Deep learning approaches for accurate wood species recognition

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ABSTRACT

Wood species identification is a crucial task in various industries, including forestry, woodworking, and conservation. Traditional methods rely on manual expertise, which can be time-consuming and error prone. Hence, an automatic wood species recognition system is developed in this study using deep learning (DL) models. In this study, three deep convolutional neural network (CNN) architectures, SqueezeNet, GoogLeNet, and ResNet-50 was tailored for wood species classification. The accuracy of the DL models was evaluated in recognizing fifty different wood species. Additionally, the wood species images were altered using JPEG Compression, Gaussian Blur, Salt and Pepper, and Speckle noises to assess the models' performance in identifying the wood species from the distorted images. Results show that the ResNET-50 based wood recognition system is the most accurate model to recognise the wood species. The implications of this research extend to forestry management, quality control in woodworking industries, and the preservation of endangered wood species in conservation efforts.

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1. INTRODUCTION

Wood is extensively utilized in the production of furniture, structures, and paper products. Various varieties of wood possess distinct features in terms of their origin, thickness, coloration, and texture. The various attributes of these qualities play a significant role in determining their optimal applications and economic worth. Misclassification may result in monetary losses due to the differences in the value and properties of each wood species [1], [2]. The selection of the appropriate wood species and quality is of utmost importance in construction, as it significantly impacts the materials utilized for constructing a roof truss. The utilization of inferior timber may result in the instability of the entire roof structure, potentially culminating in a disaster. Likewise, a range of wooden products, including furniture, requires the use of wood materials that meet specific quality standards [3]. Moreover, accurate species identification is crucial for the conservation of plant life [4], [5]. Despite international agreements, it has been found that some imported woods, such as rosewood (Dalbergia) and ebony (Diospyros), are still illegally logged [5]. Although the Convention on International Trade in Endangered Species of Wild Fauna and Flora (CITES) requires permits to trade these species, regulating the logging trade remains challenging. Various tactics such as swapping the wood species labels, mixing the endangered with other woods and forged permits are employed to trade the illegally logged wood [5]. Therefore, it is important to identify various wood species precisely [6]. Conventionally, trained human professionals are hired to recognise the wood species manually using botanical or dendrological characterization, as well as macroscopic and microscopic anatomical analysis [7]–[9] However, eye strain or lapses in concentration during manual visual inspections can lead to wood misclassification, causing substantial financial losses [4], [10], [11]. The advancement of technology has supported the work of humans that used to examine timber manually. The potential for error reduction can be achieved through the implementation of automated vision recognition systems on wood species. Moreover, the system can be used by various people, not only certain expertized people on wood but also beginners in the world of forestry.

The emergence of machine vision and image processing technologies presents a promising avenue for automating the wood identification process and improving its accuracy and efficiency. Recent research has explored the application of various image processing techniques and machine learning (ML) algorithms to the problem of wood species recognition. Computer vision-based wood identification systems have been developed that utilize expert knowledge of wood anatomy to detect and extract relevant features from images. These features, such as the patterns of wood grain, vessel distribution, and cellular structure, are then used to train classification models to recognize different wood species.

In general, wood species recognition system can be divided systematically into conventional ML and deep learning (DL). In conventional ML, feature extraction and classification are separate processes. Feature extraction involves identifying important features from images, while classification involves learning these features and categorizing query images [12]. One such approach is the use of histogram of oriented gradient (HOG) features proposed by Sugiarto *et al.* [13] to capture the textural characteristics of wood samples, coupled with support vector machine (SVM) classifiers to categorize the wood species. Tou *et al.* [14] and Khalid *et al.* [15] proposed a wood recognition system which extracted the grey-level co-occurrence matrices (GLCM) features and classified the features using the multi-layer perceptron (MLP) technique [15], [16]. Khalid [16] proposed wood identification algorithm that extracted wood features using basic grey level aura matrix (BGLAM) and statistical properties of pores distribution (SPPD) techniques, then the features were classified using the linear discriminant analysis (LDA) and k-nearest neighbour (KNN) models. Recently, Yang *et al.* [17] had used the ML approach for wood species recognition by extracting wood features using local binary pattern (LBP) and GLCM techniques and these features were then classified using back propagation neural network (BPNN) and SVM models. However, these traditional ML approaches often require significant domain expertise and manual feature engineering, which can be time-consuming and labour-intensive. To overcome the limitations of traditional ML, researchers have also explored the use of DL for wood species recognition [12].

