WOOD RESEARCH doi.org/10.37763/wr.1336-4561/67.3.488500
e-ISSN 2729-8906
67(3): 2022 488-500 pp.

A MICRO-GRAPH RETRIEVAL SYSTEM FOR CONIFEROUS WOODS USING MULTIPLE METHODS

QIZHAO LIN[1], XIN HE[2], JIAN QIU[2], HONG WANG[1]
[1]FUJIAN POLYTECHNIC OF INFORMATION TECHNOLOGY
P.R. CHINA
[2]SOUTHWEST FORESTRY UNIVERSITY
P.R. CHINA

(RECEIVED NOVEMBER 2021)

ABSTRACT

Inspired by the successful application of deep convolutional neural network, a coniferous micro-graphs retrieval framework based on deep learning and image processing technology is proposed. The idea of the proposed framework is that the texture feature of representing three section surfaces can be learned and classified by a fully CNN, and the canals can be deep learned by an U-net CNN when the data labels are available. In addition, the image processing technologies are also proposed to identify whether the growth ring boundaries are distinct and whether there is a "window-like" cross-field pitting. Finally, a coniferous micro-graphs retrieval system is realized based the proposed methods. Experimental results demonstrate that this system outperforms in terms of recognition accuracy. In addition, the system can be further developed into more intelligent coniferous retrieval system that can automatically identify more coniferous microscopic features, so as to obtain more accurate retrieval results.

KEYWORDS: CNN, deep learning, features identification, image processing technology, microscopic image, softwood, U-net.

INTRODUCTION

Wood identification is valuable in commercial, judicial, archaeological, pale-ontological and other contexts. The information of wood anatomical features makes it easier to identify rare wood species. Compared with the traditional wood recognition method, the wood recognition method based on computer technology has the characteristics of easy information sharing, persistent, high retrieval efficiency and high accuracy.

In the recent year, convolutional neural networks (CNN) attracted the attention of more and more researchers due to its potential values in not only visual object recognition (Lu and Liu 2020, Zhao et al. 2021), such as real-world inverse synthetic aperture radar object recognition (Bouchard et al. 2020, Wen et al. 2019), and object detection (Dong et al. 2020, Wu et al. 2020), but also in classification tasks (Ciga and Martel. 2021, Lickert et al. 2021), and feature extraction (Maggipinto et al. 2019, Singh et al. 2020). Meanwhile, it is also used for tree or wood identification (Hwang 2018, Ravindran 2018, Tao et al. 2020, 2021, Zhao et al. 2021). Traditional methods for wood identification are mature and have a lot of computer-aided systems or programs, such as *Insidewood* (Wheeler 2011) and *Pl@ntWood* (Sarmiento 2011). They are used by quite a few wood recognizer due to their anatomical microscopic characteristics of hardwood are based on IAWA Committee (1989). Quite a few new methods for wood identification are using artificial intelligent technologies, such as *MyWood-ID* (Tang 2018) and *Tree species recognition system* (Ibrahim 2017). However, they are not used widely, due to they learned wood features from limited wood species and features they learned are not based on IAWA Committee (1989). With nearly 30000 species of hardwood in the world, this approach is prone to the difficulty of correctly identifying species.

In this paper, a CNN-based coniferous wood (softwood) retrieval system is proposed to assist people to retrieve coniferous wood using CNN and image processing technologies to identify microscopic features which defined in Wheeler (2004).

The main contributions of this paper are as follows: *(1)* A coniferous micro-graph retrieval system which includes information subsystem and intelligent subsystem is constructed. It can be used online. *(2)* The automatic model used in this retrieval system is used to identify microscopic features, and not to identify softwood species. This pattern avoids the dilemma that the artificial intelligence technology is used to directly scan the surface of the sample, which is prone to the failure to obtain the species of wood. *(3)* The rest of the paper is organized as follows. Methods give an overview of our proposed framework. Results and experimental setup are discussed in Experiments section. Finally, conclusion and future work are presented in Conclusion section.

MATERIAL AND METHODS

The proposed coniferous micro-image retrieval framework in this paper is shown in Fig. 1. The framework includes two subsystems. The first subsystem is the feature identification by using CNN and image processing technologies called intelligent subsystem. The second subsystem is to perform retrieving softwood by microscopic feature codes called information subsystem. The proposed method is described in detail as follows.

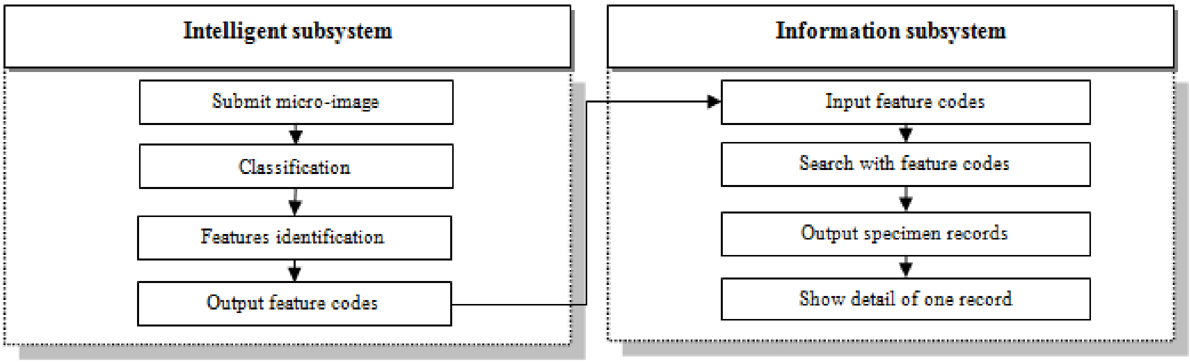

Fig. 1: The framework of proposed coniferous micro-graph retrieval system.

