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*Article*

# A Novel Method in Wood Identification Based on Anatomical Image Using Hybrid Model

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**Abstract:** Nowadays, wood identification is made by experts using hand lenses, wood atlases, and field manuals which take a lot of cost and time for the training process. The quantity and species must be strictly set up, and accurate identification of the wood species must be made during exploitation to monitor trade and enforce regulations to stop illegal logging. With the development of science, wood identification should be supported with technology to enhance the perception of fairness of trade. An automatic wood identification system and a dataset of 50 commercial wood species from Asia are established, namely, wood anatomical images collected and used to train for the proposed model. In the convolutional neural network (CNN), the last layers are usually soft-max functions with dense layers. These layers contain the most parameters that affect the speed model. To reduce the number of parameters in the last layers of the CNN model and enhance the accuracy, the structure of the model should be optimized and developed. Therefore, a hybrid of convolutional neural network and random forest model (CNN-RF model) is introduced to wood identification. The accuracy's hybrid model is more than 98%, and the processing speed is 3 times higher than the CNN model. The highest accuracy is 1.00 in some species, and the lowest is 0.92. These results show the excellent adaptability of the hybrid model in wood identification based on anatomical images. It also facilitates further investigations of wood cells and has implications for wood science.

**Keywords:** Identifying wood; anatomical wood; hybrid model; CNN-RF; automatic identification; vietnam wood

## 1 Introduction

Illegal logging is a term for logging, trading, and processing activities that are contrary to national laws and international regulations [1]. Wood is a natural composite material made of several cell and tissue types and is also a hard-fibrous structure which is the primary raw material for the wood industry [2]. Because wood species have different physical and chemical properties, there are big differences in prices and use [3], and some cases of illegal logging in natural forests continue due to the economy of timber products [4]. They are one of the key factors contributing to global deforestation and climate change producing gases that act as greenhouse gases and trading in illegal timber and wood products hurts the marketability of sustainable forestry goods [5]. Hence, rapid and accurate wood identification at the scene is necessary to combat illegal logging. Currently, wood identification is carried out by wood experts (aka foresters) who are trained in deep knowledge about wood species. However, this process takes a long time and cost, so there are few foresters who can distinguish the wood species accurately [6]. Wood identification using anatomical images is an important tool for various purposes such as determining the name of wood species and analyzing the variation of some plants [7]. Woods are material for many applications such as construction, boat building, flooring, and especially furniture. They are divided into 2 main categories including softwood and hardwood. They have some different characteristics such as structure, weight, color, fire resistance, density, and value. Hardwoods have fiber and parenchyma cells that feature holes or vascular components. While softwoods are made up of parenchyma cells, overlapping tracheids, bordered pit openings, and, occasionally, resin canals [8]. In reality, hardwood and softwood could be used for the same purposes; however, they have some different characteristics and treatments. Hardwood usually comes from low-growing trees in tropical forests, so it has a heavier density than softwoods, its structures make the used time longer so they are utilized in many applications including furniture, construction and remodeling, industrial products, and interior decoration [9]. The drawback of hardwood is that they are quite heavy, which makes them difficult to transport. Opposite hardwoods, softwoods have lower densities and brighter ones. They usually grow quicker so they are cheaper, softer, and easier to work with [10]. The difference in the anatomical structure of the two types makes their properties also different. Most hardwoods, such as beech, oak, or ash, have a higher density, resulting in better stiffness and strength and lower form and dimensional stability due to increased swelling and shrinking [11]. Softwood has a transverse section that is fine and smooth while hardwood is coarse and loose. In the radial portion, softwood is smooth and soft while hardwood is slightly uneven and harsh; and a tangential section is more flat and straight than bumpy and curved [12].

Wood identification plays an important role in modernizing the wood industry, making it simpler for non-wood professionals to distinguish woods correctly and minimize business fraud. The training cost of identifying experts is very expensive and takes a lot of time, so it is necessary to identify wood automatically. The wood processing industry in Asia has the advantage of natural resources and cheap labor, so it has a competitive price advantage compared to other markets in the world [13]. In some countries, the timber species is divided into grades based on the criteria specified in order to ensure consistency in the process and protect the wood species. Protecting forest resources is essential; therefore, a rapid wood identification system should be proposed to avoid cases of deliberate exploitation of wood that are in danger of being exhausted. Moreover, causes affecting global biodiversity are illegal logging and trade in timber and lack of forensic timber identification methods for screening questionable material and for conclusive identification of wood obtained unlawfully. These make it difficult to prosecute illegal logging offenses [14]. In 2014, the United Nations through the adoption of Resolution 23/1 promoted the development of tools to be used to combat Nillegal timber [15].

