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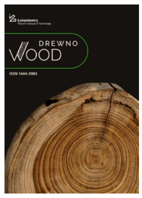

TropicWoodID: A Novel Transfer Learning Based Optimised Deep Learning Framework for Tropical Wood Categorisation

Kenan Kiliç*

Yozgat Vocational School, Department of Design, Yozgat Bozok University, Yozgat, Turkey

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The study examines the performance of various deep learning approaches in identifying tropical wood species from macroscopic images. In the study, non-optimised, transfer learning applied, and optimised convolutional neural network (CNN) models were compared. The obtained results show that the optimised models, featuring EfficientNetV2B3, exhibit remarkably high accuracy and performance in tropical wood classification. In the evaluation of the optimised models, EfficientNetV2B3 achieved the highest performance with 99.01% accuracy, 99.02% precision, 99.01% recall, and F1-score values. Xception and MobileNetV2 also achieved notable results with 98.64% and 98.02% accuracy, respectively. These results reveal that the optimised models, especially EfficientNetV2B3, are highly effective for tropical wood classification. Compared with the literature, this study has made significant progress in the field of wood species classification, especially by achieving an accuracy rate of 99.01% with the EfficientNetV2B3 model. These results demonstrate how effective deep learning models can be on complex classification problems, especially when they are optimised. In conclusion, this study recommends the use of the EfficientNetV2B3 model for the classification of tropical wood species and emphasises that this model serves as a benchmark in this field with its high accuracy, precision, and generalisation ability. In the future, it is suggested to further develop this method by testing it on different datasets and classification problems. This work provides a significant contribution to the fields of wood science and automatic species recognition.

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Introduction

The accurate identification and classification of wood species plays a crucial role across multiple sectors, including forestry, wood processing, construction, furniture production, and interior design (Topalova 2015; Teo et al. 2022). This process typically requires analysing specific physical and anatomical characteristics such as growth ring patterns, knot formations, ray structures, and surface texture to distinguish between species (Shmulsky & Jones, 2019). In many countries, such evaluations are still performed manually by experienced wood specialists. However, this traditional approach is both time-consuming and costly, and its reliance on expert judgment restricts scalability, making it challenging to meet the growing demands of the timber industry (Nguyen-Trong, 2023).

Each type of wood exhibits distinct characteristics in terms of its physical structure, anatomical features, appearance, chemical composition, economic value, and mechanical performance. As a result, accurate wood species identification is essential in various fields, including environmental studies, construction, furniture manufacturing, historical restoration, and the

* Corresponding author: kenan.kilic@bozok.edu.tr

assessment of wood-based materials (Tou et al., 2007; Vácha and Haindl, 2013).

Differences in internal composition and structural traits can be used to differentiate between wood species (Huang et al., 2020). Traditionally, identification relied on the visual analysis of both macroscopic and microscopic properties by trained professionals. While effective to some extent, this manual approach has significant drawbacks: it depends heavily on the expert's knowledge, requires considerable time, entails high costs, and lacks the scalability and precision required for high-volume or high-accuracy classification tasks (Mohan et al., 2014; Rajagopal et al., 2019; Fabijańska et al., 2021). These limitations become especially problematic in industrial settings, where fast and reliable classification of large quantities of wood is often needed. In such cases, machine learning techniques offer a promising alternative by enabling rapid and accurate identification (Kırbaş and Çifci, 2022).

The fact that the processes of identifying and classifying wood species carried out with traditional methods have various limitations and deficiencies reveals the necessity of faster, valid, economical, and practical alternatives in these areas. In response to this need, computer vision technologies that can work in integration with widely used smartphones stand out as a remarkable alternative. Various studies in the literature reveal the effective success of these technologies in classifying and recognising wood species (Martins et al., 2013; Yadav et al., 2013, 2015; Silva et al., 2017). These studies generally include macroscopic and microscopic images of wood surfaces. Macroscopic images refer to surface photographs obtained at approximately 10–15 times magnification. Microscopic images consist of images of wood sections magnified 25 to 100 times with the help of a microscope. Classification and recognition operations can be performed by extracting very different features from this data using image processing techniques. However, the main disadvantage of these systems is that special and usually quite expensive equipment is required to obtain quality images (Filho et al., 2014). This situation complicates and limits the widespread availability and practicality of the method in the field. Today, with the expectation of rapid access to information, the need for new technologies that will meet the needs of wood-working sectors and contribute to environmental sustainability is rapidly increasing (Ergün, 2024).

The automatic identification and classification of wood species typically rely on supervised learning techniques that examine the morphological structures and surface textures of wood. Some studies in the field focus on the fibre structure (Kobayashi et al., 2017; Martins et al., 2013; Ibrahim et al., 2018). Other research considers structural features, such as the pore structure, as a basis for classification (Martins et al., 2013; Khairuddin et al., 2011). Another method emphasises the analysis of surface texture details, utilising techniques like local binary patterns (Silva et al., 2017; Martins et al., 2013), grey level co-occurrence matrix (Kobayashi et al., 2017; Khalid et al., 2008), or basic grayscale aura matrices (Khairuddin et al., 2011; Khalid et al., 2008; Zamri et al., 2016). However, it has been noted that these textural features may not always be sufficient for reliably distinguishing certain wood species. To overcome these challenges, some researchers have turned to approaches incorporating spatial and frequency-based data (Yadav et al., 2015; Yusof and Rosli, 2013). Furthermore, hybrid systems combining textural, spatial, and frequency data have been developed (Barmpoutis et al., 2018; Filho et al., 2014; Zhao et al., 2014).

In the concluding stage of a typical wood species identification pipeline, a statistical or machine learning model is trained on known wood sample data and then used to classify unseen samples into their respective species. This classification step relies on the patterns and features extracted during earlier phases of analysis. Among the most widely adopted classification techniques in this context are multilayer artificial neural networks, which have been successfully applied in numerous studies for their ability to model complex, non-linear relationships in wood texture and anatomical features (e.g., Yusof & Rosli, 2013; Filho et al., 2010; Zhao et al., 2014; Ibrahim et al., 2018; Zamri et al., 2016).

Another frequently used method is the support vector machine (SVM), known for its effectiveness in high-dimensional spaces and strong generalisation performance, especially with smaller datasets. Studies such as those by Martins et al. (2013), Turhan and Serdar (2013), and Filho et al. (2014) have demonstrated the robustness of SVMs in wood classification tasks.

In addition to these two dominant approaches, other machine learning classifiers have also been employed to varying degrees of success, depending on the characteristics of the dataset and the features used. Techniques such as decision trees, k-nearest neighbours, and ensemble methods have been explored in works by Khairuddin et al. (2011), Silva et al. (2017), and Kobayashi et al. (2017), showcasing the flexibility of classification strategies in adapting to the complexities of wood species identification.

The effectiveness of these methods largely depends on how relevant and effective the selected features are. Since features are typically chosen based on an intuitive approach, their discriminatory power might be insufficient. This is especially true for large datasets containing numerous wood species, where manually selecting the most defining features can be quite a challenging process (Kırbaş and Çifci, 2022).

