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Progressive Image Resizing for wood Species Classification from Macroscopic Images

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Abstract

Wood is an important raw material used in various activities, such as building, furniture, and fuel. The timber industry is significant in many countries and has a significant financial impact. There are diverse categories of wood, each with its unique properties, and experts typically perform wood species identification through visual inspection, which is a tedious and time-consuming process. To eliminate the need for manual detection, a deep learning-based wood Classification System was proposed in this paper. The system uses a transfer learning-based convolutional neural network model that handles feature extraction. Compared to other transfer learning models such as VGG16, ResNet50, and DenseNet201, the proposed EfficientNetB7 model achieved a high validation accuracy of 99.824%, which suggests that it can be used to aid unskilled agents in wood categorization. This new strategy can save time and effort in the identification of wood species, making it an efficient method for the timber industry.

Keywords

wood classification; progressive resizing; Wood Species dataset; differential learning rates; EfficientNet, ResNet, and DenseNet

1. Introduction

Currently, wood is utilized worldwide as one of the most valuable carbon-neutral renewable resources, particularly in the building and furniture sectors. Indeed, even before the emergence of the earliest human civic establishments, our predecessors involved wood widely. They used it as a fuel for fire, a building material, furniture, and weapons. Wood is also utilized as a source from which paper or other valuable chemical compounds such as purified cellulose and cellphones, can be extracted. As a result, various tree species produce a diverse range of wood products on the market.

The arrangement of hardwoods and softwoods is the most well-known method for separating woods. Softwood is wood from confiner-type trees such as pine, whereas hardwood is wood from wide-leaved dicotyledons such as oak. Hardwood trees are commonly viewed as a top-notch wood type. Hardwood is typically distinguished by its darker hue, making it substantially more costly than other kinds of wood. The wood gathered from the hardwood trees is usually difficult to handle because of its hardness (Stelte & Sanadi, 2009). Meanwhile, end goods can endure time, and open-air components are superior to those made from less intense softwoods. Many hardwood species are commonly used to build furniture but cannot be identified by olfactory discrimination or visual inspection. Owing to the variations in the quality and pricing of different hardwood species, hardwood misclassification can result in significant economic losses.

In contrast, softwood trees provide mid- and low-tier wood. Softwood can be used to make wooden products and furniture, but with various restrictions on durability, strength, and endurance of the final product. The vast majority of softwoods have a low-density internal structure, which makes them light and easy to process. Softwood trees have an inner construction that is paler than hardwoods.

Wood can be categorized into numerous categories based on its intended use. For example, Neobalanocarpus heimii and other local names are only wood with the appropriate strength that should be used to construct trustworthy roof trusses. On the other hand, Hevea brasiliensis, also known as rubber wood, (Mohan, Venkatachalapathy & Rai 2014), can produce furniture and low-strength products. Traditionally, an expert performs wood categorization by visually inspecting timber parts. Expert should be familiar with the properties of all types of wood. A dichotomous method (wood structure analysis table) was posted as a guideline for experts to judge the tree species. However, these specialists are in short supply, which might lead to inaccurate classifications owing to weariness and, therefore, the complexity of the task. As a result, developing an automatic intelligent system for wood classification might be a promising undertaking because it would allow untrained agents to assess wood loads and obtain an accuracy that is not influenced by human factors. Another reason for identifying wood is checking for scams, as some timber merchants mix different types of wood for profit.

The motivation of this study is to design an efficient transfer-learning algorithm for the classification of wood species with the aim of attaining a superior performance. Nine types of well-known deep learning models based on CNN for wood species identification by transfer learning, including VGG16, ResNet-18, ResNet-50, DenseNet121, DenseNet169, DenseNet201, EfficientNetB5, EfficientNetB7, and EfficientNetB8 were compared. The purpose was to find a deep learning model suitable for the variant WOOD-AUTH dataset. The classification performance of the EfficientNetB7 model was found superior to that of other pre-trained models in the literature. The EfficientNetB7 model achieved the highest validation accuracy of 99.824% among all CNN models, which is encouraging.

The rest of the paper is organized as follows: Section 2 reviews the most recent wood classification studies. Section 3 provides a brief description and analysis of the wood species dataset and the proposed pre-trained models, as well as an explanation of the model training strategy. Section 4 summarizes the evaluation metrics used to analyze and evaluate the reported results and outcomes of the nine proposed classifiers. Finally, Section 5 concludes the study and discusses future work.

2. Related Research

Huang et al. (2021) presented a two-stage approach for classification of wood images. First, they used transfer-learning techniques to extract wood structural features before reducing the number of features using a Global Average Pooling layer (GAP). In the classification stage, extreme learning machines (ELM) were utilized. On the Wood Species Dataset, this approach has a recognition accuracy of 93.07%, which is higher than that of the dataset provider's approach.

Fahrurozi et al. (2016) proposed a hybrid approach for wood classification that combines gray-level cooccurrence matrix (GLCM) with various edge detection techniques such as Roberts, Prewitt, Sobel, Laplacian of Gaussian and Canny. GLCM is a popular traditional machine-learning approach for texture analysis. They discovered that the edge detection method could improve the appearance of the wood fiber in the image of the wood texture under observation. The GLCM can also provide a statistical fluctuation value for every edge detection technique. They tested their method on a four-category dataset from France's LE2i Laboratory.

Panagiotis Barmpoutis (2028) introduced a new data set called 'WOOD-AUTH,' which contains over 4200 timber images (cross-sectional, tangential, and radial sections of traditional timber structures) of 12 Greek timber species. They also proposed a novel multidimensional texture analysis-based automatic wood species recognition strategy. Each wood image is represented by the proposed methodology as a concatenation of histograms of higher-order linear dynamical systems obtained from both horizontal and vertical image patches. Finally, they classified histogram representations into 12 wood species using Support Vector Machines (SVM). Their method had an accuracy of 91.47%.

Yusof et al. (2019) designed an automatic classification system for tropical wood. Because the National Forest Institute provides a limited number of wood samples, they used transfer learning to enhance the classification accuracy of their model.