Classification

In order to identify microscopic features of softwood by an intelligent system, it need to classify micro-graphs which input due to the definition in Wheeler (2004) that microscopic features of softwood should be identified from three sections, including transverse, radial and tangential surfaces. The proposed training framework of three-section classification model in this paper is shown in Fig. 2.

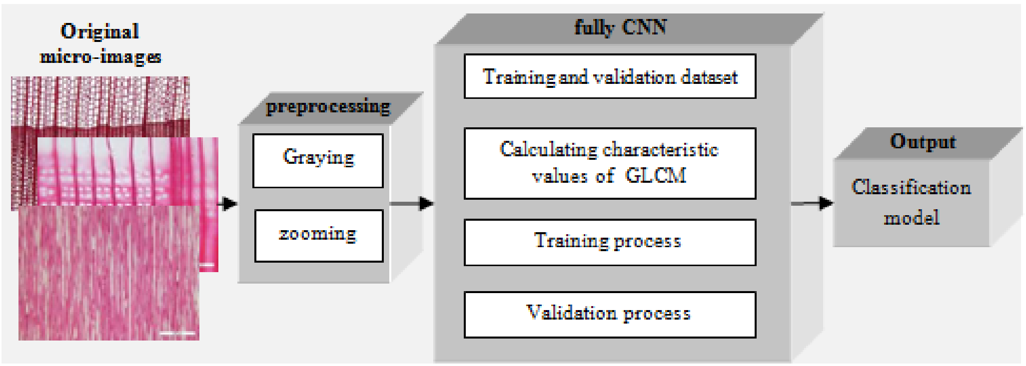

Fig. 2: Training framework of three-section classification model.

For input a micro-graph, the first step of classification is preprocessing, including graying and zooming the image, due to this classification based on gray scale and small images. To classify micro-graphs into 3 classes, the classification needs to extract texture of these images by calculating characteristic values of Gray Level Co-occurrence Matrix (GLCM), including contrast (CON), dissimilarity (DIS), homogeneity (HOMO), energy (ENT), correlation (COR), Angular Second Moment (ASM).

GLCM is the joint probability distribution of two gray-scale pixels with a distance of D in the image at the same time, which can reflect the comprehensive information about the direction, adjacent interval and change range of image gray level. The construction of gray level co-occurrence matrix is the premise of Eigenvalue calculation. In this paper, the gray level co-occurrence matrix in four directions θ (0°, 45°, 90°, 135°) is calculated. $P(i, j)$ is used to express the probability of occurrence of the distance between d-pixel and i-gray level and j-gray level in θ. CON, DIS, HOMO, ENT, COR, ASM are defined in the following Eqs. 1-6, respectively:

$$CON = \sum_{n=0}^{N_{g-1}} n^2 \left\{ \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} p(i,j) \atop |i-j| = n \right\} \tag{1}$$

$$DIS = \sum_{n=0}^{N_{g-1}} n \left\{ \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} p(i,j) \atop |i-j| = n \right\} \tag{2}$$

$$HOMO = \sum_i \sum_j \frac{p(i,j)}{1+(i-j)^2} \tag{3}$$

$$ENT = -\sum_i \sum_j p(i,j) \log(p(i,j)) \tag{4}$$

$$COR = \frac{\sum_i \sum_j (ij) p(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y} \tag{5}$$

$$ASM = \sum_i \sum_j \{p(i,j)\}^2 \tag{6}$$

Features identification

For identifying different microscopic features for softwood, two models can be used, including automatic mode based on deep learning, automatic mode based on image processing technology.

Automatic mode based on deep learning

In order to improve retrieval efficiency and accuracy, some features can be recognized by deep learning based automatic mode, such as present of axial canals as shown in Fig. 3a, present of radial canals as shown in Fig. 3b. The present of axial canals is identified by training result of the U-net (U-shaped convolutional neural network) using deep learning (Fig. 4). Changed input image, this U-net framework can used to train a model, then identify present of axial canals. The input dataset is the result of the training set image after the image feature annotation, image zooming and image graying The LabelMe (Torralba 2010) is used to annotate axial and radial canals.

