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Commentary

Machine learning-based wood anatomy identification: towards anatomical feature recognition

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Summary – Computer vision-based wood identification has been successfully applied to recognize tree species using digital images of wood sections or surfaces. However, this image-to-species approach can only recognize a limited number of species due to two main reasons: 1) the lack of a good reference database requiring high-quality standardized images from multiple individuals of hundreds or even thousands of traded timber species, and 2) species not included in the reference database cannot be identified without expert knowledge. Another bottleneck is that the feature extraction process used by these species recognition approaches is a black box, thereby creating a discrepancy between machine learning features and wood anatomical features. This discrepancy prevents wood anatomists from understanding how these machine-learning algorithms work. Here, we survey currently existing methods used in feature extraction, classification, and deep learning methods applied in wood identification along with their pitfalls and opportunities. As an example of how the field could move forward, we launch the idea of building an image-to-features-to-species identification approach based on microscopic wood images as well as text files comprising wood anatomical descriptions. If we can manage machine learning-based algorithms to recognize the main wood anatomical traits that experts use to identify species in a (semi-)automated way, this would boost wood identification in two ways: (1) extensive reference databases for each species would become less crucial as the databases are ordered at the trait level, (2) timber identification would become more feasible for species that have not yet been included in the reference database as long as wood anatomical descriptions are available.

Keywords – feature incompatibility, illegal logging, species recognition.

Introduction

Wood identification plays a vital role in forest law enforcement, conservation, timber industry, and scientific research. Accurate identification helps the fight against illegal logging, as the combination of illegal and legal logging

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activities further contributes to harmful environmental and social impacts, such as deforestation, habitat destruction, loss of biodiversity, and exploitation of local communities (Dormontt *et al.* 2015; UNODC Committee 2016, 2020; Jahanbanifard *et al.* 2019; Chandra 2022; Low *et al.* 2022). For instance, accurate wood identification tools would enable international and local authorities to enforce legal regulations such as the US Lacey Act, the Australian Illegal Logging Prohibition Act (AILPA), the European Union (EU) initiated 'Forest Law Enforcement, Governance and Trade' (FLEGT), former European Timber Regulation (EUTR) and the upcoming new EU regulation on deforestation-free supply chains (EUDR), and the international Convention on International Trade in Endangered Species of Wild Fauna and Flora (CITES COP 19 2022) (European Commission 2003, 2010, 2023; Johnson & Laestadius 2011; Dormontt *et al.* 2015; UNODC Committee 2016, 2020). Furthermore, it would promote sustainable and environmentally responsible practices across the timber supply chain (He *et al.* 2020; Olschofsky & Köhl 2020; Liu *et al.* 2022; Ravindran *et al.* 2022a,b). On the other hand, it is important to realise that not all logging operations, even if legal, adhere to sustainable practices where timber is harvested in such a way that the integrity and health of the forest ecosystem over the long term are maintained (Putz *et al.* 2022).

Unfortunately, a widely applicable and reliable method to identify woods remains elusive. A variety of wood identification methods are available, such as DNA-based methods (Lowe *et al.* 2010; Nithaniyal *et al.* 2014; Jiao *et al.* 2015, 2018, 2022; He *et al.* 2019; Yin *et al.* 2020), chemical profiling based on mass spectrometry (Musah *et al.* 2015; Evans *et al.* 2017; Zhang *et al.* 2019; Price *et al.* 2021, 2022; Deklerck 2023), near-infrared spectroscopy (Braga *et al.* 2011; Bergo *et al.* 2016; Pan *et al.* 2022), detector dogs (Braun 2013), and wood anatomy (Gasson *et al.* 2010; Wheeler 2011; Helmling *et al.* 2018; Brandes *et al.* 2020; Lens *et al.* 2020; Liu *et al.* 2022). According to the best practice guide for forensic timber identification, issued by the United Nations Office on Drugs and Crime (UNODC Committee 2016), wood anatomy remains the most commonly used approach to identify wood samples as it is quick, cost-effective, and relies on a well-established, standardized set of wood anatomical traits that have been particularly selected for the purpose of wood identification by experienced wood anatomists, for both angiosperms (IAWA Committee 1989) and gymnosperms (IAWA Committee 2004). However, in most cases, wood anatomy mostly only allows for identification up to the genus level as closely related species typically have nearly identical microscopic patterns in their wood anatomy (Wheeler & Baas 1998; Gasson 2011). That being said, all wood identification methods suffer from accuracy issues at the species level (Price *et al.* 2022).

The rapid advancement of Artificial Intelligence (AI) has aroused a surge of interest in automated Computer Vision-based Wood Identification (CVWID). This is especially true for Machine Learning (ML) which relates to a subdiscipline of AI focusing on computer algorithms with the capability to learn from data, and Deep Learning (DL) which is an ML-subcategory taking advantage of deep neural networks. These pioneering approaches enable computers to learn from expertise and improve without explicit programming, making it ideal for classifying timber species based on digital images of microscopic or macroscopic wood anatomy. The potential benefits of these methods extend to aiding the work of trained wood anatomists, whose expertise requires years of training (Lens *et al.* 2020), and allow non-experts such as customs officers to apply these wood identification methods to efficiently detect and prevent fraud (Wiedenhoeft *et al.* 2019). The process of CVWID involves two crucial steps: feature extraction and classification. In feature extraction, computer algorithms identify the critical parts of the image, while classification employs additional computer algorithms to differentiate images based on these extracted features. By comparing the image features from an unknown species with image features from known species embedded into the reference database, the computer calculates the probability of the unknown image with that of a known species. This is referred to as image-to-species recognition.