Conventional techniques for identifying and classifying wood species rely heavily on in-depth analysis of the wood's anatomical structure and require specialised expert knowledge. Using deep learning and artificial neural networks, it can classify wood quickly and effectively, and even learn to recognise new species. However, this method requires large amounts of labelled data for accurate results. Data collection and labelling can be challenging. Additionally, factors such as image quality, lighting, angle, and background can affect the model's performance and lead to inaccurate results (Ergün, 2024).

Several researchers have explored transfer learning and deep learning architectures for tree species classification, particularly when working with limited datasets. Sun et al. (2021) employed a transfer learning framework where features extracted using the ResNet50 architecture were classified through Linear Discriminant Analysis (LDA) and the K-Nearest Neighbour (k-NN) algorithm. Similarly, Fabijańska et al. (2021) attained high classification accuracy by utilising a residual evolutionary encoder network combined with a sliding window technique, applied to macroscopic imagery of 14 European wood species. Kırbaş and Çifci (2022) evaluated ResNet50, InceptionV3, Xception, and VGG19 models on the WOOD-AUTH dataset, which comprises 12 wood species, and identified Xception as the most accurate. Their approach also involved feature extraction using ResNet50 and Global Average Pooling (GAP), followed by classification via the Extreme Learning Machine (ELM) algorithm. Elmas (2021) assessed various CNN models—such as AlexNet, DenseNet201, ResNet18/50/101, and VGG16/19—on a dataset of 24,686 bark images spanning 59 tree species, where DenseNet121 yielded the best results. Miao et al. (2022) designed a hybrid framework incorporating Inception and MobileNetV3, achieving 96.4% accuracy across 16 species. Wu et al. (2021) leveraged longitudinal-section images and applied ResNet50, DenseNet121, and MobileNetV2, reaching a peak accuracy of 98.2% across 11 wood types. These results consistently support the idea that deep learning techniques are more effective than classical machine learning algorithms in the field of wood identification.

Factors such as anatomical structure, climate, soil conditions, forest density, and sunlight create difficulties in identifying wood species. Additionally, large, open datasets are often regionally limited. Transfer learning reduces data requirements and improves the generalisation ability of the model by using pre-trained neural networks (Ergün, 2024).

In this research, an optimised deep learning framework based on transfer learning is presented for the categorisation of macroscopic tropical wood images. In the research, the performances of Xception, DenseNet201, InceptionV3, InceptionResNetV2, MobileNetV2, EfficientNetV2B3, and ResNet50V2 convolutional neural network (CNN) models were evaluated by using them in three different ways: normally, in transfer learning with imagenet weights, and in transfer learning-based optimised CNN. CNNs require powerful hardware. However, today, these studies can be carried out in cloud environments that are offered free of charge without purchasing new hardware and without additional costs. A wood species that cannot be categorised or is categorised incorrectly will cause research limitations, incorrect results, and additional costs in scientific research and in the field of woodworking industrial engineering. Once these CNN models are trained for wood categorisation, they do not need to be retrained for testing purposes. Only if new wood or wood types are to be added to the system should the CNN model be retrained. In light of this information, it is extremely important to categorise with high accuracy.

The shortcomings and weaknesses of existing research are as follows:

1. Current traditional wood grading methods are difficult, time-consuming, tedious, and imprecise.
2. In studies where classical machine learning methods are used, feature extraction is difficult and yields uncertain results. It also requires expert knowledge.
3. There are many studies done with deep learning, but it does not provide high accuracy results because it is not optimised enough.
4. Unrecognised or incorrectly recognised wood industry also causes loss of time, economic loss, and production problems.

This research paper presents a transfer learning based optimised deep learning framework for tropical wood categorisation that addresses the weaknesses of past research and performs wood categorisation with fast and high accuracy. In the study, 11 classes of macroscopic tropical woods were categorised, with 11792 images from Cano Saenz et al. (2022). The main contributions of this paper are as follows:

1. With the EfficientNetV2B3 model, an extremely high accuracy rate of 99.01% was achieved, setting a new standard of success in tropical wood classification.
2. Optimised CNN models have been shown to exhibit significantly higher performance compared to non-optimised models.
3. Transfer learning applied models have been proven to provide significant increases in accuracy and other metrics, especially in architectures such as EfficientNetV2B3 and Xception.
4. The performances of different CNN architectures (Xception, DenseNet201, InceptionV3, MobileNetV2, etc.) are compared in detail, and the advantages and disadvantages of each model are revealed.
5. The results of this study provide a basis for further improving the performance of similar models by testing them on different datasets and classification problems.

The rest of the manuscript is organised as follows: Section 2 details the materials and methods, including the dataset, deep learning models, and the proposed approach. Section 3 presents the experimental results and findings. Section 4 discusses the key results and compares them with related studies. Finally, Section 5 concludes the paper with final remarks and recommendations.

Materials and Methods

1. Data set

The dataset used in the study includes eleven forest species at high risk of illegal timber trade from the Amazon and Pacific regions of Colombia. Each species is presented in folders named after its scientific name, with macroscopic digital RGB images (in jpg format) and details such as the species family, wood type, and number of images. The images reveal the structural features of wood, such as fibres, pores, veins, and parenchyma, and were obtained at 640 × 480 pixels resolution, 3.9 μm/pixel magnification, and under artificial illumination. The dataset includes scientific, local, and global trade names of species and has been verified with sources such as the International Tropical Timber Organisation (ITTO). Randomly oriented images provide diversity for training machine learning models (Cano Saenz et al., 2022). There are a total of 11792 images in the dataset. Detailed information about the types used, their features, and the total number of images is presented in Table 1. Macroscopic tropical wood images of the dataset are shown in Figure 1.

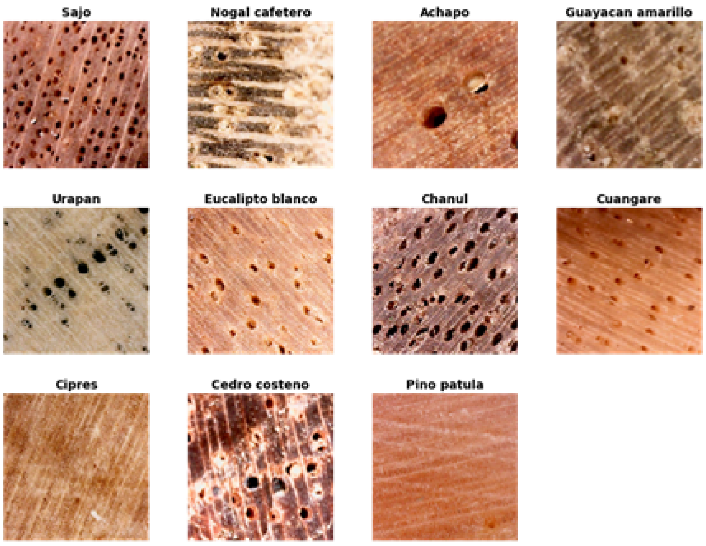

Fig. 1. Macroscopic tropical wood images of the dataset

Table 1. Features of the Dataset

Scientific Name	Family	Common Name (Colombian/Global)	Wood Type	Image Count
Campnosperma panamensis	Anacardiaceae	Sajo / Orey Wood	Hardwood	823
Cedrela odorata	Meliaceae	Cedro costeño / Cigarbox cedar	Hardwood	1128
Cedrelinga cateniformis	Fabaceae	Achapo / Cedrorana	Hardwood	1189
Cordia alliodora	Boraginaceae	Nogal cafetero / Laurel	Hardwood	929
Dialyanthera gracilipes	Myristicaceae	Cuángare / Virola / White Cedar	Hardwood	1100
Eucalyptus globulus	Myrtaceae	Eucalipto blanco / Blue gum	Hardwood	1105
Handroanthus chrysanthus	Bignoniaceae	Guayacán amarillo / Roble amarillo / Trumpet Tree	Hardwood	1106
Humiriastrum procerum	Humiriaceae	Chanul / Corozo	Hardwood	1001
Fraxinus uhdei	Oleaceae	Urapan / Fresno / Shamel ash	Hardwood	1025
Cupressus lusitanica'	Cupressaceae	Cipres / Pino Cipres	Softwood	815
Pinus patula	Pinaceae	Pino patula / Ocote	Softwood	571

