WOOD SPECIES IDENTIFICATION USING MASK RCNN-RESIDUAL NETWORK APPROACH

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Abstract:

Wood identification plays a significant role in forestry and cultural heritage. Its impact and application are more pronounced in the guide against illegal logging and ecological issues. Moreover, it is extremely difficult to identify individual wood species using the existing wood identification methods. Due to the above-mentioned reasons, there is a need to develop an accurate wood identification method that is based on computer vision. Computers react to what they see, just as human eyes react, the insights gained from computer vision as a field of artificial intelligence (AI) enable computers to extract meaningful data from visual inputs such as images and videos, and to take automated actions. Just like AI allows computers to possess thinking ability, computer vision gives them the ability to see. Computer vision, through the region-based convolutional neural network has been able to solve various visual issues that are related to videos and images accurately. However, its application to wood technology and wood related fields still remains uninvestigated. Therefore, in this study, a computer vision based mask region-based convolutional neural network (Mask R-CNN) associated with a modified residual network (ResNet) was employed as a hybrid method (Mask RCNN-ResNet) for a robust and accurate wood identification at species level. The technique of Mask R-CNN involves detecting, extracting the relevant features of visual data from a processed image, then, segmenting the target object using region of interest alignment, and mask generation to make a decision. A modified ResNet network (modified model of residual network) reduced the number of training parameters, thereby leading to an increased efficiency during computation. Mask RCNN-ResNet method is able to identify individual wood at species level with 92% identification accuracy higher than the results obtained in the existing work that used other computer-based wood identification methods on the same wood species datasets.

Key words: *Computer vision; Mask R-CNN; ResNet; Wood identification.*

INTRODUCTION

In most tropical countries, forest is a good source of income. One of the fundamental factors causing environmental challenges and destruction in tropical countries that deal in forest is the illegal deforestation or logging, which as a result causes global ecological impact (Bösch 2021). Moreover, this illegal logging has been a rewarding ecological criminal offense amounting to almost 30% of the timber trade globally with over 100 billion dollars estimate within a year (Nellemann 2012, May 2017). Among the regions of the world

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where this type of crime is predominantly high are Africa (central), Asia (southeast) and Europe (Russia) (May 2017, EU and EC 2022, European Union *et al*. 2022). Although measures to stop illegal deforestation have been put in place (Dormontt *et al*. 2015, United Nations and International Consortium on Combating Wildlife 2016, Schmitz *et al*. 2019, EU 2022, UN 2022), there is a need for stronger measures (FAOUN *et al*. 2022, Interpol 2022, ITTO 2022, Schmitz *et al.* 2022, UNDER *et al*. 2022).

Wood identification is of greatest importance in wood related work such as building construction, manufacturing, furniture work, carpentry, housing, etc, and several factors are still limiting the real-life applications of the wood identification methods. Different traditional techniques (macroscopic and microscopy) and multiple techniques (near-infrared spectroscopy (Abe *et al.* 2016, Snel *et al*. 2018, Pace *et al*. 2019), DNA barcoding (Jiao *et al*. 2015, Wagner *et al*. 2018, Akhmetzyanov *et al*. 2020), mass spectrometry (Espinoza *et al*. 2015, Zhang *et al*. 2019, Carmona *et al*. 2020), and X-ray tomography (Ge *et al*. 2018, Kobayashi *et al*. 2019, Tazuru and Sugiyama 2019) have been proposed and developed for wood identification. Macroscopic technique of identifying wood involves employing the physical features of the wood that are macroscopic and, microscopic technique of identifying wood involves employing the non-physical features of the wood (microscopic features) using the microscopes. Moreover several computer-based technologies for wood identification have been developed such as GUESS (LaPasha 1986, Wheeler and LaPasha 1987), CSIROID (Ilic 1993) and the DELTA system (Dallwitz 1980) with high identification accuracy compared to earlier wood identification methods. Due to advancement in wood identification research for timber industry, all the aforementioned computer-based technologies except the DELTA-Intkey are out-of-date (Silva *et al.* 2022).