Despite significant progress in CVWID (Filho *et al.* 2014; Ibrahim *et al.* 2017; Rosa da Silva *et al.* 2017, 2022; de Andrade *et al.* 2020; He *et al.* 2020; Lens *et al.* 2020; Verly Lopes *et al.* 2021; Figueroa-Mata *et al.* 2022; Ravindran & Wiedenhoeft 2022; Ravindran *et al.* 2022a,b; Bello *et al.* 2023; Yang *et al.* 2023), the development of a globally accessible ML-based wood identification platform remains challenging. Three main reasons can be cited. First, the current image-to-species recognition methods are not suited to identify a large number of timber species. This is because

Table 1. Compilation of traditional machine learning studies in wood-based recognition, showing the relatively low number of species (often less than 100) and low number of images (typically less than 100 per species), along with information about type of images, feature extraction algorithm, classifier used, and the (artificially high) species recognition (top) accuracy for each study.

Reference	Sp/Imgs	Ma/Mi	FX	Classifier	(Top) Accuracy (%)
Yang *et al.* (2023)	19/3000	mi	LBP+GLCM	BPNN+SVM	97.54
Chandra (2022)	5/1300	ma	–	k-NN	76
Rosa da Silva *et al.* (2022)	77/2415	mi	LPQ	SF	95
Andrade *et al.* (2020)	21/2000	ma	GLCM	SVM	97.70
Hwang *et al.* (2020a)	39/1658	ma	SIFT	SVM	99.40
Hwang *et al.* (2020b)	9/1019	mi	SIFT	SVM	79.20
Kobayashi *et al.* (2019)	18/2298	mi	SIFT	k-NN+SVM	95.30
Barmpoutis *et al.* (2018)	840 394	ma	MDTA	SVM	91.47
Hwang *et al.* (2018)	39/1557	mi	SIFT	LDA	96.30
Ibrahim *et al.* (2018)	30/3000	mi	fuzzy logic	ANN	89
Martins *et al.* (2018)	112/2240	ma	combination	ensembles	98.47
Ibrahim *et al.* (2017)	77/1221	mi	LBP	LDA	90
Zamri *et al.* (2016)	52/5200	ma	GLCM	BPNN	97.01
Filho *et al.* (2014)	41/2942	mi	CLBP	SVM	97.77
Zhao *et al.* (2014)	5/1000	ma	GLCM	BPNN	90
Martins *et al.* (2013)	112/2240	mi	GLCM+LBP	SVM	98.60
Yadav *et al.* (2013)	25/500	mi	GLCM	ANN	92.60
Yuliastuti *et al.* (2013)	10/400	ma	Gabor	MLP	95
Yusof *et al.* (2013)	52/5200	ma	GLCM	GA	98.69
Martins *et al.* (2012)	112/2240	mi	LBP+LBQ	SVM	86.47
Khalid *et al.* (2011)	52/5200	ma	GLCM	LDA+k-NN	96.35
Nasirzadeh *et al.* (2010)	37/3700	ma	LBP	k-NN	96.60
Paula Filho *et al.* (2010)	22/1270	ma	GLCM	MLP	78
Yusof *et al.* (2010)	30/3000	ma	GLCM	LBP	95.44
Tou *et al.* (2009)	6/100	ma	GLCM	k-NN	85
Tou *et al.* (2007)	5/50	ma	GLMC	LDA	72

Abbreviations: ma, macroscopic; mi, microscopic; FX, feature extraction algorithm; GLCM, gray-level co-occurrence matrix; LBP, local binary pattern; SIFT, scale-invariant feature transform; LDA, linear discriminant analysis; ANN, artificial neuro network; k-NN, k-nearest neighbor; MLP, multilayer perceptron; DT, decision tree; SVM, support vector machine; GA, genetic algorithm; BPNN, back propagation neural network. The accuracy rates cannot be compared to each other based on the datasets used in each study that have their own parameters (number of individuals, species).

these methods heavily rely on the time-consuming creation of a reference database, including representative images of as many individuals per species as possible for the more than a thousand different timber species that are being traded (Mark *et al.* 2014; Lens *et al.* 2020). Unfortunately, available image databases do not meet these criteria for most species (see Table 1). Second, the current recognition methods are not designed to recognize species that are not included in the reference database. Third, the results achieved by image-to-species methods are expressed as probabilities that an image is correctly classified, but the exact features or regions in the images that lead to such a classification generally remain unclear. This creates confusion among wood anatomists who have a hard time being convinced that the outcome of ML-based wood recognition methods is trustworthy and generally applicable when adding more species. This is referred to as 'feature incompatibility' and is further exacerbated by the fact that the meaning of the word 'feature' in ML and 'feature' in wood anatomy is different (Fig. 1). An ML feature refers to