The rapid development of science and technology in recent years is undeniable in many fields. In forest science, there are many studies of wood identification based on computer vision or machine learning. For example, three Swietenia was distinguished based on a combination of wood anatomical data and machine learning species namely Decision Tree, Naïve Bayes (NB), Support Vector Machine (SVM), and Artificial Neural Network (ANN), that are presented in the study of He et al. [16]. They used four network structures to identify three species based on 278 wood samples, their result showed that the SVM model achieved the highest accuracy of the four models, it achieved 91.4%. This research is carried out in the laboratory and the aim is to demonstrate that machine learning can be applied as a tool to distinguish woods to avoid illegal logging, besides, natural experiments are expected. In other studies about the woodworking industry [17,18], 11 types of hardwood were distinguished based on scanned images of wood surfaces by using deep learning. An intelligent identification system was proposed in the literature with more than 97% accuracy in identifying 21 wood species using the SVM model presented by Andrade et al. [19]. The proposed hardware in collecting and identifying woods based on anatomy images or the Xylo Tron platform is presented in ref [20] as an aid in anatomical wood. Some studies on wood species identification using different algorithms such as the multi-view random forest model (MVRF) [21], Mask-R CNN [22], and ROXAS–an automatic tool based on traditional image processing methods [23]. Convolutional Neural Networks (CNN) is a specific type of artificial neural network that uses perceptrons, it is widely applied to studies on image processing and for many different fields with impressive accuracy [24,25]. In general, the state of art studies are usually done in the laboratory or the number of the species and are often limited to some genera or species. In this work, the automatic wood identification system is proposed using a novel hybrid model to classify 50 commercial wood species from Asia.

Wood identification is the first task for applications in forest science. A possible approach for automated wood identification based on anatomical properties is that the accuracy does not need to rely on the human experience. The development of automated wood identification systems is of prime importance to control trade with and enforce regulations to combat illegal logging, mainly focusing on overexploited species. Microscopic images are not used in this work because this is a destructive method and the process is complex and intricate [26]. A hybrid model is built based on the backbone of its CNN model, the accuracy and speed of the model are two essential factors that determine the success of this model. The CNN model has fully connected layers, which are layers with the most parameters because they must connect all feature maps in the previous layers. The Random Forest model (RF model) is proposed to replace Fully Connected (FC) layers to reduce the number of learning parameters. The experiment results showed that the accuracy is also improved by more than 15% compared to the CNN model. This study proposed a hybrid model for sorting a dataset of 50 species in international trade (announced focus on Asian timbers) with more than 98% overall. Also, the accuracy of some classes is 1.00, and no classes have an accuracy of less than 0.95, specifically covered in the results and discussion section. This is an impressive result and has significance for forest science. Besides, the collected dataset is a small contribution to this study, based on the anatomical images of wood for further studies on the structure or structure of different types of wood [7]. The experiment results satisfied that the basic requirements are performed. However, the system only can classify 50 commercial wood species from Asia, and expanding the wood species is expected in future work.

With the desire, the accuracy and speed process is improved by replacing the last layers of the normal CNN model with the Random Forest model. In brief, the rest of the paper is organized as follows. Section 1 is the introduction. The hybrid CNN-RF model for identifying wood is introduced in Section 3. Next, experiments and discussions are presented and discussed in Section 4. The final section is the conclusions of this study.

## 2 Materials and Methods

In this section, a novel method for wood identification is presented. A hybrid model is introduced in this section to reduce the parameters of the deep learning model. Dataset and pre-processing of 50 commercial wood species from Asia are established which is a small contribution to the study. The algorithm proposed consists of extracting the features, classification, and evaluation methods.

### *2.1 Dataset and Pre-Processing*

In deep learning, the dataset affects the accuracy of trained models [27]. In this study, the dataset is macroscopic imaging of 50 wood species as a list in Table 1. They are captured using a Point Grey Flea 3 digital camera (FL3-U3-88S2C-C), and the lighting is arranged to avoid shadows to minimize under or overexposed pixels. Images were sanded for macroscopic imaging then they were collected and marked by the names of different species. Pre-processing steps are used to make sure that the input image quality of classes is the same such as the image being resized to fit the architecture of the proposed models. The dataset contains 62,105 original images with $1280 \times 960$ pixels per parent image with RGB 8-bit images of the transverse surfaces. Fig. 1 depicts the raw data used in this study, which includes wood tangential plane images on the left and anatomical wood images on the right. In this study, only macroscopic imaging is used to train the model, and images of the collected wood surface are also shown but they are not used for training. The data is divided into two groups to be suitable for training and testing the accuracy of the models. Data augmentation methods are used as rotation, scale, and zoom images to avoid the overfitting of the model [27]. The dataset for this study is collected and uploaded to *zenodo.org* (https://doi.org/10.5281/zenodo.7124060). A number of the original images is shown in Table 1, the amount in each species is not significantly different and this means that the data used for this study are balanced. Besides, the augmentation methods are applied, which is presented in below section.

