




# Computer Vision-Based Wood Identification: A Review

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**Abstract:** Wood identification is an important tool in many areas, from biology to cultural heritage. In the fight against illegal logging, it has a more necessary and impactful application. Identifying a wood sample to genus or species level is difficult, expensive and time-consuming, even when using the most recent methods, resulting in a growing need for a readily accessible and field-applicable method for scientific wood identification. Providing fast results and ease of use, computer vision-based technology is an economically accessible option currently applied to meet the demand for automated wood identification. However, despite the promising characteristics and accurate results of this method, it remains a niche research area in wood sciences and is little known in other fields of application such as cultural heritage. To share the results and applicability of computer vision-based wood identification, this paper reviews the most frequently cited and relevant published research based on computer vision and machine learning techniques, aiming to facilitate and promote the use of this technology in research and encourage its application among end-users who need quick and reliable results.

**Keywords:** computer vision; machine learning; deep learning; convolutional neural networks; image recognition; wood anatomy; wood identification; illegal logging



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## 1. Introduction

Illegal logging is one of the most pressing environmental issues, particularly in tropical countries with large forest areas and botanical groups that are highly valued in international markets. Illegal logging is currently the most profitable ecological crime worldwide, accounting for 10 to 30% of the global timber trade [1,2].

Although Amazonian forests are traditionally seen as the hotspot of illegal logging, areas such as Southeast Asia, Central Africa and Russia, home to roughly 60% of the world's forests, are unfortunately experiencing a surge in this crime [1,3]. The financial impact of illegal logging is estimated at 52 to 157 billion dollars a year [1], but, more importantly, the environmental damage, in many cases irreversible, can also have a global ecological impact [4].

Several institutional and international legal measures have been put in place to prevent overexploitation and irreversible loss of species and habitats [5–7]. Innovative programmes are emerging [8,9], solid research is under way [10–14], and research with significant impact and news items are being shared worldwide [15].

The impact of wood identification extends beyond illegal trading and ecological issues. Wood identification is paramount for the timber industry, civil and structural engineering, criminology, archaeology, art history, ethnography, and conservation and restoration, and many other disciplines.

Despite the multiple wood identification methods now available, the varied results, costs, accessibility, deployment time and limiting factors hinder their applicability to real-world identification. This paper presents an overview of the changes that have occurred in

wood identification methods and a review of computer vision-based wood identification, which is currently one of the fastest developing research areas in artificial intelligence (AI) with very promising results and high identification accuracy. In this technique, visual data are processed from any given image to extract the relevant features in order to make a decision.

### *Analogic and Digital Systems*

Historically, wood identification methods mainly comprised the study of chemical and physical and anatomical features aspects of wood. Methods such as macroscopy, which uses the physical characteristics of wood observable to the naked eye or with a 10× hand lens, and microscopy, which resorts to light compound microscopes to the observation of multiple cell typologies that constitute the wood, were the first to be used. The main limitation of these methods is that wood cannot always be identified at the species level. As a result, there has been an emergence of multiple techniques such as near-infrared spectroscopy [16–18], DNA barcoding [19–21], mass spectrometry [22–24], and X-ray tomography [25–27], with optical microscopy still used as a confirmation method for the results of these techniques.

However, an important contribution was made with the advent of computer-based technologies, which rapidly became a preferred option for constructing species databases and hosting identification tools. Several wood identification databases and software based on digital technology have been made available, including GUESS [28,29], CSIROID [30] and the DELTA system [31], three of the most significant early programmes in achieving the goal of wood identification. As a proof of concept, the importance of these systems was fundamental for the development of what is today defined as computer-assisted wood identification. The results they obtained made considerable progress compared to earlier methods, especially with regard to the time required and identification accuracy. The DELTA-Intkey for commercial timbers is the only one of these three systems still in use.

## **2. Online Reference Databases for Wood Identification**

This section briefly describes all the digital reference databases available online, to the best of our knowledge. The common objective of online identification keys is to enable and facilitate analysis of wood anatomical features and, ultimately, identification of the wood. Table 1 summarises the computer-assisted wood identification systems mentioned above.

### *2.1. Commercial Timbers: Descriptions, Illustrations, Identification and Information Retrieval*

Among the several DELTA-INTKEY online identification keys that have been developed, including CITESwoodID and Softwoods, this interactive identification key developed in 2000 and updated in 2018–2019 is an integrated database of microscopic descriptions and illustrations of 409 internationally traded hardwood taxa [32]. It covers major forest regions of the world and is freely available online.

### *2.2. Anatomy of European and North American Woods*

Created in 2000, this system includes 426 wood taxa [33] and provides an interactive identification key for the common non-commercial wood species of Europe and North America. It includes 325 hardwood species and 101 softwood species (native and introduced) with 145 features and 15 sets. It has two extra sets that isolate the features applicable to identification of modified and carbonised wood from palaeobotanical contexts. A useful feature, which is missing from the commercial timbers key, is a set that isolates the features extracted from the IAWA standards.

**Table 1.** Summary of computer-assisted wood identification systems.

Year	Name	Taxa	Area	Identification	Number of Images	Access	Comments	Reference
2000	Commercial timbers: descriptions, illustrations, identification, and information retrieval	404 hardwoods	Major forest regions of the world	Microscopic descriptions and illustrations	n.a.	Freely available	-	[32]
2000	Anatomy of European and North American Woods	325 hardwoods 101 softwoods	Europe and North America	Microscopic descriptions and illustrations	n.a.	Freely available	Includes features adapted to identification of carbonised woods from archaeological contexts	[33]
2003	Wood database of the Forestry and Forest Products Research Institute	781	Japan	Microscopic descriptions and illustrations	n.a.	Freely available	-	[34]
2004	InsideWood	7653 modern hardwoods; 235 modern softwoods; 2173 fossil hardwoods	Global	Microscopic descriptions and illustrations	58,146 modern hardwoods; 3807 fossil hardwoods; 1482 modern softwoods	Freely available	Includes 61,578 searchable images	[35]
2004	Wood anatomy of central European species	133 hardwoods and softwoods	Europe	Microscopic descriptions and illustrations	n.a.	Freely available	Includes macroscopic and microscopic images and descriptions	[36]
2005	CITESwoodID	44 CITES woods; 31 look-a-like species	Specific forest regions of the world	Macroscopic descriptions and illustrations	n.a.	Freely available	Includes abundant extra information	[37]
2005	Key to a Selection of Arid Australian Hardwoods and Softwoods	58 hardwoods and softwoods	Australia	Microscopic descriptions and illustrations	n.a.	Freely available	Detailed information about each species	[38]
2010	Brazilian Commercial Timbers	275 species	Brazil	Macroscopic features; chemical and physical tests	n.a.	Freely available	-	[39]
2011	Pl@ntwood	110 hardwoods	Amazonia	Microscopic descriptions and illustrations	n.a.	-	-	[40]
2013	Forest Species Database—Microscopic	112 hardwoods and softwoods	Tropical forests	Microscopic descriptions and illustrations	2240	Freely available	Includes 2240 searchable microscopic images	[41,42]

Table 1. Cont.

