Artificial Intelligence Methods Applied In Wood Species Identification

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Introduction

Wood identification has a very important place in fields such as plant taxonomy, wood material trade, illegal logging, archeology, conservation and restoration, art history, and even criminology (Ross, 2010). In order to rationally utilized the wood raw material, which is considered a scarce resource, and to choose the right place of use, it is necessary to correctly identify the tree species (Dogu, 2013; Wheeler & Baas, 1998). Classical wood identification methods based on examining the macroscopic and microscopic structure of wood material are accepted as the most reliable methods today (Ross, 2010). However, as these methods are labor-intensive, require relatively long preparation and examination times, and need wood anatomy specialists. So, this situation has led to a need for different diagnostic methods in recent years (Dormontt et al., 2015). The development of new technologies in the world and our expectation for rapid access to information are seen as a need for industries working with wood materials. In order to meet these needs, studies are emerging for rapid and effective species identification, which will provide a base for industrial applications. In general, while it is sufficient to determine the genus of trees in industrial fields, it is seen that species identification was required in many cases (Dormontt et al., 2015). Although some species which belong to the same genus are endangered and their trade is restricted, there is no commercial restriction for some species with similar appearance (Gasson, 2011; Shou et al., 2014; Snel et al., 2018). At the same time, it is stated that species identification is vital in many situations where information about cultural and historical structures is needed (Hwang et al., 2016). Some wood species are difficult to distinguish from each other microscopically (Tuncer, 2020). Today, image processing techniques have achieved great momentum with cutting-edge technology.

Wood anatomy

There are two groups of wood: softwoods and hardwoods. The respective characteristics for each of these species are significantly different (Figure 1). Softwoods have simpler anatomy than hardwoods, with much more related features and greater variety within each trait (Martins, 2018).

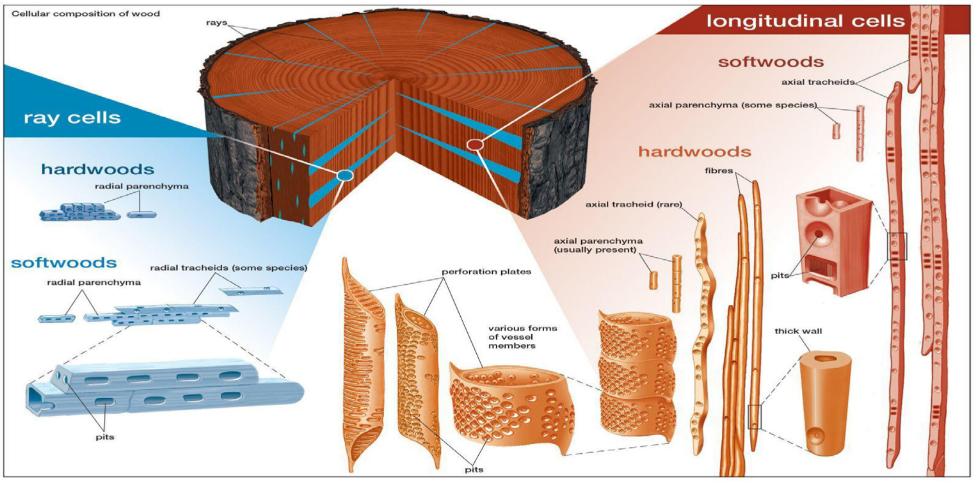

Figure 1. Types of cells are present in hardwood and softwood (Tsoumis, 2022).

Softwood consists mainly of tracheids and parenchyma, while hardwood consists of parenchyma, vessel members, fibers, and sometimes tracheids (Tsoumis, 2022). Some of these properties can be detected in different sections, so their analysis is needed (Martins, 2018). Softwood is also called conifers. Tracheids, resin canals, passage types, and rays play a key role in the diagnosis of coniferous trees. On the other hand, hardwood has complex cellular structures and clearly distinguishable cellular differences between species. Trachea, fibers, parenchyma, perforation plates, and rays are considered in the identification of leafy tree species (Hermanson & Wiedenhoeft, 2011).

Image types

The types of images are utilized as X-ray computed tomographic (CT) images, macroscopic images, stereograms, and micrographs (Figure 2) for wood identification. Macroscopic images are shooted by a standard digital camera without magnification. Stereograms are taken at 10× magnification, larger magnifications can also be used. Micrographs which are optical microscopic images are widely used in traditional wood identification. X-ray images are a slice of the images created by X-ray CT scans (Hwang & Sugiyama, 2021).