DL models, such as convolutional neural networks (CNNs), can automatically learn relevant features from image data without the need for manual feature engineering. These DL models have shown promising results in accurately recognizing wood species from images, outperforming traditional ML approaches. Several studies had proposed ResNet based model for wood species recognition [18]–[21]. Lens *et al*. [22] had proposed GoogLeNet, Alexnet, Visual Geometry Group (VGG) models to identify the wood species. Recently, Bello *et al*. [23] proposed wood species identification system using hybrid method which is Mask RCNN-ResNet approach. Based on these studies, the use of DL-based systems shows promising results in microscopic wood identification, particularly for the analysis of fibrous materials. Therefore, in this paper, three DL models namely, SqueezeNet, GoogLeNet, and ResNet-50 are investigated in terms of their accuracy in recognising the 50 wood species. Furthermore, these wood species were then distorted with JPEG Compression, Gaussian Blur, Salt and Pepper, and Speckle noises to examine the accuracy of these three DL models in identifying distorted wood images.

2. METHOD

The DL-based wood species recognition system comprises several steps, which are data input, training, testing, and output as shown in Figure 1. Firstly, wood images database will be generated, and it will be used as the input for both training and testing. The dataset will be trained using DL models, namely SqueezeNet, GoogLeNet, and ResNet-50 on MATLAB 2023a with different ‘Epoch’, ‘Batch Size’, and ‘Learning Rate’ settings. Testing will then be done to check the accuracy of the models with variations of settings. Lastly, the accuracy of the tested models will be compared.

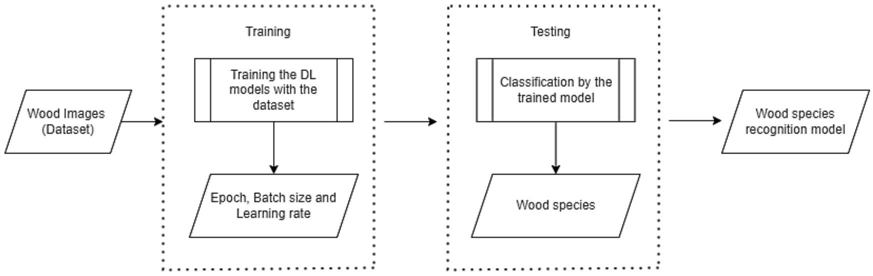

Figure 1. Flow diagram of the DL-based wood recognition system

In the context of a DL-based wood recognition system, training and testing databases are critical for constructing an accurate and robust model [24]. In this study, the database was generated using 50 different wood species images obtained from a public wood database: https://www.wood-database.com/ [25]. The 50 wood species are Bulnesia arborea, Euxylophora paraensis, Julbernardia pellegriniana, Dalbergia retusa, Berchemia zeyheri, Borassus flabellifer, Juglans cinerea, Carya tomentosa, Diospyros malabarica, Dipteryx odorata, Entandrophragma cylindricum, Eucalyptus camaldulensis, Fraxinus nigra, Dalbergia cultrate, Guibourtia ehie, Gleditsia triacanthos, Hardwickia binate, Hevea brasiliensis, Ilex opaca, Ilex mitis, Libidibia paraguariensis, Pouteria spp., Krugiodendron ferreum, Koompassia malaccensis, Laburnum anagyroides, Liriodendron tulipifera, Magnolia grandiflora, Swartzia spp., Nothofagus cunninghamii, Notholithocarpus densiflorus, Ostrya virginiana, Olneya tesota, Cordia alliodora, Paulownia tomentosa, Quercus velutina, Dipterocarpus spp., Roupala montana, Senna siamea, Swartzia cubensis, Turraeanthus africanus, Tilia americana, Ulmus americana, Umbellularia californica, Vouacapoua americana, Vachellia erioloba, Weinmannia trichosperma, Zygia racemosa, Zanthoxylum flavum, Diospyros virginiana and Oxandra lanceolata. Each wood species is distorted using different distortion methods such as Gaussian White Noise, Salt and Pepper, Speckle, Gaussian Blur, Motion Blur, and JPEG compression at five levels. Table 1 explains the five levels of the distortions applied to the wood images. Eventually, there are a total of 1,800 images for the wood images dataset which comprises of 50 original (noiseless) and 1,750 distorted wood species images. Figures 2(a) and (b) show samples of original and distorted images in the dataset. The images are labelled with their respective species names by storing the original image and distorted images of each species in a respective folder. As there are 50 species, the dataset consists of fifty folders in total.