**Table 1:** A list of the 50 species used in this study

| ID | Scientific name | Amount | ID | Scientific name | Amount |
|---|---|---|---|---|---|
| 01 | Prunus avium | 1260 | 26 | Juglans regia | 1239 |
| 02 | Eucalyptus | 1236 | 27 | Populus alba | 1242 |
| 03 | Calocedrus macrolepis | 1257 | 28 | Chukrasia tabularis A.Juss | 1241 |
| 04 | Fagus sylvatica | 1232 | 29 | Erythrophleum fordii | 1278 |
| 05 | Tilia x europaea | 1248 | 30 | Artocarpus heterophyllus | 1224 |
| 06 | Dalbergia oliveri | 1232 | 31 | Prunus armeniaca | 1243 |
| 07 | Xylia xylocarpa | 1229 | 32 | Diospyros mun | 1259 |
| 08 | Hevea brasiliensis | 1240 | 33 | Diospyros Sp | 1228 |
| 09 | Afzelia xylocarpa | 1237 | 34 | Senna siamea | 1211 |
| 10 | Shorea spp. | 1238 | 35 | Chamaecyparis obtusa | 1237 |
| 11 | Betula pubescens | 1228 | 36 | Cinnamomum verum | 1227 |
| 12 | Terminalia chebula | 1234 | 37 | Cunninghamia konishii | 1240 |
| 13 | Anadenanthera colubrina | 1253 | 38 | Entandrophragma cylindricum | 1225 |
| 14 | Dalbergia odorifera | 1224 | 39 | Fraxinus chinensis | 1282 |
| 15 | Pterocarpus indicus | 1232 | 40 | Tectona grandis | 1234 |
| 16 | Magnolia odora (Chun) Figlar & Noot. | 1253 | 41 | Pinus dalattensis | 1263 |
| 17 | Cinnamomum balansae H.Lec | 1251 | 42 | Madhuca pasquieri | 1240 |
| 18 | Sindora tonkinensis | 1263 | 43 | Quercus alba | 1225 |
| 19 | Sindora spp. | 1259 | 44 | Afzelia spp. | 1238 |

(Continued)

**Table 1 (continued)**

| ID | Scientific name | Amount | ID | Scientific name | Amount |
|---|---|---|---|---|---|
| 20 | Cupressus torulosa | 1239 | 45 | Dipterocarpus spp. | 1245 |
| 21 | Milicia excelsa | 1232 | 46 | Glyptostrobus pensilis | 1252 |
| 22 | Hymenaea courbaril | 1222 | 47 | Fagraea fragrans | 1235 |
| 23 | Acacia mangium x Acacia auriculiformis | 1235 | 48 | Canarium Bengalense Roxb | 1248 |
| 24 | Erythrophleum Fordii | 1287 | 49 | Khaya senegalensis | 1225 |
| 25 | Parashorea Stellata | 1279 | 50 | Melia Azedarach | 1224 |


**Figure 1:** Raw data of some wood species are used in this study

### *2.2 Improve Hybrid CNN-RF for Identifying Wood*

In the deep model, the number of parameters greatly affects the model's speed. Therefore, a novel hybrid model is proposed with the desire to reduce the number of parameters for the model. In this section, the foundations of the deep convolutional neural network, random forest model, improved hybrid model, and an explanation of the reason to create a model.

#### *2.2.1 Deep Convolutional Neural Network*

Neural Network is a computational system inspired by human neural networks to solve real-world problems, models are applied to solve issues such as agriculture, traffic, and medicine [27–31]. Convolutional Neural network (CNN) is a type of feed-forward neural network, and it is also the state-of-the-art method used the most in computer vision, namely to classify images. The basic architecture of the CNN includes the input layer, convolutional layers (Conv), pooling layers, fully connected layers, and output layers. The image is put into the CNN which is convoluted with the kernel to extract features of each class. The feature map includes parameters that are calculated by the convolutional kernel. In this study, CNN architecture is proposed to recognize and extract features of the wood. The input is the RBG image ($x_R$, $x_B$, $x_G$) with the size of $128 \times 128 \times 3$, which is convoluted with the kernel ($w_1$, $w_2$, $w_3$). The nonlinear activation function ($f$) is activated to aggregate the share parameters. Parameters are created while training the model, and the bias is added. Each parameter of the feature map is defined by Eq. (1).

$$y = f(x_R w_1 + x_B w_2 + x_G w_3 + b) \tag{1}$$

The pooling is a non-learnable layer, which is used to reduce the parameters and increase the speed of calculation of the model and avoid overfitting. There are types of pooling layers as max-pooling, average-pooling, or random pooling. However, the max-pooling layer is more popular, which only chooses the highest parameter in the considered region. Considering a region ($A$), the max-pooling is represented by Eq. (2).