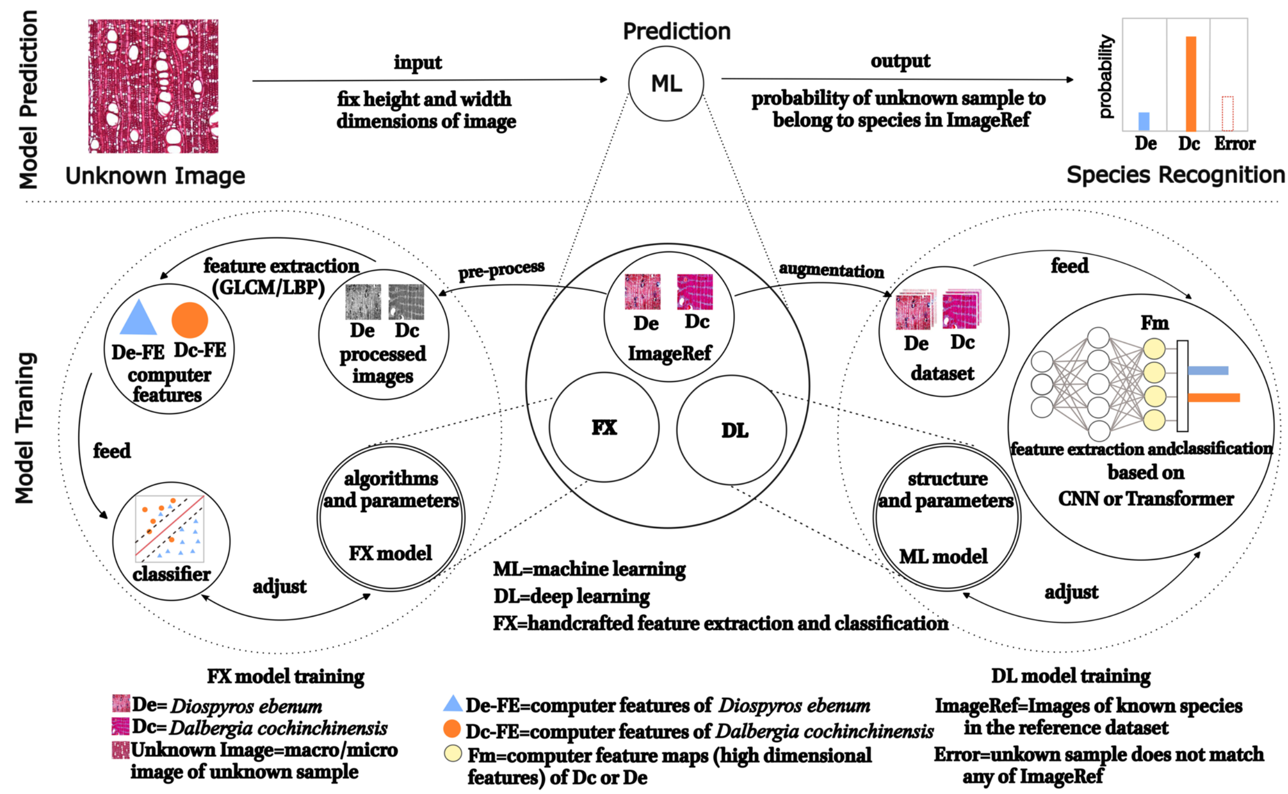

Fig. 1. Overview of machine learning image-to-species models for wood recognition. In the model training component (left), known reference images (De, Dc) are first processed; computer algorithms such as GLCM or LBP are then used to extract computer features from these images (feature extraction), after which a classifier trains the feature extraction (FX) model. On the right-hand side, the DL model training process is almost the same, with the only difference being that the CNN or Transformer algorithms incorporate both the feature extraction and classifier steps. Both FX and DL models can be used to predict whether an unknown image belongs to reference data (De or Dc) or not. If the unknown image does not belong to the reference data, there may be an error recognition result.

mathematical representations of high-dimensional vectors used for numerical calculations, while a wood anatomical feature reflects the type, shape, and arrangement of the cellular structure in wood.

To explore how ML can overcome these issues and to develop a global CVWID method that can reliably recognize hundreds or even thousands of timber species throughout the world based on wood anatomy, we need to gain insight into the history of ML-based wood identification. Here, we review the ML-based wood recognition process, including image acquisition, feature extraction and classification, summarize the main pitfalls and opportunities, and put forward a new idea for a global CVWID pipeline that does not require an extensive reference database at the species level.

Image acquisition

Although a variety type of images (e.g. scanning electron microscope images, X-ray images, fluorescence microscope images) are available for CVWID, this paper only focuses on images derived from light microscopic sections and macroscopic surfaces of wood. At the microscopic level, high-resolution images can be captured in bulk with a slide scanner in the lab or individually with a light microscope equipped with a digital camera (Martins *et al.* 2013;

Rosa da Silva *et al.* 2017). At the macroscopic level (Ruffinatto *et al.* 2015; Ruffinatto & Crivellaro 2019), images can be obtained using portable imaging equipment to develop real-time applications on-site or in the field (Tang *et al.* 2018; de Andrade *et al.* 2020; Arévalo *et al.* 2021; Figueroa-Mata *et al.* 2022). Examples are the Xyloscope (Hermanson *et al.* 2019), a digital imaging system for viewing and recording macroscopic images of wood surfaces for the open-source XyloTron platform (Ravindran & Wiedenhoeft 2020), and the more affordable XyloPhone (Wiedenhoeft 2020) and Xylorix (Tay 2019) that is adaptable to a camera of the smartphone (Ravindran *et al.* 2019, 2020, 2021; Arévalo *et al.* 2021). In addition to the global platforms like XyloTron, there are also more local platforms that are working well at a smaller scale within countries, such as iWood (He *et al.* 2021) in China and AIKO (Arifin *et al.* 2020) in Indonesia.

Images captured at various magnifications can influence machine learning algorithms for feature recognition due to the distinct textures observed at different scales, although Nguyen-Trong (2023) advocates that a 20× magnification yields favorable outcomes. When making microscopic wood sections or macroscopic surface images in the field, it is crucial to attain a specific quality threshold to enable precise identification. The challenge arises from the inherent limitations of field or on-site identification, which often restricts complex sample processing. The processing for wood surfaces may involve the use of sandpaper with varying grain sizes ranging from coarse to fine-grit to eliminate scratches and grooves left by the blade. Further polishing of the wood surface with finer grain sizes does not yield statistically better outcomes in CVWID once the quality threshold is surpassed (Owens *et al.* 2023). The same quality threshold probably also applies to quick and dirty microscope sections that are made in the field compared to more standardized lab conditions, until future algorithms can accommodate for these cutting artefacts. We envision that the future of wood identification will most likely rely on a combination of macro CVWID tools in the field or on-site complemented with microscopic tools in the lab. However, the accuracy levels of the current wood identification tools should always be cautiously interpreted, since any accurate global ML model relies on a good quality (microscopic and macroscopic) reference database, which is not yet available at the global scale for most traded timbers (Lens *et al.* 2020).

