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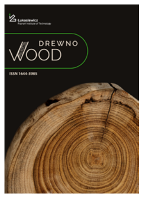

DWC (Deep Wood Classifier): A Novel Wood Species Classification Framework Based on Deep Learning

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DWC (Deep Wood Classifier) is a hybrid method that aims to achieve high accuracy and efficiency in wood species classification by combining deep learning and classical machine learning algorithms. In this method, convolutional neural network (CNN) models such as EfficientNetV2B3, Xception, and InceptionResNetV2 are optimised and trained to classify wood species. The accuracy rate is further improved when the features extracted from these deep learning models are classified with classical machine learning algorithms. The combination of EfficientNetV2B3 and SVC provides fast and effective classification with 99.56% accuracy, while Xception and Logistic Regression achieved the highest success with 99.69% accuracy. The DWC method exhibited excellent results in confusion matrix and ROC curve analyses, providing higher accuracy and more efficient training processes compared to existing methods in the literature. The combination of deep learning and classical machine learning algorithms has made DWC stand out with its high accuracy rates and fast training times. This hybrid approach offers a significant innovation in wood species classification, demonstrating superior performance compared to other methods in the field.

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Introduction

Wood has played an indispensable role in human life for thousands of years. Each wood species has its own unique physical, aesthetic, chemical, anatomical, mechanical, and economic properties. Therefore, correctly recognising wood species is very important in many areas such as ecology, woodworking, industrial engineering, the construction industry, furniture manufacturing and restoration, as well as in determining and evaluating the prices and quality of wood and products made of wood (Tou et al., 2007; Vácha and Haindl, 2013). These properties should also be considered crucial for surface quality, finishing, coating, bonding, and preservation processes, directly influencing the application range of wood materials (Kamperidou et al., 2020). In the present study, wood species recognition relies mainly on macroscopic anatomical features such as texture, grain, annual ring patterns, porosity, and density variations, which are commonly used as fundamental criteria in species identification. Classification and recognition of woods of various types, colours, and classes have become an indispensable condition for the woodworking industry.

Wood identification is extremely important for many industrial sectors, the wood trade, and wood science. It can support the production process in quality control, eliminate complexity in the timber trade, and help prevent fraud, as well as prevent illegal logging and trade of protected species (Ravindran et al., 2018;

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Hu et al., 2019). Wood has different uses and values depending on its properties. In addition, some wood species are protected both nationally and internationally. Therefore, it is extremely important to identify and classify wood species quickly and accurately, since correct classification ensures appropriate utilization in industrial applications and prevents misuses in trade and conservation (Kırbaş and Çifci, 2022). Wood species can be distinguished by differences in their composition and structure (Huang et al., 2020). The use of rapidly developing artificial intelligence applications in wood species classification is constantly increasing.

Inspection agencies should document that wood is not extracted from forests illegally. The industry also spends significant amounts of money to prevent fraud, where the timber trade might mix a noble species with a cheaper one. Identifying a wood stump or timber outside the forest is not a simple task because flowers, fruits, and leaves cannot be relied upon. Usually, this task is performed by well-trained experts, but, due to the time required for their training, very few achieve good accuracy in classification, so it is not sufficient to meet industry demands. To overcome such difficulties, some researchers have started to examine the problem of automatic forest species recognition (Filho et al., 2010; Filho et al., 2014).

In recent years, most of the applications of computer vision in the wood industry have been related to quality control, species classification, and wood defect detection (Thoman and Mili, 2007; Huber, 1970; Buechler and Misra, 2001; Cavalin et al., 2006; Vidal et al., 2011). With this information, industry and regulatory agencies have recently presented another request to the academy, namely, automatic classification of forest species. Such a classification is needed in many industrial sectors because it can provide information regarding the properties and characteristics of the final product (Piuri and Scotti, 2010).

With the rapid advancement of information technology, image processing and machine learning technologies have been widely used in wood classification. Among traditional machine learning algorithms, methods such as Linear Discriminant Analysis, Binary Tree Classification, Logical Linear Regression, K-Nearest Neighbour Classification, Bayesian Classification, and Support Vector Machines are preferred in wood identification processes (Mallik et al., 2011). These algorithms are generally based on image preprocessing and feature extraction stages. In addition, most of the existing computer-aided automatic identification systems classify wood slices using microstructure images (Filho et al., 2014; Maruyama et al., 2018). In classical machine learning approaches, feature extraction is performed first, followed by classification. The need for expert personnel in feature extraction is quite high.

Deep learning, a branch of artificial intelligence, has been making great progress in recent years. CNN has made tremendous progress in the field of image classification (Krizhevsky et al., 2012). Compared with traditional wood recognition methods, deep CNN has two important advantages: firstly, traditional methods require the extraction of various features from the wood, such as wood species, colour, axial parenchyma, wood ray, ring, channel, and texture (Sundaram et al., 2015; Baas et al., 2004). This feature extraction process is critical for accurate recognition and requires large amounts of data processing and expertise in challenging feature extraction and selection. In contrast, deep CNNs extract features by themselves to improve recognition accuracy, working only with the original data, without the need for human intervention, thus avoiding human bias. Secondly, in traditional methods, wood images are often not completely normalised due to environmental factors. Variables such as distance, height, angle, and lighting can cause images to be scaled, rotated, blurred, and otherwise altered, making recognition difficult. Deep CNN, on the other hand, is insensitive to irrelevant changes such as background, pose, illumination, and environmental objects, thus reducing the influence of external factors on recognition in wood images (Lecun et al., 2015). This research article aims to perform wood classification and recognition with high accuracy.

In the research, 41 different classes of wood species were optimised with three different CNN types, and feature extraction was performed by training with the use of the transfer learning method. To increase the classification success of the obtained features, wood images were classified using various classical machine learning classification algorithms. This method is a hybrid approach: CNN and a classical machine learning approach are used together. This method is called DWC (Deep Wood Classifier). The DWC method is a hybrid method that can classify wood with very high accuracy in a very short time. This research article was prepared to share and disseminate this method with the scientific world.

The weaknesses of the studies on artificial intelligence for wood classification found in the literature are summarised below:

1. Traditional wood grading and identification systems are costly, time-consuming, and have uncertain success rates.
2. Traditional methods require a large amount of data for learning, and time, feature extraction, and selection are quite difficult, and they also require expert knowledge.
3. Although deep learning architectures and transfer learning have yielded successful results, they have not yet been fully adapted to the field. They require

long runs and large numbers of samples to give a high level of accuracy.