Table 1. Explanation of distortions applied

Distortion type	Distortion levels
Gaussian white noise	Mean, m=0.01, 0.02, 0.03, 0.04, and 0.05.
Salt and pepper	Noise density, d=0.01, 0.02, 0.03, 0.04, and 0.05.
Speckle	Variance, v=0.1,0.2,0.3,0.4, and 0.5.
Gaussian blur	standard deviation, σ=0.5,1.0,1.5,2.0, and 2.5.
Motion blur	length of the motion, len=2,4,6,8, and 10 with the angle of motion in degrees in a counterclockwise direction, θ=0. and (len, θ)=(2,36), (4,72), (6,108), (8, 144) and (10, 180).
Jpeg compression	Quality factor=10, 20, 30, 40, and 50.

Three DL architectures, SqueezeNet, GoogLeNet, and ResNet-50 are trained to recognise the wood species using MATLAB 2023a software in this study. SqueezeNet [26], GoogLeNet [27], and ResNet-50 [28] are CNN models with a depth of 18, 22, and 50 layers, respectively. The input sizes of the three architectures are also different where GoogLeNet and ResNet-50 have an input size of 224×224, while SqueezeNet has an input size of 227×227. Table 2 explains the DL based architecture used in this study.

There are several steps to train the models in MATLAB 2023a. Firstly, the respective DL model on deep network designer [29] is chosen. Then, the architecture of the selected model needs to be fine-tuned by replacing the fully connected layers of the pre-trained models with new layers to accommodate the training class to fifty since there are fifty wood species. Next, the wood image dataset is loaded into the model and the dataset is split randomly into 70% for training, 30% for testing and 80 % training, 20% for testing. Then, training parameters such as learning rate, batch size, and epoch were set. In this study, four sets of training parameters are used to identify the most suitable parameters to recognise the wood species accurately. The training parameter sets used in this study are shown in Table 3. The performance of the trained model is evaluated based on the accuracy rate of the model trained with these parameters.

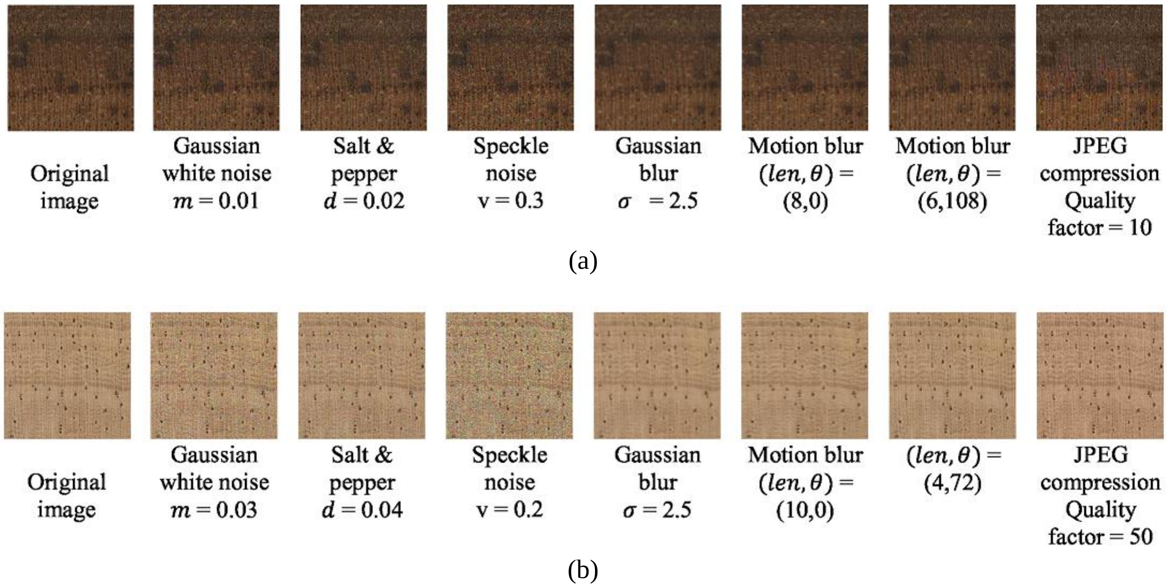

Figure 2. Sample of original image and distorted images of; (a) Hardwickia binate and (b) Hevea brasiliensis