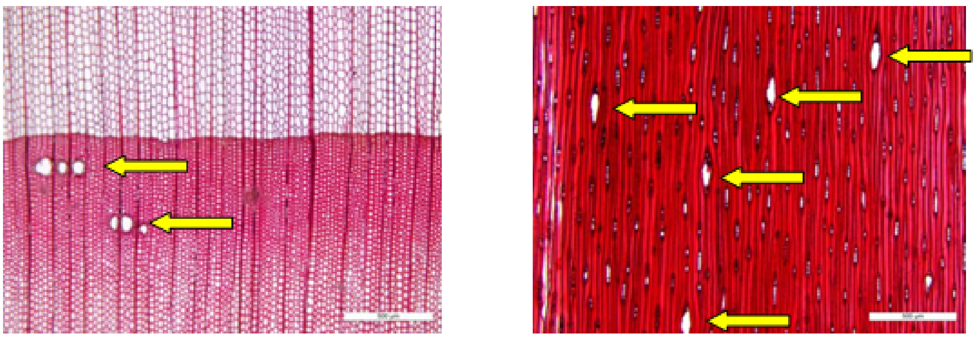

Fig. 3: An example (a) radial canals, (b) axial canals.

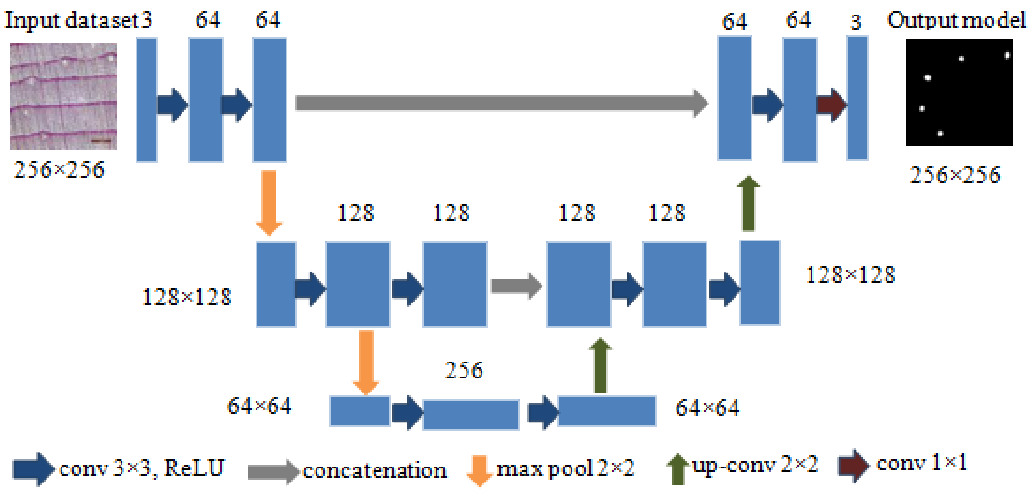

Fig. 4: An example of U-net network framework for segmenting canals.

Automatic mode based on image processing technology

After analyzing the definition of "IAWA List of microscopic features for softwood identification", it is known that some features may be identified by the computer program, including presence of growth ring boundaries, "window-like" of cross-field pitting. In order to judge whether there is distinct growth ring boundary in softwood, a computer program (Lin 2020) is designed to judge automatically, which is the result of the author's previous research. An example of "distinct" is shown in Fig. 5a. An example of "indistinct" is shown in Fig. 5b. The main processes of this program were shows as follows: *(1)* A 5× magnified cross-section color micro-graph of softwood was cropped into 20 sub-images. *(2)* Every image was binarized as a gray image according to an automatic threshold value. *(3)* The number of black pixels in the gray image was counted row by row and the number of black pixels was binarized to 0 or 100. *(4)* A transition band from early-wood to late-wood on the sub-image was identified. If this was successful, the growth ring boundaries of the sub-image were distinct, otherwise they were indistinct or absent. *(5)* If 10 of the 20 sub-images were distinct, with the majority voting method, the growth ring boundaries of softwood were distinct, otherwise they were indistinct.

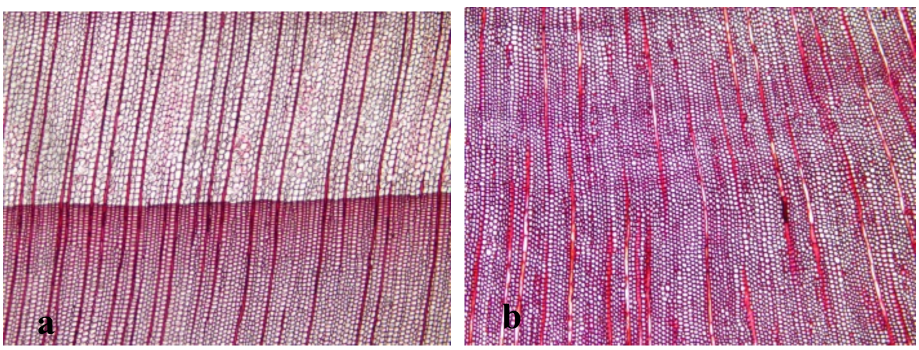

Fig. 5: Examples of presence of growth ring boundaries: (a) a "distinct" example, (b) an "indistinct" example.