2. Transfer learning method

Transfer learning is an effective technique that enables a machine learning model to apply the knowledge acquired from a previous task to a new one. Convolutional Neural Networks (CNNs) are artificial neural networks with a layered architecture capable of extracting complex features from images. However, training CNN models from the ground up is a time-consuming and computationally demanding process, requiring significant computational power. Therefore, it is generally preferred to use models that have already been pre-trained on large datasets (such as ImageNet) and have their weights fine-tuned (Shermin et al., 2018). The overall structure of the transfer learning approach utilised in this study is illustrated in Figure 2.

Fine-tuning CNN enables a model to adapt previously learned information to a new task through transfer learning. Rather than starting with random weights, using pre-trained weights offers a better starting point. By changing the last layer and retraining it, the model can be fine-tuned through backpropagation. It is also possible to choose which layers to update. Usually, the first layers learn basic features such as edges and colours, and these filters are useful for most image classification tasks (De Geus et al., 2021; Sanida et al., 2023).

This dataset, consisting of 11 classes of macroscopic images of tropical woods, was re-optimised for categorisation because it was different from the images trained on ImageNet, which was trained on 1000 classes. However, this process involved more than merely adjusting 1000 classes to 11. It was optimised with various methods to make it more stable and successful. It is presented in detail in the proposed method section of the research.

3. CNN-based deep learning models

In image classification tasks, the ImageNet dataset (Russakovsky et al. 2015), containing 1000 categories and widely used in numerous competitions, is often selected for training. Research groups generally design and train advanced, high-performing models tailored specifically for this dataset. However, despite today's modern hardware, the process of developing a new model can sometimes take days or even weeks. For this reason, researchers share the results and success rates of the models they develop on online platforms so that other researchers can access these models and make improvements on them (Kırbaş and Çifci, 2022). In light of this information, Xception, DenseNet201, InceptionV3, InceptionResNetV2, MobileNetV2, EfficientNetV2B3, and ResNet50V2 models were optimised and used for tropical wood categorisation. Basic information about each CNN model is presented below:

1. **Xception (Extreme Inception):** It is a CNN architecture developed by François Chollet that increases computational efficiency thanks to depthwise separable convolutions. This structure, which is considered an extended version of the Inception model, provides more efficient use of parameters and increases the accuracy rate by using independent filtering and point convolution between channels instead of standard convolution. It has shown superior performance on ImageNet and other datasets and is widely preferred in many computer vision (CV) applications today (Chollet, 2017).
2. **DenseNet (Densely Connected Convolutional Networks):** It is a CNN structure in which each layer establishes direct connections with all previous layers. DenseNet201 is the 201-layer version

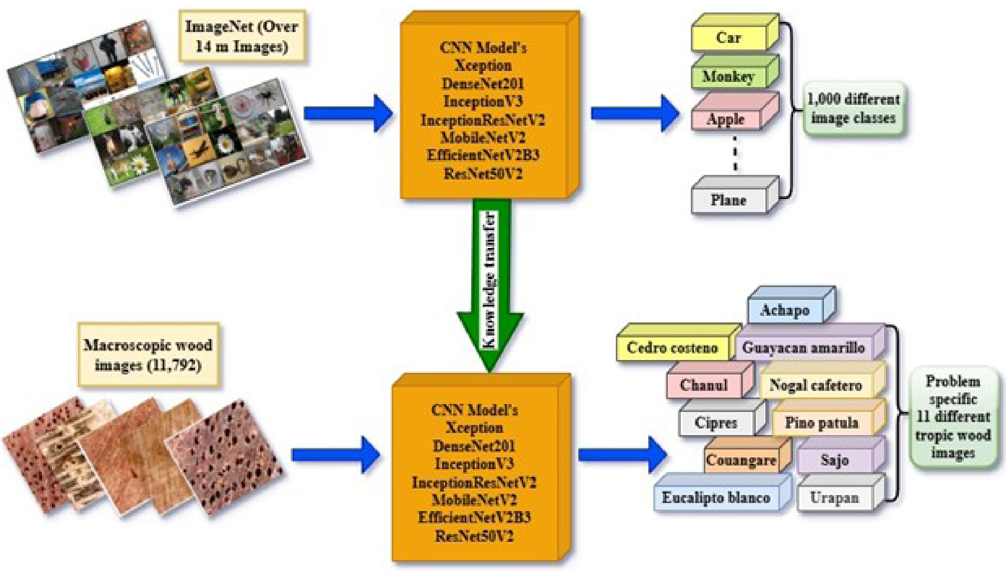

Fig. 2. General structure of a transfer learning application for tropical wood species classification

of this model. Unlike traditional CNNs, DenseNet feeds feature maps from all previous layers into each layer. In this way, deeper layers work with more feature information, increasing parameter efficiency. Additionally, this structure reduces problems such as gradient loss and speeds up the learning process. DenseNet exhibits high performance in terms of accuracy and parameter efficiency, and is often used in computer vision applications such as image classification and object recognition. DenseNet201 has a deeper learning capacity with 201 layers and achieves effective results on large datasets such as ImageNet (Huang et. al., 2017).