Table 2. Explanation on DL models

DL model	Explanation
SqueezeNet	A small CNN architecture where it is 510 times smaller than AlexNet and requires 50 times fewer parameters compared to AlexNet [26]. The layers of this model are input layer, convolution layer, fire modules such as squeeze layer and expand layer, pooling layers, final convolution layer, dropout layer, and output layer.
GoogLeNet	Each module has bottleneck and parallel convolutional filters to boost computing efficiency and decrease input detections. A deeper network compared to AlexNet that has 12 times less parameters [27]. The layers of this model are input layers, inception blocks such as 1x1, 3x3, and 5x5 convolution branches, and max pooling branch, pooling layers, and final layers.
ResNet-50	Popular backbone that performs well for a variety of tasks, such as instance segmentation and object detection; residual block and skip connection designs that enable effective optimisation even with very deep networks [28]. The layers of this model are input layer, convolution layer, max pooling layer, residual blocks, average pooling layer, fully connected layer, softmax layer, and output layer.

Table 3. Training parameter set

Training set	Parameters		
	Epoch	Batch size	Learning rate
1	50	16	0.001
2	100	16	0.0001
3	100	16	0.001
4	100	32	0.001

3. RESULTS AND DISCUSSION

3.1. Performance of the deep learning architectures

In this study, three DL architectures, SqueezeNet, GoogLeNet, and ResNet-50 were trained with four sets of training parameters (epoch, batch size and learning rate) to recognise the wood species automatically. This forms twelve DL models and their performance was evaluated in terms of accuracy rate of the wood species recognition. Tables 4 and 5 depict the accuracy of the twelve models for 70% training, 30% testing and 80% training, 20% testing, respectively. The average accuracy of the SqueezeNet, GoogLeNet and ResNet-50 models for 70% training, 30% testing are 98.25, 99.21 and 99.63 while for 80% training, 20% testing, the average accuracy was recorded as 99.38, 99.76, and 99.82, respectively. This shows that the accuracy rate for all the twelve models is higher when more dataset is used to train the models. However, the time taken for the training is longer for 80% training set compared to 70% training set. The accuracy of the model ranges from 98 to 99% which also shows that they are capable to recognise the wood species accurately even with the images being distorted. Nevertheless, with an accuracy of nearly 100%, ResNet-50 surpassed SqueezeNet and GoogLeNet, according to Tables 4 and 5 accuracy data. As a result, in comparison to the other two architectures, ResNet-50 is the best architecture for identifying wood species. In contrast to SqueezeNet and GoogLeNet, ResNet-50 requires more training time because of its deeper model than the other two. Twelve DL models employed in this study which obtained the highest accuracy rate of were compared with the state-of-the-art DL model-based wood species recognition systems and the data is presented in Table 6. All the twelve trained models were pre-trained using 80% and 20% of training and testing wood species datasets, respectively. Based on the data shown in Table 6, none of the state-of-the-art models were trained and tested with distorted wood species images and their accuracy rate is also lower compared to the accuracy rate of DL models trained in this study.

Table 4. Accuracy of the trained DL model and time taken to train the models for 70% training and 30% testing dataset splitting

Model	SqueezeNet				GoogLeNet				ResNet-50			
Epoch	50	100	100	100	50	100	100	100	50	100	100	100
Batch size	16	16	16	32	16	16	16	32	16	16	16	32
Learning rate	0.001	0.0001	0.001	0.001	0.001	0.0001	0.001	0.001	0.001	0.0001	0.001	0.001
Accuracy (%)	98.09	98.09	98.09	98.73	99.27	99.10	99.20	99.27	99.80	99.09	99.82	99.82
Error (%)	1.91	1.91	1.91	1.27	0.73	0.90	0.80	0.73	0.20	0.91	0.18	0.18
Time taken (minutes)	7.37	13.22	13.02	11.62	8.92	17.67	18.50	14.63	13.70	28.73	28.07	27.15

