Application of Variant Transfer Learning in Wood Recognition

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Wood is a material commonly found in nature and is widely used in all professions and industries. Because wood has varied growth cycles and physical properties, there are large differences in its usage and commercial price. In addition, some woods are nationally protected species. Therefore, it is of great importance to accurately identify the type of wood. Traditional wood recognition methods rely on experts and specialized equipment. To facilitate wood recognition, this paper proposes an approach for wood recognition using images. Next, a transfer learning technology was used to extract the textural features of wood, and a global average pooling (GAP) layer was used to reduce the number of features. Finally, the extreme learning machine (ELM) was used for classification. The recognition accuracy of this approach for the Wood Species Dataset was 93.07%, which was higher than the method used by the data provider. This approach had a higher recognition accuracy and a more stable recognition performance than previous approaches.

Keywords: Wood recognition; Transfer learning; Extreme learning machine

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INTRODUCTION

Due to the difference in the internal structure and composition of wood materials, wood can show completely different physical and chemical properties, resulting in different purposes and commercial prices for wood. Wood recognition aims to identify the differences between the structural characteristics and components of various kinds of wood to determine the wood species (Wiedenhoeft 2005). However, as a type of biomass material, the structural characteristics of the same kind of wood will differ due to the different ecological environments in the growing area. Therefore, accurate wood classification and recognition technology (Wheeler and Baas 1998) has been a research hotspot and a source of difficulty in the field of material engineering.

The development of wood recognition technology can be divided into three stages: artificial recognition, the retrieval stage of the feature database, and the automatic recognition of wood using a computer. The earliest wood classification and recognition technologies were mainly based on the visual characteristics of physical wood. Through the observations and comparisons by professional recognition personnel, the type of wood was gradually identified. This approach mainly depends on the professional knowledge of the recognition personnel and the macroscopic representation of the wood, which easily leads to misjudgment (Ruz *et al.* 2009). In the second stage, the results of the wood types identified by the professional recognition personnel are collected and classified. In addition, the recognition results and the corresponding macrostructures and microstructures are entered into the database. By searching for wood characteristics, this stage can provide a basis for wood recognition (Miller 1980). The recognition results of this stage still depend on manual discrimination and belong to the category of manual recognition. The third stage is the automatic recognition of wood using a computer. With the development of computer technology, wood recognition technology has emerged that no longer depends on the professional knowledge of the recognition personnel. This technology automatically extracts the feature data of wood through computer algorithms and uses machine learning, neural network models, and other approaches for automated wood recognition (Jain *et al.* 1996; Mitchell 1999).

The automatic classification of wood based on computers can also be divided into two categories. One category is to extract wood features by spectral analysis technology (Lavine *et al.* 2001; Lebow *et al.* 2007; Nisgoski *et al.* 2017), thermogravimetric curves (Francisco-Fernández *et al*. 2012; Tarrío-Saavedra *et al.* 2011), gas chromatography-mass spectrometry (GCMS) (Xu *et al.* 2013), stress waves (Rojas *et al.* 2011), and other noncomputer vision means and then use the classification and recognition technology of computer algorithms. Another category is entirely based on the computer vision method of wood classification and recognition. This method utilizes wood texture images as input data, which makes this method more convenient than the first-mentioned category of methods.

Traditional computer vision algorithms applied to wood recognition include the gray-level co-occurrence matrix (GLCM) (Tou *et al*. 2009; Wang *et al*. 2010; Fahrurozi *et al.* 2016), basic gray level aura matrix (BGLAM) (Zamri *et al*. 2016), and histogram of oriented gradient (HOG) (Sugiarto *et al*. 2017). The main tasks of these methods are to determine the method to extract the features of wood data and build the recognition model; the extracted features are only indirect features of wood types (Miller 1980). The recognition process can be divided into two steps: 1) extract and analyze sample features, and 2) determine the model structure and parameter settings. The models that are constructed based on different angles and levels to extract wood features have different recognition accuracies. Therefore, feature extraction and analysis are the main tasks of the wood classification and recognition processes.