The DWC study identified the following research questions in line with our aims and objectives:

1. RQ1 What are the advantages of the DWC hybrid approach compared to deep learning alone or classical machine learning alone? DWC combines the strengths of deep learning and classical machine learning. While deep learning provides powerful feature extraction, classical machine learning provides fast classification. This offers advantages in terms of accuracy and speed.
2. RQ2 What are the differences in performance between Xception, InceptionResNetV2, and EfficientNetV2B3 models? Can it be determined which model provides more efficient feature extraction? Xception: Provides deep feature extraction and high accuracy. InceptionResNetV2: Good at depth and generalisation, but requires more training time. EfficientNetV2B3: More efficient and faster, provides high accuracy with low computational cost.
3. RQ3 How does feature extraction in the DWC method compare to other traditional feature engineering methods? DWC provides more effective feature extraction than traditional feature engineering methods. Deep learning-based inference produces more accurate and faster results.
4. RQ4 What are the contributions of the DWC hybrid approach compared to other wood classification methods in the literature? DWC offers higher performance and speed with 99.69% accuracy. The hybrid approach combines the strengths of deep learning and classical machine learning to achieve more efficient results.

These research questions aim to delve into the key advantages of DWC, the performance of the model, and the implications of the hybrid approach. A simple schematic representation of the DWC hybrid method is given in Fig. 1.

To eliminate the weaknesses of wood classification, a DWC hybrid approach was designed that uses the transfer learning method to optimise CNNs, which provides improved wood classification accuracy and achieves high success by classifying the resulting features. This study includes 41 different forest species belonging to the Brazilian flora, prepared by the Wood Anatomy Laboratory of the Federal University of Parana (UFPR) in Curitiba, Brazil (Filho *et al.* 2014). The main points of this article are as follows:

1. The DWC method used in this article is the method with the highest accuracy, which was used for the first time with this data set and provides classification with 99.69% accuracy.
2. It is a CNN system in which the transfer learning approach and optimisation processes have been performed, and all layers have been trained from the beginning to the end. There is a fast and powerful feature extraction method that provides training in 10 epochs and results.
3. For this dataset, Xception, InceptionResnetV2 and EfficenetNetV2B3 powerful CNN models were optimized. Eight different classical machine learning classification algorithms, Random Forest, k-NN, LightGMB, SVC, Decision Tree, SGD, Logistic Regression, Extra Tree, were used. It was classified using k-fold=10 for cross-validation.
4. The highest accuracy rate was achieved with the optimised Xception CNN architecture and Logistic Regression hybrid approach. Xception extracted features in 5 minutes and 12.19 seconds in 10 epochs. With Logistic Regression, Xception classified the features coming from the CNN architecture in 253.55 seconds and achieved 99.69% accuracy. In total, 2942 woods belonging to 41 species were classified in 565.74 seconds, approximately 10 minutes. The DWC hybrid approach has achieved a very high level of wood species classification success in the literature in terms of speed and accuracy.

This study aims to develop a hybrid classification framework (DWC) that combines deep learning feature extraction with classical machine learning classifiers for fast and accurate wood species identification. The approach offers a reliable and efficient solution with practical value in quality control, timber trade, and protected species identification. Experiments on 41 species confirm that the method outperforms existing approaches in both accuracy and processing time, underscoring its potential for real-world applications.

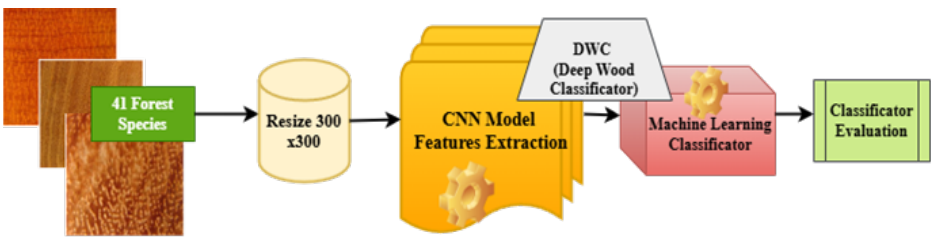

Fig. 1. Simple schematic representation of the DWC hybrid method

2. Related works

To make comparisons in the literature studies conducted within the scope of this research, references, types of pictures, wood species, picture features, techniques, and accuracy metrics are tabulated and presented as a literature summary in Tables 1 and 2.

Materials and methods

1. Data set

The Forest Species Database – Macroscopic (FSD-M) consists of 2,942 macroscopic images from 41 different forest types in the Brazilian flora. The database was

Table 1. Literature summary

Reference	Type of images	Wood species	Image features	Techniques	Accuracy
Ibrahim *et al.* (2017)	Photos of the cross-section at 10x magnification	48 species of tropical trees in Malaysia	Macroscopic images, quantity, size, and distribution of pores	Fuzzy logic and an SVM-based binary classifier	98.5%
Halid, Yusof and Khairuddin (2011)	10x magnified cross-section photos	52 species of tropical trees belonging to Malaysia	Statistical values of pore distribution and Aura Matrix	Multi-level classifier based on k-means grouping, size reduction, and k-NN	96.92%
Ibrahim *et al.* (2018).	Images of cross--sections with 10x magnification	30 different species of tropical trees from Malaysia	24 different types of statistical features	MLP and Fuzzy logic methods	89.3%
Hu *et al.* (2015).	Cross-sectional images of the size are not specified	28 different tree species were used. Its region is not specified.	SIFT-based bag--of-word	Backpropagation and the MLP classification method	90.2%
Silva *et al.* (2014).	Microscopic cross--sectional images were magnified at 2.5x.	77 different tree specimens of African origin were used	Used with LDA for dimensional reduction with local phase quantisation (LPQ)	k-NN classification algorithm	88%
Zhao and Cao (2016).	ASD FieldSpec with 4 portable spectrometers (spectral reflectance ratio curves)	5 different types of trees belonging to the Chinese region	Distribution matrices with selected eigenvalues	Use of a classifier based on the distance function	95%
Zamri *et al.* (2019)	Cross-section photos, 10x magnification	52 different types of trees from Malaysia	A new feature extraction method based on the aura matrix	Backpropagation and the MLP classification method	97.01%
Nisgoski *et al.* (2017)	Near-infrared spectroscopy waves	4 different types of trees belonging to Brazil	Data from 1500 wave spectra	MLP-based backpropagation algorithm	90%
Sundaram *et al.* (2015).	Images with a resolution of 256x256 pixels	10 different types (location information is not available)	Edge-based statistical features	MLP method	90%
Hu *et al.* (2015)	Photographic images (no cross-sectional information)	28 different types of trees (location information not available)	Histogram of SIFT key points	MLP SVM, k-NN	90.2%

acquired using a Sony DSC T20 camera with the macro function enabled. The resulting images are then in JPG format without compression and with a resolution of 3264 x 2448 pixels (Filho et al., 2014). Images from some classes of the dataset are given in Fig. 2. There are 41 species in total.