3. **InceptionV3:** It is a CNN structure developed by Google and widely used in the field of deep learning. This model uses a modular architecture called "Inception" designed to provide high accuracy in image processing tasks. Inception modules allow the network to operate more efficiently by applying convolution filters of different sizes in parallel. InceptionV3 has a deeper structure than its previous versions, providing faster results with lower computational costs. In addition, bottleneck layers and factorisation methods used to reduce the size of the model help make the model lighter. Pre-trained on large datasets such as ImageNet, InceptionV3 is a frequently preferred model for transfer learning and provides high success in various tasks (Szegedy et al., 2016).
4. **InceptionResNetV2**: It is a CNN model developed by Google and belongs to the Inception family. This architecture uses residual connections, making the powerful structures of InceptionV3 more efficient for deeper networks. Residual connections allow the network to learn faster, allowing it to generalise better to deeper structures and train more efficiently. InceptionResNetV2 has a more complex and deeper structure than its previous versions, allowing for higher accuracy on large data sets while also offering lower computational costs. This model is well-suited for transfer learning applications because it can be effectively applied to other tasks using weights trained on large datasets, e.g., ImageNet. InceptionResNetV2 is a model that stands out with its strong performance and computational efficiency in the field of deep learning (Szegedy et al., 2017).
5. **MobileNetV2:** It is a deep learning model developed by Google and optimised specifically for mobile devices. This model is designed to achieve high performance with lower computational resources. MobileNetV2 has a more efficient architecture than its predecessor and uses an innovative structure called the inverted residual block. This structure allows the model to run faster and achieve better results with limited computational power. Moreover, MobileNetV2 uses depth-separable convolutions technology to reduce the number of parameters of the network, thus making the model lighter and faster. These features make MobileNetV2 an ideal choice, especially for mobile devices and low-resource embedded systems. The model is also widely preferred for transfer learning, and its pre-trained weights can be used with high accuracy in different tasks (Sandler et al., 2018).
6. **EfficientNetV2B3:** It is a CNN model developed by Google that combines high performance and efficiency in the field of deep learning. A member of the EfficientNet family, this model is optimised for a faster and more efficient training process. EfficientNetV2B3 balances the size, depth, width, and resolution of the model by adopting the compound scaling method. This approach makes it possible to achieve higher accuracy without increasing the number of parameters of the model and the computational costs. Additionally, EfficientNetV2B3 offers faster training times than its predecessors and provides higher efficiency with fewer computational resources. The model is equipped with innovative techniques such as the swish activation function and squeeze-and-excitation blocks. These improvements increase the overall performance of the model and make learning processes more efficient. EfficientNetV2B3 is an ideal choice for applications that require high accuracy and efficiency, especially on large data sets (Tan and Le, 2021).
7. **ResNet50V2:** It is a deep learning model developed by Microsoft and is part of the Residual Networks (ResNet) family. This model represents a significant innovation in the field of deep learning. ResNet50V2 is a convolutional neural network consisting of 50 layers, and enables deep networks to be trained more efficiently, especially by using residual connections. Such connections keep the learning process stable even when the model is deeper and avoid the problem of vanishing gradients. ResNet50V2 introduces some structural improvements and more efficient training techniques compared to its previous version. ResNet50V2 introduces some structural improvements and more efficient training techniques compared to its previous version (He et al., 2016).
8. While optimising the CNNs used in the study, a 512-neuron ReLU activation dense layer (L2 and L1 regularizers were used). Over-learning is prevented with a 45% Dropout rate. Output layer: A softmax activation function containing as many neurons as the number of classes was used. Also, all these layers were trained together with the base CNN models.

4. Proposed method

In this study, an optimised EfficientNetV2B3 architecture is proposed to achieve better performance in macroscopic tropical wood image categorisation tasks. While EfficientNetV2B3 provides a strong base model in terms of high accuracy and computational efficiency, our proposed method aims to further optimise this architecture and increase its generalisation capacity.

EfficientNetV2B3 has established itself as a leading deep learning architecture, distinguished by its innovative compound scaling technique that simultaneously adjusts the network's depth, width, and input resolution to maximise performance while maintaining efficiency (Tan et al., 2021). This balanced scaling approach allows the model to extract richer features from input images and speeds up the training process by optimising resource usage across multiple dimensions of the architecture.

To further enhance efficiency and make the model more suitable for deployment, especially on devices with limited computational power, several optimisation techniques are applied. Weight pruning is one such method that removes redundant or less important parameters from the network, effectively reducing the model's size and computational complexity without significantly compromising accuracy. Quantisation complements pruning by converting the model's weights and activations from high-precision floating-point representations to lower-bit formats, such as 8-bit integers. This transformation substantially decreases memory usage and accelerates inference, which is critical for real-time applications and edge computing scenarios (Han et al., 2015).

Moreover, to improve the robustness and generalisation ability of EfficientNetV2B3, advanced data augmentation techniques are employed during training. These include geometric transformations like image rotation and horizontal flipping, as well as photometric changes such as colour distortion. Such augmentations expose the model to a diverse set of input variations, helping it learn invariant features and reducing the risk of overfitting on the training data. Alongside augmentation, regularisation methods like Dropout are integrated into the training pipeline. Dropout randomly deactivates a subset of neurons during each training iteration, which forces the model to develop redundant representations and prevents it from relying too heavily on any single feature, thus enhancing prediction stability and accuracy (Srivastava et al., 2014).

In the proposed approach, we introduce a hybrid loss function that combines the conventional cross-entropy loss with a customised regularization term. This tailored regularization component focuses on difficult or ambiguous training samples, encouraging the model to learn more discriminative features from challenging examples. By balancing standard classification objectives with targeted regularization, the loss function facilitates improved convergence and higher overall classification accuracy. This comprehensive methodology not only boosts model performance but also ensures that the model remains efficient, generalises well to unseen data, and is adaptable for practical deployment in real-world wood species classification tasks.

Transfer learning allows the EfficientNetV2B3 model originally trained on large-scale datasets to be adapted to a specific task through fine-tuning on the target dataset (He et al., 2019). This method allows the model to maintain broad feature representations while efficiently capturing patterns specific to the task. The model's effectiveness was assessed through common evaluation metrics such as accuracy, F1 score, and inference time. Experimental outcomes indicate that the proposed framework significantly enhances both classification performance and computational efficiency. These results imply that the approach is highly suitable for real-time use, especially in settings with constrained computational capabilities.

This model is a deep learning model based on EfficientNetV2B3 and is designed for image classification. The input size is set as 300x300x3, and the model is applied to transfer learning using the EfficientNetV2B3 network pre-trained with ImageNet. In the model, global max pooling was used to summarize the feature maps. BatchNormalization was applied to balance the learning process of the model, and 45% Dropout was added to prevent over-learning.

The architecture's fully connected component incorporates a dense layer containing 512 units, which utilises the ReLU activation function. To prevent overfitting and promote generalisation, both L1 and L2 regularisation methods are applied at this stage. In the final layer, a Softmax activation function is used, with the number of output nodes corresponding to the total classes in the dataset, enabling effective multi-class classification. To improve computational efficiency during training, the model leverages mixed precision through the use of the 'mixed_float16' policy. The training process is carried out using the Adam optimisation algorithm, set with a learning rate of 0.001, while the loss is computed using the categorical cross-entropy function. The effectiveness of the model is measured based on its classification accuracy.

During this training process, various hyperparameters and early stopping strategies were applied to ensure more efficient learning of the model. While the training of the model was carried out with a batch size of 64, it was planned to run for a total of 30 epochs. During training, if the monitored value does not improve, 2 epochs are waited to adjust the learning rate, while 10 epochs are required to stop the model completely if there is no improvement.