Deep learning is considered to be the most convenient and effective classification method in computer vision. The deep learning method based on a convolutional neural network (CNN) model exhibits promising effects in processing image classification problems (LeCun *et al.* 2014). However, many image samples are needed when training a CNN model. This method does not need to consider the feature extraction methods; it can obtain the features using a CNN automatically according to the training data to extract the texture features of images (Simonyan and Zisserman 2014). In image classification, there are usually not enough samples. Therefore, transfer learning technology was proposed (Pan and Yang 2010; Day and Khoshgoftaar 2017). This technique relies on the feature extractability of a model trained on other datasets. Through transferring this ability to the target dataset and retraining the fully connected part of the model, an improved classification recognition effect can be achieved. For example, Ristiawanto *et al.* (2019) and Yusof *et al.* (2020) used transfer learning technology for wood recognition, achieving high recognition accuracy. This paper applied the transfer learning technique to an open wood dataset. The accuracy of this method was limited, and the results were not as good as the accuracy of a traditional method. Therefore, some improvements to the transfer learning technology were made and a new method for wood recognition based on these improvements was proposed. Specifically, the following contributions were made:

A new approach for the recognition of wood species is proposed. In this paper's approach, transfer learning technology is used to extract wood textural features, and global average pooling (GAP) is introduced to reduce the number of features and improve the generalization ability of the model (Lin *et al.* 2013). Finally, the extreme learning machine (ELM) algorithm is used for the recognition of wood species (Huang *et al.* 2006). The combination of deep learning and machine learning can make full use of the advantages of both technologies. Deep learning has a strong ability to extract abstract features of wood image texture, while machine learning has an advantage in small sample classification.

The function of GAP is demonstrated. It is generally believed that GAP can improve the generalization ability of a model, but it will reduce the convergence speed of the network model. This paper combines GAP with ELM and avoids the disadvantage of a too-slow convergence after introducing GAP.

The remainder of the work in this paper is as follows: the dataset that was used and the proposed wood recognition method are introduced, and then the selection of experimental parameters is discussed. Finally, this paper compared many kinds of wood recognition methods and drew a conclusion.

EXPERIMENTAL

Materials

The Wood Species Dataset is a wood dataset published online by Barmpoutis in 2019 (Barmpoutis 2019). The dataset consists of samples of normal wood structures from 12 wood species that exist in Greek territory, including three cork species and nine hardwood species. The images are divided into three categories: cross-section images, radial-section images, and chord-section images. The images were taken from 15 to 20 cm away using a Nikon D3324 Megapixel Digital Camera (Nikon, Tokyo, Japan) at the wood technology laboratory at the School of Forestry and Natural Environment, Aristotle University (Thessaloniki, Greece).

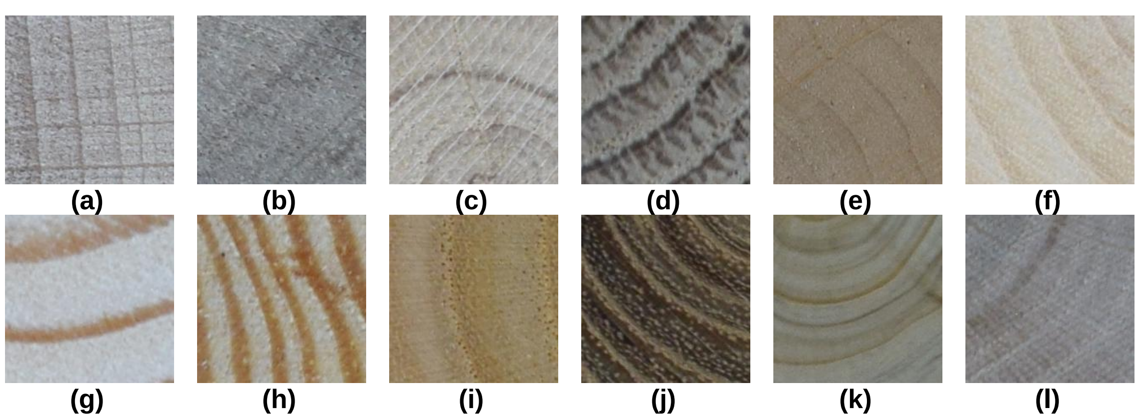

Fig. 1. Wood samples in the database: (a) *Fagus sylvatica*, (b) *Juglans regia*, (c) Castanea sativa, (d) *Quercus cerris*, (e) *Alnus glutinosa*, (f) *Fraxinus ornus*, (g) *Picea abies*, (h) *Pinus sylvestris*, (i) *Ailanthus altissima*, (j) *Robinia pseudoacacia*, (k) *Cupressus sempervirens*, and (l) *Platanus orientalis*

All images were cropped to a size of 400 by 400 pixels, but in Barmpoutis' published data, the image size was 200 by 200 pixels. At present, there are more than 8000 pictures, among which the cross-sectional data are the most common. The sample situation is shown in Fig. 1.