Regardless of the images acquired by digital imaging devices, the basic unit of computer storage is the pixel point (with 0–255 numbers indicating color brightness). A color image is created by arranging multiple pixel points both vertically and horizontally to form three RGB (Red, Green, Blue) channels. The density of these pixels determines the resolution of the image. For example, a common microscopic image taken by an optical microscope with a digital camera has a resolution of 2592 × 1944 pixels times 3 RGB channels, which leads to a computer image file having 14.7×10^6 pixel points. If multiple image data were calculated by classification algorithms directly, the computational capacity of common computers would quickly be exceeded. This leads to the first paradox: wood anatomists tend to use high-resolution images to show more details of the anatomical features, while computers prefer lower-resolution images covering a larger surface to fit their processing ability. A combined effort between experts in wood anatomy and computer vision is the way forward to finding the right balance.

To represent inter-species and intra-species variability accurately, the number of images also plays an essential role. If an image-to-species recognition approach is employed, it means that many images are required for each tree species in the reference database. But how many individuals and images per species are enough? Wood anatomists typically consider images from more than 20 individuals per species sufficient to reach statistical significance (Lens *et al.* 2020), although this minimum threshold likely needs to be upscaled for species with a wide distribution range. For ML and especially DL approaches, many more training images per category (hundreds or thousands) are required depending on the model's structure and the number of parameters (Cho *et al.* 2016; Shahinfar *et al.* 2020). Unfortunately, as shown in Table 1 and Table 2, the number of species or images per species that are being used in ML studies is relatively small (often less than 100), making present reference databases unfit for accurate wide-scale wood identification based on an image-to-species recognition approach. Indeed, few images per species typically lead to an overestimation of the recognition accuracy values in CVWID (Ravindran & Wiedenhoeft 2022). That is also the reason why the number of images is often artificially augmented for ML analyses using a wide array of image pre-processing approaches, such as binary transformation, cropping, rotation, shrinkage, magnification, and sub-images that lead to several smaller

Table 2. Compilation of DL studies in wood-based recognition, with information about the number of species and images, type of images and feature extraction AI model (standard CNN structures (LeNet, VGGs, ResNets, AlexNet, DenesNets, Inception, Xception, RCNN)).

Reference	Sp/Imgs	Ma/mi	DL model	(Top) Accuracy (%)
Bello *et al.* (2023)	12/4272	ma	Mask-RCNN+ResNet	92
Figueroa-Mata *et al.* (2022)	147/3516	ma	VGG	80.30
He *et al.* (2022)	5/585	ma	VGG	84.80
Kirbas & Çifci (2022)	12/4200	mi	ResNet, Inception, Xception, VGG	95.88
Ravindran & Wiedenhoeft (2022)	10/1709; 219/2635	ma	ResNet	98.5; 97.1
Ravindran *et al.* (2022a)	17/4045	ma	ResNet	98.00
Ravindran *et al.* (2022b)	22/6393	ma	ResNet	95.20
Arévalo *et al.* (2021)	84/4108	ma	ResNet	97.30
Fabijańska *et al.* (2021)	14/312	ma	ResNet	98.70
Ravindran *et al.* (2021)	24/1419	ma	ResNet	97.00
Verly Lopes *et al.* (2021)	11/1789	ma	custom CNN	94.00
Wu *et al.* (2021)	459 781	ma	ResNet, DenseNet, MobileNet	98.20
Zhu *et al.* (2021)	10/1216	mi	RCNN, SPP, FPN	83.80
de Geus *et al.* (2020)	281/5620	ma	DenseNet	98.70
He *et al.* (2020)	26/10 237	ma	custom CNN	99.30
Lens *et al.* (2020)	112/2240	mi	GoogLeNet, Alexnet, VGG, ResNet	96.40
Olschofsky & Köhl (2020)	6/300	ma	Inception	98.00
Ravindran & Wiedenhoeft (2020)	10/193	ma	ResNet	82.4
Ravindran *et al.* (2020)	31/3126	ma	ResNet	97.7
Kwon *et al.* (2019)	5/33 815	ma	LeNet2, LeNet3, MiniVGGNet4	98.00
Ravindran *et al.* (2019)	38/2187	ma	ResNet	97.00
Figueroa-Mata *et al.* (2018)	41/2942	ma	LeNet	98.03
Mata-Montero *et al.* (2018)	41/2939	ma	ResNet	97.77
Paul & Clostre (2018)	7/115	ma	custom CNN	94.00
Ravindran *et al.* (2018)	10/2303	ma	custom VGG	97.5
Kwon *et al.* (2017)	5/16 865	ma	LeNet	99.30
Hafemann *et al.* (2014)	112/2240	ma/mi	custom CNN	97.32

Abbreviations: Sp, species; Imgs, images; ma, macroscopic; mi, microscopic; custom CNN, custom Convolutional Neural Network designed by the authors. Also here, species recognition (top) accuracy is often artificially high and only a limited species can be recognized in each of the studies.

images based on a single original image (Fabijańska *et al.* 2021; He *et al.* 2021; Yang *et al.* 2023). The downside of this pre-processing is, however, that some smaller-scale traits in the image may be lost or are no longer recognizable. Therefore, various strategies, such as incorporating overlapping regions during the cropping process, are employed to mitigate this issue. Another issue with these original reference images is that they are generally derived from only transverse orientation planes and have a similar low magnification that further impedes observations of small-scale wood anatomical traits, such as vessel pits.