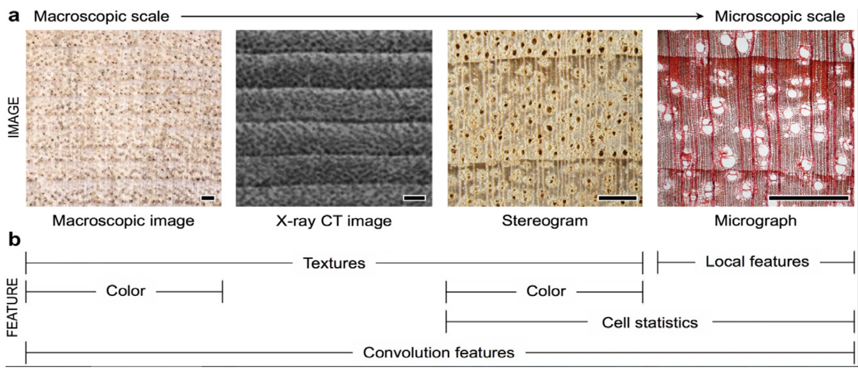

Figure 2. Preferred properties by image type a) types of images available from wood, b) corresponding extractable image properties. (Scale bars = 1 mm). (Hwang & Sugiyama, 2021).

Identification of Wood Species

Wood species identification for computer vision typically focuses on microscopic or macroscopic images of wood samples. Wood surface images photographed at 10-15× magnification are used in the macroscopic situation (Fabijańska et al., 2021). Microscopic techniques make use of images of samples obtained by microscopy at magnifications ranging from 25 to 100× (Yadav et al., 2015; Silva et al., 2017). The main limitation of method is that they require special equipment to acquire images (Filho et al., 2014).

The microscopic description of wood is based on three different cuts that form three distinct sections in the wood sample: the cross section (horizontal cut), the radial section (the vertical cut through the wood core), and the tangential section (tangential vertical cut of the bark). For identification, images of three different sections are analyzed. This is so complex that a list of anatomical features has been developed by the International Association of Wood Anatomists (IAWA) (Wheeler, 1989).

Although analysis of microscopic wood anatomy is currently the most reliable method to provide initial identification, only specialists can perform this task with accuracy. The training required to train an experienced wood anatomist can take decades and there are very few wood anatomists available in the world (Dormontt et al, 2015), so automation of this process is important. There are also studies that use microscopic images and define them by measuring various anatomical features (Ergun, 2021a; Jiang et al., 2013; Turhan & Serdar, 2013; Boztoprak & Ergun, 2017; Ergun, 2021b).

Image-Based Traditional Methods

Traditional identification is slow and costly, experts must determine the wood type by examining the cross-sectional features of the wood (Ibrahim et al., 2018). The distinguishing features of the wood such as vessel arrangement, pore orientation, ray, parenchyma, fiber and other information presented on the surface should be determined. Next, their species are identified according to the tree type identification standard defined by the IAWA list (Ruffinatto et al., 2015).

In image-based classification, images must be converted to numerical data for analysis by classification algorithms. A widely used technique in the wood species recognition problem is the use of recognition models based on texture features. In this context, Gray Level Co-Occurrence Matrices (GLCM) are generally used. By comparing the gray level differences between the pixels on the image with GLCM, various features including the image texture characteristic are found. The resulting properties form the inputs for wood classification applications. (Piuri & Scotti, 2010; Tou et al., 2009; Sun et al., 2011; Mallik et al., 2011; Martins et al., 2013; Hasan et al., 2013; Yadav et al., 2013; Khalid et al., 2008).

A typical wood type identification method includes two important steps feature extraction and classification. Feature extraction methods; boundary detection algorithm, Gray Level Co-occurrence Matrix (GLCM) (Manik et al., 2020), color test statistical method (Zhao, 2013), etc. includes.

The final step in defining a typical tree type is to train tree samples to create a statistical model and then use a classifier to classify new samples by wood species. The most popular classification methods are support vector machine (Martins et al., 2013; Turhan & Serdar, 2013; Filho et al., 2014; Barmpoutis et al., 2018; Souzas et al., 2020), KNN (Kobayashi et al., 2015), neural network (Ibrahim et al., 2018; Filho et al., 2010; Yusof & Rosli, 2013; Zhao et al., 2014; Huang et al., 2020), etc. But other classifiers are also applied (Kobayashi et al., 2017; Khairuddin et al., 2011).

Microstructures of wood samples are analyzed via a microscope in different sections. Microscopic identification of wood is based on three different cuts that form three distinct segments in the wood sample: cross-section, radial, and tangential. Several image processing techniques are utilized to analyze images of different sections to aid the identification process. Methods for different types of images, such as macroscopic and stereograms, are usually cross-sectional. Important information from other sections such as radial and tangential is ignored (Martins, 2018).

Wood species classification mainly depends on the identification of morphological differences in cell structures such as canals, axial parenchyma, and rays (Castellani & Rowlands 2008; Wiedenhoeft 2005). These morphological differences were determined in all three parts of the wood. For experts, wood recognition involves recognizing structural features on the wood surface. Some experienced wood-recognition professionals can determine the wood type by observing the wood cross-section. These features are evident throughout the wood since trees grow vertically (Huang et al., 2021). Barmpoutis et al. (2018) experiment showed that the recognition accuracy of a wood section image is relatively high.