Miao et al. (2022) developed a new classification method based on an improved CNN. First, they developed the W_IMCNN model, which recognizes wood species using mobilenetV3 and Inception networks. In terms of training speed and recognition rate, the proposed model outperformed the others. They created an updated version of the WOOD-AUTH dataset. The proposed framework achieved recognition rate of 96.4% and 98.8% using the created and original WOOD-AUTH datasets, respectively.

Sun et al. (2021) suggested using deep learning for wood species classification to significantly enhance the generalization and accuracy of the model. The proposed scheme was divided into three stages. First, they used a ResNet50 model to extract image features after acquiring wood images with a 20X magnifying glass. The features were then refined using linear discriminant analysis (LDA). Finally, 25 rare wood species were identified by using the KNN classifier.

Kobayashi et al. (2019) presented an approach for classifying wood images that integrates X-ray computed tomography (CT), a non-invasive and non-destructive laboratory-scale technique, with machine learning. They used GLCM and local binary patterns (LBP) to classify the CT image of six hardwood species. They had a prediction accuracy of 99.5%.

De Geus et al. (2020) introduced an essential dataset of wood timber microscopic images in their study. There were 281 species in the dataset and three types of wood sections: transverse, radial, and tangential. They compared transfer learning and state-of-the-art classic feature extraction techniques for wood species classification. They used four pre-trained models to assess the transfer learning method. The pre-trained models include InceptionV3, DenseNet, ResNet, and SqueezeNet.

They used LBP, the Local Phase Quantization (LPQ), and Rotation Invariant Local Phase Quantization (RI-LPQ) to evaluate a classic feature extraction approach. The traditional feature extraction methodology had an accuracy of 84.23%, whereas the transfer learning-based approach had an accuracy of 98.75%. According to their findings, deep learning techniques for wood species recognition have outperformed the traditional feature-extraction approaches.

Neethu and Syla (2021) created a new dataset that contains three of the most familiar tree species on Indian land. They used the LBP and GLCM statistical feature extraction methods. The resulting features from both methods were merged into a single feature vector and classified using a multi-SVM. Their model achieved a classification accuracy of 97.2%.

The surface pattern of wood is defined not only by pores but also by lines. Ghapar et al. (2021) proposed a new feature extraction technique using statistical line distribution (SPLD) characteristics to identify distinctive line features of each wood species. They discussed the need to have a personalized feature extractor that works only with a specific wood pattern, such as the statistical characteristics of pore distribution (SPPD). When combined with SPPD features, the SPLD achieved an accuracy of 88%, which increased to 99.5%. Furthermore, the recognition accuracy was 100% when SPPD, SPLD, and Basic Grey Level Aura Matrix features were combined, demonstrating that SPLD is a necessary personalized feature for wood species classification.

Haoran et al. (2021) created a solid wood board recognition system based on the CSPDarkNet. To create the ECA-CSPDarkNet model, they combined it with an efficient channel attention (ECA) mechanism. They created a dataset of 9,000 images of nine solid wood board surface textures. The ECA-CSPDarkNet model performed well in terms of both speed and accuracy. It achieved a 5.88 ms inference time per single image, and 98.44% recognition rate.

Recently, many studies have utilized deep learning models to detect and classify plants and plant leaf diseases. For example, Wang & Zan, et al. (2022) created MatDet, which is a novel three-stage model for detecting tomato maturity. Firstly, they utilized ResNet-50 as the backbone network. In addition, they employed RoIAlign to develop more concise bounding boxes. Finally, they improved the model's ability to detect tomato maturity in complex environments, such as fruit interferences, branch background clutter, and varying light scenes by including a Path Aggregation Network (PANet). The suggested framework had an mAP of 96.14%, indicating a significant step forward in the progress of ecological cultivation.

Hu et al. (2022) used remote sensing UAV photos to detect and classify various severity levels of pine tree diseases to control and prevent disease in pine forests. They used efficient channel attention (ECA), and hybrid dilated convolution (HDC) modules to improve the accuracy of the DDYOLOv5 model after preprocessing the dataset to increase it. In addition, they selected a low- confidence threshold to reduce the percentage of incorrect detections. Compared with the original YOLOv5, RetinaNet, and Faster R-CNN, the proposed technique significantly improved the recall, precision, and F1 score.

The yield of chilli crops is negatively affected by chilli leaf diseases. Naik et al. (2022). developed an automatic technique for classifying the five primary leaf diseases of chilli to aid in maintaining and managing the quality of chilli crops. Images were captured using a digital camera and assigned to the appropriate class. They used transfer learning to assess the efficiency of 12 pre-trained models. Additionally, they showed that adding more data can enhance the model performance and reduce overfitting. To improve their research findings, they created a squeeze-and-excitation-based convolutional neural network (SECNN) model. Various datasets were used to evaluate the performance. The model had a 99.28% recognition rate for the classification of the 43 distinct classes.

Krbaş & Cifci (2022) recently developed a transfer learning-based system for automatically classifying 12 wood species. They compared the performance of various deep learning architectures, such as VGG19, Inception V3, ResNet-50, and Xception. The WOOD-AUTH dataset was used to train and test the proposed models. The experimental results demonstrated that the Xception model outperformed the other models, with a classification accuracy of 95.88%.

Maruyama et al. (2018) presented an image-based method for automatic identification of native wood charcoal species. For this purpose, features based on two configurations of the Local Binary Patterns (LBP) along with state-of-the-art machine learning classifiers and representation learning using Convolutional Neural Networks were evaluated. In addition, they created an image database comprising 44 wood charcoal species. The best results for the handcrafted and automatically learned features were 93.9% and 95.7% recognition rates, respectively.

In this study, we performed a comparison to develop and analyze the performance of nine transfer learning-based classifiers for classifying wood into 12 species. We used progressive resizing and differential learning rates approaches to improve the performance of the classifiers while training them using the Fastai library. In addition, various data augmentation strategies have been used to reduce overfitting and increase dataset size. Finally, several metrics were used to demonstrate the efficiency of the proposed models on the validation and test sets.