In order to identify the "Window-like" of cross-field pitting as shown in Fig. 6a, a program was designed based on similarity calculation. This program must be based on a standard image library, in which the images were cropped from the original microscopic images.

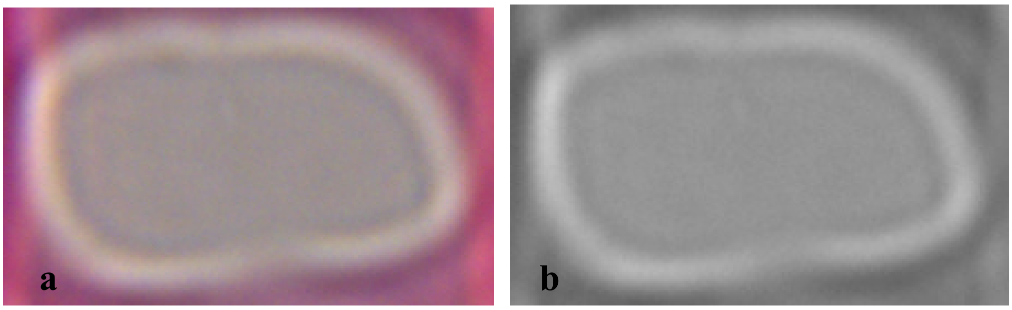

Fig. 6: Examples of "window-like" cross-field pitting: (a) an origin image, (b) a gray image.

To calculating similarity of two images, the submitted image was converted to gray image, as shown in Fig. 6b, and then compared with the gray image of standard image library one by one. The main processes of this program calculated two similarities based on histogram, Hamming distance respectively. The main calculation processes of similarity based on histogram is shown as follows: *(1)* Scale the image to 128 × 128 pixels. *(2)* Convert the image into a 256-level gray scale image. *(3)* Crop the image into 16 images with 32 × 32 pixels. *(4)* Obtain the statistical histogram of each image. *(5)* Calculate the similarity of two images by Eq. 7:

$$simHist(G,S)=\frac{1}{N}\sum_{i=1}^{N}\left[1-\frac{|g_i-s_i|}{Max(g_i,s_i)}\right] \tag{7}$$

where: g and s are the statistical gray level histogram, as shown in Fig. 7, and N is the number of color space samples.

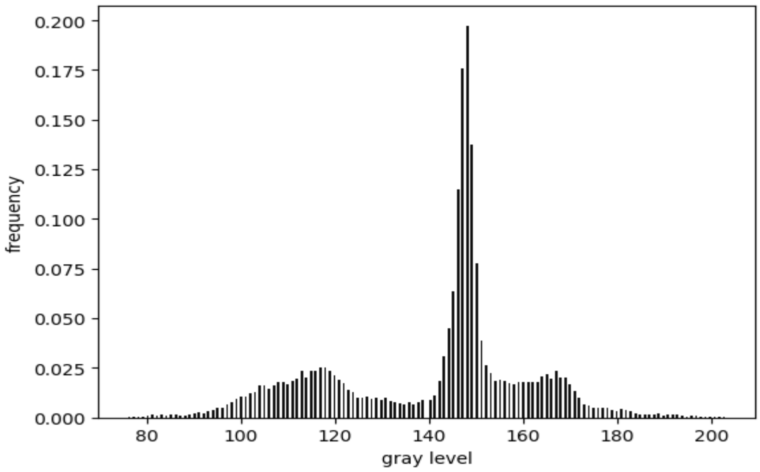

Fig. 7: Histogram of Fig. 6b.

The main calculation processes of similarity based on Hamming distance is shown as follows: *(1)* Scale the image to 8 × 8 pixels. *(2)* The scaled image is converted to 256 level grayscale images. *(3)* Calculate the average gray level of all 64 pixels. *(4)* Compare the gray level of each pixel with the average value. If it is greater than or equal to the average value, it is recorded as 1; if it is less than the average value, it is recorded as 0. *(5)* Combine the results of the previous step in a fixed order to form a 64 bit integer, that is, the fingerprint of this picture. *(6)* Obtain the Hamming distance D by comparing the fingerprints of two images. *(7)* Calculate the similarity of two images by Eq. 8 and the final similarity of two images is calculated by Eq. 9:

$$simHam(G,S) = 1 - \frac{D}{n} \tag{8}$$

$$sim(G,S) = 0.5 \times simHis(G,S) + 0.5 \times simHam(G,S) \tag{9}$$

Dataset and implementation

According to the literature review, there are not public datasets for softwood micro-graphs retrieval problem. 345 microscopic slides were collected from 115 softwood species. Imaging was performed with a digital camera (LEICA DMC4500) mounted on a light microscope (LEICA DM2000 LED). 1000 images of 2560 × 1920 pixels were captured using Leica Application Suite (Version 4.9.0). They were classified into 6 categories, including transverse surfaces, radial surfaces, tangential surfaces, axial canals, radial canals and standard images. There were sample micro-graphs in the dataset, as shown in Fig. 8.