$$S_{\max} = Max(A) \tag{2}$$

The neural network has a basic structure including Conv layers, pooling layer, and the fully connected layer, then soft-max is usually used as a classifier. The soft-max function is used in cases where classes need to classify and it is defined by Eq. (3).

$$S\left(\overline{y}_j\right) = \frac{\exp\left(\overline{y}_j\right)}{\sum_{j=1}^{K} \exp\left(\overline{y}_j\right)} \tag{3}$$

where: $\overline{y}_j = w^T x_j$; $w^T$ is the weight matrix, and $K$ is the number of the class. The loss function is used to decrease the error between the predicted and actual classes. Cross-Entropy is a loss function, which is very sensitive to the difference between y and $\overline{y}$ so it is often used to optimize the accuracy of models, it is defined by Eq. (4).

$$L\left(y, \overline{y}\right) = \sum_{j}^{K} y_j . \log_2^{\overline{y}} \tag{4}$$

#### 2.2.2 Random Forests (RF)

Random forests (RF) is a type of nonlinear classifier by the vote of a decision tree and it is used a lot in real-work problems. This is an algorithm based on a decision tree and improved bagging and bootstrapping techniques. The decision trees (N) are created on the randomly selected data and features. The predicted result is aggregated from the votes of the tree decision. With the use of random selections of variables, trees are divided into multiple nodes (M) and the default is usually the square root of the total number of variables. In this model, part of the training dataset is used to evaluate for errors called Out-of-bag (OOB) which is used to estimate the error generated by combining the individual predict results and then aggregated in the RF model as well as used to estimate variable importance using the Importance function. Let $V_i$ is a variable important to $X_j$, the V is defined by Eq. (5). The advantages of the random forest are good handling of the noise and improved speed by important variables [31]. Moreover, one factor that makes RF more popular is that only two parameters ($N$, $M$) are required to be optimized [32].

$$V_i(X_j) = N^{-1} \sum e_{OOB_n^j} - e_{OOB_n} \tag{5}$$

where $N$ is the total number of trees of the model and is the error of predicted $i^{th}$.

#### 2.2.3 Improve Hybrid CNN-RF Model

The hybrid model is developed in many different applications, and they demonstrate the effect of the accuracy and speed of the model. For instance, studies [33,34] indicate improved accuracy. However, the hybrid in the study of Agarap [35], specifically, CNN-SVM is not effective in accuracy compared to CNN. In brief, hybrid models can be beneficial or harmful in terms of model accuracy for different applications, which should be carefully selected by the authors. In this study, a hybrid CNN-RF is proposed to identify woods. Random Forest replaces the fully connected layer, which is applied to classify the woods from the feature map extracted from the CNN model. Compared with CNN, the RF model uses more effectively with advantages of RF such as reducing overfitting, improving the accuracy of the model, and can sort less from CNN. The structure of the proposed model to identify wood is presented in Fig. 2, which illustrates the framework of proposals, firstly, the image through pre-processing steps including resizing, converting color space to suit the input layer of the model and reducing the noise from the camera and environment. Next, the CNN is applied to extract the feature, then the output of the CNN is the input of the RF model, it classifies the 50 species of wood. In brief, the hybrid CNN-RF includes three stages: pre-processing, the CNN model to extract the features, and the RF model as the classifier.

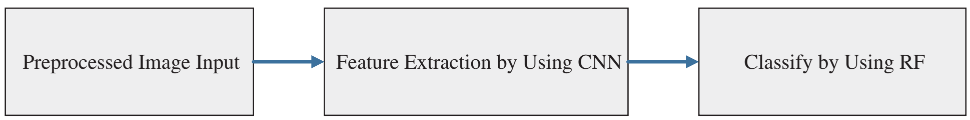



**Figure 2:** Describe the process of identifying woods using a hybrid model

*Stage 1. Pre-processing*

The dataset includes 50 wood species, which are collected from the wood workshops and labs in Vietnam, then the preprocessing stage is applied to improve the resolution of the image. Hence, the first step is to segment, resize and normalize the image for the input layer and the size of $128 \times 128$ with RBG color space. In this stage, the dataset is constructed and manually labeled for each class. The data is divided into training data, and test data. The image input affects the accuracy of the model during feature extraction. Therefore, denoising from the camera and light of the environment is needed to improve the quality image and enhance the accuracy of the system [36,37] that is defined in Eq. (6).

$$K = \alpha \sum_{i=0}^{N} D_i e^{2i} \tag{6}$$

where $\alpha$ is the ratio constant between the pixel size and the actual size; $D_i$ is the distortion coefficient of the $i^{th}$ pixel; N is the number of pixels; and $e$ is the Euclidean distance between the coordinate of the ith pixel and the optical center of the image.