Year	Name	Taxa	Area	Identification	Number of Images	Access	Comments	Reference
2014	Forest Species Database—Macroscopic	41 hardwoods and softwoods	Brazil	Macroscopic descriptions and illustrations	2942	Freely available	Includes 2942 searchable macroscopic images	[43,44]
2016	MacroHOLZdata	150 hardwoods and softwoods	Global	Macroscopic descriptions and illustrations	n.a.	Free of charge on request	Available in English, German and Spanish	[45]
2018	Forest Species Classifier	112 hardwoods and softwoods 41 hardwoods and softwoods	Brazil	Macroscopic and microscopic illustrations	5182	Freely available Freely available	-	[46]
2018	Charcoal	44 hardwoods	Brazil	Microscopic features	528	Available for research only	-	[47]
2019	Charkey	507 hardwoods and softwoods	French Guiana	Microscopic descriptions and illustrations	n.a.	Freely available	Highly detailed SEM images	[48]
n.a.	Softwood Retrieval System for Coniferous Wood	180 softwoods	China	Microscopic descriptions and illustrations	≥1000	n.a.	Under development	[49]
2021	UTForest—UTFPR Classificador	44 hardwoods and softwoods	Brazil	Macroscopic descriptions	1318	Freely available	-	[50]
Under development	Mader app	n.a.	n.a.	Microscopic features	26,000	n.a.	Database with 1000 images per species	[51]

n.a.—not available.

### 2.3. Wood Database of the Forestry and Forest Products Research Institute

This online database created in 2003 focuses on the identification of 781 Japanese tree species, substantiating the descriptions on the IAWA list of hardwood features [52]. It includes a multiple-entry key and an image database and is freely available online [34].

### 2.4. InsideWood

Developed in 2004, InsideWood is by far the largest and best-known online identification key [35]. It is a multiple access key based on the IAWA hardwood list [52] and is freely available online. It includes keys for hardwoods, softwoods and fossil hardwoods, and more than 10,030 microscopic anatomic descriptions covering all regions of the world, with more than 63,435 searchable images. It is a centralised database that integrates all the anatomical data available for modern wood.

### 2.5. Wood Anatomy of Central European Species

This is a completely revised and updated version of Schweingruber's work [53], created in 2004 [36] and last updated in 2007. It is a web-based identification key with 133 species, accompanied by macroscopic and microscopic descriptions. It also provides information such as sample preparation, staining and other procedures, and is freely available online.

### 2.6. CITESwoodID

CITES (Convention on International Trade in Endangered Species of Wild Fauna and Flora) [54] is an agreement that was drawn up in 1963 after a meeting of members of IUCN (The World Conservation Union). One of many initiatives intended to contribute to the goals of the agreement, CITESwoodID was developed in 2005 [37] and last updated in 2017. As the name indicates, the platform focuses on CITES species and is an interactive identification key of macroscopic descriptions with an integrated database. It includes illustrations of 44 CITES protected woods and 31 look-a-like trade species. It provides comprehensive, detailed information about each species, with advice on how to avoid misinterpretations, and numerous explanatory notes of the relevant features and procedures for description and identification. It is freely available online.

### 2.7. Key to a Selection of Arid Australian Hardwoods and Softwoods

Stemming from doctoral research [38], this interactive key focuses on Australian woods. It is hosted on the Lucid website and includes 58 wood-producing species of arid Australia, particularly non-commercial species. It is mostly based on specimens from northeast South Australia, southwest Queensland and far western New South Wales and is freely available online.

### 2.8. Brazilian Commercial Timbers—Interactive Wood Identification Key

As the name suggests, this is an interactive identification system focusing on Brazilian species. Made available in 2010 [39], it was developed in collaboration with the Forest Products Laboratory (LFP) and the Brazilian Forest Service (SFB). It is hosted on the Lucid website and includes 275 species, among them Brazilian CITES-listed timber species. All the nomenclature was revised in 2020 according to the Brazilian Flora Species List. The key works by analysing macroscopic features and chemical and physical tests on the woods. It is freely available online.

### 2.9. Pl@ntwood

Pl@ntwood [40] was developed in 2011 and is described by the authors as an interactive graphical identification tool based on the IDAO system, specifically designed to be user friendly. It comprises 110 Amazonian tree species belonging to 34 angiosperm families and includes microscopic morphological features.

#### 2.10. *The Forest Species Database—Microscopy (FSDM)*

Created in 2013, this online database [41,42] comprises 2240 microscopic images of 112 species, 85 genera and 30 families of both hardwoods and softwoods. It is freely available online.

#### 2.11. *The Forest Species Database—Macroscopy (FSDM)*

This online database for forest species identification [43,44] was made available in 2014. It includes 2942 macroscopic images of 41 Brazilian forest species and is freely available online.

#### 2.12. *MacroHOLZdata*

MacroHOLZdata [45], created in 2002 and made available for the first time in 2016, is another interactive identification key with an integrated database for macroscopic wood descriptions. Completely redesigned in 2022, it is available in German, English and Spanish, and includes 150 common hardwood and softwood commercial timbers. The database is free of charge.

#### 2.13. *Forest Species Classifier*

Made available in 2018, Forest Species Classifier is the result of a master's degree [46]. It is a user-friendly online database focusing on Brazilian forest species. It uses macroscopic [43] and microscopic [41] databases and includes microscopic images of 112 species and macroscopic images of 41 species, with a total of 5182 images. It is freely available online.

#### 2.14. *UTForest—UTFPR Classificador*

This new version of the Forest Species Classifier platform [50] has been available since 2021. It allows macroscopic identification of 44 native species of Brazil and includes 1318 images.

#### 2.15. *Charcoal*

Developed in 2018, this database comprises charcoal samples of 44 Brazilian hardwood forest species, using 528 images [47,55]. It is available for research purposes only.

#### 2.16. *CharKey*

This 2019 electronic identification key is described by the authors [48] as the first computer-aided identification key designed for charcoals from French Guiana. It uses SEM photographs to illustrate the anatomical features of 507 species belonging to 274 genera and 71 families. Most of the descriptions were taken from D tienne et al. [56], and follow the IAWA list of microscopic features for hardwood identification [52]. The key contains 289 "items", and its main aim is to identify specimens to the genus level. It is freely available online.