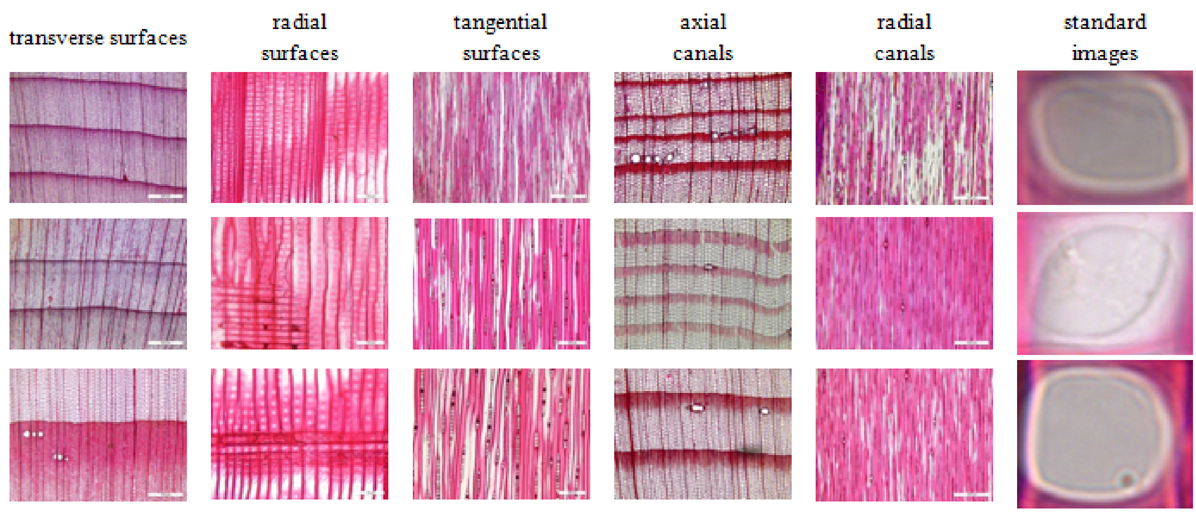

Fig. 8: Sample micro-graphs in the datasets.

Training of the model

Deep learning training of the fully CNN and U-net model was based on hardware platform of GeForce GTX 1070 GPU and Keras framework. In Centos 7.0 operating system, Tensorflow (Perez 2019) back-end engine was used and Python 3 language was used for programming.

Preparation for image processing

100 micro images with a magnification of 50 times were selected from the set of transverse-surface images for the experiment of judging whether there is distinct growth ring boundary. 400 cropped images were cropped from radial-surface images, which had a magnification of 400 times, preparing for the standard images and the experiment of judging whether exist "Window-like" of cross-field pitting.

Evaluation metrics

To evaluate the performance of the fully CNN model and the U-net model, different metrics were used, such as precision, accuracy, mean accuracy (mA) and. These metrics were defined in the following Eqs. 10, 11 and 12, respectively. Precision refers to the image proportion that is accurately judged. The loss function loss is binary cross entropy, and the measurement method is accuracy:

$$\text{Pricision} = \frac{\text{TP}}{\text{FP} + \text{TP}} \tag{10}$$

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{NP} + \text{TN} + \text{FN}} \tag{11}$$

$$mA = \frac{\sum Accuracy}{M} \tag{12}$$

where: TP - true positive, FP - false positive, TN - true negative, FN - false negative, N – the total number of images in the category; M - the total number of the category.

RESULTS AND DISCUSSION

The training result of the proposed fully CNN has high accuracy, as shown in Fig. 9a. The train result of the proposed U-net has high accuracy, as shown in Fig. 9b.

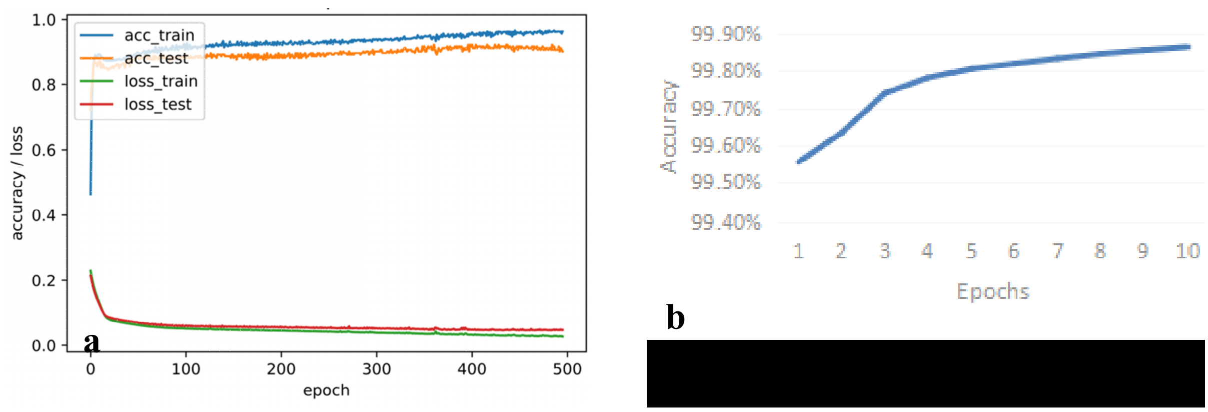

Fig. 9: Curve of training of: (a) the fully CNN, (b) the U-net.