Table 2. Optimised model summary of the EfficientNetV2B3 model

Layer (type)	**Output Shape**	**Param #**
efficientnetv2-b3 (Function)	(None, 1536)	12,930,622
batch_normalization (BatchNorm)	(None, 1536)	6,144
dense (Dense)	(None, 512)	786,944
dropout (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 11)	5,643
Total params		13,729,353
Trainable params		13,617,065

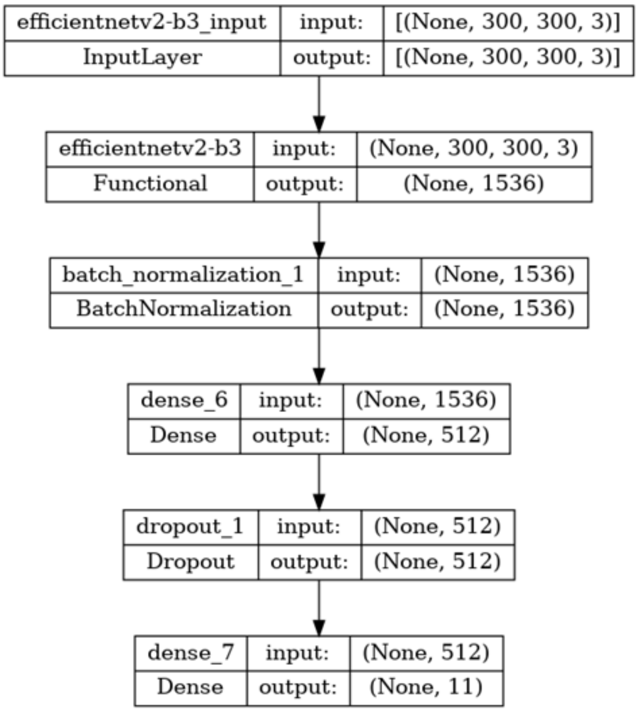

Fig. 3. Schematic representation of the optimised EfficientNetV2B3 model

Additionally, when the training accuracy falls below the specified 90% threshold, the model accuracy metric will be monitored, while if the threshold is exceeded, the monitoring will be performed based on the validation loss. The learning rate will be reduced by a factor of 0.5 if the specified improvement is not achieved. The model receives confirmation from the user every 5 epochs on whether to continue training or not. The number of batches to be run during each epoch is calculated depending on the size of the training dataset. To manage all these processes, the MyCallback class is used to assign model-specific callback functions. The optimised model summary of the EfficientNetV2B3 model used in the research is given in Table 2. The schematic representation of the optimised EfficientNetV2B3 model is given in Figure 3.

The proposed method improves classification performance by applying optimisation techniques and advanced data augmentation strategies to the EfficientNetV2B3 model. Optimisation methods such as weight pruning and quantisation reduce computational and memory requirements, making the model suitable for low-resource environments. Regularisation techniques like Dropout help prevent overfitting and increase the model's ability to generalise. A hybrid loss function tailored to the task improves the model's ability to classify complex samples. The results indicate that this approach is effective and reliable, particularly when working with large datasets under resource limitations. Future research may focus on applying this method to broader datasets and different problem domains to further enhance performance.

5. Evaluation Metrics

- **Precision:** It is the proportion of true positive results (TP) out of all positive predictions made (TP + FP).

$$\text{Precision} = \frac{TP}{TP+FP} \quad (1)$$

- **Recall:** It is the ratio of true positives (TP) to total true positives (TP + FN).

$$\text{Recall} = \frac{TP}{TP+FN} \quad (2)$$

- **F1-Score:** It is the harmonic mean that measures the balance between precision and recall.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (3)$$

- **Accuracy:** It is the ratio of correct predictions (TP + TN) to total samples (TP + TN + FP + FN).ahminlerin (TP + TN) toplam örneklere (TP + TN + FP + FN) oranıdır.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

- **ROC (Receiver Operating Characteristic) Curve:** The ROC curve is a graph showing the true positive rate (TPR) and the false positive rate (FPR).

$$TPR = \frac{TP}{TP+FN}, \quad FPR = \frac{FP}{FP+TN} \quad (5)$$

- **AUC (Area Under the Curve):** AUC represents the area under the ROC curve and is a metric that measures the classification ability of the model.

$$AUC = \int_0^1 TPR\ dFPR \quad (6)$$

- **Confusion Matrix: A** Confusion Matrix is a table containing four basic values (TP, TN, FP, FN). An example of a confusion matrix is given in Table 3.

Experimental Results

For the categorisation of tropical woods from macroscopic images, different CNN architectures were used in their bare form without being optimised. The performances of these architectures are presented in Table 4.

Table 4 presents a comparison of various CNN models based on accuracy, precision, recall, and F1-score metrics. Among them, EfficientNetV2B3 delivered the best performance, achieving the highest accuracy (0.9296), precision (0.9307), and recall (0.9296), with a training time of 37.34 minutes. These results demonstrate that EfficientNetV2B3 is both an efficient and effective choice compared to the other models.

Although DenseNet201 took the longest training time with 40.38 minutes, it succeeded with high accuracy (0.8326) and strong metrics. However, long training time may be a disadvantage in terms of efficiency.

Table 3. Example confusion matrix

	Predicted Positive	Predicted Negative
Actual Positive	*TP*	*FN*
Actual Negative	*FP*	*TN*

Table 4. Performance of transfer learning and non-optimised CNN models

CNN Models	Duration	Precision	Recall	F1-score	Accuracy
Xception	35.53 min.	0.6423	0.6214	0.6208	0.6214
DenseNet201	40.38 min.	0.8422	0.8326	0.8313	0.8326
InceptionV3	36.39 min.	0.5763	0.5090	0.5055	0.5090
InceptionResNetV2	38.37 min.	0.0394	0.1087	0.0447	0.1087
MobileNetV2	36.28 min.	0.7052	0.6813	0.6848	0.6813
EfficientNetV2B3	37.34 min.	0.9307	0.9296	0.9296	0.9296
ResNet50V2	37.01 min.	0.6123	0.5942	0.5855	0.5942

Table 5. Performances of CNN models without transfer learning and without optimisation

CNN Models	Duration	Precision	Recall	F1-score	Accuracy
Xception	40.25 min.	0.5819	0.5825	0.5787	0.5825
DenseNet201	38.08 min.	0.7561	0.7492	0.7489	0.7492
InceptionV3	36.18 min.	0.7257	0.7153	0.7152	0.7153
InceptionResNetV2	38.52 min.	0.7734	0.7641	0.7583	0.7641
MobileNetV2	36.18 min.	0.0121	0.1099	0.0218	0.1099
EfficientNetV2B3	39.08 min.	0.5090	0.3786	0.3601	0.3786
ResNet50V2	37.43 min.	0.7084	0.7048	0.7013	0.7048

Table 6. Performance of optimised CNN architectures

CNN Models	Duration	Precision	Recall	F1-score	Accuracy
Xception	58.10 min.	0.9866	0.9864	0.9864	0.9864
DenseNet201	74.01 min.	0.9786	0.9784	0.9784	0.9784
InceptionV3	38.45 min.	0.9692	0.9679	0.9677	0.9679
InceptionResNetV2	51.34 min.	0.9656	0.9648	0.9648	0.9648
MobileNetV2	37.43 min.	0.9804	0.9802	0.9803	0.9802
EfficientNetV2B3	50.57 min.	0.9902	0.9901	0.9901	0.9901
ResNet50V2	42.07 min.	0.9517	0.9512	0.9510	0.9512

MobileNetV2 and Xception showed moderate performance with shorter training times (36.28 and 35.53 minutes). MobileNetV2 (precision: 0.7052, recall: 0.6813) gave moderate results, while Xception had lower metrics. InceptionV3 and InceptionResNetV2 showed low performance and were the weakest models with an accuracy of 0.5090 and 0.1087, respectively.

Table 5 presents the performance of CNN architectures when the weights from Imagenet were taken and the layer training was turned off in the tropical wood categorisation.