#### 2.17. *Softwood Retrieval System (SRS) for Coniferous Wood*

The Softwood Retrieval System (SRS) for Coniferous Wood [49] is an online identification key with descriptions and micrographs of 180 Chinese coniferous wood species (155 species with descriptions and microphotographs and 25 species with only microphotographs) from nine families and more than 1000 images showing anatomical details. The system is searchable by an interactive multiple-entry key. The microphotographs were collected from slices of 115 coniferous species provided by the Wood Collection of the Chinese Academy of Forestry (Beijing, CAFw) and 40 coniferous species from the Herbarium of Southwest Forestry University (Kunming, SWFUw). The descriptions use features from the IAWA List of Microscopic Features for Softwood Identification [57]. The system supports three retrieval methods for coniferous wood retrieval: species name, anatomical characteristics, and microscopic anatomical images (in test).



### 2.18. Mader App

This mobile app is under development. Its goal is to contribute to the global wood identification effort and the fight against illegal logging using AI [51]. The project comprises 26 species, with a vast image database of 1000 images per species, aiming to obtain maximum intraspecific variability for each species. The images were taken using a portable microscope and the app aims to obtain real-time recognition of samples. Preliminary data from the authors indicate that accuracy is 95%. The authors intend to make the app available soon on the Play Store, and the database used will be freely available for neural network training [51].

## 3. Computer Vision-Based Wood Identification

The digital systems described above are the foundation of the systems which, despite their limitations, are currently used to identify wood, mostly based on computer vision technology. They are applicable to several fields of research and industry, including neurobiology, autonomous vehicles, and facial recognition. Computer vision systems process visual data from any given image or video to extract the required and relevant features to make a decision [58].

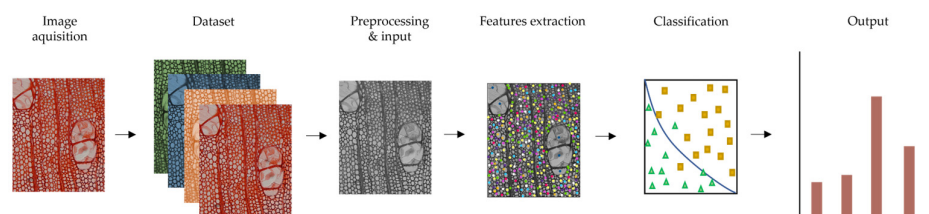
This image recognition ability, also known as image classification, is one of the most important research areas in AI and is most frequently based on supervised learning. In this case, the network is required to create a model that learns from labelled images to determine classification rules, then it classifies the input data based on these same rules (generally used for image classification). In the case of unsupervised learning, it is the model that obtains unknown information through unlabelled data (generally used for image clustering) [59].

Machine learning can also decide what to do without human assistance from the data recognised by computer vision (input data), using predesigned algorithms [60,61]. This removes the need to teach the model the necessary features or procedures for wood identification [62].

Computer vision technology is very appealing to many researchers because of its verifiable potential for field application [63] and proven ability to recognise and quantify wood structure variations that are not easily discernible using strictly “human” analysis. It is also an affordable resource [64] and, therefore, scalable. However, for the software to correctly interpret the specific architecture structure of the samples analysed to such a high level of precision, reference material must be constantly entered into the image database so that it can recognise natural variations in wood structure [12].

Computer vision-based wood identification is the real-world application of combining two types of software with different approaches within AI [65,66].

Figure 1 shows a pipeline of this method.



**Figure 1.** General scheme of machine learning method for image classification (based on [62,67]).

### 3.1. Machine Learning

Machine learning operates primarily as software that recognises patterns from input images that are processed to define a descriptive structure to which the unknown image will be referenced [68]. This involves various stages, as follows.

### 3.2. Image Acquisition

The most frequently used types of image are macroscopic images (obtained without magnification using a normal digital camera) [69–72], stereograms (stereoscopic images obtained with hand lens magnification, ca. 10×) [65,66,73–75], micrographs (optical microscopic images) [76–78], SEM images (up to 10,000×) [79], and X-ray computed tomography (CT) images [26,80].

Light control and uniformity are significant issues in image processing [66,81,82]. They include techniques that are used to filter and normalise image brightness [83–85].

### 3.3. Image Datasets

Image dataset construction or availability is one of the most significant factors among the multiple issues that can affect the performance of computer vision-based wood identification systems.

The more extensive the dataset is, the more naturally occurring biological variations within a species will be accessed and learned by the model. However, because constructing a dataset of wood samples is such a difficult and time-consuming task, most studies use wood collections for references [41,69,74,81,86–89].

This limitation is countered to some extent by initiatives such as ImageNet [90]. Aiming to advance computer vision and deep learning research, the ImageNet dataset was made freely available to researchers worldwide. It contains 14.2 million images across more than 20,000 classes. A similar process is under way with herbaria digitalisation [91–93]. However, despite the efforts made [42,78,87,94,95], the lack of free access to worldwide wood image datasets continues to be the main constraint for computer vision-based wood identification [62].

Table 2 shows the main currently available datasets that have useful data for computer vision-based wood identification research.

**Table 2.** Wood image datasets available for computer vision-based wood identification research, adapted from [62].

Dataset	Description	Image Type	Number of Species	Number of Images	Accessibility	Reference
CAIRO	Commercial hardwood species of Malaysia	Stereo	37	3700	Inaccessible	[96]
FRIM			52	5200		[97]
LignoIndo	Commercial hardwood species of Indonesia		809	4854		[98]
ZAFU WS 24	Wood species at Zhejiang A&F University		24	480		[75]
RMCA	Commercial wood species of Central Africa		77	1221		[78]
XDD	Major Fagaceae species of Japan	Micro	18	2449	Open	[87]
	Lauraceae species of East Asia		39	1658		[94]
WOOD-AUTH	Wood species of Greece	Macro	12	4272		[95]
UFPR	Wood species of Brazil		41	2942		[44]
UFPR		Micro	112	2240		[42]

### 3.4. Image Processing

Machine learning comprises two independent procedures: feature processing, also known as extraction (extraction of relevant features from input images), and classification (learning extracted features and querying image classification). There is, however, a previous step to image processing.

Pre-processing aims to convert the image into data that a specific algorithm can use to extract the required features, thus reducing computational complexity and facilitating subsequent processing [99]. The techniques used for this include greyscale conversion and image cropping [71,74,78,88,100,101], filtering [83,85], image sharpening [74,102] and denoising [79,103,104].



Another important pre-processing procedure is data splitting, where the dataset is split into subsets, most commonly training, validation, and test sets. Data splitting is ultimately used to create a training set, a validation set and a test set in order to later evaluate the model performance. To understand the reasons for these sets, one should think that machine learning systems mimic the human learning process based on examples. From this training set, the system will learn to generalise in order to correctly classify the images. The validation set is used to avoid the system learning the images “from memory” during this generalization process. Finally, the test set is used to check the reliability of the learning process. The use of these distinct data samples is one of the earliest pre-processing steps needed to evaluate any model’s performance.