Table 2. Literature summary

Reference	Type of images	Wood species	Image features	Techniques	Accuracy
Kwon *et al.* (2017)	Cross-sectional images taken with an iPhone 7 mobile phone	5 different types of softwood belonging to Korea	-	CNN models (LeNet3, MiniVGGNet, vb.)	99.3%
Hafemann *et al.* (2014)	Microscopic images with 100x magnification	112 different species of trees belonging to Brazil	-	CNN model trained with 224x224 pixel patch data	97.32%
Barmpoutis *et al.* (2018)	Photos taken with the Nikon D3300 at a distance of 15-20 cm, 24 MP resolution	12 different tree species of Greece	Bag of spatial features (vertical-horizontal parts)	SVM classification algorithm usage	91.47%
Souza *et al.* (2020)	Zeiss Discovery V 2080 stereomicroscope in size 12	46 different species of trees belonging to Brazil	2080 square images	A hybrid method and classification by combining LBP and SVM	97.67% (F1 score, based on class)
Lens *et al.* (2020)	1024 × 768 pixels with an Olympus CX40 microscope	112 different species of trees belonging to Brazil	Microscope images: 2240 images of 112 species	Feature extraction with LBP, GABOR, HOG, GLCM Classification by SVM, k-NN, RF, MLP, and RF	95.6%
Fabijańska *et al.* (2021)	Cross-sectional images ranging from 81 × 1315 pixels to 224 × 13975 pixels	14 different types of trees found in Europe	600 dpi and 1200 dpi PNG images	Different CNN models VGG16, ResNet50, InceptionV3	98.7%
He *et al.* (2021)	Sony DSC 20T 3,264 × 2,448 pixel images	41 different tree species of Brazil	2942 images in JPG format 1120 x 1120 cropped	VGG 16IncepitonV3, DenseNet121-169-201, InceptionResnetV2 vb.	98.81%
Kırbaş and Çifci (2022)	Cross-sectional, radial, and tangential section images	12 different tree species of Greece	24 Megapixel Nikon D3300 camera	Xception, Inception, VGG19 CNN modelling	95.88%
Miao *et al.* (2022)	Cross-sectional, radial, and tangential section images	12 different tree species of Greece	24 Megapixel Nikon D3300 camera	A new model called W_IMCNN, based on Inception and mobilenetV3 networks	98.8%
Ergün (2024)	Macroscopic images: more than 8000 images	A total of 11 tree species from Colombia and the Amazon (10 tree species are present in the study)	640 × 480 pixels, depending on CMOS sensor size	Transfer learning to use CNN architectures to optimise ShuffleNet	96.04%

Fig. 2. Images of some wood classes (Filho et al., 2014)

3264 x 2448 has been resized to 300 x 300 for deep learning studies and ease of processing, so that it can be suitable for inputs of CNN architectures.

The dataset used in this study originates from the Brazilian flora, which is one of the most diverse ecosystems worldwide. Brazil's forests contain a large variety of commercial hardwood species with complex anatomical structures, making them an ideal case for testing advanced classification methods. The FSD-M dataset has also been widely adopted in previous studies, ensuring comparability and benchmarking of results.

2. Methodology

In this research, both the transfer learning approach and optimised CNN architectures and classical machine classification algorithms were used together. Three CNN architectures and eight different classical machine learning algorithms used in the research are introduced in the methodology section.

Deep learning is fundamentally based on artificial neural networks. These structures can monitor large amounts of data by learning from their representatives. As a result, deep neural networks have more hidden layers compared to traditional neural networks. Within deep neural networks, labelled input values are passed to nonlinear activation functions to produce a specific output with specific weights (Schmidhuber, 2015). The goal of training a deep neural network is to minimise the error value by optimising these weights (Ergün and Kılıç, 2021).

Classical machine learning algorithms are basic methods that are often used to learn patterns from data and make predictions. These algorithms can operate on labelled or unlabeled data and are generally simpler, more understandable, and more computationally efficient. Additionally, the understandability and interpretability of the model are among the advantages of these algorithms.

2.1. Transfer learning

In image analysis studies, when there is not enough data, the transfer learning method is generally preferred in studies with CNN architectures. This method allows the parameters of a network previously trained on a similar task to be used on the new task. The CNN to be trained for the new task is initialised with the weights of the pre-trained network, and then the parameters are updated with a certain number of training steps (Fırıldak and Talu, 2019). However, the images used in these methods contain a lot of meaningful and meaningless information, and the CNN architectures used also contain a lot of parameters and require high memory consumption (Kılıç et al., 2024).

2.2. CNN-based deep learning models

In image classification problems, the ImageNet dataset, which is frequently used in competitions and consists of 1000 classes, is usually used as training data (Russakovsky et. al., 2015). Researchers design new and different CNN models on different images of 1000 classes. These models are also publicly available for development and use. Developing a new CNN model is time-consuming and complex. It is quite common to optimise these ready-made models and use them in research.

In this research, three different CNN models that are up-to-date and powerful were optimised and included. These CNN models are Xception, InceptionResNetV2, and EfficientNetV2B3. Brief explanations about these CNN models are given below:

Xception's key feature is depth-separable convolution, which separates the learning of channel-based and spatial-based features. This helps capture complex patterns while reducing computational complexity. Additionally, Xception uses redundant connectivity to address issues of lost gradients and representational bottlenecks by creating shortcuts within the network (Chollet, 2017).

InceptionResNetV2 is a combination of the Inception structure and the residual network (ResNet) connection. The reason for choosing the residual link is that it will eliminate the distortion problems during deep construction and provide precise feature information, such as texture, size, colour, location, etc. The inception module is a combination of multiple convolution and pooling layers, and all feature maps are combined into a single vector in the result part (Szegedy et. al., 2017).

EfficientNetV2B3 is a member of the EfficientNetV2 family developed by Google Research, which provides high efficiency and accuracy in deep learning tasks. It offers faster training using less computational power and memory than previous versions. It increases efficiency by optimising the balance between depth, width, and resolution with the "compound scaling" strategy. It exhibits high performance, especially in image classification and data visualisation (Tan et al., 2021).

The model architectures used in the research use Xception, InceptionResNetB2V3, and EfficientNetV2B3 networks, which were pre-trained on the ImageNet dataset, using the transfer learning method. These CNN models were preferred as basic feature extractors because they provide high accuracy and computational efficiency in different image classification tasks. The base model is structured with top layers removed (include_top=False), and global pooling (pooling='max') is applied to summarise spatial features. This structure is made compatible with the next classifier layer.

The input size of the models was determined to represent the RGB images with a resolution of 300x300 in the dataset used. A mixed precision training policy was implemented to improve the training performance of the model and optimise the computational time. This policy enables the use of float16 and float32 data types together and maintains numerical stability while increasing training speed on supported hardware.

After feature extraction, a Batch Normalisation layer is added to normalise the activations, increase the convergence speed of the model, and improve the regularity. Next, a Dense layer with 512 neurons and using the ReLU activation function is placed. This layer is supported by L2 and L1 regularisation to prevent over-learning. The L2 regularisation (l=0.016) applies a penalty proportional to the square of the weights, while the L1 activity and bias regularisations (l=0.006) add penalties based on the absolute value of the activations and biases.