3. The Dataset

The wood species dataset, which is a variant of the "WOOD-AUTH" dataset (Barmpoutis et al.2028) was used in this study. The wood species dataset includes over 8000 wood images of 12 common hard- and soft- wood species found in the Greek domain. The image size in the "WOOD-AUTH" dataset was 400 × 400 pixels, whereas all images in the wood species dataset were 200 × 200 pixels. Images were captured at a 15-20 cm distance using a Nikon D3300 digital camera with a resolution of 24 megapixels at Aristotle University of Thessaloniki's Laboratory of Wood Technology. In contrast to the "WOOD-AUTH" dataset, which includes cross, radial, and cordwood sections, the wood species dataset primarily uses cross-sectional data. **Figure 1** depicts the samples of the 12 wood species in the dataset.

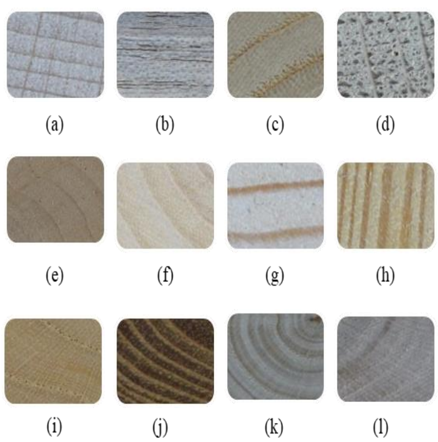

Figure 1. Samples of wood species dataset: (a) Fagus sylvatica, (b) Juglans regia, (c) Castanea sativa, (d) Quercus cerris, (e) Alnus glutinosa, (f) Fraxinus ornus, (g) Picea abies, (h) Pinus sylvestris, (i)Ailanthus altissima, (j) Robinia pseudoacacia, (k) Cupressus sempervirens, (l) Platanus orientalis.

4. Transfer learning models

Advances in deep learning and transfer learning have paved the way for automatic recognition systems in many areas of daily life, including plant disease, pest, and weed identification in agriculture, healthcare, the environment, aeronautics, transportation, and remote sensing. In addition, recent trends in wood species classification have emphasized the use of CNNs. A CNN comprises a series of layers in which a differentiable function changes one volume of activations to another. The design of a CNN consists of three various layers: Convolutional Layer, Pooling Layer, and Fully Connected Layer. The convolutional layer is the fundamental building block of a CNN and is where most of the processing occurs. It begins by computing the output of neurons associated with specific input areas. Then, before transferring the input through the subsequent layer, an activation function such as Sigmoid, ReLU, or Leaky ReLU adds non-linearity. A pooling layer (width and height) reduces the dimensionality along the spatial dimensions. Finally, using a traditional feed-forward neural network, the Fully Connected layer determines the class scores (Sahili & Awad 2022). Deep learning model training is difficult because training data is either expensive or difficult to collect, and there is a need for wood-domain-specific pre-trained models. Consequently, robust classifiers must be trained on more commonly encountered data from various domains. Transfer learning is a powerful method for overcoming dataset constraints and reaping the full benefits of deep CNN architectures (Nowakowski 2021).

We frequently stack extra layers in Deep Neural Networks to handle complex problems, which improves performance and accuracy. The reason behind the addition of more layers is that these layers may learn more complex characteristics over time. In contrast, the conventional CNN model has a maximum depth threshold. Furthermore, He et al. (2016) proposed Residual Neural Networks (ResNets) that comprise Residual Blocks. The concept of residual blocks has facilitated the training of deep networks. Furthermore, ResNet skip connections address the vanishing gradient issue in deep neural networks by allowing the gradient to take an extra shortcut. We used ResNet18 and ResNet50 pre-trained models in this study, with accuracies of 97% and 98.3%, respectively.

Unlike classical CNNs, the core idea behind DenseNets (Huang et al. 2017) is that each layer is linked to every other layer, resulting in a Densely Connected Convolutional Network. This is similar to ResNet but with some significant differences. First, DenseNets appends the output feature maps of the layer to the input feature maps instead of summing them. In DenseNet, the input of a layer concatenates the feature maps from the previous layers. The DenseNet architecture comprises several dense blocks, each adding new features on top of the existing feature maps. Three models from the DenseNet family, namely Densenet121, Densenet169, and Densenet201, were used in this study, and their performances were compared.

Tan and Le presented a new family of models called EfficientNets, which accomplished much-preferred efficiency and accuracy over past ConvNets (Tan & Le 2019). Prior to EfficientNets, the most commonly used method for scaling up ConvNets was to increase only one of three dimensions: - number of layers (depth), number of channels (width), and image quality (resolution). EfficientNet is a convolutional neural network that utilizes a compound coefficient to scale all depth/width/resolution aspects equally. They achieved this equilibrium by scaling each dimension using a fixed ratio. **Figure 2** illustrates the key differences between standard convolutional neural networks (ConvNets), ResNets, and DenseNets.

5. Training details

Rather than building a convolutional neural network from scratch, this study employed transfer learning to create the classifier. To implement the classifier, we used the Fastai Pytorch library, (Howard et al. 2020) which simplifies the initial setup for neural network training integrated with the pre-trained models from the Timm library (Wightman et al. 2021). Our experiments were performed in Python using a Kaggle NVIDIA TESLA P100 GPU.