More specifically, the system will interpret the images extracted from the designated training set as nothing more than a combination of pixels. Each pixel will have a specific intensity represented by a number, and in this way a matrix of numbers is formed. Image processing is based on extracting elements such as points, blobs, angles, corners and edges, and the patterns they form. Variability in the anatomy of each wood species is represented as patterns of distinct pixel intensities, arrangement, distribution, and aggregation. The variations detected by computer vision will be learned by machine learning. This process is the fundamental operating system of computer vision for all applications, including wood identification [62].

After the extracted features have been learned, a classification model is established by a classifier and a test set is formed to evaluate the system’s learning. The images are then input, allowing the classification model to complete the identification through feedback of the predicted classes of each image [62].

Computer vision detects and “sees” the input image using multiple feature extraction algorithms, while machine learning selects the types of features to be extracted, in most cases texture and local features.

Texture features work with the combination and arrangement of image elements (pixel intensities and resulting patterns) [65,74,96,102,105]. The most frequently used techniques are grey level co-occurrence matrix (GLCM), grey level aura matrix (GLAM), local binary pattern (LBP), higher local order autocorrelation (HLAC), and Gabor filter-based features (GFBB). Despite the individual capabilities of each technique, texture fusion of different types of texture features has shown superior classification accuracy [101,106,107].

Local features differ from texture features by not describing an image as a unit, but by describing significant and important specific features (keypoints) such as edges, corners or points. The most frequently used algorithms are scale-invariant feature transform (SIFT), speeded up robust features (SURF), oriented features-from-accelerated-segment-test (FAST) and rotated binary-robust-independent-elementary-feature (BRIEF) (ORB), and Accelerated-KAZE (AKAZE).

Beyond features typology, factors such as dimensionality reduction and feature selection are also important, as a large number of features extracted from an image can substantially reduce the computational efficiency of classification models. To achieve this balance, methods such as R AutoEncoder [108], principal component analysis (PCA), linear discriminant analysis (LDA), and genetic algorithms (GA) are used for dimension reduction of data sets [109].

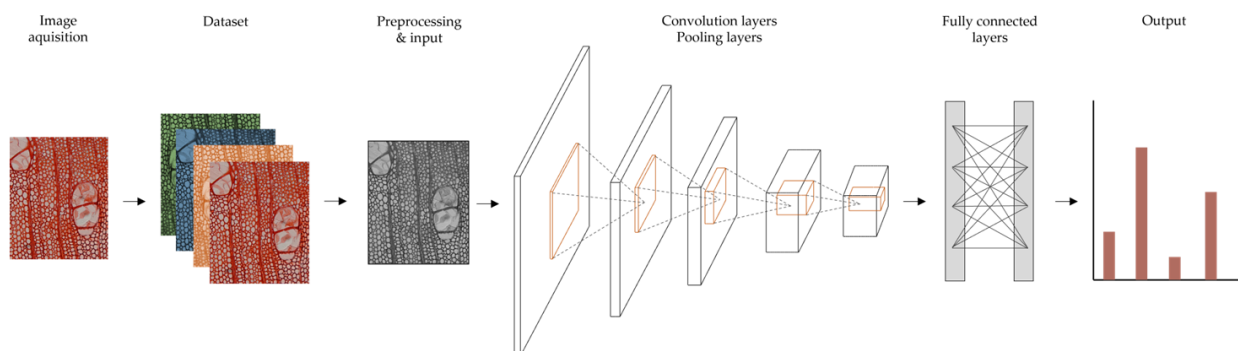
Another important element is the classification models created to learn the extracted features and establish classification rules. The most frequently used classifiers are k-nearest neighbours (k-NN), support vector machines (SVM), and artificial neural networks (ANN) [110,111]. These classification procedures can be executed either in on-site hardware [112] or on a cloud-based interface [89].

Machines can be easily misled by factors such as the source of images, which can be acquired in the field using mobile phones [89] or in a laboratory-controlled environment [70,113], and variables including different thicknesses, orientation, staining, digital artefacts and other variations, which is why many thin sections from historical wood collections are useful only to the trained human eye [10].

#### 4. Deep Learning

Deep learning is among the most notable and promising of the many branches of machine learning research.

As a neural network that attempts to simulate the function, structure and behaviour of the human brain (Figure 2), it has the capacity to process and “learn” large amounts of data [114,115].



**Figure 2.** General pipeline of deep learning models for image classification (based on [62,67]).

Its multiple different architectures include ANN [116], deep neural networks (DNN) [117], recurrent neural networks (RNN) [118], deep reinforcement learning (DRL) [119], and convolutional neural networks (CNN) [120]. The fields to which these have been applied are so vast that they are very difficult to summarise, but they include computer vision [121], forensic research [122], climate science [123], machine translation [124], classic literature [125] and bioinformatics [126], to name just a few.

Among these multiple architectures, it is mostly ANNs and CNNs that are applied to wood characterisation and identification.

Table 3 summarises this research and the applications of deep learning technologies.

##### 4.1. Artificial Neural Networks (ANN)

Artificial neural networks are not only one of the main investigation methods, but also constitute the foundation of deep learning [62]. These mathematical structures inspired by biological neural networks are a form of supervised or unsupervised learning that show high ability to learn from examples given to them and extrapolate the information when applied to future non-identified samples. This ability to reproduce, model and “learn” nonlinear processes has given ANNs widespread applications in multiple disciplines [78,116].