To further prevent over-learning, a Dropout layer with a ratio of 0.45 was added, which adds randomness and disables a certain proportion of neurons. Finally, a Dense layer with a softmax activation function produces outputs for n-classes by extracting probabilities for each class. Here, it represents the number of classes in the training dataset and is determined dynamically.

The model was compiled with the Adam optimisation algorithm with adaptive learning rates (learning_rate=0.001). A categorical cross-entropy loss function suitable for multi-class classification tasks is used, and accuracy is monitored as the main success metric during the training process. This architecture aims to achieve high classification performance by striking a balance between powerful feature extraction, computational efficiency, and effective regularisation. This structure was used in the same way as in 3 different CNN models; the models were trained, and feature extraction was performed. Adam was used as the optimisation algorithm. The dataset was divided into 70% training, 15% validation, and 15% test for CNN models.

To make the model training process more efficient and under control, various parameters and a special callback mechanism are defined:

– batch_size: Number of data used in each iteration (64).
– epochs: Total number of epochs in the training (10).

– patience: Number of epochs expected to adjust the learning rate if the monitored metric does not improve (1).
– stop_patience: Maximum wait before stopping training if no improvement (5).
– threshold: Accuracy is monitored before the training accuracy reaches 90%, after which validation loss is monitored.
– factor: Learning rate reduction factor (0.5).
– ask_epoch: The number of epochs to receive approval from the user for training continuation (5).
– batches: Total number of iterations in each epoch.

Callback Mechanism: MyCallback dynamically adjusts the learning rate, provides early stopping to prevent over-learning, and offers manual training control. The EfficientNetV2B3 model summary is given in Table 3, the Xception model summary is given in Table 4, and the InceptionResNetV2 model summary is given in Table 5. 1536 features from the EfficientNetV2B3 batch normalisation layer, 2048 features from the Xception batch normalisation layer, and 1536 features from the InceptionResNetV2 batch normalisation layer were classified using classical machine learning algorithms without selection and reduction.

Table 3. EfficientnetV2B3 Model summary

Layer (Type)	Output Shape	Param #
efficientnetv2-b3 (Functional)	(None, 1536)	12,930,622
batch_normalization (BatchNormalization)	(None, 1536)	6,144
dense (Dense)	(None, 512)	786,944
dropout (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 41)	21,033
Total params		13,744,743
Trainable params		13,632,455

Table 4. Xception model summary

Layer (Type)	Output Shape	Param #
xception (Functional)	(None, 2048)	20,861,480
batch_normalization (BatchNormalization)	(None, 2048)	8,192
dense (Dense)	(None, 512)	1,049,088
dropout (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 41)	21,033
Total params		21,939,793
Trainable params		21,881,169

Table 5. InceptionResNetV2 model summary

Layer (Type)	Output Shape	Param #
inception_resnet_v2 (Functional)	(None, 1536)	54,336,736
batch_normalization (BatchNormalization)	(None, 1536)	6,144
dense_2 (Dense)	(None, 512)	786,944
dropout_1 (Dropout)	(None, 512)	0
dense_3 (Dense)	(None, 41)	21,033
Total params		55,150,857
Trainable params		55,087,241

2.3. Classical machine learning classification algorithms

Random Forest is a tree-based ensemble algorithm. It classifies decision trees using random sampling and voting. Each decision tree is represented by a basic mathematical expression as follows:

$$\mathrm{h(x)} = \sum_{j=1}^{m} 1mI\left(x \in R_j\right) \cdot c_j \tag{1}$$

This expression checks whether the prediction called h(x) belongs to region (Rj) within the decision tree for data point x. If x belongs to this region, the class prediction value of that region is multiplied by cj. Finally, the class predictions of all regions are added, and h(x) gives the prediction result of Random Forest (Breiman, 2001).

K-NN classifies data points based on the labels of the k nearest neighbours around them. The mathematical model of k-NN is as follows:

$$\hat{y} = \mathrm{mode}\left(y_i \,\middle|\, i \in \arg \min_{(i')\mathrm{Distance}} (x, x_{i'}) \right.$$
$$\left. \text{for } i' \in \{1,2,\ldots,K\} \right) \tag{2}$$

This statement correctly expresses the basic mathematical model of the k-NN algorithm (Cover and Hart, 1967).

LightGBM is basically a decision tree-based gradient boosting algorithm. The total prediction is the sum of multiple decision trees:

$$F(x) = \sum_{i=1}^{N} T_i(x) \tag{3}$$

It expresses the mathematical model of LightGBM (Ke et al., 2017).

SVM finds the optimal hyperplane between two classes and classifies the data with this hyperplane. The SVM mathematical model is basically as follows:

$$f(x) = sgn\left(\sum_{i=1}^{n} \alpha_i y_i K(x, x_i) + b\right) \tag{4}$$

It mathematically expresses the basic decision function of the SVM classifier (Cortes and Vapnik, 1995).

Decision Tree creates a tree structure representing the dataset and classifies the data points using this structure. Each internal node represents a feature test, and each leaf node makes a class prediction.

$$N_j\text{: if } x_i \leq \theta_j \text{ then } T(x) = T_j \tag{5}$$

This expression represents a decision node (Quinlan, 1986).

Stochastic Gradient Descent (SGD) is an optimisation algorithm in machine learning that iteratively updates parameters. It calculates the gradient of the loss function using only one sample (or a small group) at each iteration and updates the parameters accordingly. This enables faster learning and lower computational cost on large datasets.

$$\theta_{t+1} = \theta_t - \eta \nabla_\theta J(\theta_t; x_i, y_i) \tag{6}$$

It expresses the mathematical model of SGD (Kingma, 2014).

Logistic Regression is a statistical model used for classification. Logistic regression classifies using a linear regression model. That is, it estimates the probability that a data point belongs to a particular class. Logistic regression estimates class probabilities using a logit function.

$$P(y = 1 \mid x) = \frac{1}{1+e^{-(b_0+b_1x_1+b_2x_2+\cdots+b_px_p)}} \tag{7}$$

This expression represents the mathematical model of logistic regression (Hosmer et al., 2013).

Extra Trees works similarly to Random Forests, but with more randomness in growing each tree. When building a decision tree, a random subset of features is selected, and a split is performed at each node. This process increases the generalisation power of the model by reducing the risk of overfitting.

$$\hat{y} = \frac{1}{N} \sum_{i=1}^{N} f_i(x) \tag{8}$$

The Extra Trees mathematical model can be generally expressed as follows (Geurts et al., 2006).

In research, K-fold cross-validation is a technique used to more reliably assess the accuracy of the model. A K-fold = 10 was applied in the research. This method is used especially in machine learning and statistical modelling processes and helps measure the generalisation ability of the data set. 90% of the dataset is used as training and 10% as testing; this is applied to the entire data in a rotating manner (10 times training and testing).