The web pages of the coniferous retrieval system are shown in Fig. 10, which are shown in the order in their occurrence of using.

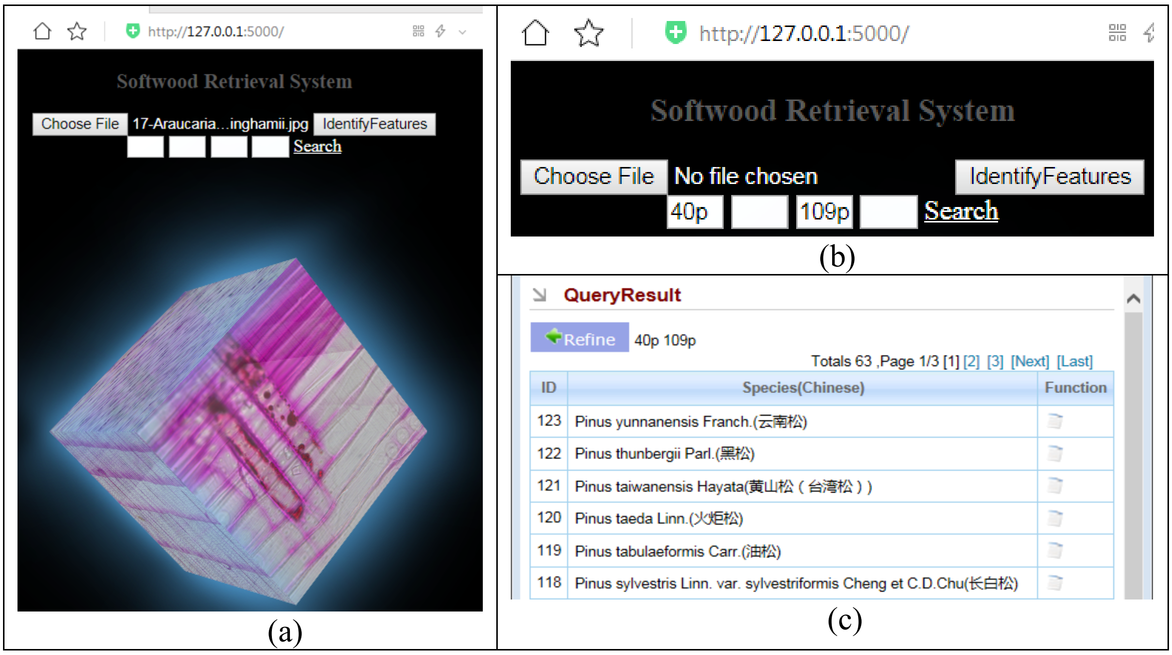

Fig. 10: a) The main page of the coniferous retrieval system, b) the result of "IdentifyFeatures" click, and c) the result of "Search" click.

In the main page as shown in Fig. 10a, users can choose a micro-graph file for identifying coniferous micro-graph characteristic codes after clicked "IdentifyFeatures". As shown in Fig. 10b, different file of micro-graph may get different feature code after "IdentifyFeatures" click. As shown in Fig. 10c, if there are not enough features automatically recognized by the system, an editing interface can be obtained by clicking the "Refine" button, and the coniferous micro-graph characteristic codes can be manually edited.

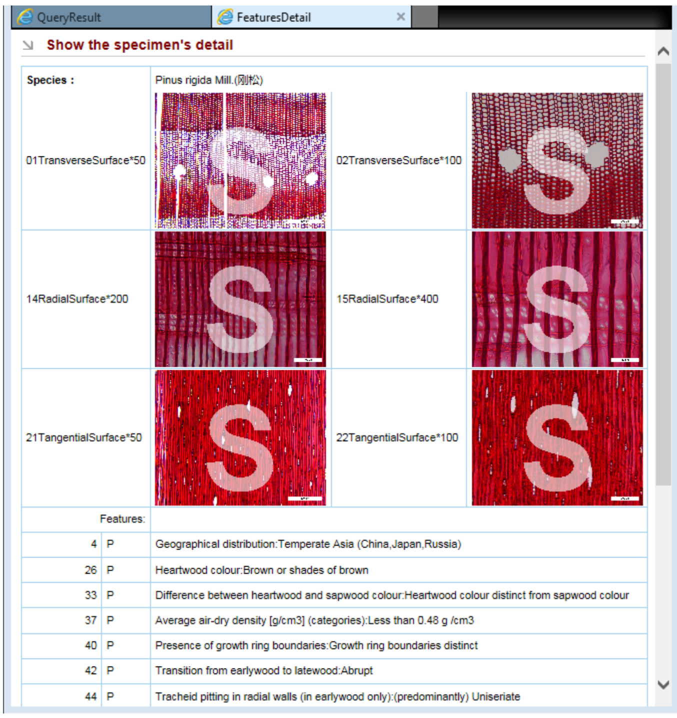

Fig. 11: The result of "Function" click.