In wood structure, the classification of wood species mainly depends on identifying the morphological differences of tissue structures, such as conduits, axial parenchyma, and wood rays, in different tree species (Wiedenhoeft 2005; Castellani and Rowlands 2008). These morphological differences can be observed through the three facets of wood. Wood recognition by human experts involves the recognition of structural features on the woodcut surface. Some experienced wood recognition experts can identify the wood type by observing a wood cross-section. Because trees grow vertically, these characteristics are pronounced across the wood. In the Barmpoutis *et al.* (2018) experiment, it was shown that the recognition accuracy of a wood cross-section image was relatively high, so this paper adopted the cross-section data from the Wood Species Dataset for classification and recognition.

Methods

Based on some problems existing in the application of transfer learning technology to wood recognition, the authors made improvements and proposed a new method for wood recognition. The structure of the new method is shown in Fig. 2. It consisted of three parts: the first part was wood feature extraction based on transfer; the second part was feature dimension reduction based on global average pooling (GAP); and the third part was a wood classifier based on extreme learning machine (ELM).

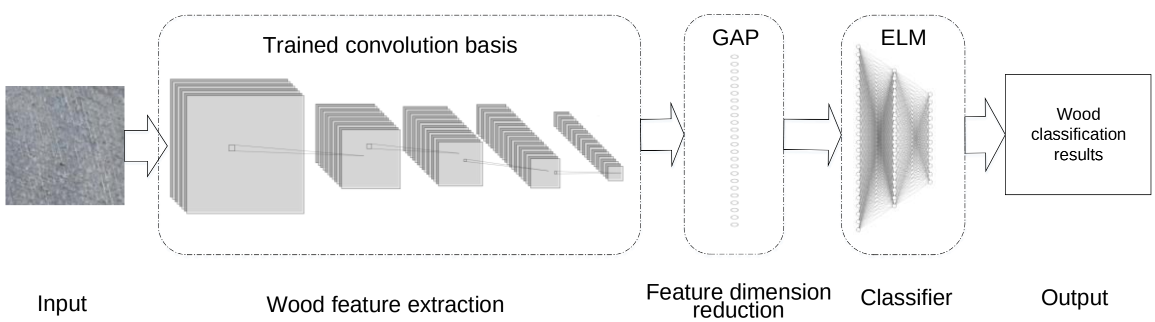

Fig. 2. Method structure

Feature Extraction Based on Transfer

In traditional image recognition tasks, image features are extracted first, such as the GLCM, scale-invariant feature transform (SIFT) features, and HOG features. Then, the features are classified and recognized. This type of research is complicated, and the discernibility of the extracted features to the classification target determines the final recognition effect. However, in recent years, image classification and recognition based on deep learning has been considered the fastest and most effective method. Deep learning simulates the visual function of the human brain by constructing a CNN and adjusts the network parameters after training with many data samples to make it capable of extracting, classifying, and recognizing image features. The recognition effect of this method is determined by the data, and it is generally believed that more training data results in a better recognition effect.

However, in general experiments, due to the cost of data acquisition, the data volume is limited, such that it is not enough to train the recognition accuracy of a CNN to achieve a high level. To solve the problem of insufficient samples, some researchers proposed the concept of transfer learning, which transfers the feature extraction ability of a model trained on other datasets to another model. Then, the classifier part of the model is retrained, which increases the recognition accuracy of the model. For the image recognition model, the structure and parameters of the convolution basis parts of other CNN models are transferred.

Global Average Pooling

The global average pooling (GAP) is a network structure proposed by Lin (2013), which has great potential for deep CNN networks. In general, a deeper convolutional layer results in a larger field of view. However, this method uses only the flattened layer to flatten the output feature map of the convolutional layer and pass it to the classifier. This operation results in too much input data and too many model parameters for the classifier, which reduces the training speed and easily leads to overfitting. In addition, the feature map of CNN is directly connected to the classifier, which confuses the function of each feature map. However, the GAP network layer compresses each feature map into a feature so that the extracted information of each feature map can correspond to a semantic feature. The network parameters and the overfitting phenomenon in the model will be greatly reduced after introducing the GAP network layer.