It is interesting to see the discrepancy between the small image datasets that are currently being used in ML-based recognition studies on the one hand. On the other hand, the long tradition of wood anatomy has been generating hundreds of thousands of wood anatomical slides in institute collections worldwide and has led to a wealth of published wood anatomical descriptions and images (Wheeler 2011; Koch *et al.* 2018; Sugiyama *et al.* 2020; Haneca *et al.* 2022). Part of the available wood anatomical data is publicly available via InsideWood (InsideWood 2004-onwards; Wheeler 2011), the largest and best-known online wood anatomical database in the world — containing

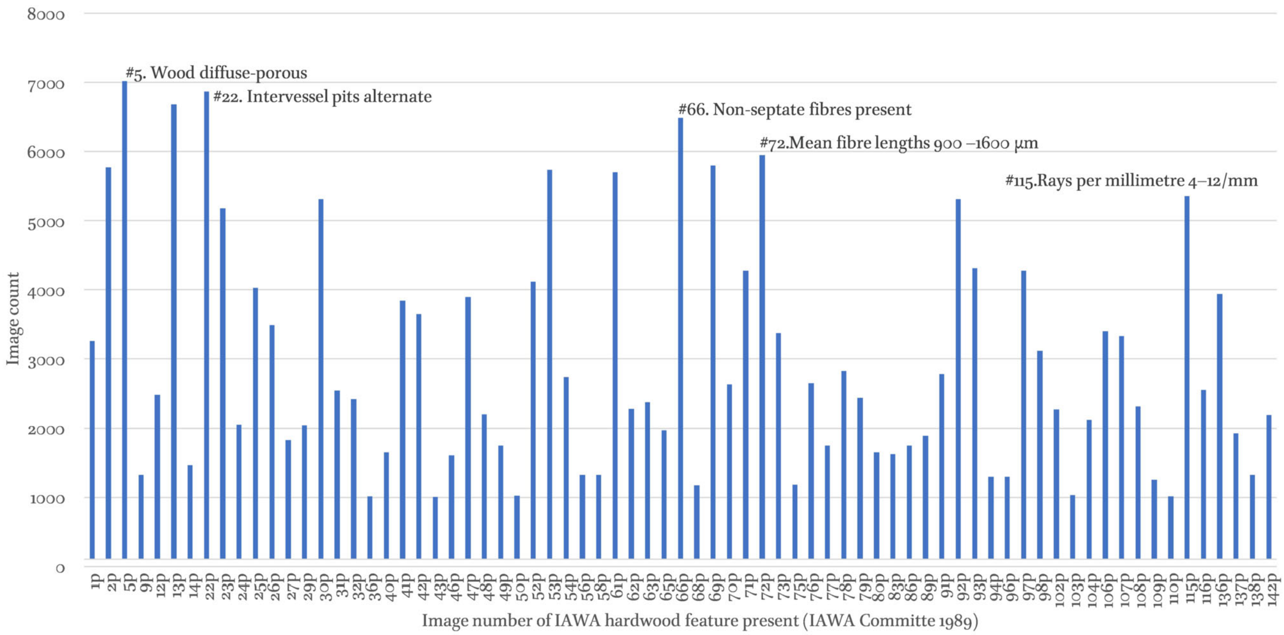

Fig. 2. 73 IAWA hardwood features with more than 1000 images on the InsideWood website (extracted June 2022). Of the 163 hardwood features, 156 have more than 100 images, and 99 have more than 500 images. This set of images is sufficient to make multiple mutually exclusive datasets for deep learning.

over 50 000 images that cover more than 10 000 species, along with wood descriptions following the standardized IAWA hardwood and softwood lists (Fig. 2; Wheeler *et al.* 2020).

Feature extraction and classification

Handcrafted feature extraction

Computer vision features can be identified by handcrafted algorithms that can be used to analyze and classify different features of wood images. These algorithms are designed by computer experts who came up with processes of manually designing and selecting specific image features, such as edges, corners or textures. Gray-Level Co-occurrence Matrices (GLCM) (Haralick *et al.* 1973) algorithm is a popular handcrafted algorithm for feature extraction of wood anatomical images (see references in Table 1). GLCM analyzes the spatial relationships in images based on pixel intensities, allowing the algorithm to detect larger-scale wood anatomical traits, such as wood growth ring boundaries, vessels, and rays as viewed in transverse sections. The Local Binary Pattern (LBP) algorithm (Ojala *et al.* 1994) is another popular algorithm used in wood anatomy (Table 1) and changes the 0–255 color values around a central pixel into a 0/1 binary value making it effective in capturing and representing the features that have repetitive patterns or distinctive textures. While GLCM and LBP focus more on larger, pattern-like traits in wood images, the Scale-Invariant Feature Transform (SIFT) algorithm (Lowe 1999) detects smaller-scale anatomical traits (like septate fibres, vessel pits, mineral inclusions) by focusing on local parts of an image (Hwang *et al.* 2018, 2020a,b).

We can draw two conclusions from these general handcrafted feature extraction algorithms that were not initially designed to extract features from wood images. First, they can still be used to identify a number of anatomical traits, indicating that a comprehensive analysis and further research on manually extracted features could offer an opportunity to expand our domain knowledge and cultivate a deeper understanding of wood. Second, the discrepancy between handcrafted feature extraction and IAWA features remains, making it hard for wood anatomists to trust the recognition results.