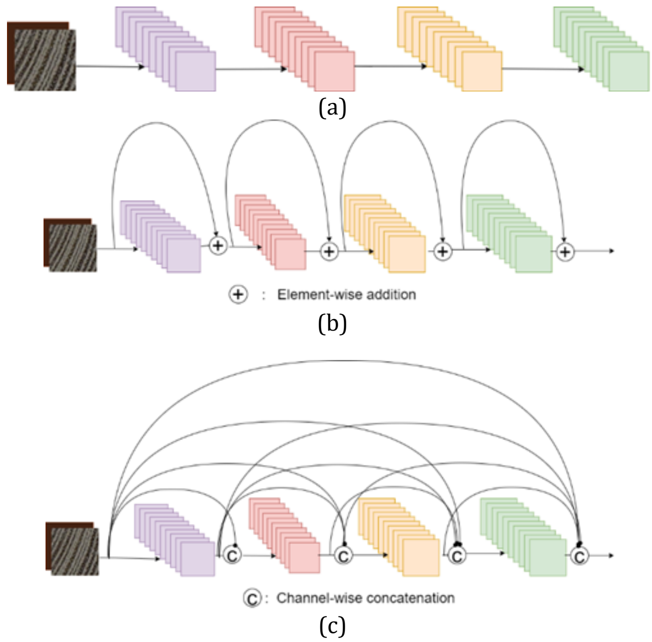

Figure 2. Comparison between ConvNets, ResNets and DenseNets. (a) Standard ConvNets, (b) ResNet concept, and (c) One Denseblock in DenseNet

First, we divided the training dataset into two parts: a training set with 80% of the Wood Species Dataset (4567 images) and a validation set with 20% of the images (1141 images). All the images were resized to 456 × 456 pixels. Data augmentation is a popular technique for increasing the size and diversity of training data. Image augmentation is commonly used to improve computer vision performance and has evolved into a common implicit regularization approach to avoid overfitting. In this study, we utilized Albumentations (Buslaev et al 2020) a quick and adaptable open-source library with numerous image transform operations. We applied horizontal flipping, vertical flipping, shift scale rotation, random brightness contrast, random resized crops, and cut out. To improve model generalization, progressive image resizing is another form of data augmentation employed here for model training. It works by starting training using small images to help complete the training much faster and gradually increase the image size. Resizing images from smaller to larger sizes during training provides an entirely new dataset to train the model. To apply progressive resizing, we started model training with a smaller image size of 64 × 64 pixels. Then we unfreeze the weights from that model to find the optimal learning rate by employing the Cyclical Learning Rate (CLR) approach introduced in (Smith 2017) to train another model on images of larger size (128 × 128), and finally repeating the same process by increasing image dimension to 256 × 256. **Figure 3** depicts the progressive image resizing process.

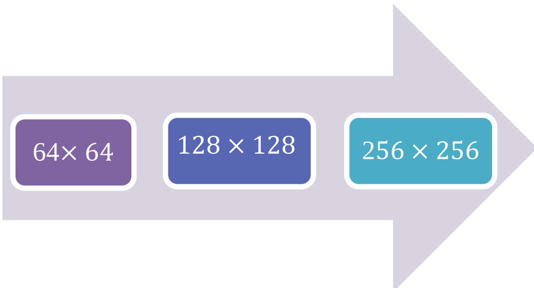

Figure 3. Gradually increasing the size of the training images.

Training was organized into three phases, each corresponding to a different dimension of the input image.

Phase-1: In this phase, random resized crops of 64×64×3 pixels were created, and the pre-trained model was trained for ten epochs using a learning rate of 3e-3.

Phase-2: The entire output network phase 1 was fine-tuned for another ten epochs using random resized crops of size 128×128×3 and a learning rate suggested by the CLR.

Phase-3: Finally, the entire network was fine-tuned for ten epochs with randomly resized crops of 256×256×3. It was fine-tuned for another ten epochs using the discriminative learning rate proposed in (Howard & Ruder 2018). The earliest layer was trained using a learning rate equal to the learning rate divided by ten, and the last layer is trained with the learning rate suggested by CLR. Learning rates within the range of these two values were used to train the middle-layers. **Table 1** summarizes the learning rate values for the three stages associated with the various pre-trained models used in this study.

Table 1 Summarization of the learning rate values for the proposed models.

Model	Stage 1 LR	Stage 2 LR	Stage 3 LR	Discriminative LRs
VGG16	3e-03	4.786300996784121e-05	3.0199516913853586e-06	(3.0199516913853586e-07, 1.4454397605732084e-04)
ResNet18	3e-03	6.309573450380412e-08	1.0000000474974513e-04	(1.0000000474974513e-05, 5.754399462603033e-05)
ResNet50	3e-03	3.981071640737355e-05	6.309573450380412e-08	(6.309573450380412e-09, 2.0892961401841602e-06)
DenseNet121	3e-003	8.317637839354575e-05	1.2022644514217973e-04	(1.2022644514217973e-05, 1.737800776027143e-04)
DenseNet169	3e-03	3.981071640737355e-05	6.309573450380412e-08	(6.309573450380412e-09, 1.737800776027143e-04)
DenseNet201	3e-003	3.981071640737355e-05	1.0964781722577755e-07	(1.0964781722577755e-08, 3.311311302240938e-05)
EfficientNetB5	3e-03	1.318256749982538e-07	8.317637839354575e-05	(8.317637839354575e-06, 1.737800776027143e-04)
EfficientNetB7	3e-03	2.089296234771609e-04	5.754399462603033e-05	(1.58489319801447e-07, 5.754399462603033e-06)
EfficientNetB8	3e-03	6.918309954926372e-05	2.0892962347716094e-04	(2.0892962347716094e-05, 1.4454397605732084e-04)

6. Experimental Results and Discussion

Various metrics were used in this study to assess the model quality. The confusion matrix for a multi-class classifier is shown in **Figure 4**, where the total number of classes is given by "N."

	Predicted Class				
Actual class		C_1	C_2	…	C_N
	C_1	C_{11}	C_{12}	…	C_{1N}
	C_2	C_{21}	C_{22}	…	C_{2N}
	⋮	⋮	⋮	⋮	⋮
	C_N	C_{N1}	C_{N2}	…	C_{NN}

Figure 4. Confusion matrix for a multi-class classifier

A confusion matrix, which represents the performance of the classifier, compares the predicted classes with the actual classes. For a binary classifier, matrix is divided into four categories. These were True Positives (TP), True Negatives (TN), False Positives (FP) and False Negatives (FN). The model correctly predicts the positive class, resulting in TP. Furthermore, TN is the result in which the model correctly predicted the negative class. However, FP is an outcome in which the model mispredicts a positive class.