The features extracted based on the transfer model are remarkably different from traditional machine learning methods in terms of the order of magnitude. As shown in Table 1, the number of features extracted based on Residual Network 50-Layer (ResNet50) model (He *et al.* 2016) is even larger than the original input. For this reason, the GAP layer was introduced into the model. Experimental results show that this operation could greatly reduce the number of features, decrease the overfitting of the model, and improve the recognition accuracy of the model.

Table 1. Feature Number Comparison

Model	Input Size	Input Numbers	Flatten Output Numbers	GAP Output Numbers
ResNet50	200,200	40k	100k	2048

Extreme Learning Machine

The extreme learning machine (ELM) is a classifier method proposed by professor Guangbin in 2004 (Huang *et al.* 2004). In terms of structure, ELM is similar to the fully connected network of a single hidden layer, consisting of three parts: the input layer, hidden layer, and output layer. The hidden layer was responsible for mapping the input data into a high-dimensional space and activating it, while the output layer was responsible for solving the results of the target task. The calculation for Eq. 1 is as follows,

$$H(x) = \sigma(w \times x + b) \times \beta \tag{1}$$

where σ is the activation function, w is the connection weight of the input layer and the hidden layer, b is the offset of the connection between the input layer and the hidden layer, and β is the connection weight between the hidden layer and the output layer. In ELM, w and b are determined by random seeds, and they are not influenced by training data. In addition, β is solved by the matrix formula, and there was no bias between the hidden layer and the output layer.

ELM had a short training time and high recognition accuracy. The forward propagation process in ELM in the classification process was completely similar to the fully connected network and could replace the fully connected part in the transfer learning to complete the classification task. Moreover, for the fully connected network, the introduction of GAP reduced the convergence speed, but the parameters of the extreme learning machine were directly solved by matrix operation, which was not affected by GAP.

RESULTS

To verify the effectiveness of the proposed method in wood recognition, comparative experiments were conducted with the CNN method based on the deep learning and transfer learning methods and multitexture analysis method proposed by the data contributors:

1. Convolutional neural network: the image classification and recognition algorithm proposed by Lekun, a pioneer of machine learning, won the championship at the ImageNet competition in 2014. This algorithm set off a wave of applications of CNN models in image classification. This method requires a large amount of data, so few people directly use this method for wood recognition.

2. Transfer learning: this method solves the problem where CNN requires a high data volume, and it is usually used to address image classification tasks with small sample sizes. Ristiawanto *et al.* (2019) and Yusof *et al.* (2020) applied transfer learning to wood image classification and obtained good classification recognition results.

3. Transfer learning using GAP: because the fully connected structure in transfer learning is similar to ELM, a group of transfer learning experiments using the GAP layer was designed in addition.

4. Multitexture analysis method: the wood recognition method proposed by Barmpoutis *et al.* (2018) extracted the texture features of wood in the vertical and horizontal directions and used a support vector machine (SVM) as a classifier. In the dataset exposed by Barmpoutis *et al.* (2018), this method had a higher recognition accuracy than the traditional wood classification algorithm.

The present method used ResNet50 as the transfer object. Figure 3 shows that the recognition accuracy of the method in this paper was relatively high, and the recognition ability for various types of wood was relatively stable. The accuracy of the transfer learning method was also improved after the introduction of GAP. The order of recognition accuracy from high to low was the authors' method (93.07%), the multitexture method (91.47%), transfer learning using GAP (86.43%), traditional transfer learning (80.82%), and CNN (77.86%). Figure 3 shows that the authors' method had the highest recognition accuracy for the six kinds of wood numbered 1, 2, 6, 7, 10, and 12.

Barmpoutis' experiment demonstrated that the multitexture analysis method is superior to GLCM, SIFT, BGLAM, *etc*. The confusion matrix for the current method is shown in Fig. 4, and the confusion matrix for the Barmpoutis method is shown in Fig. 5, which indicates that the recognition accuracy of the current method for three types of wood was lower than 90%. The recognition accuracy reached 100% for wood specie 10. The overall recognition accuracy of the 12 types of wood was 93.07%. In the Barmpoutis method, five types of wood had an accuracy of less than 90%, and three types of wood had an accuracy of 100%. The overall recognition accuracy was 91.47%. Based on this data, it can be determined that this paper's method of recognition of wood species was more stable and accurate than the other methods.