**Table 3.** Research and applications of deep learning technologies.

Reference	Database	Species Geographic Origin	Image Type	Section Type	Number of Species	Anatomically Similar Species	Number of Images	Image Analysis Program	Pre-Processing Images	Features Descriptor	Classifiers	CNN Model	Classification Accuracy
[127]	Samples from natural forests	Canary Islands (Spain)	Biometric data	Transverse Tangential Radial	2	Yes	n.a.	WinCell	PCA	n.a.	Feedforward multilayer perceptron network	n.a.	92.0%
[79]	No specific source	Global	SEM	Transverse	7	No	101	n.a.	LDA	GLCM	Multiple classification methods		Hardwoods vs. softwoods (LOOCV) 89%, (EVT) 93%. 7 species (LOOCV) 81%, (EVT) 80%.
[128]	Samples from natural forests	Turkey	Micro	Transverse Tangential Radial	3	Yes	n.a.	n.a.	n.a.	n.a.	SVM with linear kernel function	n.a.	95.2%
[77]	LWA-UFP	Brazil	Micro	n.a.	112	No	2240	n.a.	n.a.	GLCM LBP	SVM LBP	n.a.	SVM—98.6% LBP—86%
[129]	LWA-UFP	Brazil	Macro	Transverse	41	No	2050	n.a.	n.a.	LBP GF CLBP Colour-based features	SVM	3-ConvNeta	95.77%
			Micro		112	No	2240			LBP GLCM LPQ LPQ + GLCM	SVM		97.32%
[71]	LWA-UFP	Brazil	Macro	Transverse	41	No	2942	n.a.	n.a.	Texture fusion strategy	Two-level divide-and-conquer	n.a.	97.77%
[130]	Samples from natural forests	Iberian Peninsula	Biometric data	Transverse Tangential Radial	2	Yes	n.a.	WinCell	n.a.	Resilient backpropagation algorithm	Feedforward multilayer perceptron network	n.a.	81.2%
[131]	Samples from the timber industry	Korea	Macro	Transverse	5	Yes	33.730	n.a.	n.a.	n.a.	n.a.	LeNet3	99.3%
[78]	TXWD-RMCA	Democratic Republic of the Congo	Micro	Transverse	77	No	1221	CellB (version 3.2, Olympus)	GSC	LPQ LBP LDA	LDA KNN	n.a.	88% species level 89% genus level 90% family level

Table 3. Cont.

Reference	Database	Species Geographic Origin	Image Type	Section Type	Number of Species	Anatomically Similar Species	Number of Images	Image Analysis Program	Pre-Processing Images	Features Descriptor	Classifiers	CNN Model	Classification Accuracy
[86]	LWA-UFP	Brazil	Macro	Transverse	41	No	47,024	n.a.	IMAGE DATA GENERATOR class of KERAS	n.a.	n.a.	Resnet50	98.3%
[112]	SJRw; MADw; RBw	Central and South America, Africa	Stereo	Transverse	10	Yes	2303	n.a.	n.a.	n.a.	End-to-end trained image classifiers	VGG16	87.4%–97.5%
[47]	LWA-UFP	Brazil	Micro	Transverse	44	No	528	n.a.	n.a.	LBP	RF SVM	n.a.	93.9%
			Macro		41		2942			Inception_v3	n.a.	TL	95.7%
[132]	LWA-UFP	Brazil	Micro	Transverse	112	No	2240	n.a.	n.a.	n.a.	n.a.	n.a.	Scale dataset 100% Macroscopic dataset 98.73% Microscopic dataset 99.11%
[133]	Samples from the timber industry	Korea	Macro	Transverse Tangential	5	Yes	33,815	n.a.	n.a.	n.a.	n.a.	Multiple models ensemble	98%
[134]	FFPRI	Japan	NIR-HSI	Tangential Radial & between the two planes	38	No	n.a.	n.a.	n.a.	n.a.	n.a.	PCA	90.5%
[135]	SJRw; MADw; RBw	Central and South America	Micro	Transverse Tangential Radial	3	Yes	n.a.	n.a.	n.a.	n.a.	SVM	n.a.	91.4%
[136]	TXWD-RMCA; HNM; MADw; CM, Inc.; OSU; PV	Central America and Central Africa	DART-TOFMS	Slivers for metabolome profiling	10	No	n.a.	n.a.	Binning threshold	n.a.	RF	n.a.	82.2%
[73]	Samples from natural forests	Amazonia Atlantic region	Macro	Transverse	21	No	2000	n.a.	Adaphisteq	GLCM	SVM	n.a.	97.7%

Table 3. Cont.

Reference	Database	Species Geographic Origin	Image Type	Section Type	Number of Species	Anatomically Similar Species	Number of Images	Image Analysis Program	Pre-Processing Images	Features Descriptor	Classifiers	CNN Model	Classification Accuracy
[66]	TXWD-RMCA; HNM; MADw; CM, Inc.; OSU; PV	Central America and Central Africa	Stereo	Transverse	10	No	n.a.	n.a.	n.a.	n.a.	n.a.	ResNet34	Species level 81.9% Genus level 96.1%
[81]	DSB-FWRC	North America	Stereo	Transverse	10	No	1869	n.a.	n.a.	n.a.	n.a.	Inception V4_ResNetV2	92.6%
[137]	2012 ImageNet	Brazil	Stereo	Transverse Tangential Radial	281	No	n.a.	n.a.	n.a.	RiLPQ	kNN	DenseNet	98.8%
[69]	CVLO-CELOS	Suriname	Macro	Transverse	14	No	1.2 million	n.a.	Threshold	n.a.	n.a.	Inception-v3	98%
[76]	[76]	Neotropical regions	Micro	Transverse	112	No	2240	n.a.	n.a.	LBP	SVM	ResNet101	95.6%
[138]	Samples from Lumber yard	North America	Macro	Tangential	11	No	3158	n.a.	n.a.	n.a.	SGD optimizer Adam optimizer	ResNet-50 DenseNet-121 MobileNet-V2	98.2%
[139]	GACD	Global	XRF	Tangential Radial & in between the two planes	48	No	n.a.	n.a.	n.a.	n.a.	n.a.	1D CNN model	99%
[72]	Collected from trunks of leafing trees	Europe	Macro	Transverse	14	No	n.a.	n.a.	n.a.	Train set	n.a.	Residual convolutional encoder network	Wood patch classification—93% Wood core classification—98.7%
[140]	TXWD-RMCA	Democratic Republic of the Congo	Micro	Transverse Tangential Radial	77	No	n.a.	n.a.	GSC	LPQ	MVRF	n.a.	95%

n.a. not available. Institutions: CM, Inc.—Carlton McLendon, Inc.; CVLO-CELOS—Centrum voor Landbouwkundig Onderzoek/Centre for Agricultural Research in Suriname; DSB-FWRC—Department of Sustainable Bioproducts/Forest and Wildlife Research Center; FFPRI—Forestry and Forest Products Research Institute (Japan); GACD—Garman Art

Conservation Department, SUNY—Buffalo State; HNM—IB—Herbario Nacional de México; Instituto de Biología; LWA-UFP—Laboratory of Wood Anatomy at the Federal University of Parana; MADw—USDA Forest Products Laboratory Wood Collection of Madison, Wisconsin; OSU—Oregon State University; PV—Private vendor; RBw—Botanic Garden of Rio de Janeiro, Brazil; SJRW—Samuel J. Record Collection; TXWD-RMCA—Tervuren Xylarium Wood Database—Royal Museum for Central Africa. Models & Techniques: DART-TOFMS—Direct Analysis in Real Time, Time of Flight Mass Spectrometry; EVT—External validation test; GLCM—Grey level co-occurrence matrix; GSC—Grey scale conversion; kNN—k-nearest neighbours; LDA—linear discriminant analysis; LOOCV—Leave-one-out-cross-validation; MVRF—Multi-view random forest; PCA—Principal component analysis; RF—Random Forests; RiLPQ—Rotation Invariant Local Phase Quantisation; SGD optimizer—Stochastic gradient descent; SVM—Support vector machine; TL—Transfer learning; XRF—X-ray fluorescence spectrometry.



