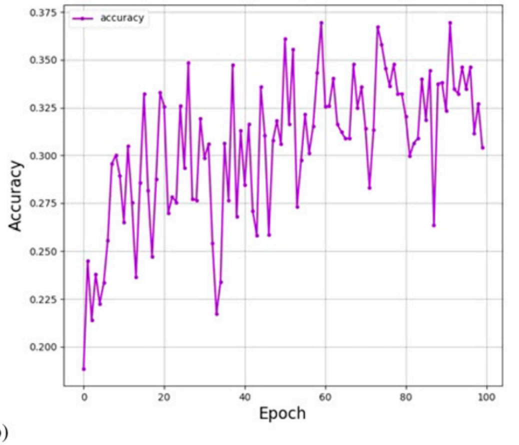
As shown in Table 2, there is a quick way to get the data in the table, 10 genera bamboo differ in their organizational characteristics, some of them belong to scattered bamboo, and some belong to cluster bamboo. In scattered bamboo, the vascular bundles from out of bamboo to inside of bamboo mainly transitions from semiopen to open type, while in cluster bamboo, the vascular bundles from growing species mainly transitions from tight waist type to broken waist type, on the other hand, it is caused by the different dimensions of its cross section. However, these data are enough to prove that the cross-sectional organizational characteristics of each genus of bamboo are different, so it is also a possible way for us to identify them from the organizational level. Using image techniques, anatomical statistical features such as the shape, size, number, and distribution of bamboo cells can be extracted from cross-sectional images. The vascular bundle and fiber are the most evident and characteristic anatomical element, so the difference of organizational characteristics data can prove its particularly is a vital breakthrough point.

Intergeneric Identification

After the two transfer learning models are trained for 100 epochs, the corresponding curve of loss and accuracy can be obtained (Figs 3 and 4). From the approximate trend in Fig 3(b), the accuracy of fine-tuning-FC fluctuates greatly, and fluctuates up and down with the increase of the number of epoch times, on the contrary, the overall trend of fine-tuning-AL is stable, and its loss decreases and



(a)



(b)

Figure 3. The curve of loss and accuracy of fine-tuning-FC model (a) the curve of loss of 10 genera bamboo (b) the curve of accuracy of 10 genera bamboo.

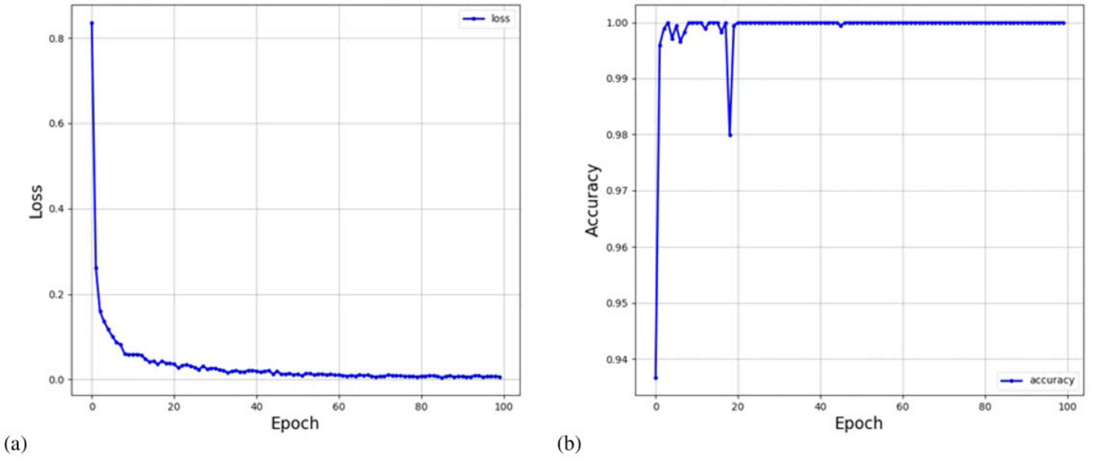


Figure 4. The curve of loss and accuracy of fine-tuning-AL model (a) the curve of loss of 10 genera bamboo (b) the curve of accuracy of 10 genera bamboo.

accuracy increases with the increase of epoch times, it's clear that fine-tuning-AL performs better than fine-tuning-FC. In particular, the loss value of fine-tuning-AL decreases rapidly from 0.84 to 0.07, then slowly approaches 0, and finally drops to the minimum value of 0.006, and the accuracy increases sharply at the beginning of the epoch, and the accuracy reaches 100% only by 20 epochs (Fig 4[a] and [b]).