Furthermore, an FN occurs when the model incorrectly predicts the negative class. Unlike binary classification, multi-class classification does not include positive or negative classes. Instead, the TP, TN, FP, and TN were defined for each class.

The entry C_{ij} indicates the number of samples predicted as class "j" while belonging to the class "i". As demonstrated in Fig. 4, the green cells on the diagonal of the matrix, C_ij where i = j, represent the TPs for class "i". The ideal classifier is one with zero values in non-diagonal entries. Equations 1, 2, 3, and 4, respectively, Ezz-Eldin et al. (2021), give TP, TN, FP, and FN for class "k".

$$\mathrm{TP}(k) = C_{kk} \tag{1}$$

$$\mathrm{TN}(k) = \sum_{\substack{i,j=1 \\ i\neq k, j\neq k}}^{N} C_{ij} \tag{2}$$

$$\mathrm{FP}(k) = \sum_{\substack{i=1 \\ i\neq k}}^{N} C_{ik} \tag{3}$$

$$\mathrm{FN}(k) = \sum_{\substack{j=1 \\ j\neq k}}^{N} C_{kj} \tag{4}$$

The most commonly used metric for evaluating machine-learning classification models is accuracy Jierula (2021). This is the proportion of correct predictions to the total number of evaluated instances. This determines how close the measured value is to the actual value. It is defined in Equation 5 as:

$$\text{Accuracy (Acc)} = \frac{TP + TN}{TP + TN + FP + FN} = \frac{\sum_{i=1}^{N} C_{ii}}{\sum_{i,j=1}^{N} C_{ij}} \tag{5}$$

Figure 5 depicts the class distribution of the wood species dataset (training and testing). Class 3 contained the most images (1024) in the training set, whereas class 2 contained only 200 images. Furthermore, the other ten classes contain many images, indicating a significant skew in the class distributions. When there is a class imbalance in a dataset, accuracy can become a misleading measure of model performance. As a result, a confusion matrix was utilized to assess the model's performance using Precision, Recall, and F1 score metrics for each class. However, each class is dependent only on the TP. TN elements were not considered in terms of precision and recall.

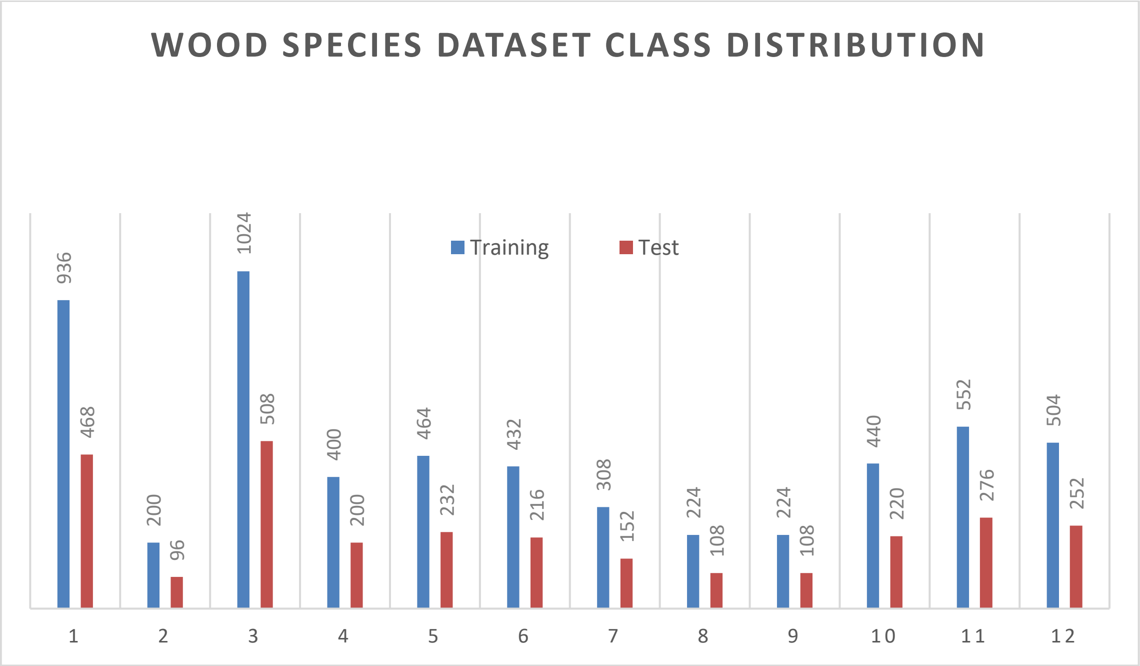

Figure 5. class distribution of Wood Species Dataset

Precision denotes the accuracy of the model is. This was calculated by dividing the percentage of TP elements by the total number of positively predicted units (the row sum of the actual positives). Recall, however, measures how well the model identifies positive labels. This was calculated by dividing the percentage of TP elements by the total number of positively classified units (the column sum of the predicted positives). Equations 6 and 7 provide precision and recall for the class "k."

$$\mathrm{Precision(k)} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} = \frac{\mathrm{C_{kk}}}{\sum_{i=1}^{N} \mathrm{C_{ik}}} \tag{6}$$

$$\mathrm{Recall(k)} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} = \frac{\mathrm{C_{kk}}}{\sum_{j=1}^{N} \mathrm{C_{kj}}} \tag{7}$$

The weighted average of all classes was used to compute overall precision and recall. The weighted average Precision and Recall were calculated by dividing Precision and Recall by the sample size for each class. In other words, the contribution of each class to the average is weighted by size.