In the field of wood differentiation and identification, examples of research applying ANNs include:

- Esteban et al. [127] used a feedforward multilayer perceptron (MLP) network, which uses a similar structure to ANN to distinguish between *Juniperus cedrus* and *J. phoenicea* var. *canariensis*, obtaining a 92% probability of correctly differentiating the species;
- Mallik et al. [79] applied SEM to wood cross sections with 1500× magnification to obtain species-level identification through the shape, number, area and distribution of earlywood tracheids, processed by image segmentation, object recognition and statistical methods. Their results showed that when distinguishing between hardwoods and softwoods, a 0.89 accuracy was obtained using leave-one-out cross-validation and 0.93 using an external validation test (EVT), and when differentiating seven wood species, they obtained a 0.81 accuracy using one-leave-out cross-validation and 0.80 using an EVT;
- The same microscopic features analysis was applied by Martins et al. [77], who used microscopic transverse sections applying local phase quantisation (LPQ), local binary patterns (LBP) and grey-level co-occurrence matrix (GLOM) to identify Brazilian species. The process was applied to 112 species, 85 genera and 30 families, obtaining a recognition rate of 98.6% for differentiation of hardwoods and softwoods and 86% for discrimination of the 112 species;
- Turhan [128] used the SVM as a machine learning algorithm to differentiate *Salix alba*, *S. caprea* and *S. eleagnos*, obtaining a 95.2% success rate;
- Filho et al. [71] used a two-level divide-and-conquer classification strategy to differentiate 41 species of Brazilian flora, obtaining the highest accuracy level, of 97.77%;
- Esteban et al. [130] used a multilayer perceptron (MP) to differentiate *Pinus sylvestris* L. and *P. nigra* Arn subsp. *salzmannii* (Dunal) Franco, obtaining 81.2% accuracy in the testing set;
- Silva et al. [78] used microscopic images of cross sections of 77 commercial wood species from the Democratic Republic of the Congo for surface texture analysis, reporting 88% successful identifications at species level, 89% at genus level and 90% at family level.
- He et al. [135] applied machine learning classifiers SVM, Naive Bayes (NB), Decision Tree C5.0 and ANN) to discriminate between *Swietenia macrophylla* King, *S. mahagoni* (L.) Jacq and *S. humilis* Zucc. The best results were obtained with SVM, with an overall accuracy of 91.4%;
- Deklerck et al. [136] used machine learning not for image-based data processing, but for metabolome profile obtained through direct analysis in real-time (DART™) ionisation combined with time-of-flight mass spectrometry (TOFMS) to study the heartwood of 175 samples of 10 species of the *Meliaceae* family. Combining these techniques resulted in accuracy levels of 82.2%;
- de Andrade et al. [73] generated 2000 macroscopic images of 21 species using a smartphone and samples manually polished with a knife to replicate field conditions. A grey level co-occurrence matrix for the development of classifiers based on SVM was used, resulting in accuracies of 97.7%;
- Silva et al. [140] used 77 Congolese wood species as a reference base for applying a multi-view random forest (MVRF) model for species-level identification. To ensure information was not missed, the authors used images of the three anatomical planes. The results showed that the concatenation of features from the transverse and tangential planes clearly outperforms transverse-only analysis, while adding the radial plane minimally improves the results obtained. The use of the MVRF model outperformed concatenation of LPQ features. The results showed that the supplementary information added using three planes analysis and the model type considerably improve the final results. Moreover, when evaluating the performance of the systems developed, using the k-fold cross-validation scheme could have led to overestimation of the results, so the authors applied a leave-k-tree-out approach during cross-validation.

The results showed that implementing this approach dramatically decreased accuracy compared with traditional cross-validation schemes.

#### 4.2. Convolutional Neural Networks (CNN)

Convolutional neural networks are one of the most significant applications of ANNs. In the AI context, a CNN is a class of feedforward ANN that has been successfully applied to digital image processing analysis.

A CNN processes images more effectively by applying filtering techniques to ANNs [115]. This is a powerful and accurate way of solving classification problems, and CNNs are mainly credited for their role in image analysis, recognition, and classification. The architecture of a CNN typically has multiple layers between input and output: three convolutional layers, a pooling layer and a fully connected layer. These layers process different tasks during the image's course. As the images progress through the distinct layers, features such as edges, colours and shapes are extracted and interpreted. These features are then learned and classified by the deep neural network, resulting ultimately in the network's ability to identify a specific object [62,115,141]. Other advantages are the capacity of automatically recognise important features without human supervision.

CNNs have difficulty dealing with variance in the data presented, as tilted or rotated images. This results in a limitation to encode an object's orientation and position or process spatially invariant data.

Research examples applied to wood identification include:

- Hafemann et al. [129] applied the CNN model 3-ConvNeta to identify macro images of 41 species and micro images of 112 species. The results obtained 95.77% accuracy for macroscopic images and 97.32% accuracy for microscopic images;
- Kwon et al. [131] applied six LeNet and MiniVGGNet CNN models to identify five Korean softwood species (*Cryptomeria japonica*, *Chamaecyparis obtuse*, *Pinus koraiensis*, *P. densiflora*, *Larix kaempferi*), using an iPhone 7 camera to obtain macroscopic images of rough sawn surfaces from cross sections. Of all the CNN models tested, LeNet3 achieved the highest results and stability, with two extra layers added to the original LeNet architecture. The identification accuracy obtained was 99.3%. The authors reported that the software weight of the CNN created is small enough for installation on a mobile device such as a smartphone;
- Maintaining the objective of ensuring field applicability, Kwon et al. [133] acknowledged the real-world limitations of not including longitudinal wood surfaces. Using mobile device cameras to obtain macroscopic images, they applied a combination of models, obtaining the best results with LeNet2, LeNet3 and MiniVGGNet4. Their results showed an overall accuracy of 98% and an improvement on their earlier study, particularly in the case of *P. koraiensis* and *P. densiflora*;
- Figueroa-Mata et al. [86] applied deep convolutional networks for identification of 41 Brazilian forest species from xylotheque samples at species level, achieving an accuracy of 98.3%;
- Ravindran et al. [112] used CNNs to identify 10 neotropical species in the *Meliaceae* family (*Cabrlea canjerana*, *Carapa guianensis*, *Guarea glabra*, *G. grandifolia*, *Khaya ivorensis*, *K. senegalensis*, and the CITES-listed *Swietenia macrophylla*, *S. mahagoni*, *Cedrela fissilis*, and *C. odorata*), using only the transverse surface. The results showed an accuracy of 87.4 to 97.5%;
- To develop an automatic classification system for charcoal, Maruyama et al. [47] applied two LBP configurations of as texture descriptors. As state-of-the-art machine learning classifiers, SVM and random forests (RF) have shown the best results. Inception\_v3 CNN was applied for representation learning evaluation. The database comprised 44 charcoal samples from Brazilian native species from natural forests. The authors reported that both handcrafted features and RL achieved results of around 95% recognition rate;