Table 5. Accuracy of the trained DL model and time taken to train the models for 80% training and 20% testing dataset splitting

Model	SqueezeNet				GoogLeNet				ResNet-50			
Epoch	50	100	100	100	50	100	100	100	50	100	100	100
Batch size	16	16	16	32	16	16	16	32	16	16	16	32
Learning rate	0.001	0.0001	0.001	0.001	0.001	0.0001	0.001	0.001	0.001	0.0001	0.001	0.001
Accuracy (%)	99.71	98.29	99.71	99.82	99.80	99.71	99.71	99.80	99.83	99.80	99.83	99.83
Error (%)	0.29	1.71	0.29	0.18	0.20	0.29	0.29	0.20	0.17	0.20	0.17	0.17
Time taken (minutes)	7.63	15.40	14.58	13.48	10.87	20.85	19.88	16.52	17.38	32.40	32.60	33.10

Table 6. Comparison of the DL architecture used in this study with the state-of-the-art DL models-based wood species recognition system

DL-model	Trained with distorted images	Tested with distorted images	Accuracy rate (%)	Error (%)
3-ConvNet [30]	No	No	95.80	4.20
LeNet [31]	No	No	99.30	0.70
ResNet101 [22]	No	No	96.40	3.60
Residual convolutional encoder network [19]	No	No	98.70	1.30
InceptionV4_ResNetV2 [32]	No	No	92.60	7.40
DenseNet [33]	No	No	98.80	1.20
VGG16 [34]	No	No	88.70	11.30
MobileNetV2 [35]	No	No	98.13	1.87
Densenet121 [35]	No	No	99.52	0.48
SqueezeNet (epoch=50, batch size=16, learning rate=0.001)	Yes	Yes	99.71	0.29
SqueezeNet (epoch=100, batch size=16, learning rate=0.0001)	Yes	Yes	98.29	1.71
SqueezeNet (epoch=100, batch size=16, learning rate=0.001)	Yes	Yes	99.71	0.29
SqueezeNet (epoch=100, batch size=32, learning rate=0.001)	Yes	Yes	99.82	0.18
GoogLeNet (epoch=50, batch size=16, learning rate=0.001)	Yes	Yes	99.80	0.20
GoogLeNet (epoch=100, batch size=16, learning rate=0.0001)	Yes	Yes	99.71	0.29
GoogLeNet (epoch=100, batch size=16, learning rate=0.001)	Yes	Yes	99.71	0.29
GoogLeNet (epoch=100, batch size=32, learning rate=0.001)	Yes	Yes	99.80	0.20
ResNet-50 (epoch=50, batch size=16, learning rate=0.001)	Yes	Yes	99.83	0.17
ResNet-50 (epoch=100, batch size=16, learning rate=0.0001)	Yes	Yes	99.8	0.20
ResNet-50 (epoch=100, batch size=16, learning rate=0.001)	Yes	Yes	99.83	0.17
ResNet-50 (epoch=100, batch size=32, learning rate=0.001)	Yes	Yes	99.83	0.17

3.2. Performance of the proposed deep learning based wood species recognition system

The accuracy rate of the trained models was further examined using fifteen wood images which comprises of Bulnesia arboreea, Euxylophora paraensis, Julbernardia pellegriniana, Dalbergia retusa and Berchemia zeyheri wood species images which were distorted randomly by one of the distortion types, Gaussian White Noise, Salt and Pepper, Speckle, Gaussian Blur and JPEG compression at different level compared to the one used to generate the training and testing dataset. For this task, six models were chosen out of twelve trained models based on their higher accuracy rate (around 99.8%) in Table 6. The six models were: i) SqueezeNet (Epoch=100, Batch size=32 and Learning rate=0.001), ii) GoogLeNet (Epoch=50, Batch size=16 and Learning rate=0.001), iii) GoogLeNet (Epoch=100, Batch size=32 and Learning rate=0.001), iv) ResNet-50 (Epoch=50, Batch size=16 and Learning rate=0.001), v) ResNet-50 (Epoch=100, Batch size=16 and Learning rate=0.001), vi) ResNet-50 (Epoch=100, Batch size=32 and Learning rate=0.001). The image quality of the fifteen images were evaluated using a well-known Image Quality Assessment (IQA) metric, Feature Similarity Index Metric ($FSIM_c$) [36]. $FSIM_c$ computes the quality score based on the features similarity between the test and its reference images. In this case, the reference image is a noiseless image which refers to the original wood image and test images are the fifteen distorted wood images. The $FSIM_c$ score ranges between 0 to 1 where a high FSIM value denotes great similarity between images, implying that the test image is having a high image quality as the original image. A low FSIM value, on the other hand, suggests that the test image is not as high quality as the original image. Table 7 displays the accuracy rate attained from the trained models. Referring to Table 7, the ResNet-50 model trained with Epoch=50, Batch size=16 and Learning rate=0.001 recorded the highest recognition accuracy, which is 96.38%, with the SqueezeNet model having the lowest accuracy rating of 87.80% when compared to the other models. This demonstrated once more that the distorted wood species images could be recognised by the ResNet-50 model accurately. Furthermore, it is discovered that for images with FSIMc scores less than 0.9, the accuracy rates for both the GoogLeNet and SqueezeNet models were lower. This shows that these models are not able to accurately recognise wood species images which have higher distortion levels.