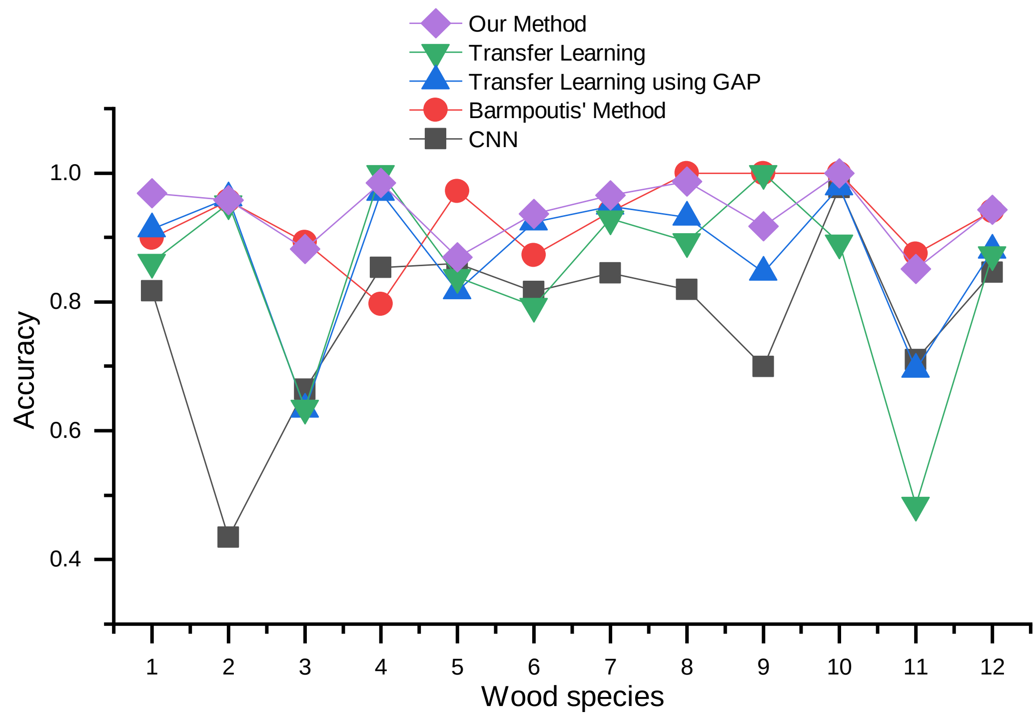

Fig. 3. Comparison of the experimental diagram

DISCUSSION

This paper's proposed approach used transfer objects, GAP, and ELM as the three parts. The selection of transfer objects was an important part of the method, but the models that were used to select the transfer objects were not specified. Many image recognition models could be used as transfer objects, and there may be different choices for different wood datasets. Additionally, it is unclear whether the GAP network layer was necessary. To achieve the best recognition effect, determine the transfer objects, and demonstrate the necessity of the GAP network layer, comparative experiments were designed.

Transfer Object Selection

For image classification tasks, the commonly used models for transfer learning include VGG16, VGG19, InceptionV3, ResNet50, and other network models (Simonyan and Zisserman 2014; He *et al.* 2016). These models have won the ImageNet image classification contest over the years. To select the model with the best recognition effect, comparative experiments on these models were conducted using ELM instead of the fully connected part in transfer learning, which does not use GAP to the network layer. As shown in Table 2, ResNet50 had the best classification effect for transfer characteristics, with an accuracy of 82.12%. Therefore, ResNet50 was used as the transfer object.