Equations 8 and 9 calculate the weighted average Precision and Recall, respectively:-

Weighted Average Precision

$$= \sum_{k=1}^{N} \mathrm{Precision(k)} \times \mathrm{W_k} \tag{8}$$

Weighted Average Recall

$$= \sum_{k=1}^{N} \mathrm{Recall(k)} \times \mathrm{W_k} \tag{9}$$

The F1 score (Grandini et al. 2021) uses the harmonic mean concept to combine Precision and Recall measures to determine the ideal trade-off between them. The F1 score has a value between 0 and 1. The F1 score for class "k" is given by the following equation:-

$$\mathrm{F1\ score(k)} = \frac{2 \times [\mathrm{Recall(k)} \times \mathrm{Preceision(k)}]}{[\mathrm{Recall(k)} + \mathrm{Preceision(k)}]} \tag{10}$$

The F1 score in a multi-class classifier should include all classes. The weighted average F1 score computes the F1 score for each class separately but adds them together using a weight calculated according to the sample size of

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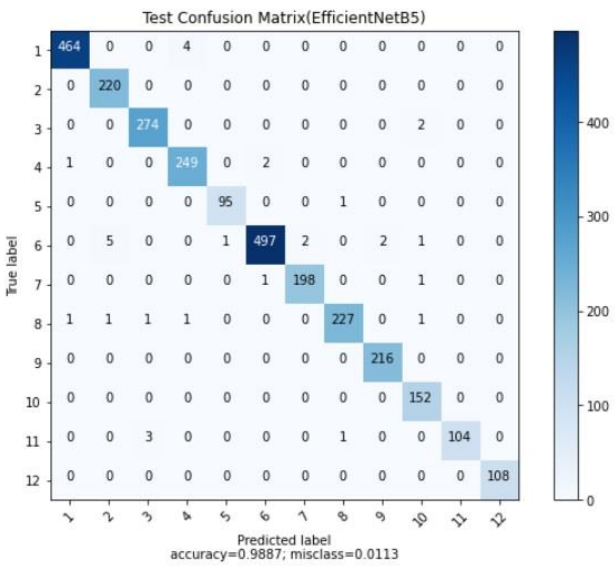
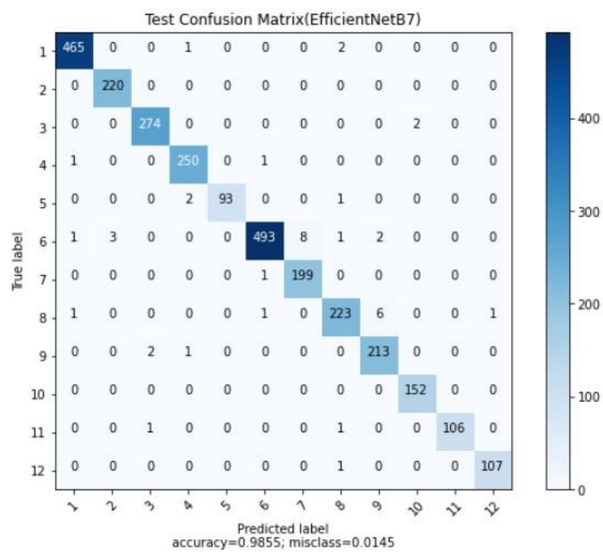
every class. Equation 11 calculates the weighted average F1 score.

$$\text{Weighted Average F1} = \sum_{k=1}^{N} \text{F1 score(k)} \times W_k \qquad (11)$$

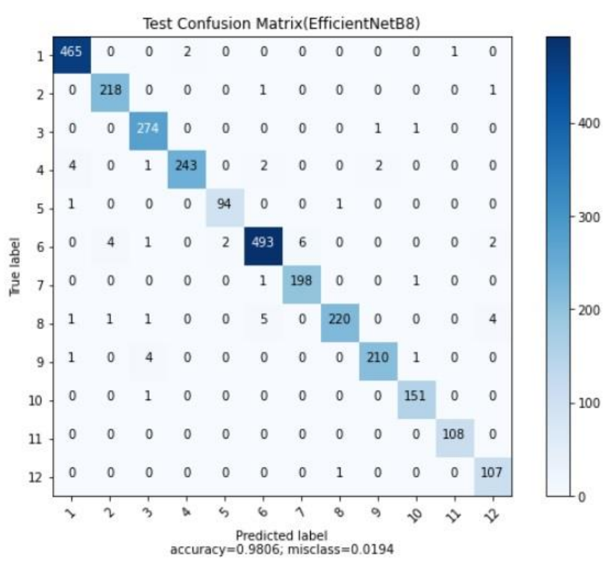
Figure 6 shows the test confusion matrices for the nine pre-trained models proposed in Section 4. As defined above, EfficientNetB5 had the best precision, recall, and F1 score among the models. It achieved 99% precision, 98.9% recall, and an F1 score.



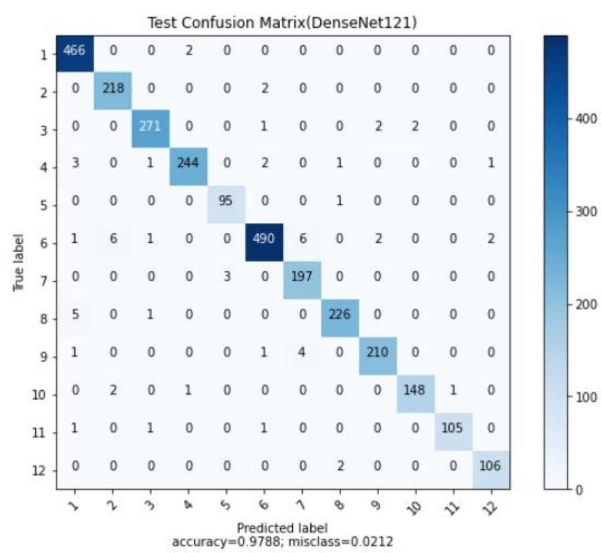
(a)