Features classification

In computer vision, a classifier is a computer algorithm that analyzes images and assigns them to predefined categories. Depending on whether or not there is human expertise guidance available, classification can be divided into unsupervised (no human expertise involved) or supervised (image annotation by human experts). Unsupervised classification employs algorithms to automatically identify patterns and structures in images without relying on pre-existing labels or training examples. Supervised classification requires a large amount of labeled training data to identify new, unlabeled images from species that are included in the reference database. Below, we only discuss the three main supervised classifiers based on the algorithm properties: statistical-based classifiers, rule-based classifiers, and perceptron classifiers.

Some data are simple enough to be classified using a linear function to assign images to categories (linear classifier), while other data are more complex and require non-linear classifiers to model the relationships between image features and the output categories. Support Vector Machine (SVM) (Cortes & Vapnik 1995; Table 1) is among the common statistical-based classifiers used in wood studies. This classifier achieves excellent separation of high-dimensional, non-linear data through a series of complex computations, which can reach high species recognition accuracy in wood identification (Rosa da Silva *et al.* 2017, 2022; Hwang *et al.* 2020b).

Classification can also be implemented by rules. The Decision Tree (DT) algorithms (Quinlan 1986; Salzberg 1994; Lewis 2000), which are composed of many 'if-else' rules to explain the classification principle, have good explainability due to the clear rules. Nevertheless, they are prone to overfitting, meaning that the accuracy is often artificially high, which makes DT not that convenient for wood recognition (Pan & Kudo 2011). Multiple decision trees can be combined to form a Random Forest (RF) (Ho 1998), which afterward, can be computationally strengthened via the AdaBoost algorithm that can improve the accuracy of weak classifiers by several orders of magnitude (Freund & Schapire 1997). Both RF and AdaBoost can be used to assess the importance of anatomical features based on their classification rules (Hwang *et al.* 2020a), and sometimes can even outperform SVM with respect to classification accuracy in wood identification studies (Sun *et al.* 2015).

Perceptron classifiers (Rosenblatt 1958) work by imitating how human brain neurons receive and process information. If a perceptron classifier initially obtains a wrong classification, it can adjust its parameters until it obtains the correct result. Stacking MultiLayer Perceptrons (MLP) (Werbos 1974) as a tool to build a classifier, also known as Artificial Neuron Network (ANN) classifier, forms the foundation of modern deep learning. However, ANN for wood recognition does not reach the high accuracies obtained by SVM (Yadav *et al.* 2013; Yuliastuti *et al.* 2013; Zhao *et al.* 2014; Zamri *et al.* 2016), because the full potential of ANN cannot be reached without high computational power and a suitable ANN network model.

To summarize, classifiers are applicable to wood classification, but some perform much better than others. Since the classifiers only classify the data into categories, i.e. species in case of image-to-species wood identification, they do not solve the unexplainability issue in wood recognition. In addition, classifiers are not designed to classify species that are not present in the reference database.

Deep learning-based wood recognition

During the last two decades, machine learning has entered the era of deep learning (LeCun *et al.* 2015) due to a combination of massive increase in data, rapid development of computer hardware (mainly GPU: Graphic Processing Units), and major advances in algorithms (Hinton & Salakhutdinov 2006). For instance, deep Convolutional Neural Networks (CNNs) exemplify a process where image features are initially extracted through mathematical convolution operations (Lecun *et al.* 1998). Subsequently, these features are input into a network structure comprising stacked layers of neurons, known for their deep architecture. Training this network through multiple rounds can result in more efficient feature extraction and enhanced classification accuracies compared to traditional machine learning methods (Lens *et al.* 2020). This superiority is attributed to the universal approximation capabilities inherent in neural networks, as established by Hornik *et al.* (1989, 1990) and Leshno *et al.* (1993).

The evolution of CNN structures includes various architectures such as the VGG series (Simonyan & Zisserman 2015), which emphasizes low-level features and simplicity for ease of implementation. The ResNet series (He *et al.* 2016) has gained prominence due to its ease of training, while the EfficientNet series (Tan & Le 2019) boasts fewer parameters yet remains effective in capturing features. However, CNNs are often viewed as black boxes, meaning it is difficult to understand the exact details (neuron parameters) of how the network arrived at its decision. In other words, it is difficult to interpret the thought process of the network as we lack an understanding of how it learns, extracts and classifies the features. Despite our incomplete knowledge of the process involved, humans can still assign a specific task to the algorithm to identify species based on the images (He *et al.* 2020; Lens *et al.* 2020).

In contrast to CNNs, the Vision Transformer (Vaswani *et al.* 2017) adopts a different strategy for feature extraction, treating image components similarly to how words are handled in Transformers designed for Natural Language Processing (NLP) (Dosovitskiy *et al.* 2021; Radford *et al.* 2021). Transformer is a neural network architecture that has achieved breakthroughs in ML-based NLP (e.g., ChatGPT). The Vision Transformer excels at capturing broader correlations in images compared to CNNs, particularly in the case of microscopic wood anatomical images. These images typically lack a prominent central object, but are characterized by intricate patterns composed of points, lines, edges, and so forth (Zhang *et al.* 2021).

Both supervised CNNs and Vision Transformers heavily depend on a priori data, which is typically available as labeled data provided by experts. These labels typically consist of a large amount of data, which is divided into a small number of categories. The commonly used dataset, ImageNet-1K (Deng *et al.* 2009), is a dataset of more than 1.2 million images consisting of 1000 common object categories with more than 1000 images per category. Microscope wood image datasets for ML recognition, however, are considerably smaller (as shown in Table 2). That is why the wood datasets require data augmentation, which involves generating smaller sub-images from the original image, as well as transfer learning, which makes training small datasets easier (Thrun & Pratt 2012). Recent CNN-based recognition systems for macroscopic images that trained image-to-species models by ImageNet transfer learning resulted in a series of successful applications (Ravindran *et al.* 2019; de Andrade *et al.* 2020; He *et al.* 2020; Ravindran *et al.* 2020, 2021, 2022a,b; Arévalo *et al.* 2021; Kirbas & Çifci 2022; Bello *et al.* 2023; and see Table 2).