Subsequently, the generalization ability of the model with the weights trained by fine-tuning-AL is tested. According to Table 3, the model achieves the two best performance with the accuracy of 100%, while the remaining eight genera have above 99.4% accuracy, this essentially means that EfficientNet with fine-tuning-AL yields the maximum prediction performance for those genera: all items in the test set are correctly classified to their real genera. In addition, we quantify the performance of the model with three additional dimensions of data as follows. From the predicted genera, the precision, recall, and F1 scores are calculated using Eqs 2-4, respectively, then the performance is shown in Table 3. A larger number in precision, recall, and F1 represents a better classification, with corresponding to the maximum performance, from these data, we can see that the trained model performs very well regardless of the dimension and has strong generalization ability, combining these individual genus accuracies yields an overall accuracy of 98.7%. In terms of confusion matrix, the blocks on the diagonal represent the number of correctly identified images, the horizontal coordinate is the true labels, and the vertical coordinate is the predicted labels, each genus of bamboo can be mapped one by one to observe which genera are misclassified. It can be seen from the Fig 5 that almost all of the 200 testing images of each genus of bamboo are correctly recognized. Only 188 images of *Gigantochloa apus* were identified correctly, and the remaining 12 images were identified as *Bambusa emeiensis* and *Oligostachyum sulcatum*, 8 images of *Indosasa sinica* were

Table 3. Accuracy of the fine-tuning-AL model to identify testing dataset (%).

Bamboo species	Accuracy	Precision	Recall	F1
Acidosasa edulis	99.9	99.0	100	99.5
Bambusa emeiensis	99.6	96.2	100	98.1
Dendrocalamus latiflorus	100	100	100	100
Gigantochloa apus	99.4	100	94.0	96.9
Indosasa sinica	99.5	100	95.0	97.4
Oligostachyum sulcatum	99.4	95.2	98.5	96.8
Phyllostachys edulis	100	100	100	100
Schizostachyum funghomii	99.9	99.0	100	99.5
Sinobambusa tootsik	99.8	99.0	99.5	99.2
Thyrsostachys siamensis	99.9	99.0	100	99.5