Table 7. Accuracy rate obtained from the DL trained models

Wood species	Distortion type	Distortion level	$FSIM_c$	Parameters	DL model					
					SqueezeNet	GoogLeNet		ResNet-50		
				Epoch	100	50	100	50	100	100
				Learning rate	0.001	0.001	0.001	0.001	0.001	0.001
				Batch size	32	16	32	16	16	32
Bulnesia arboreea	Gaussian white noise	m=0.027	0.882	Accuracy rate (%)	88.50	92.10	92.30	97.30	97.24	97.15
		m=0.034	0.765		87.20	92.00	92.00	98.34	98.31	95.10
		m=0.041	0.653		87.00	91.20	91.50	96.54	96.50	96.50
Euxylophora paraensis	Salt & pepper	d=0.025	0.962		97.43	97.37	89.34	97.90	97.50	97.47
		d=0.033	0.853		97.67	96.32	92.60	98.12	98.12	97.39
		d=0.041	0.743		98.53	96.74	93.25	97.45	97.45	97.45
Julbernardia pellegriniana	Speckle	v=0.27	0.779		67.30	86.30	86.50	93.25	93.20	92.50
		v=0.36	0.749		60.50	82.50	82.50	93.58	93.55	89.55
		v=0.45	0.724		54.90	80.10	80.30	94.15	94.10	90.36
Dalbergia retusa	Gaussian blur	σ=1.1	0.951		96.45	95.67	82.45	95.75	95.70	95.69
		σ=1.4	0.710		97.21	92.59	86.73	97.60	97.60	95.92
		σ=1.7	0.656		96.50	95.78	94.25	96.70	95.83	95.79
Berchemia zeyheri	JPEG compression	Quality factor=35	0.992		94.19	94.56	95.40	95.56	95.52	95.50
		Quality factor=28	0.989		95.43	94.23	93.60	95.80	95.60	94.75
		Quality factor=21	0.9834		98.15	95.56	94.25	97.68	97.60	96.47
Average of accuracy rate (%)					87.80	92.20	89.80	96.38	96.25	95.17

4. CONCLUSION

In this paper, a DL based wood species recognition system is proposed. Three DL architecture, SqueezeNet, GoogLeNet, and ResNet-50 were trained to recognize fifty wood species images. The models were trained with 1800 wood images which consists of 1,750 distorted and fifty original images. The images were distorted to train the models to recognize the wood species accurately even though the image is distorted. This is because it is difficult to obtain noiseless images due to the dusty environment in timber factories. The performance of the models was evaluated in terms of the accuracy of wood species recognition. Based on the results obtained, ResNet-50 based wood species recognition outperformed SqueezeNet, and GoogLeNet based wood species recognition models. This shows that the ResNet-50 model trained with Epoch=50, Batch size=16, and Learning rate=0.001 can recognize the wood species even though the wood images are noisy. The ResNet-50 based wood species recognition system can enable more efficient and accurate tracking of timber supply chains, helping to combat illegal logging and ensure sustainable forest management practices. This work can be future enhanced by training the models with more wood species images. Furthermore, more DL architectures such as EfficientNet-b0, DarkNet-53, and DarkNet-19 can be trained to recognize the wood species.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Derived data supporting the findings of this study are available from the corresponding author [HR] on request.

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