A feed forward multilayer perceptron (MLP) network was employed by Esteban et al. (2009) to differentiate Juniperus cedrus species from J.phoenicea var. canariensis species. Likewise, in Esteban et al. (2017), a multilayer perceptron (MP) was employed for identifying the difference between Pinus sylvestris L. and P. nigra Arn subsp. salzmannii (Dunal) Franco. In Mallik et al. (2011), a species-level identification of hardwoods, softwoods and other seven wood species was conducted by applying SEM to process cross sections of wood using image segmentation, object recognition and statistical methods. Martins et al. (2013) in an effort to identify between Brazilian hardwoods and softwoods species, conducted experiment on 112 wood species, 85 genera and 30 families by applying microscopic features analysis using local phase quantization (LPQ), local binary patterns (LBP) and grey-level co-occurrence matrix (GLOM). Salix alba, S. caprea and S. eleagnos were differentiated in Turhan and Serdar (2013) using the Support Vector Machine (SVM). The work of Martins et al. (2013) was similar to the work of Filho et al. (2014), in which 41 species of Brazilian flora were differentiated using 2-level divide-and-conquer classification method. A surface texture analysis of cross sections of 77 commercial wood species was conducted in da Silva et al. (2017) using their microscopic images.

A hybrid of SVM, Naive Bayes (NB), Decision Tree and ANN was used by He et al. (2019) to differentiate between Swietenia macrophylla King, S. mahagoni (L.) Jacq and S. humilis Zucc. Deklerck et al. (2019) studied the heartwood of 175 samples of 10 species of the Meliaceae family using machine learning-based method for metabolome profile got via direct analysis in real-time ionization in combination with time-of-flight mass spectrometry. A smartphone and manually refined samples of field-like conditions were used by De Andrade et al. (2020) to generate 2000 macroscopic images of 21 species, which were classified using a SVM based classifiers. A multi-view random forest (MVRF) model was used by Da Silva et al. (2022) for species-level identification of 77 Congolese wood species. This was similar to the work of De Geus et al. (2020) in which the DenseNet CNN was applied for the recognition of 281 species using microscopic transverse, radial and tangential image datasets. Also, deep convolutional neural networks were applied in Wu et al. (2021) to identify 11 hardwoods of North American species from tangential plane images only. The CNN model 3-ConvNeta was used by Hafemann et al. (2014) for the identification of macro and micro images of 41 species and 112 species respectively.

Six LeNet and Mini VGGNet CNN models were applied by Kwon et al. (2017) for the identification of five Korean softwood species using the camera of a smartphone to acquire macroscopic images from cross sections. This was similar to their other effort where they combined LeNet2, LeNet3 and MiniVGGNet4 models to identify macroscopic images of wood captured by using mobile cameras (Kwon *et al*. 2019). Deep convolutional networks were applied by Figueroa-Mata et al. (2018) for species identification of 41 Brazilian forest species from xylotheque samples. CNNs were used by Ravindran et al. (2018) for the identification of 10 Neotropical species in the Meliaceae family using only the transverse surface. CNNs were applied in creating the three models used in Oliveira et al. (2018) in addition to the databases developed by Filho et al. (2014) and Martins et al. (2013) to identify cross sections of 2942 wood macroscopic images of 41 species and 2240 microscopic images of 112 species. A deep CNN approach was applied in Kanayama et al. (2019) to near-infrared hyperspectral imaging using a principal component algorithm for the identification of 120 samples of 38 hardwood species. The macroscopic field identification programme XyloTron was compared by CNN in Ravindran and Wiedenhoeft (2020) using an ImageNet pre-trained ResNet34 CNN to identify 10 Meliaceae species.

By using a smartphone, 1869 macroscopic images of the end-grain of 10 xylarium hardwood species of North American were acquired and analyzed in Lopes et al. (2020) using the InceptionV4-ResNetV2 CNN. Lopes et al. (2021) also applied generative adversarial network (GAN) to 119 hardwood species of Xylarium Digital Database (Kobayashi *et al*. 2019), generating meaningful hardwood species microscopic cross-sectional images. Recognition experiment was conducted on Cedrella odorata, a CITES-protected wood species and compared with 13 other tropical tree species in Olschofsky and Köhl (2020) by applying a CNN-based Inception-v3, pre-trained with 1.2 million images for the recognition and classification of features. Lens et al. (2020), in order to identify tree species, applied the ResNet101 CNN and SVM for microscopic analysis of 112 mainly Neotropical species using only transverse sections. A hybrid of X-ray fluorescence spectrometry and a CNN was applied in Shugar et al. (2021) for the identification of 48 hardwoods and softwoods specimens from 66 datasets using either radial or tangential sections. Classification experiment on wood patch and 312 wood core scanned images of 14 European softwood and hardwood tree species was conducted by Fabijanska et al. (2021) using a residual based CNN. However, these aforementioned techniques are not accurate enough to identify individual wood species.