When Table 5 is examined, DenseNet201 and InceptionResNetV2 models achieved strong results by exhibiting the highest performance with accuracy values of 0.7492 and 0.7641, respectively. InceptionV3 also showed good performance with 0.7153 accuracy, while ResNet50V2 provided moderate results with 0.7048 accuracy. Xception performed average with an accuracy of 0.5825. MobileNetV2 yielded very low accuracy (0.1099) and yielded poor results across other metrics. Finally, EfficientNetV2B3 showed poor performance with low accuracy (0.3786) and metrics. Overall, DenseNet201 and InceptionResNetV2 stand out as the most successful models, while MobileNetV2 and EfficientNetV2B3 exhibited lower performance.

The performances of the optimised and transfer learning CNN architectures are given in Table 6.

The Xception model had the highest precision (0.9866), recall (0.9864), F1-score (0.9864), and accuracy (0.9864) values with 58.10 minutes of training time. This result shows that Xception is a very powerful model and exhibits excellent performance in classification tasks. However, since the training time is longer than that of other models, it may be a factor to consider in terms of time efficiency.

Although DenseNet201 took the longest training time with 74.01 minutes, it performed quite successfully with high accuracy (0.9784), precision (0.9786), recall (0.9784), and F1-score (0.9784) values. However, considering the training time, it is a more time-consuming model than Xception, which can be a disadvantage in terms of efficiency.

EfficientNetV2B3 stands out with high accuracy (0.9901), precision (0.9902), recall (0.9901), and F1-score (0.9901) with 50.57 minutes of training time. This model can be considered a very strong option in terms of overall efficiency, as it offers both high performance and a reasonable training time.

MobileNetV2 achieved very good results with high accuracy (0.9802), precision (0.9804), recall (0.9802), and F1-score (0.9803) with 37.43 minutes of training time. Although the training time is short, it is quite powerful in terms of performance and, therefore, can be an ideal option for applications that require fast training.

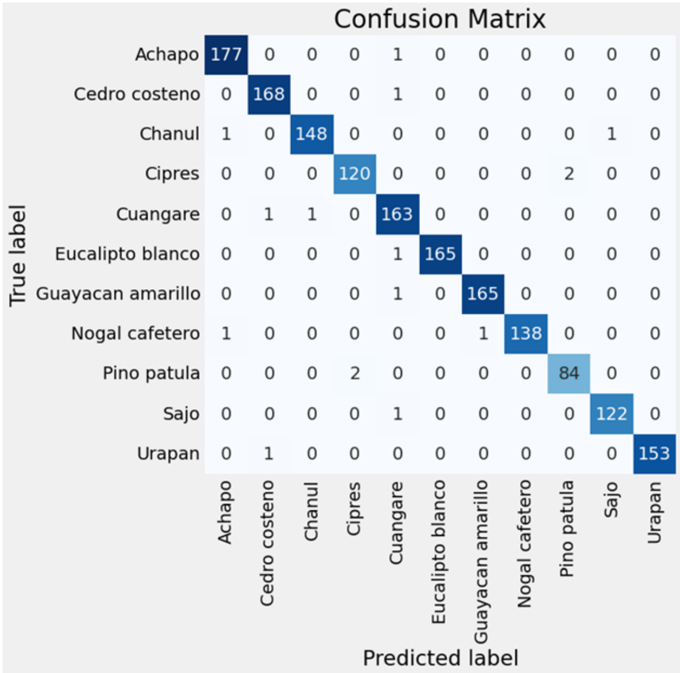

Fig. 4. Confusion matrix of the optimised EfficientNetV2B3 CNN architecture

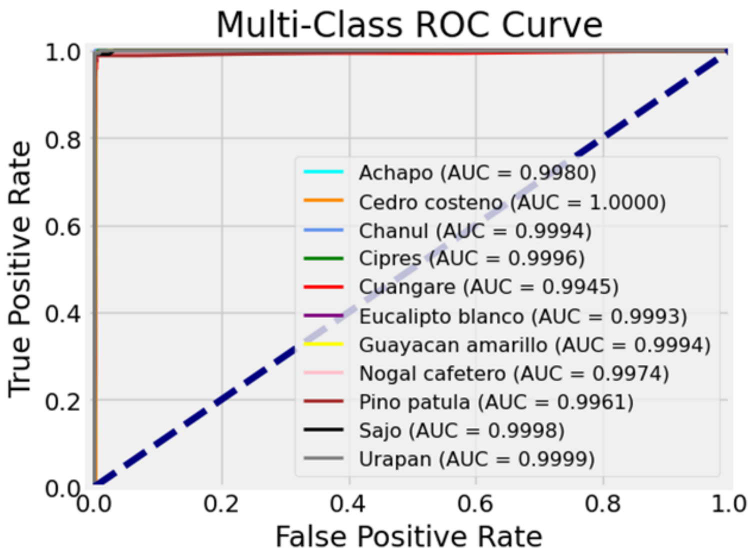

Fig. 5. ROC Curve of the optimised EfficientNetV2B3 CNN architecture

InceptionV3 and InceptionResNetV2 are models that exhibit good performance with training times of 38.45 and 51.34 minutes, respectively. InceptionV3 achieves good results with 0.9679 accuracy and robust metrics, but InceptionResNetV2 shows similar success with slightly lower accuracy (0.9648). While both models are powerful, they do not perform as well as MobileNetV2 and EfficientNetV2B3.

Finally, the ResNet50V2 model is the one with the lowest performance, with the lowest accuracy (0.9512) and metrics (precision: 0.9517, recall: 0.9512), with 42.07 minutes of training time. This model underperformed relative to the others.

Overall, Xception, DenseNet201, and EfficientNetV2B3 provide the highest performances, while MobileNetV2 provides an impressive result with fast training time. InceptionV3 and InceptionResNetV2 remained at average levels. ResNet50V2 stands out as the model with the weakest performance, with lower accuracy and metrics. Model selection should be made according to the balance between accuracy and training time; models such as MobileNetV2 and EfficientNetV2B3 can be preferred for applications requiring fast training, while models such as Xception and DenseNet201 will be more suitable for applications targeting high accuracy.

Table 7. Classification report of the optimised EfficientNetV2B3 CNN model

Classes	Precision	Recall	F1-Score	Support
Achapo	0.9888	0.9944	0.9916	178
Cedro costeno	0.9882	0.9941	0.9912	169
Chanul	0.9933	0.9867	0.9900	150
Cipres	0.9836	0.9836	0.9836	122
Cuangare	0.9702	0.9879	0.9790	165
Eucalipto blanco	1.0000	0.9940	0.9970	166
Guayacan amarillo	0.9940	0.9940	0.9940	166
Nogal cafetero	1.0000	0.9857	0.9928	140
Pino patula	0.9767	0.9767	0.9767	86
Sajo	0.9919	0.9919	0.9919	123
Urapan	1.0000	0.9935	0.9967	154
Accuracy			0.9901	1619
Macro Avg	0.9897	0.9893	0.9895	1619
Weighted Avg	0.9902	0.9901	0.9901	1619

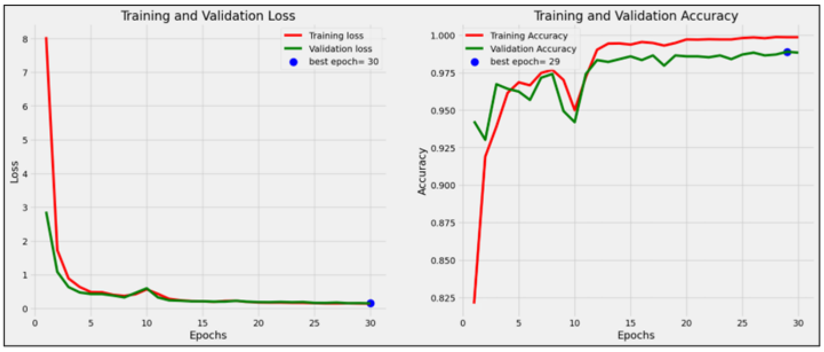

Fig. 6. Graph of training and validation loss, and graph of training and validation accuracy

Since it is extremely important to categorise each tropical wood correctly, EfficientNetV2B3, which gives high accuracy (0.9901), is recommended for use in research and studies within the scope of this article.