*Stage 2. CNN architecture–Feature extraction*

In classification, feature extraction is a vital phase and affects the system's accuracy. Therefore, the parameters of the CNN model are selected and evaluated carefully through experiments, and the CNN model with the suitable parameters is shown in Section 3. The proposed CNN model is presented in Fig. 3, it is applied to extract features of each species. Input is the RGB image with a size of $128 \times 128$. Then, the image convolutes with the kernel to minimize the parameters. The kernel with the size of $3 \times 3$ is used in this study. The model has three blocks of convolution and six convolutional layers (Conv). Batch normalization is used after Conv layers to normalize features to the zero mean states, reducing overfitting for the model. The conv blocks have a similar structure, the input is convoluted with kernels of size ($3 \times 3 \times 16$), then the feature map is created by the ReLU activation function. Adam optimizer and a learning rate of 0.001 are used for stochastic gradient descent. The final layer is the flattened layer, and this is the input layer for the Random Forest model.

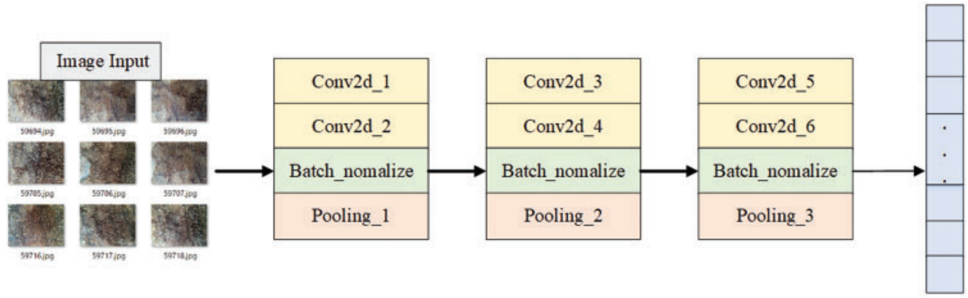



**Figure 3:** Illustration of the proposed CNN architecture

*Stage 3. Random Forest–Wood identification*

In the CNN model, the fully connected layers are usually a feed-forward neural network, then the Softmax activation function is used instead of the ReLU function. In this study, we propose to replace the last classes with the RF model. The model's input is the CNN model's output after flattening. The dataset of the form ($X^n_{train}$, $y^n$) at $X^n_{train}$ is the $n^{th}$ training data with the corresponding label $y$. After the CNN training process, each sample ($X_{train}$, $y$) is extracted from the features by the CNN model and the output is an array ($X_{RF}$) corresponding to label $y$. Random Forest is trained with the data ($X_{RF}$, $y$). In the hybrid CNN-RF model, the CNN model is applied for feature extraction from the raw image, then these features are fed into the RF model as classification layer of the CNN model. The entire proposal model is shown in Fig. 4. The parameters of the model are presented in the below section, and as presented, the RF model has two parameters to optimize that is N and M, they are selected based on pretests from data namely N = 100, and M is the default value.

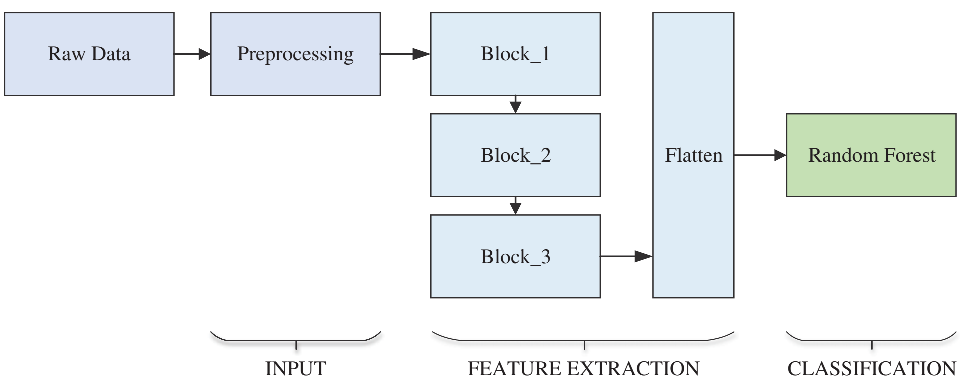



**Figure 4:** General of the proposed hybrid model

In the training phase, the K fold cross-validation is used with K = 5 with the ratio for the testing dataset being 0.2. The model is evaluated based on the sensitivity (recall), precision, and macro F1-score for each species, which are shown in the below section through experiments.

## 3 Results and Discussions

With the development of forest science, much research is performed to protect and enhance the quality of the forest [38,39]. Because the economic values of some woods are large, they are gradually exhausted, identifying the types of wood that can protect precious trees, and prevent fraud in the trade. In this work, data is collected from the local workshops and laboratories including 50 species.