- Oliveira et al. [132] used databases developed by Filho et al. [71] and Martins et al. [77] to access cross sections of 2942 wood macroscopic images of 41 species and 2240 microscopic images of 112 species, applying CNNs to create three models. Based on the results, the authors reported 100% recognition accuracy for the scale model, 98.73% for the macroscopic model, and 99.11% for the microscopic model;
- Kanayama et al. [134] applied a deep CNN approach to near-infrared hyperspectral imaging (NIR-HSI) using a principal component (PC) algorithm to identify 120 samples of 38 hardwood species. The results obtained showed 90.5% accuracy;
- A CNN was also used by Ravindran and Wiedenhoeft [66] to compare the macroscopic field identification programme XyloTron, using an ImageNet pre-trained ResNet34 CNN, with mass spectrometry to differentiate 10 *Meliaceae* species used by Deklerck et al. [136]. The results showed identification accuracy of 81.9% at the species level and 96.1% at the genus level compared to 74.9% and 91.4%, respectively, in the work by Deklerck et al. [136];
- Lopes et al. [81] applied the InceptionV4\_ResNetV2 CNN to analyse macroscopic images of the end-grain of 10 xylarium North American hardwood species, producing 1869 images using a smartphone fitted with a 14× macro lens. Their results showed an accuracy of 92.6%;
- de Geus et al. [137] applied the DenseNet CNN to recognise 281 species, using the largest dataset of microscopic transverse, radial and tangential images available at the time. Rotation invariant LPQ (RiLPQ) showed the best results of the feature descriptors used. The authors reported an identification accuracy of 98.8%;
- Olschofsky and Köhl [69] applied Inception-v3, an image classification model using a CNN for feature recognition and classification, pre-trained with 1.2 million images. The CITES-protected species *Cedrella odorata* was chosen and compared with 13 other tropical tree species for recognition. The results with the pre-trained CNNs had 98% accuracy, but when other tree species not used for training were added, the classification accuracy fell to 87%;
- The ResNet101 CNN, associated with an SVM as classifier, was applied by Lens et al. [76] to species-level identification of 112 mainly neotropical tree species, using only transverse sections but focusing on microscopic rather than macroscopic analysis. The results showed successful identification in 95.6% of cases;
- Wu et al. [138] applied deep convolutional neural networks (CNNs) for the identification of 11 rough saw hardwood North American species based on tangential plane images only. CNNs ResNet-50, DenseNet-121, as well as MobileNet-V2 were tested, resulting in an overall accuracy of 98.2%.
- Shugar et al. [139] combined X-ray fluorescence spectrometry (XRF) and a CNN to identify 48 wood specimens of both hardwoods and softwoods, mostly from heartwood and using either tangential or radial sections. They reported 99% identification accuracy from the 66 datasets;
- In the study by Fabijańska et al. [72], a CNN with residual connections was tested to identify 312 wood core scanned images of 14 European softwood and hardwood tree species, developing a wood patch classification and a wood core classification. The results showed that the proposed model correctly recognised patch images in 93% of cases and wood core images in 98.7%. Comparison of the results also showed that this model outperformed the state-of-the-art convolutional neural network-based model.

#### 4.3. Generative Adversarial Networks (GANs)

Within deep learning, GANs [142] are described as neural networks that can learn to generate realistic samples from the data on which they were trained.

They use a neural network as a generator that takes a random distribution of data as input and learns to map that information to output the desired distribution of data. A second neural network, known as a discriminator (a binary classifier), will use the input and output images to determine the probability of the image originating as a training image

(real) or on the generator (fake), thus assessing the most likely class to which the output image belongs [143].

Generative adversarial networks can produce highly realistic images using CNNs in an unsupervised manner [144]. Their application extends to multiple fields of scientific research, but they remain poorly explored in wood sciences [145–147].

- Addressing the possibility of eliminating economic and processing burdens in acquiring images of worldwide wood species for machine-learning training purposes, Lopes et al. [144] accessed 119 hardwood species references on the publicly available Xylarium Digital Database [87]. Applying a style-based GAN, they successfully generated highly realistic and anatomically meaningful synthetic microscopic cross-sectional images of hardwood species which they reported as virtually indistinguishable from real cross-sectional images.
- To evaluate the resemblance, quality and pattern evaluation between the synthetic and real cross sections, a structural similarity index measure (SSIM) and Fréchet inception distance (FID) were applied and a visual Turing test (VTT) was performed by wood anatomists to confirm the usefulness and realism of the GAN-generated images. The results showed that the artificially generated images were indistinguishable from real microscopic cross-sectional images.
- The authors [144] reported that it is even feasible to generate synthetic hybrids based on microscopic cross-sectional images from two parental species. This would have considerable implications on wood science and technology, especially for estimating the wood permeability, strength, density, or hydraulic potential, for example, of a species that has not even been planted.

## 5. Field Applicable Wood Identification Systems

One of the most interesting features of computer vision-based wood identification systems is their field application capability. Despite the consensus that it will be a long time before this technology becomes readily available not only to researchers and law enforcement bodies, but also the general public, it is evident that this goal is reachable. Programmes already developed or under development to respond to field application needs include:

### 5.1. MyWood-ID

Described as an automated wood identification mobile app [89], MyWood-ID uses a smartphone with a retrofitted macro lens and machine vision for macroscopic wood identification. The system uses a database of 20 species of timber native to Malaysia and provides a simple and effective way to acquire macroscopic wood digital images. The images are then uploaded to a cloud server via an internet connection for immediate identification results. It is intended to be cost-effective, easily accessible and intuitive, and to provide fast results.

These characteristics are evident when compared with other field deployable systems [64,74]. As differentiating features of their wood identification system, the authors cite its portability, lower initial cost, faster field deployment time, intuitive use, and continual online database update. However, it requires a constant internet connection for results and is operating-system-dependent (running only on iPhone 6 and 7). The main limitation of this system is the lack of consistent light control for wood image acquisition, although the authors indicate that this can be mitigated using the learning capability of a deep learning algorithm. The results achieved by this system have an accuracy of 96% to 98%. It is a paid app.