In the research, the EfficientNetV2B3 model stood out as the best-performing model with high accuracy (0.9901), precision (0.9902), recall (0.9901), and F1-score (0.9901) values and became the recommended method. The classification success of this model has been achieved with very high results in terms of accuracy and other metrics. However, additional evaluation metrics such as the confusion matrix, ROC curve, and classification report are presented to further evaluate the success of the model. The optimised EfficientNetV2B3 CNN architecture is given in Figure 4. The ROC curve for the optimised EfficientNetV2B3 is given in Figure 5.

The classification report presents the precision, recall, and F1-score for each class. It offers insights into the model's performance per class, highlighting areas where the model excels and where it may need improvement. All these evaluation metrics help us understand the reasons behind the high accuracy of the EfficientNetV2B3 model in more detail and enable us to evaluate the overall performance of the model more comprehensively. The classification report of the optimised EfficientNetV2B3 CNN model is given in Table 7.

This classification report demonstrates that the model performs well. Precision, Recall, and F1-Score values range from 0.97 to 1.00 for all classes, indicating that the model both makes accurate predictions and successfully captures true positives. The overall accuracy is quite high at 99.01%, proving that the model works almost perfectly. Macro and weighted averages also indicate a balanced performance. In conclusion, this model performs extremely well for the given classification task and can be used safely in practical applications.

If the training and validation loss graph shows that the loss values of the model are decreasing regularly and there is no overfitting, the model has learned in a balanced way. If the training and validation accuracy graph shows that both accuracy values are high and close to each other, the model is successful on both training and validation data. When these two graphs are evaluated together, it is concluded that the model is well-trained, can generalise, and does not overfit. This shows that the study was successful. The training and validation loss and accuracy graphs are presented in Figure 6.

When the train and validation losses are examined, it is observed that the proposed model does not overfit during the training phase, and the loss values decrease steadily. Despite the overfitting of the model, the early stopping function was used. When the train and validation accuracy were monitored, both accuracy values increased and decreased proportionally during 30 epochs. These values prove that the training and validation accuracies of the model are stable and consistent.

Discussion

This study compares its findings with previous research on wood species recognition and classification. The results of these comparisons are summarised in Table 8. It is important to note that the datasets used in different studies may vary, and any comparison of methods should be conducted using the same database. However, a study was conducted on this dataset by Ergün 2024. There are 11 classes in the dataset. However, Ergün (2024) conducted a study on 10 classes in his research.

The classification performance achieved in this study is highly significant. However, some limitations must also be taken into consideration. The data set used only includes 11 tropical tree species selected from the Colombian region, which may limit the direct generalisation of the findings to different regions or a wider range of the performance of the model may vary if the number of species increases or samples from regions with different environmental conditions are added. Therefore, cross-validation of data sets and geographical expansion of data diversity are targeted in future studies.

The images were obtained under standard and controlled conditions, which ensured a fair comparison of the models. However, in real field conditions, factors such as light, background, and resolution can affect model performance. CNNs are generally known to be robust against such changes (Barmpoutis et al., 2018; Fabijańska et al., 2021).

Table 8 presents a comparison of various studies on the recognition and classification of wood species in terms of techniques, data set sizes, number of classes, and accuracy rates. Our study achieved a significant improvement over other studies in the literature by achieving an accuracy rate of 99.01% with the proposed method. This result demonstrates the effectiveness and generalisation ability of deep learning models, especially in a complex task such as tropical wood classification.

When the studies in the literature are examined, it is seen that the accuracy rates vary between 77.52% and 97.34%. For example, in the study conducted by Tang et al. (2018), a large dataset containing 100 classes was used, and an accuracy of 77.52% was achieved. This shows that the accuracy rate may decrease as the number of classes increases. In contrast, in the study conducted by Rostina et al. (2020), an accuracy rate of 96.00% was achieved using a smaller dataset containing 3 classes. This shows that higher accuracy rates can be achieved in cases where the number of classes is small.

In our study, a dataset of 11792 images containing 11 classes was used, and an accuracy rate of 99.01% was achieved. This result is one of the highest accuracy rates in the literature, and achieving this success, especially in a dataset with a relatively high number of classes, proves the effectiveness of the proposed method. Additionally, in the study conducted by Ergün (2024), an accuracy rate of 97.34% was achieved using a dataset of 10,792 images containing 10 classes. Our study surpassed this result with more classes and a larger dataset, demonstrating the superiority of the proposed method.

In terms of the techniques used, traditional methods (k-NN, SVM) and simple artificial neural networks (ANN) generally had lower accuracy rates, while deep learning models (CNN, ResNet, Inception, etc.) provided higher accuracy rates. In particular, modern architectures such as InceptionResNetV2 have achieved accuracy rates as high as 97.34%. The proposed method used in our study surpassed these models and reached an accuracy rate of 99.01%. This shows that the proposed method is more effective than existing deep learning models.

In conclusion, our study achieved a higher accuracy rate in a complex task such as tropical wood classification compared to other studies in the literature. This success proves the effectiveness and generalisation ability of the proposed method. In the future, it is recommended that this method be tested on different data sets and classification problems to further improve its performance.

The comparison of this research with the study conducted by Ergün (2024) using this dataset is given in Figure 7.

The performances of the models proposed by Ergün (2024) and the models proposed in this study were compared. In both studies, the accuracy values obtained using different deep learning architectures were examined. In Ergün's (2024) study, DenseNet201 and InceptionResNetv2 models achieved high accuracy values, such as 96.98% and 97.34%, respectively, while in the proposed study, Xception and EfficientNetV2B3 models achieved higher accuracy values, such as 98.64% and 99.01%. Particularly, the EfficientNetV2B3 model attracted attention by achieving the highest accuracy value in both studies. As a result, although both studies achieved high accuracy values on different models,

Table 8. A comparison of different studies on wood species recognition and classification