	Fagus sylvatica	Juglans regia	Castanea sativa	Quercus cerris	Alnus glutinosa	Fraxinus ornus	Picea abies	Pinus sylvestris	Ailanthus altissima	Robinia pseudoacacia	Cupressus sempervirens	Platanus orientalis
Fagus sylvatica	96.85%	0.00%	0.00%	0.00%	0.00%	1.57%	0.79%	0.00%	0.00%	0.00%	0.00%	0.79%
Juglans regia	0.00%	95.83%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	4.17%
Castanea sativa	0.00%	3.23%	88.17%	1.08%	0.00%	0.00%	1.08%	1.08%	1.08%	3.23%	0.00%	1.08%
Quercus cerris	0.00%	1.56%	0.00%	98.44%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Alnus glutinosa	0.00%	0.82%	0.00%	0.00%	86.89%	0.00%	0.82%	2.46%	1.64%	0.00%	0.00%	7.38%
Fraxinus ornus	0.00%	0.00%	0.00%	0.00%	2.13%	93.62%	1.06%	2.66%	0.00%	0.00%	0.53%	0.00%
Picea abies	0.68%	0.00%	0.00%	0.00%	0.68%	2.05%	96.58%	0.00%	0.00%	0.00%	0.00%	0.00%
Pinus sylvestris	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	1.35%	98.65%	0.00%	0.00%	0.00%	0.00%
Ailanthus altissima	0.00%	0.00%	2.35%	0.00%	1.18%	0.00%	0.00%	2.35%	91.76%	0.00%	0.00%	2.35%
Robinia pseudoacacia	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%	0.00%	0.00%
Cupressus sempervirens	2.70%	0.00%	0.00%	0.00%	1.35%	4.05%	0.00%	6.76%	0.00%	0.00%	85.14%	0.00%
Platanus orientalis	0.00%	3.77%	0.00%	0.00%	0.94%	0.00%	0.00%	0.00%	0.94%	0.00%	0.00%	94.34%

Fig. 4. The confusion matrix for this paper's method

	Fagus sylvatica	Juglans regia	Castanea sativa	Quercus cerris	Alnus glutinosa	Fraxinus ornus	Picea abies	Pinus sylvestris	Ailanthus altissima	Robinia pseudoacacia	Cupressus sempervirens	Platanus orientalis
Fagus sylvatica	89.90%	1.01%	2.02%	2.02%	1.01%	1.01%	1.01%	0.00%	0.00%	0.00%	0.00%	2.02%
Juglans regia	0.00%	95.65%	0.00%	4.35%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Castanea sativa	0.71%	0.00%	89.29%	4.29%	0.00%	2.14%	0.00%	0.00%	0.00%	1.43%	0.71%	1.43%
Quercus cerris	0.00%	0.00%	7.41%	79.63%	0.00%	0.00%	7.41%	0.00%	0.00%	1.85%	3.70%	0.00%
Alnus glutinosa	0.00%	0.00%	0.00%	0.00%	97.22%	0.00%	0.00%	0.00%	0.00%	0.00%	2.78%	0.00%
Fraxinus ornus	0.00%	0.00%	0.00%	0.00%	2.13%	87.23%	0.00%	0.00%	0.00%	0.00%	8.51%	2.13%
Picea abies	0.00%	0.00%	0.00%	0.00%	0.00%	3.03%	93.94%	3.03%	0.00%	0.00%	0.00%	0.00%
Pinus sylvestris	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%	0.00%	0.00%	0.00%	0.00%
Ailanthus altissima	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%	0.00%	0.00%	0.00%
Robinia pseudoacacia	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%	0.00%	0.00%
Cupressus sempervirens	0.00%	0.00%	3.13%	0.00%	1.56%	6.25%	0.00%	0.00%	1.56%	0.00%	87.50%	0.00%
Platanus orientalis	2.94%	1.47%	0.00%	0.00%	0.00%	1.47%	0.00%	0.00%	0.00%	0.00%	0.00%	94.12%

Fig. 5. The confusion matrix for the Barmpoutis method

Table 2. Transfer Object Accuracy

Model	Input	ELM Input	Training Accuracy	Testing Accuracy
VGG16	200,200	6,6,512	95.96%	69.94%
VGG19	200,200	6,6,512	96.56%	72.15%
InceptionV3	200,200	4,4,2048	76.63%	45.59%
ResNet50	200,200	7,7,2048	98.16%	82.12%

Verification of the Role of GAP

Although the recognition accuracy of ResNet50 as the transfer object was higher than that of other models, the combined method was overfitted, and the recognition accuracy was limited. To improve the recognition accuracy, the GAP network layer was added after the transfer feature structure. As shown in Table 3, after the GAP was added, the number of input features of the ELM classifier decreased and the recognition accuracy improved, among which the recognition accuracy based on ResNet50 transfer features reached 93.07%.