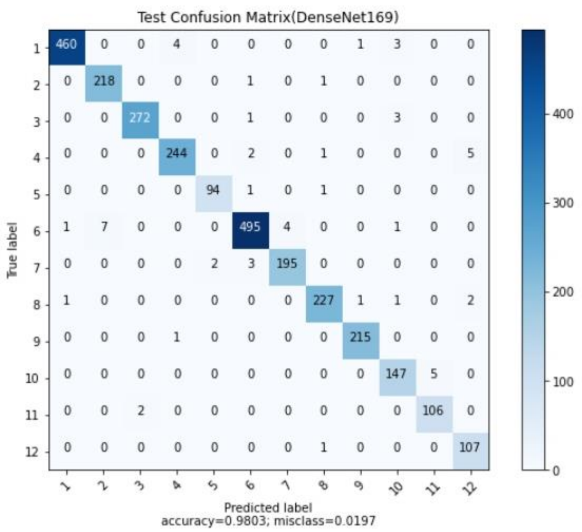
(b)



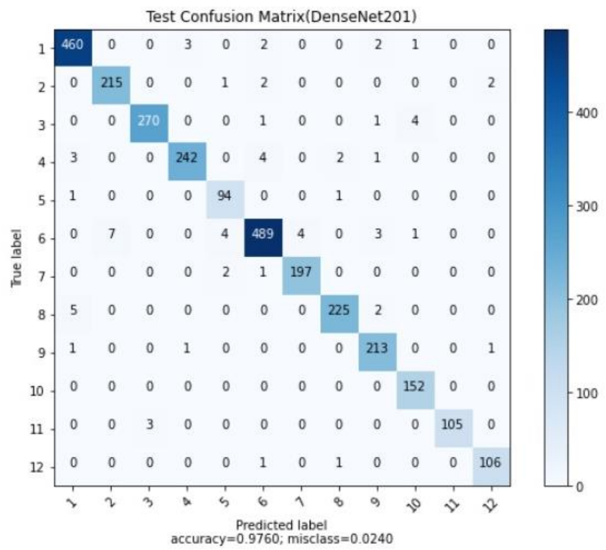
(c)



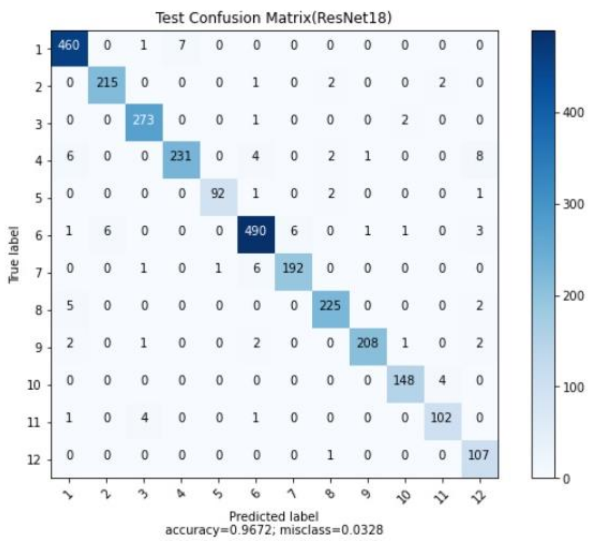
(d)


Test Confusion Matrix(DenseNet169)
True label
Predicted label
accuracy=0.9803; misclass=0.0197

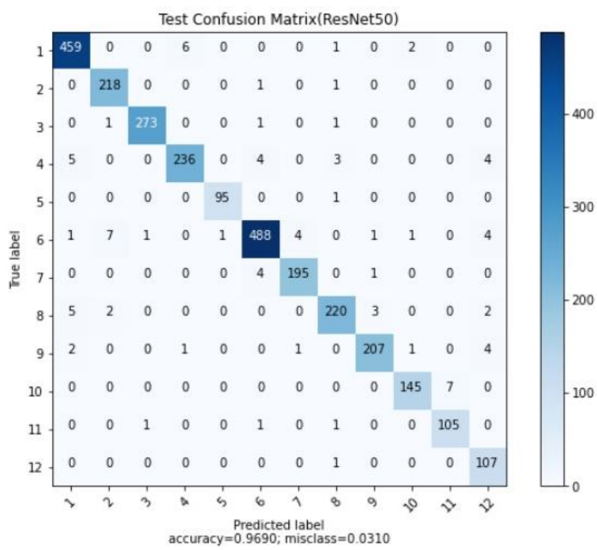
(e)


Test Confusion Matrix(DenseNet201)
True label
Predicted label
accuracy=0.9760; misclass=0.0240

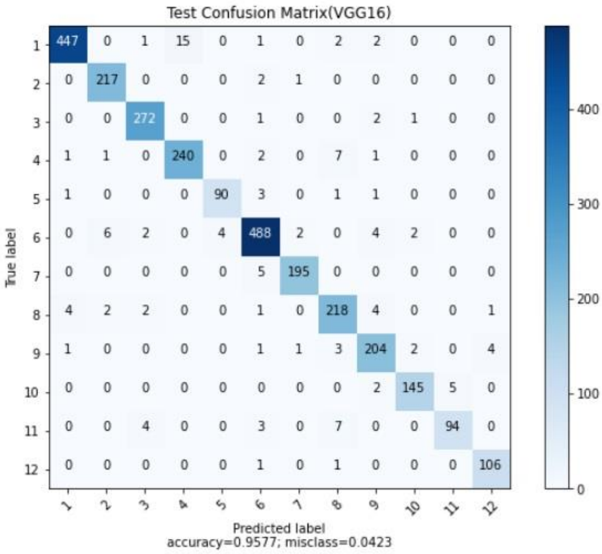
(f)


Test Confusion Matrix(ResNet18)
True label
Predicted label
accuracy=0.9672; misclass=0.0328

(g)


Test Confusion Matrix(ResNet50)
True label
Predicted label
accuracy=0.9690; misclass=0.0310

(h)



(i)

Figure 6 Test set Confusion Matrix for all proposed models

The validation and test classification accuracies for the nine proposed pre-trained models described in Section 4 are shown in **Figure 7**. The proposed models were tested using a test set of 2836 images. Except for the VGG16 model, the simulation shows that the validation accuracy is greater than the test accuracy by a maximum of 1.5% for all proposed models. For example, although the EfficientNetB7 and EfficientNetB8 achieved 99.82% validation accuracy, EfficientNetB5 achieved 98.87% test accuracy. The ResNet18 model achieved a test accuracy of 96.72%. This result implies that the proposed models generalize well, and thus learn to predict the test dataset perfectly. Furthermore, the results for these models showed significant differences in the types of training, validation, and test datasets used for evaluation. Because the VGG16 model was overfitted and dropout regularization was used, the test accuracy was 2.4% higher than the validation accuracy. The validation and test accuracies of the VGG16 model are 93.33% and 95.77%, respectively.