The parameter settings used in the classical machine learning algorithms used within the scope of the research are given in Table 6.

These parameters are the basic parameters of the classification algorithm that is generally used. Experiments were made with default parameter settings so that they could be used without the need for expert knowledge.

Table 6. Parameter settings of classical machine classification algorithms

Model	Parameters
Random Forest	100 decision trees (n_estimators=100), parallel processing (n_jobs=-1), fixed randomness (random_state=42).
K-Nearest Neighbors	5 neighbors (n_neighbors=5), parallel processing (n_jobs=-1).
LightGBM	100 estimators (n_estimators=100), learning rate (learning_rate=0.1), silent output (verbose=-1), fixed randomness (random_state=42).
SVM (Support Vector Machine)	Linear kernel (kernel='linear'), regularisation parameter (C=1.0), fixed randomness (random_state=42).
Decision Tree	Unlimited maximum depth (max_depth=None), Gini impurity criterion (criterion='gini'), fixed randomness (random_state=42).
SGD (Stochastic Gradient Descent)	SVM-like loss function (loss='hinge'), L2 regularisation (penalty='l2'), maximum iterations 100 (max_iter=100).
Logistic Regression	Multinomial for multi-class problem (multi_class='multinomial'), L-BFGS solver (solver='lbfgs'), fixed randomness (random_state=42).
Extra Trees	100 trees (n_estimators=100), Gini impurity criterion (criterion='gini'), parallel processing (n_jobs=-1), unlimited depth (max_depth=None).

3. Experimental setup

The experiments were conducted on Kaggle, a platform that organises machine learning and data science competitions. The NVIDIA Tesla T4 GPU was used for CNN model training. Tesla T4 is a graphics processing unit optimised for machine learning and deep learning applications, and is often preferred to meet powerful computational requirements. This GPU has a 16 GB GDDR6 memory capacity and offers high parallel processing power, providing a speed advantage, especially when working with large data sets. The experiments in the research are done on Kaggle, which provides a powerful graphics card and 30 hours of free usage per week. Thus, there is no need for a new and powerful system to use the DWC method.

The dataset of 41 different classes was first resized to 300 x 300. This is because the CNN models Xception and InceptionResNetV2B3 expect 299 x 299 input sizes as input. These CNN models can also resize the image themselves. At the same time, reducing the data set brings about faster work. CNN models were trained in all layers with the parameters and values given in the methodology section, and feature extractions were made. These features are taken from the batch normalisation layer. The extracted attributes were saved as features and targets in an Excel file in xlsx. Format.

The recorded features and targets were further classified using classical machine classification algorithms defined as K-fold = 10. To see the developments, a classification report was printed in each K-fold. At the end of the experiment, the average classification report was printed, and the classification reports were recorded. Feature extraction and classification took approximately 10 minutes to complete. The schematic representation of the DWC hybrid method is given in Fig. 3.

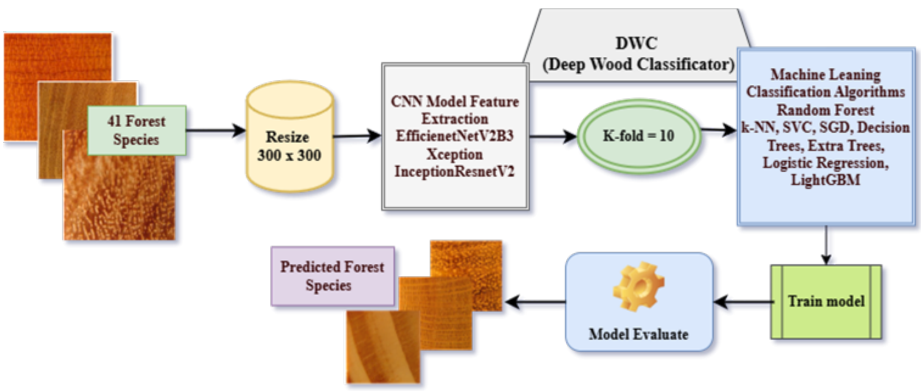

Fig. 3. Schematic representation of the DWC hybrid method

Algorithm 1. DWC – Hybrid Wood Species Classification

```
procedure DWC_Train_Evaluate(D, CNN_SET, CLS_SET, K):
    Resize all images to 300×300 pixels
    Apply data augmentation on training folds only
    Split dataset D into K=10 stratified folds
    for each fold f = 1..K do
        (TR, TE) ← training/testing split
        for each cnn ∈ {Xception, EfficientNetV2B3,
InceptionResNetV2} do
            Fine-tune CNN on TR
            Extract deep features from the penultimate layer
        end for
        Fuse features by concatenation
        for each clf ∈ {SVC, Logistic Regression, Random Forest,
                        XGBoost, Gradient Boosting, Decision Tree,
                        Naive Bayes, KNN} do
            Train clf on TR features
            Predict labels on TE features
            Compute Precision, Recall, F1, Accuracy, ROC–AUC, Confusion
Matrix
        end for
        Select classifier with best macro-F1 score
    end for
    Aggregate results across folds (mean ± std)
    Identify Logistic Regression as the best overall classifier

procedure DWC_Infer(x):
    Resize x to 300×300
    Extract features from each CNN
    Fuse features
    Predict label ŷ and probability p̂ with Logistic Regression
    return (ŷ, p̂)
end procedure
```

The steps of the proposed DWC hybrid classification framework are summarised in Algorithm 1. The procedure DWC_Train_Evaluate describes the training and evaluation process, while DWC_Infer outlines the inference stage.

4. Evaluation metrics

This article provides a detailed review of metrics commonly used to evaluate the performance of machine learning classification algorithms. These metrics are:

$$F1-Score = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall} \tag{9}$$

$$Accuracy = \frac{TP+TN}{TP+FN+FP+TN} \tag{10}$$

$$Precision = \frac{TP}{TP+FP} \tag{11}$$

$$Recall = \frac{TP}{TP+FN} \tag{12}$$

A confusion matrix is a table used to evaluate the performance of a classification model. This table visually presents the relationships between model-predicted and actual values.

AUC-ROC Score (Area Under the Receiver Operating Characteristic Curve): It is a measure used to evaluate classification performance. It represents the area under the ROC curve and shows the performance at different threshold values. The AUC-ROC value ranges from 0 to 1, and the closer it is to 1, the better the performance of the algorithm.

These metrics are used to evaluate the performance of different classification algorithms on the dataset. Throughout the article, the results obtained using these metrics are examined in detail.