In addition to the advancements in transfer learning for extracting features from wood images, one can leverage feature visualization techniques such as Class Activation Mapping (CAM) (Zhou *et al.* 2016), Gradient-weighted Class Activation Mapping (Grad-CAM) (Selvaraju *et al.* 2017), and Grad-CAM++ (Chattopadhyay *et al.* 2018). These techniques, commonly employed in computer vision and deep learning, aim to visualize the pixels or regions of an image that significantly contribute to a specific neural network's prediction for a particular class. Feature visualization produces a heatmap that accentuates areas pivotal to the neural network's prediction. Brighter regions indicate higher importance or activation for the predicted class, while darker regions are deemed less relevant. This visualization helps interpret the model's decision-making process and gains insights into the features or patterns the model uses for predictions (He *et al.* 2020). In other words, this tool allows wood anatomy experts to inspect the areas in the image that the image-to-species ML algorithms selected, which largely solves the issue of feature unexplainability in wood anatomy.

Too soon to celebrate — major bottlenecks of ml-based wood recognition

Although new DL methods are becoming more powerful and offer advantages compared to the more traditional ML methods, there are still several bottlenecks to overcome before obtaining an ML-based wood recognition pipeline that yields reliable accuracy rates for hundreds or thousands of timber species. There are two fundamental challenges we need to tackle. First and foremost, a new unified reference wood image dataset needs to be developed, containing a sufficient number of high-quality images (both within a single species and across species) from correctly identified species (linked to a herbarium voucher) to serve as a basis for all image-to-species ML studies. As long as the image-to-species reference database is far from complete, there will always be many tree species that are not in the database. This means that the ML algorithms will always have limited applications at a global scale without an inclusive database. As the original high-resolution images of wood anatomy cannot be directly fed to ML algorithms because of the current computational limitations, one way to increase the number of images per species is to generate smaller, preferably overlapping sub-images from the original images to avoid losing smaller-scale traits (Fabijańska *et al.* 2021; He *et al.* 2021; Yang *et al.* 2023; see also section on image acquisition). Another way we could increase the number of images is by incorporating images from all three orientation planes, rather than utilizing only one. While it is acknowledged that transverse section images generally exhibit superior accuracy (Barmpoutis *et al.* 2018; Figueroa-Mata *et al.* 2018; de Geus *et al.* 2020; Yang *et al.* 2023), longitudinal section images offer additional diagnostic features that help to identify species (Wheeler & Baas 1998; Gasson 2011; Lens *et al.* 2020; Wu *et al.* 2021; Rosa da Silva *et al.* 2022). Therefore, integrating images from all three orientations will enhance the effectiveness of ML identification (Kirbas & Çifci 2022). It is important, however, to always use precise orientation planes, especially for the radial planes, because a light deviation from the radial planes generates much shorter rays. Ultimately, filling the major gaps in this reference dataset, both in terms of number of images per species and number of species, will require a joint effort from all the major wood collection institutes in the world to digitize their microscopic slide collections and upload them in the same open-access cloud infrastructure (Lens *et al.* 2020). This will prove advantageous for CNN models and, notably, Vision Transformer models. The Transformer architecture, with its increased parameter count, necessitates a substantial volume of data — ranging from tens of thousands to even millions of images — for effective training, surpassing the requirements of CNNs.

A second challenge we need to overcome is that the fundamental principle of DL remains a black box. As explained before, heatmaps generated by visualization technology can be used to better understand how the DL model is actually working, which offers the chance for wood anatomy experts to validate the outcome of the model.

Towards a robust, GLOBAL wood identification pipeline

Recent developments in ML reveal promising solutions for current bottlenecks in wood recognition

Recent trends in ML show an ever-increasing demand for data that are generated by different techniques, which are referred to as multimodal data. Multimodal deep learning (Ramachandram & Taylor 2017) will likely become a game changer in wood recognition. This cutting-edge methodology may allow analyzing both macroscopic and microscopic images of wood from the same species along with the published wood description in the form of a text file. An interesting way forward may be the self-supervised learning model SimCLR (Chen *et al.* 2020), which has the potential to generate an automatic textual description for images, known as captioning. The downside of this model, though, is (1) that training data for image captioning should include captions, which entails significantly more effort compared to standard annotation tasks, and (2) SimCLR requires substantial computational resources. Another trend that will become more prominent in the near future is that ML algorithms will be able to directly process raw, high-resolution anatomical images due to the increasing computing power of GPUs (He *et al.* 2020).

From an annotation perspective, ML is developing from supervised learning (time-consuming annotation is required by wood anatomists) toward unsupervised learning (expert knowledge not required). The so-called contrast learning approach has made remarkable progress in recent years and states that annotation of data is not always necessary (Wu *et al.* 2018; van den Oord *et al.* 2019; Chen *et al.* 2020). This new self-supervised ML method does not require a large amount of well-labeled data and is considered a promising new development for future ML (Yeh *et al.*

2022), especially since these kinds of new methods have been proven to gain better recognition accuracy than those based on supervised learning (Chen *et al.* 2020). The common method of self-supervision is to process unsupervised data by introducing supervised signals from other modalities. For example, by using a large amount of text description information as a supervised signal from wood descriptions belonging to rare or endangered species that are poorly represented in reference image databases, more accurate recognition of these species may be achieved.