To address these limitations, a computer vision based mask region-based convolutional neural network (Mask R-CNN) (He *et al.* 2020) associated with a modified residual network (ResNet) is proposed in this study as a hybrid method (Mask RCNN-ResNet) for a robust and accurate wood identification at species level. The technique of Mask R-CNN involves detecting, extracting the relevant features of visual data from a processed image, then, segmenting the target object using region of interest alignment, and mask generation to make a decision (Bello *et al*. 2021a). A modified ResNet network (modified model of residual network) reduced the number of training parameters, thereby leading to an increased efficiency during computation. Mask RCNN-ResNet method is able to identify individual wood at species level with 92% identification accuracy higher than the results obtained in Barmpoutis (2017) and Barmpoutis et al. (2018) that used other computer-based wood identification methods on the same wood species datasets.

MATERIALS AND METHODS

This section presents the materials and methods employed in achieving the objectives of this study.

Data acquisition and description

Most images used for wood identification have their individual characteristics. Macroscopic images for example, are most often used because, they need no magnification, as they are obtained using a digital camera) (Filho *et al*. 2014, Barmpoutis *et al*. 2018, Olschofsky and Köhl 2020, Fabijanska *et al*. 2021). Stereoscopic images (Stereograms) need to be magnified because they are obtained with hand lens (Tou *et al*. 2007, Khalid *et al*. 2008, Wang *et al*. 2013, De Andrade *et al*. 2020, Ravindran *et al*. 2020). Optical microscopic images (Micrographs) (Martins *et al*. 2013, Da Silva *et al*. 2017, Lens *et al*. 2020), SEM images (Mallik *et al*. 2011), and X-**ray** computed tomography images (Kobayashi *et al*. 2019, Wiedenhoeft 2020) are other images that serve the wood identification experimental purposes. The experiment conducted in this study employed WOOD-AUTH (dataset) (Barmpoutis 2022).

WOOD-AUTH dataset comprises macroscopic wood species of Greece, macro by image type, 12 in number of species (3 softwood species and 9 hardwood species), 4272 in number of images, and cross, radial and tangential in wood sections. They are all 400×400 pixels in size. The 12 species (3 softwood species and 9 hardwood species) on which the model were trained and tested in ratio 70:30 are 1) Fagus sylvatica (European beech or common beech), 2) Juglans regia (Persian walnut, English walnut, Carpathian walnut, Madeira walnut, or common walnut), 3) Castanea sativa (Sweet chestnut, Spanish chestnut), 4) Quercus cerris (Turkish oak or Austrian oak), 5) Alnus glutinosa (European alder or black alder), 6) Fraxinus ornus (Manna ash or South European flowering ash), 7) Picea abies (Norway spruce or European spruce), 8) Pinus sylvestris (Scots pine (UK), Scotch pine (US) or Baltic pine), 9) Ailanthus altissima (Tree of heaven), 10) Robinia pseudoacacia (Black locust), 11) Cupressus sempervirens (Mediterranean cypress or Italian cypress), and 12) Platanus orientalis (Oriental plane tree or oriental sycamore). Fig. 1 shows 6 labeled samples of the wood species in a row.

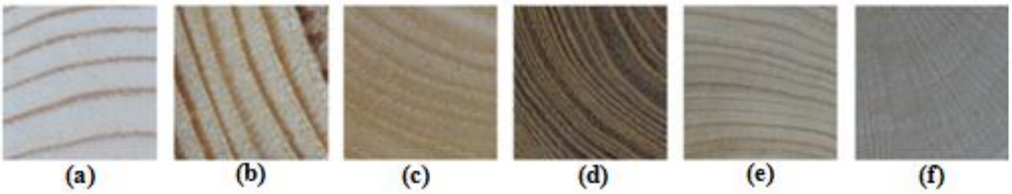

Fig. 1.
Six different samples of wood species from WOOD-AUTH database: (a) Picea abies (*Norway spruce or European spruce****), (b) Pinus sylvestris (****Scots pine (UK), Scotch pine (US) or Baltic pine****), (c) Ailanthus altissima (****Tree of heaven****), (d) Robinia pseudoacacia (****Black locust****), (e) Cupressus sempervirens (****Mediterranean cypress or Italian cypress****), (f) Platanus orientalis (****Oriental plane tree or oriental sycamore****).***