### 5.2. MyWood-Premium

This is an update of the previous app, developed by FRIM (Wood Anatomy Lab of Forest Research Institute Malaysia) and UTAR (Universiti Tunku Abdul Rahman) [148]. The updated version comprises a database of 100 wood species native to Malaysia. It is

available only on iPhone, iPod touch and Mac, and requires iOS 8.0 or later. It recommends the Ollo-clip™ Macro Lens with 21× magnification for optimum performance. It is a free app.

### 5.3. Xylorix

Another recent approach to rapid field wood identification is Xylorix [149,150], a platform that combines a suite of apps, tools and services. Xylorix Inspector is a wood identification mobile app that uses macroscopic features for automated identification. It is based on trained AI models to automatically identify the wood genus or species. However, a Xylorix WIDK-24X01 illuminated macro lens must be attached to the mobile phone camera for correct performance. It is available on either Apple iOS or Android operating systems and is supported by most mobile phones. Of the 24 species in the system database, 11 are free and the other 13 are paid.

### 5.4. XyloTron

XyloTron is a paid, open-source, image-based macroscopic field identification programme designed for wood and charcoal identification [64,151]. It features adjustable and controlled visible light, UV illumination capacity, and all the necessary software to control the device, capture images, and deploy the trained classification models.

It works by capturing high-quality images of wood or charcoal samples with visible or UV light. The identification accuracy for wood is described as 97.7%, increasing with the use of UV light to 99.1% (e.g., identification confusion between *Albizia* sp., fluorescent, and *Inga* sp., not fluorescent) and 98.7% for charcoal.

One limitation is that it is not a simple or easily deployable on-site system to use, because it requires a permanent connection to a laptop computer.

Ravindran and Wiedenhoeft [66] compared the performance of XyloTron and MS for species- and genus-level identification of 10 species of *Meliaceae*. The results showed a similar species-level accuracy of the XyloTron and MS models, but higher genus-level accuracy with XyloTron [66].

### 5.5. XyloPhone

To overcome visual aberrations (field distortion and spherical aberration), uncontrolled light sources, high prices, and a lack of real field applicability, Wiedenhoeft [82] proposed the XyloPhone. Described as an open-source, 3D-printed imaging attachment adaptable to virtually any smartphone for macroscopic image capture, it is a small, closed plastic box that provides a fixed focal distance, exclusion of ambient light, and a choice of visible or UV illumination. It is powered by a rechargeable external battery and a commercially available lens, making it affordable and, according to the author, providing comparable image quality to XyloTron.

To document features such as evenness of illumination, distortion, maximum resolution, and spherical aberration, the author compared the XyloPhone + iPhone (XPi), the XyloPhone + Samsung (XPs), the Ollo Clip 14× + iPhone (OCi), and the Xylorix + iPhone, with two distinct configurations. He reported that XyloPhone's optical performance, especially when used with more recent smartphones, is clearly superior to the lenses/lighting arrays of other systems [82].

### 5.6. WIDER

WIDER is a battery-charged portable system that uses spectroscopy measurement and machine-learning-based identification software. It comprises a database of 15 species and the authors [152] reported accuracy results of 95%. It is part of a larger project that was completed in 2021 and brought into use by USAID PEER Cycle 8 (Development of Wood Identification System and Timber Tracking Database to Support Legal Trade). The same project developed the ECVT 4D Dynamic [152] technology for monitoring tree physiological processes.



### 5.7. IMAIapp

IMAIapp [153] is a wood identification mobile app that uses a lens attached to a smartphone. Its purpose is to use convolutional neural networks (CNN) capable of carrying out timber identification through machine learning of macroscopic elements observed in photo enlargements. The difficulty of the problem lies in the number of classes that the method is required to recognise automatically, from a total of 400 wood species and a high number of macroscopic images. EfficientNet architecture is enhanced by a novel approach for pre-processing that combines computer vision and data augmentation techniques applied to the original dataset. The use of classification models based on deep learning is the leading technique with the best performance at present, and the innovative approach to increase the quality of the training data makes the model integrated in IMAIapp robust to rotation, illumination and zoom invariants. This means the app can be used in the field. Using TensorFlow Lite libraries for Apple and Google platforms, the application works standalone, is 100% executable from the mobile device and does not require a connection to the Internet. IMAIapp is therefore a design using an edge-computing method that is intended to avoid computing constraints on the mobile device on which it is installed. The project is under development and the app will be free for Android and iOS.

## 6. Discussion

In the last 100 years, what we now call the traditional wood identification method based on anatomical descriptions has followed well defined, standardised features to successfully distinguish and identify the multiple families, genera and species of angiosperm and gymnosperm trees. However, despite the many positive aspects of this method, it is now evident that it is reaching its limit.

The main limitations are the identification uncertainty at species level, the time-consuming methodology, the lack of anatomists with the necessary training for the task, and the associated costs of these professionals, mainly when on-site identifications are required. These limitations have a notable impact on the type of monitoring that can be carried out, e.g., in the fight against illegal logging. Faster, more accurate and economically scalable methods are urgently needed.

As a valuable response to this need, the results obtained so far by computer vision-based identification (CVBI) of wood and, in particular, deep learning approaches, clearly demonstrate that this method has enormous potential for wood identification and quantitative wood anatomy.

Despite the many obstacles remaining, this method is steadily adapting to overcome limitations such as inter- and intra-anatomical variability, high anatomical resemblance, non-homogeneous illumination, staining or deformed samples, and limited image databases, among many other issues.

Of all the resources discussed, deep learning appears to be the most significant and promising solution in AI developments, and CNN models applied to wood sciences are one of the leading and most rapidly evolving systems. CNNs have exhibited a notably more efficient capacity and accuracy for quantitative wood anatomy and feature recognition, alongside computer cost reduction.

Field-deployable identification systems appear to be the most important and impactful option in computer vision-based wood identification. This resource, based on advances in communication technologies, will enable more prolific, increasingly accurate and faster screening by authorities without human prejudice, particularly with regard to illegal timber and charcoal trading.

Computer vision-based identification technology could become one of the most effective and unavoidable weapons in the fight against the illegal timber and charcoal trade, as it enables individuals who are untrained in traditional identification to obtain highly accurate and legally binding identifications on the spot.

The multiple future contributions of the technologies underpinning CVBI for wood sciences are difficult to fully envision at present. However, it is of utmost importance to



overcome or at least mitigate the limitations that are severely hampering the development and implementation of these systems.

Two of the most pressing issues are the limited number of digital databases, which are specific to geographically restricted areas/species or inaccessible to the global research community, and the lack of extensive field testing and verification hindering the accuracy quantification of the systems.

The most urgent actions required are the construction of a freely accessible global digital wood image database, the availability of this tool in a cloud-based system for access everywhere, by everyone, and priority inclusion of CITES-listed species and their look-a-likes.

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