Another recent promising aspect of ML is the ability to recognize data not included in the reference database, called zero-shot learning (Pourpanah *et al.* 2022). Simply put, zero-shot learning allows computers to apply what they have learned from images in the reference database to images from unknown species outside the database, making them good at figuring out the unknown. Importantly, to achieve recognition of unknown categories of data outside the reference dataset, zero-shot learning requires pre-training on images that are highly relevant to the target classification, meaning that a large-scale wood image database is a prerequisite for this pre-training. Since these pre-training options are not possible for a global CVWID model, it has not yet been developed to such a level that it can be practically applied in wood identification, but the concept of this zero-shot learning approach has proven to be theoretically feasible (Fei-Fei *et al.* 2006).

In summary, in recent years, ML has moved toward larger models and unsupervised domains. By pre-training a large amount of unlabeled data and then performing transfer learning on a smaller dataset, it is possible to achieve more accurate results than the more traditional supervised methods. Regarding model architecture, Vision Transformer has better global feature extraction capability than CNN. Interestingly, Vision Transformer's intrinsic advantage of multimodal processing can lead to unprecedented applications in wood recognition by (1) identifying timber species that are not yet included in the reference database, and (2) by lowering the necessity of having a huge, well-labeled reference dataset with a substantial number of images per species for as many species as possible. Evidently, a high-quality, representative, global reference collection will always remain important for any future application in wood recognition.

Conclusions and suggestions for further research

In this ML-based wood identification paper, we discuss a number of traditional feature extraction and classifier algorithms that have been regularly used in wood identification studies, and state that they are often outcompeted by the more advanced deep learning methods that integrate feature extraction and classification in a complex mathematical way. Recent advances in DL methodologies and increased computational power offer unprecedented opportunities to improve wood recognition. Examples of important recent breakthroughs are, among others, (1) multimodal deep learning where different types of data (text in wood descriptions combined with digital images of wood sections or surfaces) can be integrated, (2) self-supervised contrast learning enabling wood recognition based on a largely unsupervised (i.e., not labeled or not annotated by wood anatomists) image dataset, 3) applying methodologies in ML models via image heatmaps that allow wood anatomists to link computer vision features with anatomical features, and 4) zero-shot learning with the potential to recognize species that are not included in the reference database. However, despite all these advances in image-to-species ML algorithms that assign an unknown wood image to the correct species name, we are still struggling to overcome the lack of one global, labelled, digital image reference database for thousands of timber species (Lens *et al.* 2020; Hwang & Sugiyama 2021; Verly Lopes *et al.* 2021; De Blaere *et al.* 2023). To further improve ML-based wood identification in a short time frame, we propose to focus on the following three aspects:

(1) One way to move CVWID forward is to build image-to-features ML model(s) that focuses on automatically detecting anatomical wood features as an intermediate step, and then employ a features-to-species search via for instance InsideWood (InsideWood 2004-onwards; Wheeler 2011; Wheeler *et al.* 2020). This can be achieved by re-labeling existing wood anatomical images to obtain suitable image datasets for most of the IAWA features (IAWA

Committee 1989, 2004). Or perhaps even better, we might combine the image-to-features ML model with the features-to-species model and develop a Feature Recognition AI (FRAI) in CVWID. The main advantage of this FRAI model over existing image-to-species ML models is that it does not rely on the existing incomplete species-based image reference databases, but instead would rely on (novel) trait-based reference image databases that easily allow more than 1000 images per trait for most IAWA features (Fig. 2). Therefore, this commentary paper shows that there is a strong theoretical basis for developing an image-to-features-to-species ML model with heatmap visualization that could be a promising new avenue to boost wood identification in the near future.

(2) More attention should be paid to the problem of 'feature incompatibility' since wood anatomists need to understand which parts in images are used for species recognition by machine learning. In addition to heatmaps generated by feature visualization, there are several ways to visualize traits. Some examples include exploring the potential of applying computer vision to extract anatomical features through the investigation of feature extraction methods like SIFT (a widely used local feature detection algorithm), studying the explainability of ML-based wood recognition methods such as CNN or Vision Transformer, examining the fitting ability of neural networks to recognize anatomical features of wood, and conducting mathematical modeling and evaluations to assess feature compatibility.

(3) Publicly available wood description and image data are an essential first step to further develop unsupervised recognition methods to also identify rare species for which there are insufficient wood samples available in collection institutes worldwide. More specifically, we can apply the principle of self-supervised multimodal contrast learning to further improve wood recognition, by combining descriptive text and images to increase the classification accuracy of unknown or poorly sampled species that are not necessarily included in the 'classical' image reference database. The vast amount of standardized wood anatomical descriptions contain a hidden treasure of information for ML methods, especially in the field of wood anatomy that reached a consensus about a standardized set of traits used to identify timbers (IAWA Committee 1989, 2004). Much of the older literature, published in journals or books that are inaccessible via the internet, will likely be unlocked by ongoing digitization efforts that make these wood anatomical descriptions applicable for global wood identification pipelines. At the same time, our IAWA community should take action to boost the creation of a global shared image dataset containing a sufficient number of high-quality images for each species for at least all the traded timbers. As suggested by Lens *et al.* (2020), this global image dataset can only be compiled in the coming years if the large wood collection institutes join forces and digitize their slide collection in an appropriate, standardized way. This global effort would boost the development of a reliable, global wood identification pipeline that should become freely accessible for all (non-) academic stakeholders in their endeavors to identify wood samples from past times (e.g. fossils, samples in archaeological sites or natural history collections), or to inspect modern imported logs that may have been illegally cut.

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