Using CNN in Wood Identification

The difficulty of classifying species with similar morphological and anatomical features has required the development of techniques to detect the main features that help to obtain a reliable classifier (Murat, 2018). Conventional classification and recognition of wood species is time-consuming and requires detailed knowledge and experience of wood anatomy. Therefore, convolutional neural networks (CNN), a deep learning tool, have replaced traditional methods. In the following, studies with CNN in the literature for wood recognition are given. Some methods are applicable only to hardwood, while others are more general and can be applied to both hardwood and softwood. Recently, studies with micro and macro images have been elaborated on.

Sun et al. (2021), a transfer learning method based on a small dataset was proposed to recognize tree species. This method used ResNet50 feature extraction, LDA key feature optimization, and KNN classifier. A total of 25 tree species were selected for training and testing. The samples were obtained from wood factories in China's Yunnan Province, Wood Herbarium of Southwest Forestry University (SWFU). 120 images were selected for each species and 3000 images were obtained for 25 species.

Fabijańska et al. (2021) used a network of convolutional encoders in a sliding window arrangement for tree species identification. The study was limited to a macroscopic dataset of 14 hardwood and softwood species commonly found in Europe. They further extended the divide-and-conquer classification strategy proposed by Hafemann et al. (2014). A model with ResNet-inspired jump connections (He et al., 2016) was proposed and a patch-based, floating window strategy was applied regardless of image spatial resolution. Especially, the use of a sliding window setup also increased the number of training examples, as many train patches can be extracted from a single input image. The source code of the proposed method was published with the dataset to facilitate duplication of results and a direct comparison with future competitors.

Ravindran et al. (2018) implement the VGG16 model to 10 neotropical species macroscopic images. Lens et al. (2020) compared the performance of CNN models on a microscopic dataset of 112 neotropical wood species. The results showed that the CNN models significantly outperformed the classical classifiers. ResNet gave the best results with classification rates of 98%. The ResNet model (Hu et al., 2019) was used to describe nine timber types. The above-mentioned studies deal with high-quality images. Therefore, Lopes et al. (2020) tested the performance of the ResNet v2 model by applying it to images taken from a commercial mobile phone with a macro lens. The model identified 10 hardwood species with an accuracy of 92%, significantly lower than images carefully acquired with specialized equipment. Also, cutting-edge CNN models require fixed-size inputs that are not always available (Fabijańska et al., 2021).

In a similar study (Huang et al., 2021), a new approach for tree species recognition was proposed for 12 wood species using the same database (Barmpoutis 2019). Transfer learning technology was used to extract wood textural features. Global average pooling (GAP) was introduced to reduce the number of features and improve the generalization ability of the model (Lin et al. 2013). An extreme learning machine (ELM) algorithm was used for wood species recognition. Based on the ResNet50 model, the number of extracted features is even greater than the original input. Therefore, the GAP layer has been added to the model. Experimental results showed that this process can greatly reduce the number of features, reduce the overfitting of the model, and improve the recognition accuracy of the model. The combination of deep learning and machine learning can take advantage of both technologies. While deep learning has a strong ability to extract abstract features of wood image texture, machine learning has an advantage in small sample classification (Huang et al., 2021).

In another study (Kirbas & Cifci, 2022), transfer learning was used to classify tree species in the Wood-Auth dataset. The current study is based on the dataset obtained at the Wood Technology Laboratory of the Aristotle University of Thessaloniki, School of Forestry and Natural Environment (Barmpoutis et al., 2018). The data set consists of macroscopic images of 12 tree species belonging to three different tree section types, cross-section, radial, and tangential. Transfer learning adapts it to the relevant problem using pre-trained models rather than developing a deep learning model from scratch. The classification performances of ResNet-50, Inception V3, Xception, and VGG19 deep learning architectures with transfer learning were evaluated. ResNet (Residual Network) (He et al., 2016) was developed to avoid the problem of vanishing gradients in multilayer deep networks. It has 50 layers of which there are 48 convolutional layers. Inception network is based on the simultaneous application of filtering and pooling in convolutional layers. It works with modules. Inception V3 the number of parameters can be reduced without reducing network efficiency (Szegedy et al., 2015). Xception network offers two different approaches in addition to the improvements in Inception V3. These are deep convolution and point convolution (Chollet, 2017). VGGNet has two structures, VGG19 and VGG16. The VGG16 network has 41 layers. It consists of 13 convolutional layers, three fully connected layers, pooling, activation function, dropout, and classification layers. The VGG19 network has 47 layers. It has more convolution layers than VGG16 (Simonyan & Zisserman, 2014).

Experimental findings indicated that Xception outperformed the other models in the study and the Wood-Auth dataset, providing a classification accuracy of 95% (Kırbaş & Farmer, 2022).

In general, studies have used a regional database and focused on a certain number of species. We are aware that the datasets used in the studies are not the same and that the comparisons of different methods should be made on the same database. Many studies have been published together with the dataset to ease replication of results and a direct comparison with future competitors.

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