Model development and requirements for the image segmentation

The proposed model, Mask RCNN-ResNet is a hybrid model with the following characteristics: 1) Smaller optimal filter size for the extraction of smaller and complex features, 2) Region proposal for the utilization of multi-scale semantic features, and 3) Mask generation for the classification of individual wood at species level. The residual model was modified to solve some notable issues during back-propagation process. Fig. 2 shows the framework of the Mask RCNN-ResNet for wood species identification.

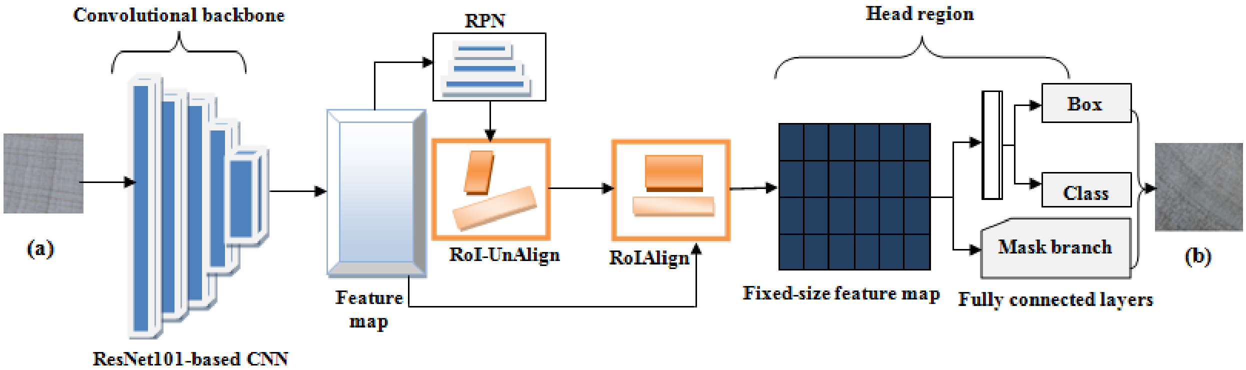

Fig. 2.
Framework of the Mask RCNN-ResNet for wood species identification: (a) Wood species input, (b) Wood species output.

For the implementation of the proposed image segmentation model, the following applications are installed 1) Graphic processing unit (GPU), 2) Keras, 3) Tensorflow (Abadi 2016) and 4) Opencv-python. The hyper-parameters used in training the network model are as follows: 1) Learning rate is 0.001, 2) Weight decay is 0.0001, 3) Momentum of learning is 0.9, 4) Dimension of the image (minimum) is 512, 5) Dimension of the image (maximum) is 512, 6) Detection confidence (minimum) is 0.5, 7) Number of batches is 5, 8) Size of batch is 200, 9) Epochs are 5. 10) Iterations per epoch are 5, 11) Steps per epoch are 1000, 12) Validation steps are 5, and 13) Mask shape is 28×28. As shown in Fig. 2, Fig. 3 and Fig. 4, the process of the proposed model development involves associating Mask R-CNN with a modified residual network (ResNet).

Modified model of residual network (ResNet)

Most of the issues in networks are due to the activation layers of the ResNet that are skipped during the process of back-propagation. Moreover, the lack of descriptive equation for the unstable ResNet parameters is the reason for inaccuracy of the gradient equation. Furthermore, there is no clarification by the training process of the layer that has more training advantage over another. To solve the abovementioned issues, and, to achieve the objectives of the study, residual network was modified and proposed using the back-propagation algorithm. In addition to this solution, the use of new gradient equation also allowed new rules made of different parameters for ResNet to be obtained whereby optimal filter size that is smaller than ResNet was provided for the extraction of smaller and complex features. This approach reduced the number of training parameters, thereby leading to an increased efficiency during computation. By making use of a deep network that comprises a set of blocks fit enough for solving the issues of gradient vanishing, the performance of ResNet was greatly improved. Fig. 3 shows the residual network's block, and Fig. 4 shows the architecture of (a) residual network and (b) enhanced residual network.