Raw data is resized to $128 \times 128$ with RGB color space to suit the architecture proposed model. Normalizing input data is necessary to increase the accuracy of the classification and augmentation data methods are applied to avoid overfitting and ensure the diversity of the training data [40] that includes rotation, zoom, width shift, height shift, and horizontal flip, it is described in Table 2. The augmentation methods are applied to enhance the quality of the dataset and to make sure that the number of images in each species is the same. The dataset is divided by the number shown in Table 3 and notice that the evaluating dataset is used independently, this data is held out and not used for training phases. In the evaluating phases, data is not augmented because 100 images for each species are collected and only used for this process. The test dataset is enough to evaluate the accuracy of the hybrid model that is presented below.

**Table 2:** Description of the parameters of the algorithms used for data augmentation

| Setting | Value |
|---|---|
| Rotation range | 20.0 |
| Zoom | 0.1 |
| Width shift range | 0.1 |
| Height shift range | 0.1 |
| Horizontal flip | True |

**Table 3:** Description of dataset which is used for the training and testing phases

| | Augmentation | |
|---|---|---|
| | Before | After |
| Deep CNN phases | 57,105 | 513,900 |
| Evaluation phases | 5,000 | 5,000 |

In a CNN model, the last layer of the model is usually a fully-connected network, all neurons from the feature map have been flattened and the softmax functions as a classifier. The input is an RBG image, which is taken by the camera then it is resized to suit the required size of the model. After each conv layer, normalization is applied and after each block, the max-pooling is used to reduce the parameters then is the flattened layer. Finally, the classifier is the RF model, which has a mission that identifies the wood. The CNN model is proposed to extract the feature on the input image, 6 Conv layers are applied with the size of a kernel of $3 \times 3$. The architecture of the proposed model is presented in Table 4, it consists of 6 convolutional layers, three max-pooling layers, and a flattened layer to flatten the feature map, which is the input of the random forest model. The processing speed and accuracy are two important factors in this work so the kernel is used, which has a small size to reduce the parameters of the model. Besides, normalization is also used after each conv layer. This model uses the random forest as a classifier instead of softmax. Random forest is used because of some reasons. Firstly, the RF model has only two parameters that need to be optimized, it can be adjusted easily. Next, the model does not have an overfitting problem because it is determined by the decisions of many trees. Finally, the CNN-RF model achieved superior results compared to other models. The result shows that this method has higher accuracy than convolutional neural networks, and it is presented below. All programs are set up on a Tesla K80 GPU provided by Google Colab.

**Table 4:** The layer parameters of the proposed model

| Layer | Size | Channels | Kernel |
|---|---|---|---|
| Input | $128 \times 128$ | 3 | - |
| Conv_1 | $128 \times 128$ | 32 | $3 \times 3$ |
| Conv_2 | $128 \times 128$ | 32 | $3 \times 3$ |
| Max-pooling | $64 \times 64$ | 32 | $2 \times 2$ |
| Conv_3 | $64 \times 64$ | 64 | $3 \times 3$ |
| Conv_4 | $64 \times 64$ | 64 | $3 \times 3$ |
| Max-pooling | $32 \times 32$ | 64 | $2 \times 2$ |
| Conv_5 | $32 \times 32$ | 128 | $3 \times 3$ |
| Conv_6 | $32 \times 32$ | 128 | $3 \times 3$ |
| Max-pooling | $16 \times 16$ | 128 | $2 \times 2$ |
| Flatten | - | - | - |
| Random forest | Classifier | | |

The RGB image has three channels namely Red, Blue, and Green which are data to train the model. Next, the feature is extracted by convoluting the kernel, the architecture includes 3 blocks with differences in the number of kernels. Bock_1 has two Conv layers and a max-pooling layer, besides, after the Conv layer, a normalized layer is applied. The size of the kernel in block_1 is $3 \times 3$ and max-pooling is $2 \times 2$ and has a stride of 1. The output of block_1 consists of 32 feature maps. Similarly, the bock_2 and block_3 include the conv layers and max-pooling layers. The output of block_2 produces 64 feature maps output and block_3 is 128 feature map outputs. Finally, the flattened layer is used to create input for the random forest model, which calculates based on the vote of the decision tree value. Fig. 5 visualizes the model works of the model, and the feature maps after each block_conv are shown. In this work, speed processing and accuracy are two important factors, so the image is convoluted with a kernel of size $3 \times 3$ to reduce the parameters compared to a larger kernel size. After the training process, test data is used to evaluate the accuracy of the model. The wood identification is carried out using a hybrid CNN-RF model proposed in this study. The accuracy of the model is tested on 5000 images for 50 species, namely, each class has 100 images to evaluate the accuracy of the model through 3 evaluation values: recall, precision, and F1-score. The evaluating dataset is not used in the training process. The accuracy is satisfied in some categories with an accuracy of 1.00, and the lowest is 0.95, 0.92, and 0.95 for three evaluated values of recall, precision, and F1-score, respectively. The overall accuracy is calculated by Eq. (7), in this case, this is 98.14%.

$$Accuracy_{overall} = \frac{\sum TP + TN}{\sum TP + FP + TN + FN} \tag{7}$$

where TP is True Positive; TN is True Negative; FP is False Positive; FN is False Negative.