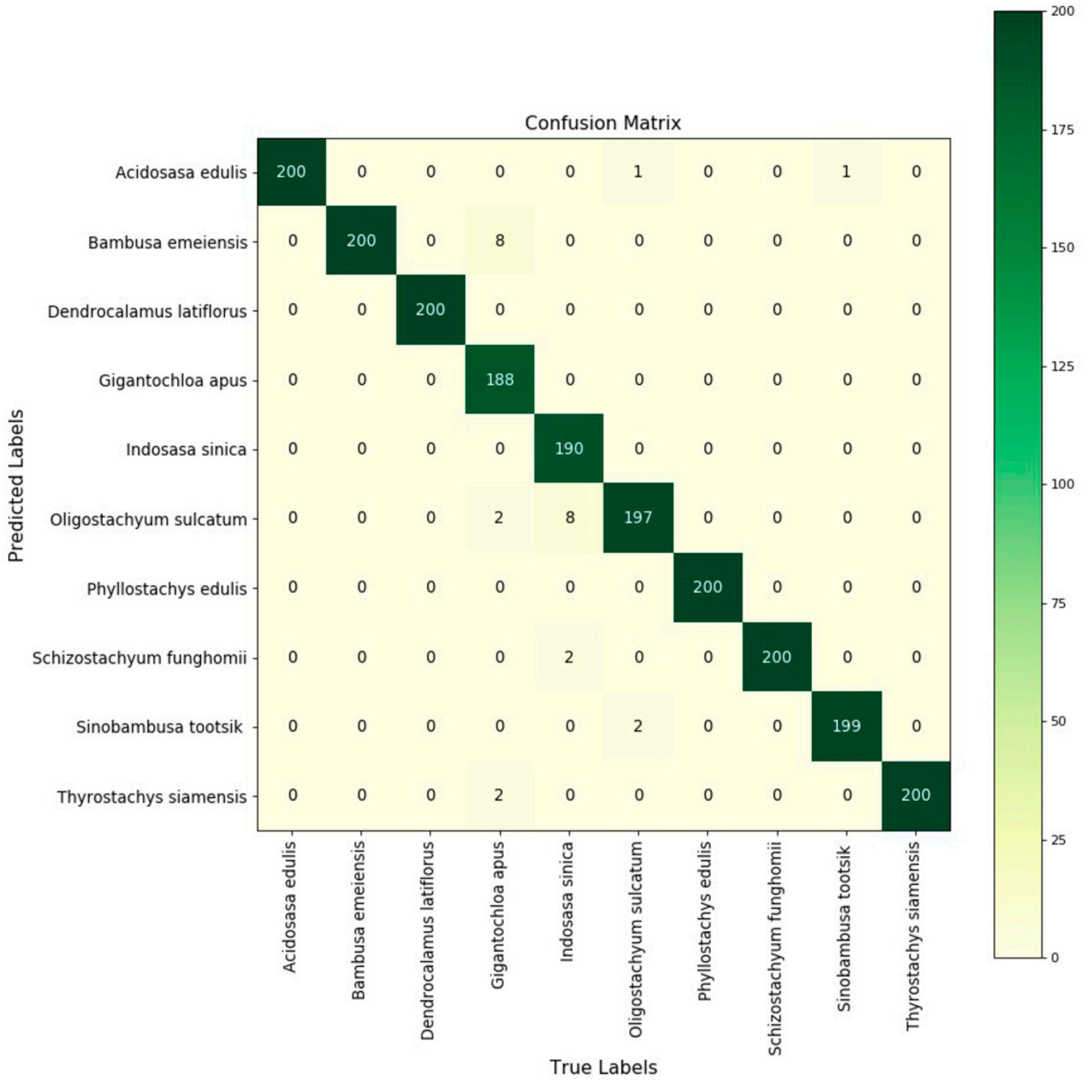


Figure 5. The confusion matrix of fine-tuning-AL model on testing dataset.

identified as *Oligostachyum sulcatum*, 2 as *Schizostachyum funghomii*, and 1 of the *Thyrsostachys siamensis* images was identified as *Acidosasa edulis*. For the testing dataset, it simulates the real situation, just like randomly input a cross-sectional scanner image into the trained weight model, it can output the bamboo genus category predicted by the computer. Through the confusion matrix, we can know which genera are easy to be misclassified, and realize which genera are misclassified, so that we can expand the database, for the genera that are easily misclassified, the number of its training dataset is increased and the model is continued to train, thus achieving best.

CONCLUSIONS

Classification of bamboo plays an important role in the bamboo industry. Automatically classification of bamboo is possible as computer technology developed in recent years. This study demonstrated the reliability and effectiveness of EfficientNet to be performed for bamboo classification by identifying the vascular bundles in the cross-sectional of the bamboo culm. The model was trained by 10 bamboo species belonging to 10 genera, we confirmed that fine-tuning with all layers is useful comparing with fine-tuning with fully connected layer for the identification of bamboo as a better performance was obtained by both network families, the results indicated that the fine-tuning with all layers model can identify bamboo with the accuracy of 98.7%, computer vision and deep learning are a promising technology to identify bamboo according to the cross section of bamboo. For future work, the dataset will be expanded by including more bamboo species, we expect to promote the method and application in this paper and form a practical automatic bamboo recognition product. Last but not least, we are working to select the most compact network model and export to Android, making it an independent tool suitable to work on a smartphone.

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