As shown in Fig. 11, the page displayed the detail of one record belongs to a coniferous species, including micro-graphs and feature code with description.

Performance of three-section classification

After obtaining the three-section classification model, the code written in Python 3 language was tested in Windows 7 operating system under Spyder (Anaconda3) software. The classification model obtained by training was used to test and verify 100 pieces of coniferous three-section images covering 37 species of images without deep learning. The accuracy of this model test is 90%. The classification accuracy of the model is not high for three-section microscopic digital images whose magnification is greater than 200. The comparison of training results of the three models is shown in Tab. 1. The fully CNN proposed in this paper has highest mean accuracy.

Tab. 1: Comparison of training results of the three models.

Model	Accuracy (%)			mA (%)
	transverse	radial	tangential	
Fully CNN	98.18	94.51	93.48	95.39
CNN	96.97	66.19	100.00	87.71
SVM	96.36	90.32	88.89	91.86

Performance of feature identification

Based on the segmentation model trained by the U-net neural network architecture constructed in this paper, 24 micro images with axial canals were segmented, and only one sample did not obtain axial canals, with an accuracy of 95.83%. In the segmentation test of 8 samples without axial resin channel, only 1 sample mistakenly regarded the damaged part of the section as the canals, with an accuracy of 87.50%. The average accuracy rate was 91.44%. No damaged sections can improve the segmentation accuracy of axial canals segmentation model. Axial canal has more inclusions, so the accuracy of axial canal segmentation model is reduced. The accuracy of the segmentation model can be improved by improving the U-net neural network architecture, increasing the training atlas and improving the data set enhancement.

The test results show that the accuracy of the proposed segmentation model for micro images with radial canals is 90%. The accuracy of micro images segmentation test without radial canals is 82.35%. The average accuracy was 86.18%. The abundance of spindle canals may result in their incorrect identification. The accuracy of segmentation model can be further improved by increasing the sample size of training set. Based on image processing technology, accuracy of a method (Perez 2019) for identifying presence of growth ring boundaries was used in this paper reached 98%, including “distinct” and “indistinct” feature.

Under the condition of setting the threshold of similarity of 0.8, 100 microscopic images were cropped and tested. The test results showed that 78 images obtained the feature of “Window-like”, 70 were correct, and the accuracy was 89.74%. According to the Wheeler (2004), there are 85 of 124 features which can identified from micro-graphs, however, this paper only studied on 5 features. In the next work, more features can be studied and included in this retrieval system.

Compared with the existing research, there are two innovations and differences in this paper. First, the coniferous wood retrieval system proposed in this paper integrates the anatomical feature information subsystem and the anatomical feature intelligent subsystem, but not only provides the anatomical feature retrieval, such as *Insidewood* (Wheeler 2011) and *Pl@ntWood* (Sarmiento 2011). Second, different from *MyWood-ID* (Tang 2018) and *Tree species recognition system* (Ibrahim 2017) attempt to identify tree species by learning the macro image of wood through neural network, the anatomical feature intelligent retrieval subsystem proposed in this paper identifies the micro features of coniferous wood instead of directly identifying tree species. It assists people in identifying the anatomical features of coniferous wood. On this basis, combined with the anatomical feature retrieval subsystem, the level of computer-aided conifer wood recognition is improved.

CONCLUSIONS

This study examines a coniferous micro-graph retrieval system combined with Convolutional Neural Networks and image processing technologies, and the proposed system employs the novel softwood identification architecture. The system starts from identifying the microscopic features of softwood, and retrieves the identified features to identify the species or reduce the range of possible species. This pattern is consistent with the process of wood identification, avoiding the dilemma that the artificial intelligence technology is used to directly scan the surface of the sample, which is prone to the failure to obtain the species of wood. Besides, the intelligent subsystem can identify 5 microscopic features of softwood. In addition, the system can be further developed into more intelligent coniferous retrieval system that can automatically identify more coniferous microscopic features, so as to obtain more accurate retrieval results.

ACKNOWLEDGMENT

This work was supported by the National Keypoint Research and Invention Program in 13th Five-Year of China under Grant 2016YFD0600702 and Key Laboratory of Bamboo Resources Development & Utilization (Sanming University), Fujian Province University. We are grateful to Research Institute of Wood Industry, Chinese Academy of Forestry for providing softwood specimens.

REFERENCES

1. Bouchard, K., Maitre, J., Bertuglia, C., Gaboury, S., 2020: Activity recognition in smart homes using UWB radars. Procedia Computer Science 170: 10-17.
2. Castellani, M., Rowlands, H., 2008: Evolutionary feature selection applied to artificial neural networks for wood-veneer classification. International Journal of Production Research 46(11): 3085-3105.