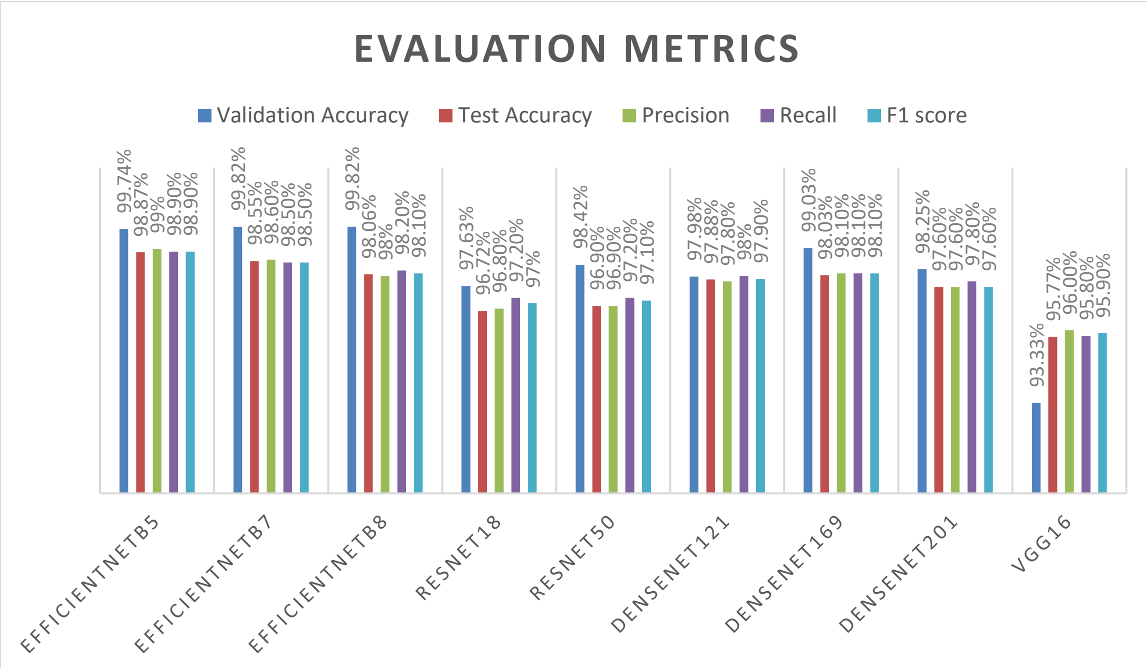


Figure 7 Evaluation metric for the nine proposed models

Table 2 shows a comparison between the proposed study and previous studies in the field of wood species recognition and classification. Readers should be aware that the datasets used in these various studies are not the same and that comparisons of different methods should be made on the same database. As can be seen, the developed model, EfficientNetB7, outperformed the other two models that used the same dataset. The accuracy was enhanced by 8.354% for the SVM model, Barmpoutis et al. (2018) and 3.944% for the Xception model, Kırbaş & Çifci (2022).

Table 2 Comparison of our model and various studies conducted on recognition and classification of wood species.

Reference	Dataset	Model	Accuracy
Huang et al. 2021	WOOD-AUTH	ResNet50 (Features) + Global Average Pooling + ELM Classifier	93.07%
Yusof et al. 2019	Forest Research Institute of Malaysia (FRIM)	ResNet-50	98.8%
Miao et al. 2022	WOOD-AUTH	Inception and mobilenetV3	98.8%
Sun et al. 2022	Commercial images of 3000 wood species	ResNet50 + KNN Classifier	99.4%
De Geus et al. 2020	wood timber microscope	DenseNet	98.75%

Neethu & Syla 2021	Indian Dataset	Multi-SVM with LBP and GLCM features	97.2%
Haoran et al. 2021	Solid Wood Board	CSPDarkNet	98.44%
Kırbaş & Çifci 2022	Variant WOOD-AUTH	Xception	95.88%
Maruyama et al. 2018	Brazilian native wood charcoal species	Local Binary Patterns (LBP) along with Inception_v3 convolutional neural network	95.7%
Barmpoutis et al. 2018	Variant WOOD-AUTH	SVM Classifier	91.47%
	Variant WOOD-AUTH	**Our proposed EfficientNetB7 model**	**99.824%**

7. Conclusion and Future Work

In this study, we classified 12 wood species using nine different pre-trained models from four families. The models were trained for 30 epochs on the Wood Species Dataset and demonstrated a good recognition rate for all classes. The dataset was divided into 4567 training images and 1141 validation images. In contrast, the test set contained 2836 images. We also demonstrated the importance of data augmentation in increasing the size of the training set and improving model generalization. We used cyclical and discriminative learning rates, which are two cutting-edge techniques, to determine the best learning rates for increased accuracy and speed. The best validation accuracy was 99.82% for EfficientNetB7 and EfficientNetB8, whereas the lowest validation accuracy was 93.33% for VGG16. Owing to the skewed distribution of classes in the training and testing sets, all the models were evaluated using the test set and four metrics: accuracy, F1 score, weighted average recall, and weighted average precision.
Future research should focus on deploying the model as a mobile application to help untrained workers identify different wood species.

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