Technical	Number of Images in the Data Set	Number of Classes	Purpose of the Research	Accuracy (%)	References
k-NN	600	6	Texture classification in the recognition of wood species	85.00	(Tou et al. 2009)
Artificial Neural Networks (ANN)	500	25	Classification of hardwood species	92.60	(Yadav et al. 2013)
3-Layer Deep CNN	2050	41	Recognition of forest species	95.77	(Hafemann et al. 2014)
Artificial Neural Networks (ANN)	1500	10	Classification of wood species	90.00	(Sundaram et al. 2015)
ANN, SVM, k-NN	2800	28	Recognition of wood species	90.20	(Hu et al 2015)
Compression Network	101.546	100	Macroscopic wood identification	77.52	(Tang et al. 2018)
SVM	4272	12	Texture analysis in the recognition of wood species	91.47	(Barmpoutis et al. 2018)
ResNet34	965	10	Wood identification	81.90	(Ravindran and Wiedenhoeft 2020)
5-Layer Deep CNN	3000	3	Determination of wood species	96.00	(Rostina et. al. 2020)
InceptionV4_ResNetV2	1869	10	Identification of North American hardwoods	92.60	(Lopes et. al. 2020)
ResNet-50, Inception V3, Xception, VGG19	3552	12	Classification of wood species	95.88	(Kırbaş and Çifci 2022)
RestNet18, GoogLeNet, VGG19, Inceptionv3, MobileNetv2, DenseNet201, InceptionResNetv2, EfficientNetb0, ShuffleNet	10,792	10	Tropical wood classification (Macroscopic images)	IncepitonResnNetV2 97.34 Recommended method: Modified ShuffleNet 96.04	(Ergün 2024)
Xception DenseNet201 InceptionV3 InceptionResNetV2 MobileNetV2 EfficientNetV2B3 ResNet50V2	11,792	11	Tropical wood classification (Macroscopic images)	99.01	Proposed method

EfficientNetV2B3 and Xception models gave more successful results in the proposed study. This shows that model selection and architecture optimisation have a significant impact on accuracy.

In order to evaluate how applicable the model is in real-world applications, especially in environments with limited hardware, an analysis supported by concrete data on computational complexity was conducted. The optimised EfficientNetV2B3 architecture used in this study has approximately 13.6 million learnable parameters and is approximately 55.6 MB in size. The total floating point operations (FLOPs) performed by the model in each inference is approximately 1.9 billion, which shows that it offers a lighter and more efficient structure, especially when compared to deep structures (e.g., DenseNet201: ~4.3 billion FLOPs).

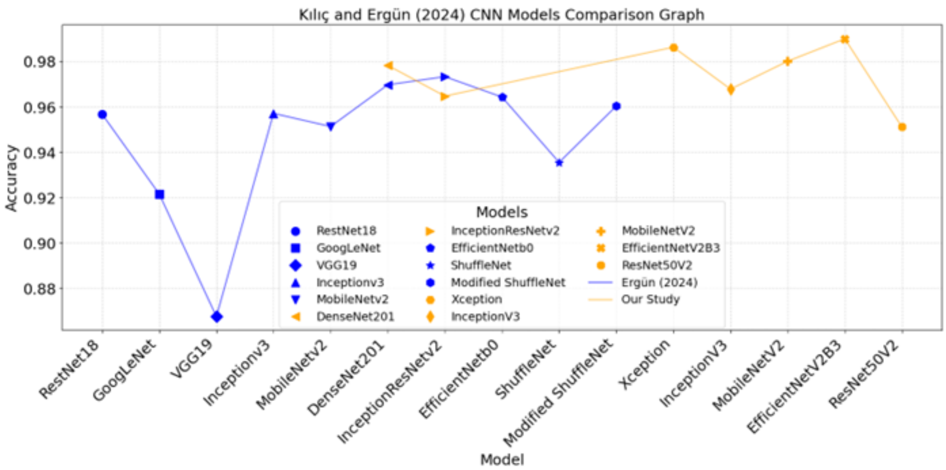

Fig. 7. Accuracy performance comparisons of Kılıç and Ergün (2024)

The inference time was tested directly on Kaggle's T4x2 dual GPU environment. In this environment, the inference time for an image averaged between 58 and 65 milliseconds. When the same model was tested on a local CPU (Intel i7-8750H, 2.2 GHz, 16 GB RAM), this time it increased to approximately 410 milliseconds. These results demonstrate that the model is well-suited for real-time use, particularly on GPU-supported online platforms and edge devices.

The model's training process was also carried out entirely on Kaggle. Training took approximately 49 minutes over a total of 30 epochs with mini-batches consisting of 64 samples. During this time, Dropout and L1/L2 regularisers were used in the model trained with mixed precision to prevent overfitting. Additionally, optimisation techniques such as weight pruning were applied to reduce the model's memory footprint, making it lightweight and portable.

This structure can be easily integrated into systems running on low-resource environments such as TensorFlow Lite, Core ML, and ONNX Runtime, providing an accessible, low-cost, and effective solution for researchers in the field or mobile application developers.

There are some important factors to consider in terms of the practical applicability of the model. The optimised EfficientNetV2B3 model developed in this study achieved a very high accuracy rate of 99.01% in the classification of tropical wood species. However, the model's structure, which contains 13.7 million parameters, requires hardware or cloud computing infrastructure with sufficient processing power for real-time applications. In terms of data dependency, the fact that the current dataset only covers 11 species originating from Colombia indicates that the model may require additional training for wood diversity in different geographical regions. Furthermore, the fact that all images in the dataset were taken under standard artificial lighting conditions highlights the need to additionally evaluate the model's performance under natural lighting conditions.

For mobile applications and environments with limited hardware resources, it is considered that the MobileNetV2 model tested in this study could offer a viable alternative with its 98.02% accuracy rate and lower number of parameters. In light of these findings, it is important to conduct detailed investigations of the model's performance on different hardware platforms and comprehensive field tests in open environments in future studies.

Conclusions

This study concentrated on classifying tropical wood species using macroscopic images and assessed the performance of several deep learning models, with and without optimisation and transfer learning. The findings indicate that deep learning models, particularly when optimized and fine-tuned, can achieve impressive accuracy in wood species classification. The proposed approach, utilizing the EfficientNetV2B3 model, surpassed other state-of-the-art methods by reaching an exceptional accuracy of 99.01%, setting a new benchmark in tropical wood classification.

The comparison of different CNN architectures revealed that EfficientNetV2B3, Xception, and DenseNet201 are the best-performing models, while EfficientNetV2B3 emerges as the most effective model due to its high accuracy, precision, recall, and F1 score. The ability of the model has the ability to generalise well across 11 tropical wood species, which highlights its robustness and suitability for complex classification tasks. Additionally, MobileNetV2 has demonstrated a strong balance between performance and training efficiency, making it a viable option for applications requiring faster training times.

The study also highlighted the importance of model optimisation and transfer learning. While unoptimised models such as InceptionResNetV2 and InceptionV3 performed poorly, their optimised counterparts achieved significantly higher accuracy, highlighting the critical role of fine-tuning in deep learning applications. Moreover, the comparison with previous studies, including Ergün (2024), demonstrates that the proposed method outperforms existing approaches even with a larger dataset and more classes.

Evaluation metrics such as complexity matrices, ROC curves, and classification reports provided comprehensive insights into the performance of the models. High precision, recall, and F1 scores across all classes validate the reliability of the proposed method. Training and validation loss and accuracy curves further confirmed that the models were well trained with no signs of overfitting, ensuring their generalizability to new data.

In conclusion, this study successfully demonstrated the effectiveness of deep learning models, especially EfficientNetV2B3, in the classification of tropical wood species. The proposed method, a transfer learning based optimised deep learning framework for tropical wood categorisation, has achieved state-of-the-art performance by outperforming previous studies and offering a reliable and robust solution for wood species identification. Future work can investigate the application of these models to other datasets and classification tasks, and further optimisation to reduce training times and computational costs. The findings of this study make significant contributions to the field of wood science and provide a strong foundation for future research in automatic wood species classification.

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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