Experiments and results

Since CNNs are architectures that have powerful feature extraction in images, classification was primarily done using CNNs. It was observed that

Table 7. CNN architectures and test results

CNN Model	Time	Precision	Recall	F1-Score	Accuracy
EfficientNetV2B3	7 min. 8.26 sec.	0.9883	0.9864	0.9864	0.9864
Xception	5 min. 12.19 sec.	0.9898	0.9887	0.9885	0.9887
InceptionResNetV2	5 min. 28.45 sec.	0.9749	0.9706	0.9705	0.9706

Table 8. Classification results of CNN features with classical machine learning algorithms

CNN Model + Classification Algorithms	Time	Precision	Recall	F1-Score	Accuracy
EfficientNetV2B3 + Random Forest	194.69 sec.	0.9944	0.9942	0.9942	0.9942
EfficientNetV2B3 + k-NN	74.92 sec.	0.9940	0.9939	0.9939	0.9939
EfficientNetV2B3 + LightGBM	4536.28 sec.	0.9926	0.9925	0.9925	0.9925
EfficientNetV2B3 + SVC	108.45 sec.	0.9957	0.9956	0.9956	0.9956
EfficientNetV2B3 + Decision Tree	320.54 sec.	0.9425	0.9419	0.9419	0.9419
EfficientNetV2B3 + SGD	134.22 sec.	0.9946	0.9946	0.9946	0.9946
EfficientNetV2B3 + Logistic Regression	184.07 sec.	0.9957	0.9956	0.9956	0.9956
EfficientNetV2B3 + Extra Tree	94.75 sec.	0.9947	0.9946	0.9946	0.9946
Xception + Random Forest	168.29 sec.	0.9957	0.9956	0.9956	0.9956
Xception + k-NN	104.24 sec.	0.9960	0.9959	0.9959	0.9959
Xception + LightGBM	4917.51 sec.	0.9919	0.9918	0.9918	0.9918
Xception + SVC	132.43 sec.	0.9967	0.9966	0.9966	0.9966
Xception + Decision Tree	220.40 sec.	0.9728	0.9725	0.9725	0.9725
Xception + SGD	187.75 sec.	0.9966	0.9966	0.9966	0.9966
Xception + Logistic Regression	253.55 sec.	0.9970	0.9969	0.9969	0.9969
Xception + Extra Tree	121.57 sec.	0.9954	0.9952	0.9953	0.9952
InceptionResNetV2 + Random Forest	182.13 sec.	0.9814	0.9810	0.9810	0.9810
InceptionResNetV2 + k-NN	74.12 sec.	0.9791	0.9786	0.9786	0.9786
InceptionResNetV2 + LightGBM	4763.49 sec.	0.9797	0.9793	0.9793	0.9793
InceptionResNetV2 + SVC	103.24 sec.	0.9852	0.9850	0.9850	0.9850
InceptionResNetV2 + Decision Tree	285.51 sec.	0.9102	0.9092	0.9092	0.9092
InceptionResNetV2 + SGD	194.28 sec.	0.9584	0.9541	0.9552	0.9541
InceptionResNetV2 + Logistic Regression	229.32 sec.	0.9842	0.9840	0.9840	0.9840
InceptionResNetV2 + Extra Tree	96.67 sec.	0.9837	0.9833	0.9833	0.9833

Xception had 98.87% accuracy, EfficientNetV2B3 had 98.64% accuracy, and InceptionResNetV2 had 97.06% accuracy in the classification test. The results of 3 different CNN models optimised for feature extraction in the DWC hybrid method and trained using the transfer learning approach are given in Table 7. The metrics used in the research are given according to a weighted average.

According to this table, it can be noticed that although the test was successful with a very high accuracy, there were wood species that could not be recognised. Based on the idea that these results can be improved for error-free and accurate recognition under all conditions, research has been conducted to create different approaches, and then classical machine learning algorithms have been used to classify the extracted features in different ways. CNN models achieved reasonable test accuracy in 10 epochs between 5 and 7 minutes. However, it has been observed that the DWC method proposed here brings better test accuracy results in a short time. The test results where the features extracted in CNN models were used with K-fold = 10 in classical machine learning algorithms are given in Table 8.

This study compares the performance of DWC, a proposed hybrid approach that evaluates combinations of different CNN models and classical machine learning classifiers. The CNN models used are EfficientNetV2B3 (1536 features), Xception (2048 features), and InceptionResNetV2 (1536 features), and the features obtained from these models are classified with various classical classifiers such as Random Forest, k-NN, LightGBM, SVC, Decision Tree, SGD, Logistic Regression, and Extra Trees. These deep learning models were first used to extract features from the data, and then these features were classified with different machine learning algorithms. Performance evaluations were made with metrics such as accuracy, precision, recall, and F1-score, and the training time of each model was also measured. This study analyses the effectiveness of different combinations, taking into account both the accuracy of the model and the processing process.

The combination of EfficientNetV2B3 and SVC showed the highest performance with 99.56% accuracy. This combination not only provides high accuracy, but also the training time (108.45 seconds) is reasonable. The combinations of EfficientNetV2B3 with Logistic Regression and Random Forest also achieved accuracies of 99.56% and 99.42%, respectively. These combinations also provided high accuracy, with training times of 184.07 seconds and 194.69 seconds, respectively. These times are slightly longer than the combination with SVC. The combination resulted in a low accuracy of 94.19%. This reflects a situation where the model is less efficient in terms of simplicity and accuracy of the classifiers.

The combination of Xception and Logistic Regression exhibited the highest performance with 99.69% accuracy. This combination also has a reasonable training time of 253.55 seconds. High accuracy and reasonable training time make this combination an efficient option. The combination of Xception and SVC also shows high performance with 99.66% accuracy. This combination achieved a very fast result with a training time of 132.43 seconds. The combination of Xception and SGD also achieved 99.66% accuracy, and the training time was 187.75 seconds, which is again fast and efficient. The combination of Xception and Decision Tree performed significantly lower than the others, with 97.25% accuracy. The training time was 220.40 seconds, which is a moderate time but not very efficient in terms of accuracy. The combination of Xception and LightGBM required a very long training time (4917.51 seconds), and the accuracy dropped to 99.18%. This does not provide a large improvement in accuracy, but it does indicate that the training time is unnecessarily long. The combination of Xception and k-NN achieved 99.59% accuracy with a short training time of only 104.24 seconds. This combination provides high accuracy with fast training time, but with a very small loss in accuracy.

The combination of InceptionResNetV2 and SVC shows the highest performance with 98.50% accuracy. This combination is also quite fast in terms of training time at 103.24 seconds, so it is an efficient option for applications that want to get fast and accurate results. The combination of InceptionResNetV2 and Logistic Regression also achieved 98.40% accuracy and was trained for 229.32 seconds. The combination of InceptionResNetV2 and Extra Tree shows similar performance with 98.33% accuracy, but the training time is shorter at 96.67 seconds. The combination of InceptionResNetV2 and Decision Tree exhibited the lowest performance with 91.92% accuracy. The training time was 285.51 seconds, which is a reasonable time but a very low result in terms of accuracy. The combination of InceptionResNetV2 and LightGBM required a long training time (4763.49 seconds) while the accuracy only reached 97.93%. This is inefficient in terms of training time because the accuracy gain is limited. The combinations of InceptionResNetV2 and Random Forest and InceptionResNetV2 and k-NN achieved 98.10% and 97.86% accuracy, respectively. The training times are reasonable at 182.13 seconds and 74.12 seconds, but slightly lower in accuracy compared to higher combinations.