Table 3. Accuracy After Introducing GAP

Model	Input	ELM Input	Training Accuracy	Testing Accuracy
VGG16	200,200	512	97.89%	83.41%
VGG19	200,200	512	97.6%	81.43%
InceptionV3	200,200	2048	72.95%	46.42%
ResNet50	200,200	2048	99.07%	93.07%

To understand the phenomenon that the classification accuracy improved after GAP dimension reduction, these outputs were decomposed with singular value decomposition (SVD), and then the t-distributed stochastic neighbor embedding (T-SNE) dimension reduction visual analysis method was used to analyze the data visually. Through these operations, the data changes from high dimensional space to two-dimensional space. Finally, the Matplotlib (version: 2.0.1) library in python (Python Software Foundation, v.3.6.5, Wilmington, DE, USA) was used for drawing operation. The results are shown in Figs. 6 and 7. Figure 6 shows the dimension reduction results without GAP operation, and Fig. 7 shows the dimension reduction results after GAP operation. Figures 6 and 7 show that several kinds of wood numbered 3, 9, and 11 had gathered, and the texture features extracted based on ResNet50 could describe the wood features.

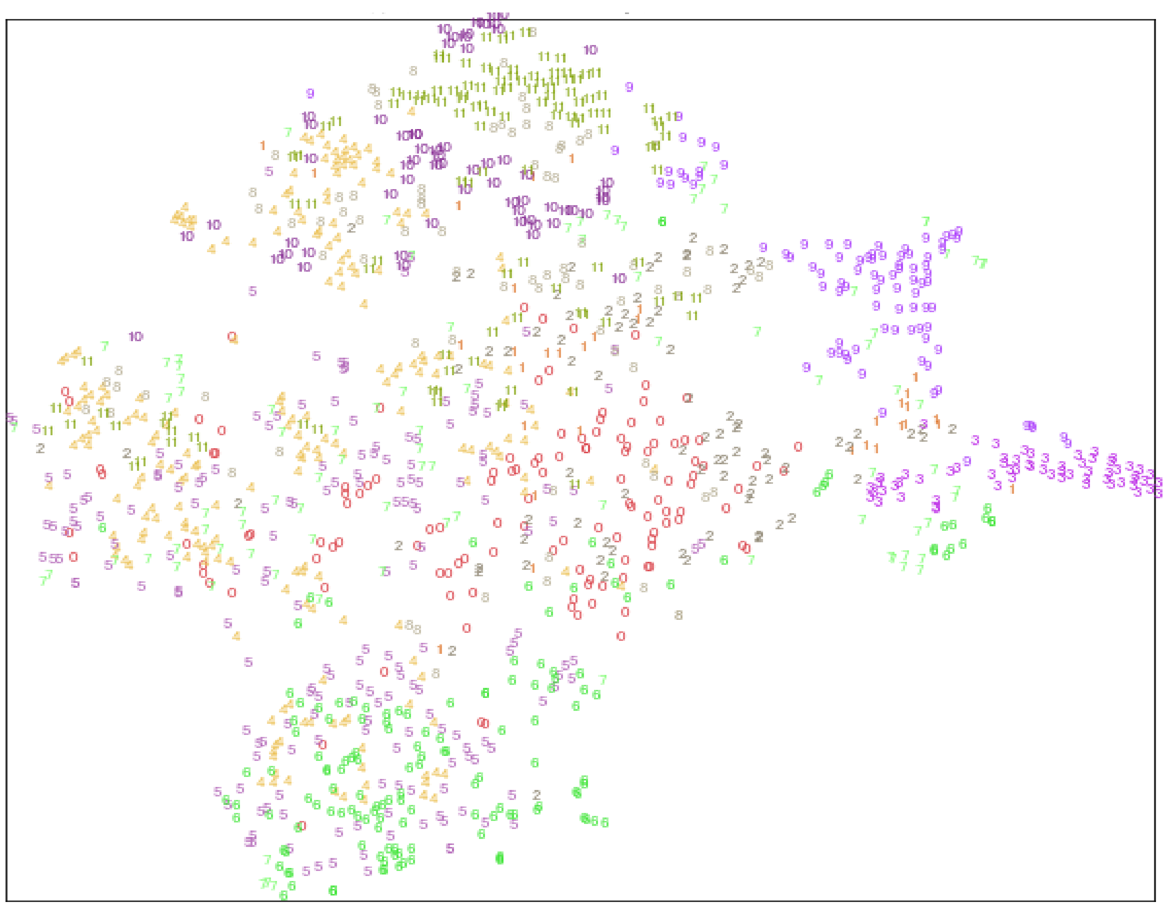

Fig. 6. ResNet50 output dimensionality reduction visualization

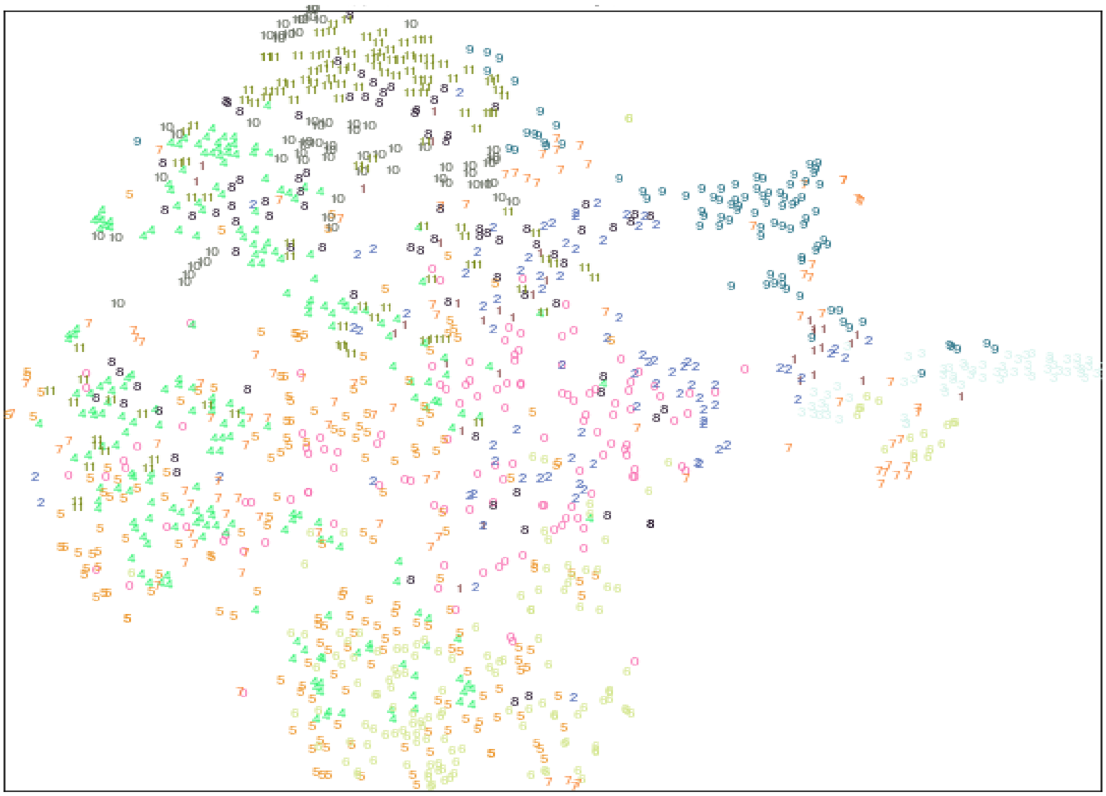

Fig. 7. ResNet50 and GAP output dimensionality reduction visualization

Comparing the differences between Figs. 6 and 7 reveals that that the data after dimension reduction did not change much. In addition, the K-means algorithm was used to cluster the data, and then the Rand index, mutual information, and other clustering indicators was used to evaluate the data (Krishna and Murty 1999). The data after dimension reduction by GAP did not affect the clustering effect. The GAP output data removed redundant information from the original output, which did not affect the representation of the abstract characteristics of wood texture and was helpful to reduce the number of inputs and parameters of the classification model. Therefore, the authors' next research goal is to achieve semantic wood recognition and to improve the defects of the present method with respect to the identification of wood structure.

Table 4. Clustering Evaluation Table

	Rand Index	Mutual Information	Homogeneity	Completeness	V-measure
Raw output	0.1971	0.3355	0.3492	0.3857	0.3666
GAP output	0.1972	0.3292	0.34322	0.38665	0.3636

CONCLUSIONS

1. Compared with other deep learning methods and the methods proposed by data contributors, the proposed wood recognition method based on variant transfer learning reaches 93.07%, which has higher accuracy and more stable recognition effect. This shows that the method will be more reliable in actual detection.

2. This paper's method combined the methods of deep learning and machine learning and overcame the shortcomings of slower convergence speed after the introduction of global average pooling in traditional transfer learning.
3. These experiments established that the transfer learning method could extract the texture features of wood well, and it was shown that the introduction of global average pooling could improve the accuracy of wood recognition.
4. The proposed method could extract the texture features of wood images and produce the results of wood classification. However, this method could not classify wood according to the wood structure as done by human experts.

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