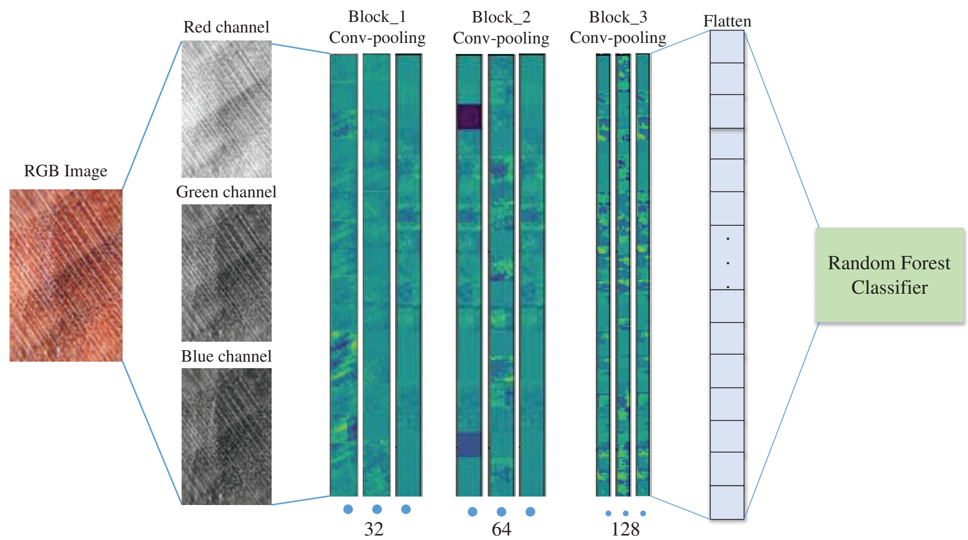



**Figure 5:** Visualizing the model works of the model, the feature maps after each block_conv

A convolutional neural network (CNN) is built to compare the proposed model's effectiveness. The structure of the CNN model has similarities to the proposed CNN model for the hybrid model, but the classifier has a different structure. The last layer of the CNN is the dense layer and the activation function is softmax. Besides, the number of parameters in this layer is very large due to the connection to all previous feature maps. The structure of the CNN model is applied to compare with the proposed model as shown in Fig. 6. With the CNN, test data is used to evaluate the accuracy of the model including 5000 images, which is similar to the test dataset with the CNN-RF model. Test results are evaluated via Recall, precision, and F1-score. The evaluation value for the three evaluated parameters is 0.8234; 0.8312; 0.8242 respectively. The lowest recall, precision, and F1-score value are 0.63; 0.56; 0.59, respectively, and class ID 33 (*Diospyros Sp).* The maximum value of recall in this method is 0.98 in class ID 18 (*Sindora tonkinensis*) and the precision is 1.00 in class ID 02 (*Eucalyptus*). Fig. 7 presents the graph to describe the evaluated results of each class of two models, specifically, Fig. 7a evaluated effects while using a proposed hybrid model, and Fig. 7b shows the results while using a normal CNN model which has the structure as Fig. 6. The accuracy of the two models is presented in Table 5, which shows the hybrid CNN-RF model achieved a high accuracy of 98.14% for overall accuracy. The last layer of CNN is softmax with an overall accuracy of 82.34%, which is 14.8% lower. Besides, the different hybrid models are also built with the same structure as the CNN-RF model, only replacing the last classifier layer. In this work, many structures are recommended to enhance the accuracy of the wood identification including a normal CNN model with the classification layer using the softmax function and replacing the last layer with K-Nearest Neighbors (KNN), Support Vector Machine (SVM) respectively. After experiments, results show that the hybrid model between CNN and RF achieves high efficiency in terms of system accuracy and processing speed. Moreover, RF is more popular and used by this model as only two parameters are required to be optimized as presented in Section 2.2.2. Besides, the speed of the hybrid model achieves 23 fps (frame per second) to meet the processing speed of real-time applications. The experimental results show that the proposed model efficiently identifies different species of wood. Table 6 shows the comparison with the state-of-the-art approaches, namely the Support vector machine (SVM) of Martins et al. [41], K-nearest neighbors (KNN) of Rosa da Silva et al. [42], VGG16 of Ravindran et al. [43], and ResNet101 of Lens et al. [44].