3. Ciga, O., Martel, A.L, 2021: Learning to segment images with classification labels. Medical Image Analysis 68(3): 101912.
4. Dong, Z., Wang, M., Wang, Y., Zhu, Y., Zhang, Z., 2020: Object detection in high resolution remote sensing imagery based on convolutional neural networks with suitable object scale features. IEEE Transactions on Geoscience and Remote Sensing 58(3): 2104-2114.
5. Hwang, S.W., Kobayashi, K., Zhai, S., Sugiyama, J., 2018: Automated identification of lauraceae by scale-invariant feature transform. Journal of Wood Science 64(2): 69-77.
6. Ibrahim, I., Khairuddin, A.S.M., Talip, M.S.A., Arof, H., Yusof, R., 2017: Tree species recognition system based on macroscopic image analysis. Wood Science and Technology 51(2): 431-444.
7. IAWA Committee, 1989: IAWA list of microscopic features for hardwood identification: with an appendix on non-anatomical information. IAWA Bull 10(3): 219-329.
8. Lickert, H., Wewer, A., Dittmann, S., Bilge, P., Dietrich, F., 2021: Selection of suitable machine learning algorithms for classification tasks in reverse logistics. Procedia CIRP 96(2): 272-277.
9. Lin, Q., He, T., Sun, Y., He, X., Qiu, J., 2020: A computer-aided method for identifying the presence of softwood growth ring boundaries. PLoS ONE 15(9): e0235727.
10. Lu, L., Liu, B., 2020: Revealing the multisensory modulation of auditory stimulus in degraded visual object recognition by dynamic causal modeling. Brain Imaging and Behavior 14(4): 1187-1198.
11. Maggipinto, M., Beghi, A., McLoone, S., Susto, G.A., 2019: Deepvm: a deep learning-based approach with automatic feature extraction for 2d input data virtual metrology. Journal of Process Control 84: 24-34.
12. Perez, R.O., 2019: Using tensorflow-based neural network to estimate gnss single frequency ionospheric delay (Iononet) - Sciencedirect. Advances in Space Research 63(5): 1607-1618.
13. Ravindran, P., Costa, A., Soares, R., Wiedenhoeft, A.C., 2018: Classification of cites-listed and other neotropical *Meliaceae* wood images using convolutional neural networks. Plant Methods 14(1): 25.
14. Sarmiento, C., Détienne, P., Heinz, Ch., Molino, J.F., Grard, P., Bonnet, P., 2011: Pl@Ntwood: A computer-assisted identification tool for 110 species of Amazon trees based on wood anatomical features. IAWA Journal 32(2): 221-232.
15. Singh, S., Chauhan, V.K., Smith, E., 2020: A self controlled RDP approach for feature extraction in online handwriting recognition using deep learning. Applied Intelligence 50(7): 2093-2104.
16. Tang, X.J., Tay, Y.H., Nordahlia, A., Lim, S.C., 2018: MyWood-ID: Automated macroscopic wood identification system using smartphone and macro-lens. CIIS 2018: Proceedings of the 2018 International Conference on Computational Intelligence and Intelligent Systems 37-43.
17. Tao, H.E., Shibiao, M.U., Zhou, H., Junguo, H.U., 2021: Wood species identification based on an ensemble of deep convolution neural networks. Wood Research 66(1): 1-14.

18. Tao, H., Li, C., Zhao, D., Deng, S., Jing, W., 2020: Deep learning-based dead pine trees detection from unmanned aerial vehicle images. International Journal of Remote Sensing 41(21): 8238-8255.
19. Torralba, A., Russell, B. C., Yuen, J., 2010: Labelme: online image annotation and applications. Proceedings of the IEEE 98(8): 1467-1484.
20. Wen, Z., Liu, D., Liu, X., Zhong, L., Lv, Y., Jia, Y., 2019: Deep learning based smart radar vision system for object recognition. Journal of ambient intelligence and humanized computing 10(3): 829-839.
21. Wheeler, E., Baas, P., Gasson, P. E., 2004: IAWA list of microscopic features for softwood identification. IAWA Bull 10(3): 219–332.
22. Wheeler, E., 2011: Inside wood – a web resource for hardwood anatomy. IAWA Journal 32(2): 199-211.
23. Wu, X., Senalik, C.A., Wacker, J., Wang, X., Li, G., 2020: Object detection of ground-penetrating radar signals using empirical mode decomposition and dynamic time warping. Forests 11(2): 230.
24. Zhao, S., Xu, T., Wu, X. J., Zhu, X.F., 2021: Adaptive feature fusion for visual object tracking. Pattern Recognition 111(9): 107679.
25. Zhao, Z., Yang, X., Ge, Z., Guo, H., Zhou, Y., 2021: Wood microscopic image identification method based on convolution neural network. BioResources 16(3): 4986-4999.

QIZHAO LIN*, HONG WANG
FUJIAN POLYTECHNIC OF INFORMATION TECHNOLOGY
COLLEGE OF INTERNET OF THINGS AND ARTIFICIAL INTELLIGENCE
FUZHOU, FUJIAN 350003
P.R. CHINA
*Corresponding author: 1575177305@qq.com

XIN HE, JIAN QIU*
SOUTHWEST FORESTRY UNIVERSITY
COLLEGE OF MATERIAL SCIENCE AND ENGINEERING,
KUNMING, YUNNAN 650224
P.R. CHINA
*Corresponding author: qiujian@swfu.edu.cn