The average classification report for the proposed method, which achieves the highest accuracy with Xception and Logistic regression, is presented in Table 9.

Table 9. Xception + Logistic Regression average classification report

Class	Precision	Recall	F1-score	Support	Class	Precision	Recall	F1-score	Support
1	1.0000	1.0000	1.0000	53	23	1.0000	1.0000	1.0000	43
2	1.0000	0.9898	0.9949	98	24	1.0000	1.0000	1.0000	51
3	1.0000	0.9730	0.9863	37	25	0.9895	0.9792	0.9843	96
4	1.0000	1.0000	1.0000	99	26	0.9800	0.9899	0.9849	99
5	1.0000	1.0000	1.0000	56	27	1.0000	0.9767	0.9882	43
6	1.0000	1.0000	1.0000	67	28	0.9875	1.0000	0.9937	79
7	1.0000	0.9804	0.9901	51	29	1.0000	1.0000	1.0000	62
8	1.0000	1.0000	1.0000	78	30	1.0000	1.0000	1.0000	59
9	1.0000	1.0000	1.0000	99	31	1.0000	1.0000	1.0000	58
10	1.0000	1.0000	1.0000	53	32	1.0000	1.0000	1.0000	99
11	1.0000	1.0000	1.0000	94	33	1.0000	1.0000	1.0000	58
12	1.0000	1.0000	1.0000	63	34	1.0000	1.0000	1.0000	99
13	1.0000	1.0000	1.0000	86	35	1.0000	1.0000	1.0000	63
14	0.9802	1.0000	0.9900	99	36	1.0000	1.0000	1.0000	80
15	0.9899	0.9899	0.9899	99	37	1.0000	1.0000	1.0000	63
16	1.0000	1.0000	1.0000	64	38	1.0000	1.0000	1.0000	41
17	0.9880	1.0000	0.9939	82	39	1.0000	1.0000	1.0000	48
18	1.0000	1.0000	1.0000	55	40	1.0000	1.0000	1.0000	75
19	1.0000	1.0000	1.0000	46	41	1.0000	1.0000	1.0000	72
20	1.0000	0.9885	0.9942	87	Accuracy			**0.9969**	2942
21	1.0000	1.0000	1.0000	92	Macro avg	0.9977	0.9968	0.9972	2942
22	0.9897	1.0000	0.9948	96	Weighted avg	0.9970	0.9969	0.9969	2942

In this classification report, the overall performance of the model is quite high. In particular, precision, recall, and F1-score values are very close to 1 for most classes. That is, the model appears to make perfectly accurate predictions in most classes. Especially, most of the precision, recall, and F1-score values of each class are 1.0000, which means that the model classifies each class perfectly.

The confusion matrix of the Xception and Logistic regression methods with the highest accuracy recommended in the DWC method is given in Fig. 4.

The best ROC curve obtained in the DWC method is given in Fig. 5.

This study compares the performance of combinations of CNN models and classical machine learning classifiers, thoroughly investigating how different combinations perform in terms of accuracy, processing time, and overall effectiveness. The results obtained from the combination of the CNN models (EfficientNetV2B3, Xception, and InceptionResNetV2) and various classical machine learning algorithms (Random Forest, k-NN, LightGBM, SVC, Decision Tree, SGD, Logistic Regression, Extra Trees) show significant differences in terms of both the accuracy and processing time of the model.

DWC combines the deep feature extraction power of a deep learning model with the fast and efficient classification capabilities of classical machine learning algorithms. For example, combinations such as Xception and Logistic Regression are ideal examples of such an approach, offering both high accuracy and acceptable training times. This method can be very useful, especially in applications that require high accuracy and also require attention to processing time. It is strongly recommended to avoid combinations with very long training times to increase efficiency.

Combinations with DWC are shown to be optimised to provide reasonable training times while improving classification accuracy. This method is suggested as a recommended approach to achieve practical and efficient results in real-world applications.

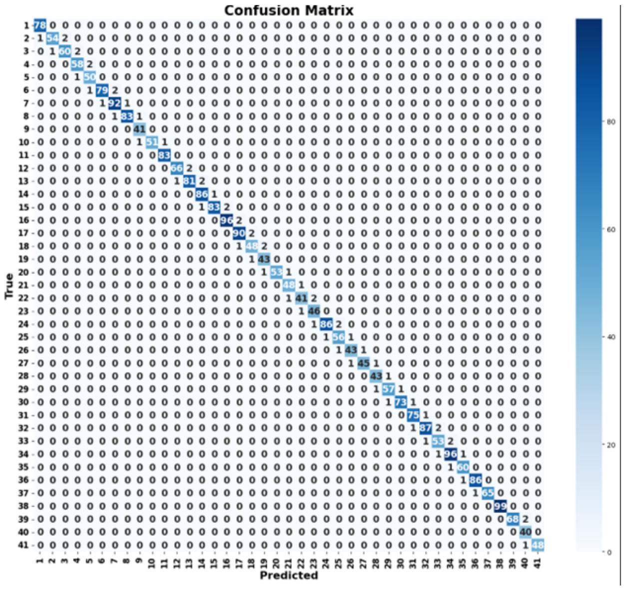

Fig. 4. DWC hybrid method: Confusion matrix of using Xception + Logistic regression

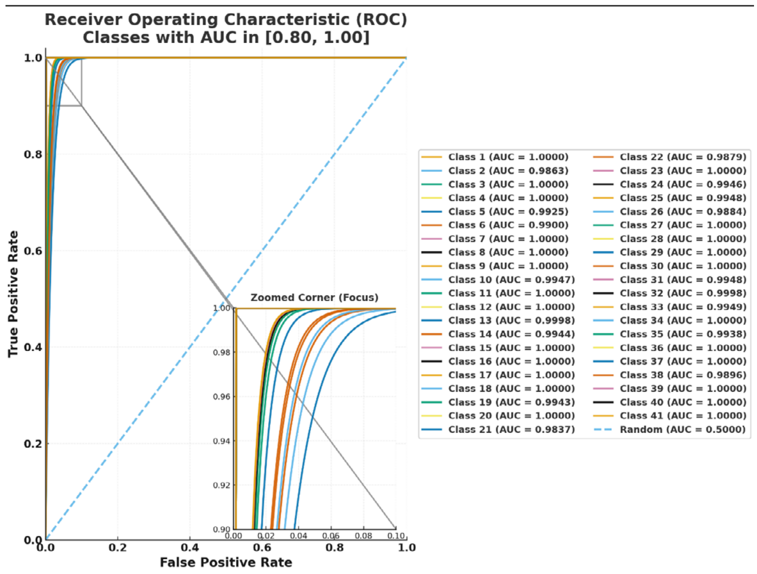

Fig. 5. DWC hybrid method: ROC curve of using Xception + Logistic regression

Discussion

In this study, combinations of different deep learning models and classical machine learning algorithms were evaluated, and the results were compared with similar studies in the literature. Although the results are parallel to existing studies, they also reveal some important differences and innovations.