Because the used test datasets in these studies are different from the table doesn't show the other models are not suitable for wood identification. This table is only presented to demonstrate the adaptability of the proposed model in wood identification. It is a means to identify timber to combat illegal logging, it helps the forester to know exactly the wood species through the images.

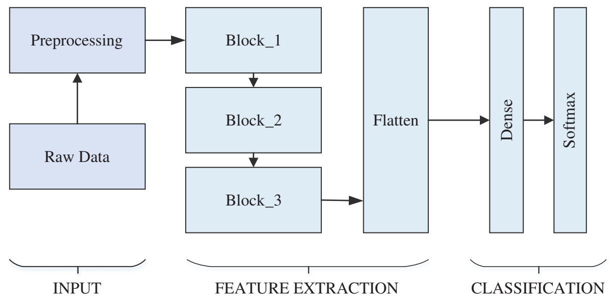
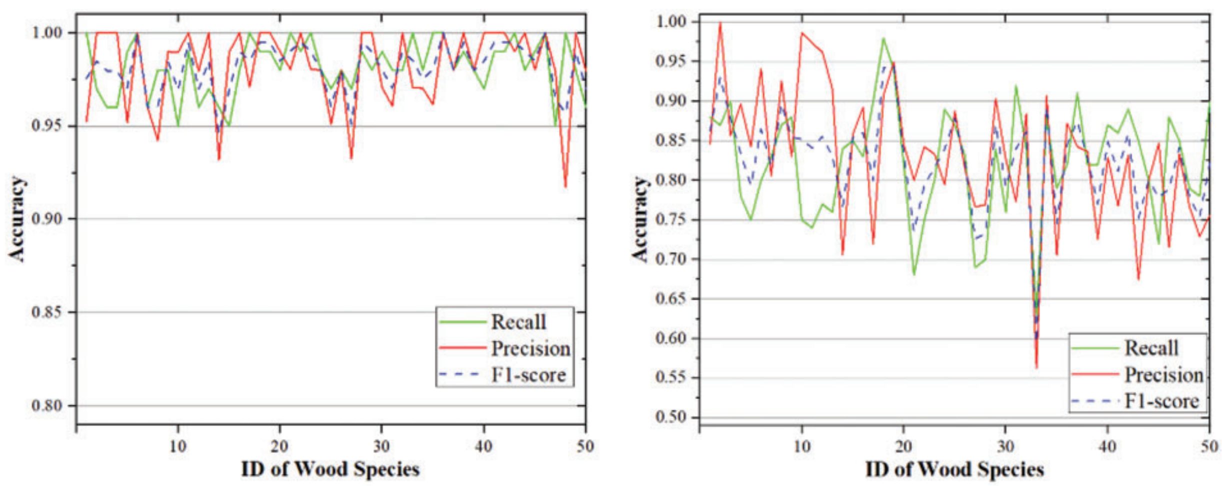



**Figure 6:** Illustration of the traditional CNN model




(a) (b)

**Figure 7:** The accuracy of identification of 50 wood species using two models; (a) using the hybrid model; (b) using the CNN model

**Table 5:** Comparison of evaluation index of the hybrid model and CNN model

| Architecture | Recall (%) | Precision (%) | F1-score (%) |
|---|---|---|---|
| CNN-Softmax | 82.34 | 83.12 | 82.72 |
| CNN-KNN | 91.23 | 92.38 | 91.80 |
| CNN-SVM | 89.10 | 90.23 | 89.66 |
| **CNN-RF** | **98.14** | **98.19** | **98.15** |

**Table 6:** Comparison with the state-of-the-art approaches

| Approach | Accuracy (%) |
|---|---|
| SVM [41] | 79.30 |
| KNN [42] | 87.40 |
| VGG16 [43] | 88.70 |
| ResNet101 [44] | 96.40 |
| **CNN-RF** | **98.14** |

## 4 Conclusions

The development of automated wood identification systems is of prime importance to control trade with and enforce regulations to combat illegal logging, mainly focusing on overexploited species. This study uses an automatic wood identification based on anatomy images using a hybrid model to replace the last layers of the CNN model. The experimental results demonstrated that the accuracy and speed of the model are boosted. The RF model replaces the last layers of the CNN model to optimize the number of parameters. The proposed hybrid model is satisfied with 15.80% higher than the CNN model. Especially, the model speed is three times higher than the CNN model. These have significance for the wood industry because they reduce the costs and time in identifying wood species. In addition, anatomical data of 50 common wood species were also collected in this study. The wood species are prioritized in this work because these are wood groups with high economic value, so they are exploited a lot leading to the risk of depletion. In future work, research is continuing to develop data sources of many species of wood to increase the system's ability to identify. Many approaches will be researched to enhance the quality of wood identification, namely different structures will be expected to develop the wood identification and the algorithm can be considered to apply many fields. This approach will be deployed as a powerful support device for foresters to reduce the wood illegal case.

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