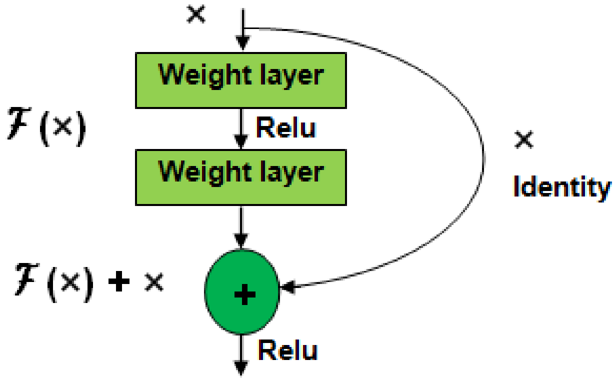

Fig. 3.
Block architecture of a residual network (He et al. 2016).

The two-layer block of the residual network was built using the formula presented in Equation (1).

$$H(x) = F(x, \{W_i\}) + x \quad (1)$$

where: x is the input of building block, $H(x)$ is the output vectors of building block and in the training process, $F(x, \{W_i\})$ is the learned residual mapping.

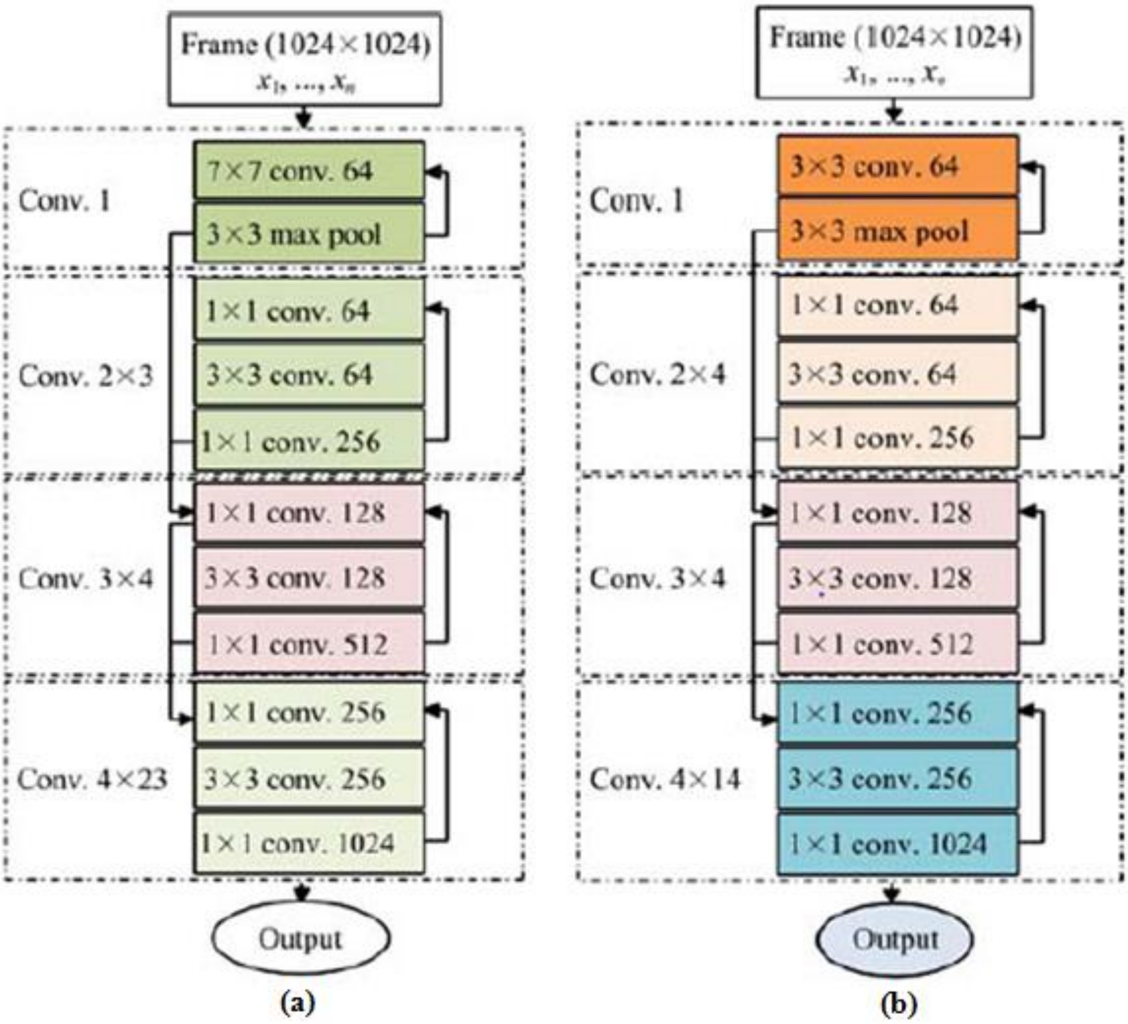

Fig. 4.
Architecture of (a) residual network and (b) enhanced residual network (Bello et al. 2021b).

Based on Fig. 4(b), which is the enhanced residual network, training of the convolutional layers that have the best block was conducted as follows: 1) Repeating 1st convolution block one time, 2) Repeating 2nd convolution block four times, 3) Repeating 3rd convolution block four times, 4) Repeating 4th convolution block fourteen times. To obtain satisfactory results from the proposed framework in this study, loss functions in their combination were applied in bounding box regression training, predicting object class, and generating mask branch. In accomplishing the task, the loss function was used as presented in Equation (2).

$$L = L_{ce} + L_{be} + L_{me} \quad (2)$$

where: L is the loss function, L_{ce} is the classification error, L_{be} is the bounding box error, L_{me} is the mask error. The segmentation accuracy was measured by using the formula presented in Equation (3).

$$\mathrm{IOU} = \frac{A \cap B}{A \cup B} \quad (3)$$

where: IOU is the intersection over union that determines the magnitude of overlap between the predicted bounding box, which is represented by *A* and the ground-truth bounding box, which is represented by *B*. The values of IOU considered in conducting this work are from 0.50 to 0.95 with mAP@*X* notation, where *X* represents the threshold value used in computing the metric. The precision-recall is computed only after establishing matches for all the images. While precision is the total number of correct instances produce by the model, recall is the total number of correct instances that the model can produce. They are conducted as shown in Equation (4) and Equation (5).