In the literature, the classification of wood species is usually done by microscopic images, spectroscopic data, and photogrammetric analysis. The studies generally result in high accuracy rates, but there are limitations in processing times and computational efficiency. For example, in the study by Ibrahim et al. (2017), 98.5% accuracy was achieved in the classification of 48 tropical wood species using an SVM-based binary classifier. Similarly, Khalid et al. (2011) achieved 96.92% accuracy using K-means clustering and k-NN algorithms for 52 tropical wood species. These studies are generally based on macroscopic images and wood pore properties, but processing times are usually longer.

In contrast, high accuracies were achieved with the deep learning models used in this study, especially models such as EfficientNetV2B3 and Xception. For example, the combination of EfficientNetV2B3 and SVC provided 99.56% accuracy, while the combination of Xception and Logistic Regression showed the highest performance with 99.69% accuracy. These accuracies are higher than those of many studies in the literature, revealing the advantages of deep learning methods in such classification tasks.

Although high accuracies have been achieved in many literature studies, processing times remain a significant problem. Zhao and Cao (2016) classified 5 different wood species using spectrometer data and achieved 95% accuracy, but such devices can have longer processing times on large data sets. Similarly, Silva et al. (2014) achieved 88% accuracy with the k-NN algorithm using microscopic images for 77 wood species of African origin, but the processing time was long.

In this study, by using fast classifiers such as EfficientNetV2B3 and k-NN combination, high accuracy and short processing times were achieved. EfficientNetV2B3 and k-NN achieved 99.39% accuracy in just 74.92 seconds. On the other hand, some options, such as the combination of Xception and LightGBM, provided increased accuracy, but the training time was unnecessarily long (4917.51 seconds). This suggests that it is important to strike a balance between training time and accuracy, similar to some literature studies. Although Zamri et al. (2019) achieved 97.01% accuracy with Backpropagation and MLP methods, the training time is quite long, which imposes limitations on fast classification requirements.

In the literature, classical machine learning methods such as SVM, k-NN, Random Forest, and MLP are widely used. Ibrahim et al. (2018) achieved 89.3% accuracy with MLP and Fuzzy logic methods, while Halid et al. (2011) achieved 96.92% accuracy using K-means grouping and k-NN in their study. However, in this study, the results obtained with deep learning models (especially EfficientNetV2B3 and Xception) were superior in terms of accuracy and computation when compared to classical methods. The combination of Xception and SVC showed significant success with 99.66% accuracy and 132.43 seconds of training time.

The InceptionResNetV2 model achieved the highest accuracy rate of 98.81% in the study conducted by He et al. (2021). However, it seems that this model can be preferred in practical applications, especially thanks to its advantages, such as short training time. For example, the combination of InceptionResNetV2 and SVC achieved 98.50% accuracy in just 103.24 seconds, which is an efficient solution. This result is close to the high accuracies seen in studies with microscopic images, such as Lens et al. (2020), but allows faster results. However, these findings are limited to the FSD-M dataset, which contains 41 species of Brazilian flora. Therefore, the results should not be generalised to global wood species without further validation on more diverse datasets.

Conclusions and recommendations

This study evaluates combinations of CNN models and classical machine learning algorithms for wood species classification and compares the performance of both methods. The results obtained show significant differences, especially in terms of accuracy, processing time, and overall effectiveness.

The main findings and performance analysis are as follows:

1. CNN Model Performance: EfficientNetV2B3, Xception, and InceptionResNetV2, the CNN models used in the study, made classification with high accuracy rates. Xception achieved the highest success with 98.87% accuracy, while EfficientNetV2B3 and InceptionResNetV2 achieved 98.64% and 97.06% accuracies, respectively.
2. Classical Machine Learning Models: Features obtained with deep learning models are classified with classical machine learning algorithms. These combinations show significant improvements in both accuracy and processing time. For example, the combination of EfficientNetV2B3 and SVC exhibited the highest performance with 99.56% accuracy and was a highly efficient option with a training time of 108.45 seconds. In terms of accuracy, Xception and Logistic Regression achieved the highest level of success with 99.69% accuracy.
3. Processing Times: Some combinations required long training times, while others achieved high accuracies in a short time. For example, EfficientNetV2B3 and k-NN achieved 99.39% accuracy in 74.92 seconds, while combinations such as Xception + LightGBM had considerably longer training times (4917.51 seconds).
4. DWC Method: Combining the inferences of deep learning models with classical machine learning algorithms, the DWC method provided both high accuracy and acceptable training times. This approach increased the classification accuracy and also offered improvements in terms of efficiency.

Classification Reports:

1. Combination of Xception and Logistic Regression: this combination showed the highest performance with 99.69% accuracy, and in the classification report, the precision, recall, and F1-score values are around 1.0000 for most of the classes. This means that the model recognises every class almost perfectly.
2. Confusion Matrix and ROC Curve: the confusion matrix and ROC curve of the Xception + Logistic Regression method, which gives the best results, visually show the correct classification performance and overall effectiveness of the model.
3. Comparison with literature: this study achieved higher accuracies compared to methods such as microscopic images and spectroscopic data used for wood species classification. Deep learning models, especially EfficientNetV2B3 and Xception, provide higher accuracy in such classification tasks.
4. Training time and efficiency: although some studies in the literature have high accuracy, processing

times are a significant problem. In this study, with the right model and algorithm combinations, high accuracy and reasonable training times were achieved. This provides a solution that meets the requirements for fast classification.
5. DWC method and its potential: the DWC method combines the deep feature extraction power of the deep learning model with the fast classification capabilities of classical machine learning algorithms, providing highly effective results. This approach increases efficiency in real-world applications while also providing high accuracy and making it possible to obtain practical results.

This study demonstrates the effectiveness of combinations of deep learning models and classical machine learning algorithms, revealing that the DWC method offers a potential solution to provide high accuracy and efficient training times. It should be noted that the conclusions of this study are restricted to the Brazilian FSD-M dataset. Caution is required when extending these results to other wood species worldwide, and future research with larger and more geographically diverse datasets is necessary.

Future work may focus on the use of larger and more diverse datasets, transfer learning techniques, hyperparameter optimisation, energy and processing time efficiency studies, integration into real-world applications, and comparative analysis with other methods in the literature. These approaches will be useful both for improving performance and for generalising these methods to a wider range of applications.

Conflict of interest

The author(s) declare(s) that there is no conflict of interest concerning the publication of this article.

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