$$P = \frac{True\ positive}{True\ positive + False\ positive} \quad (4)$$

$$R = \frac{True\ positive}{True\ positive + False\ Negative} \quad (5)$$

where: *P* and *R* are the precision and the recall respectively. The outcome of a model is true positive when positive instance is correctly predicted. The outcome of a model is false positive when positive instance is incorrectly predicted. The outcome of a model is false negative when negative instance is incorrectly predicted. To calculate average precision, the area under precision-recall curve is taken and the recalls are segmented evenly to different parts. Equation (6) and (7) are used for calculating AP and mean of AP (mAP) as follows.

$$\mathrm{AP} = \sum_{n=1}^{N} [\mathrm{R}(\mathrm{n}) - \mathrm{R}(\mathrm{n}-1)].\max \mathrm{P}(\mathrm{n}) \quad (6)$$

where: *N* represents the number of precision-recall points produced, *P(n)* and *R(n)* represent the precision and recall with the lowest nth recall respectively.

$$m\mathrm{AP} = \frac{1}{\mathrm{N}} \sum_{i=1}^{N} AP_{\mathrm{i}} \quad (7)$$

where: AP_i = the *AP* of class *i*, and *N* = the number of classes.

RESULTS AND DISCUSSIONS

As presented in Fig. 2, the proposed framework of the Mask RCNN-ResNet for wood species identification is a hybrid model of Mask R-CNN and a modified ResNet network (modified model of residual network). The main metrics employed for the evaluation of the experiment results are precision, recall, average precision (AP), IoU, and mean average precision (mAP). The segmentation experiment on the WOOD-AUTH for wood identification at species level using the proposed method and Mask R-CNN produced the results presented in Table 1. Mask RCNN-ResNet method achieved a 0.92 mAP, which is higher than the 0.90 mAP achieved by the Mask R-CNN method. Based on all the results obtained, Mask RCNN-ResNet shows high performance and segmentation accuracy. Fig. 5 and Fig. 6 show the identification at species level of the six different samples of the wood species from WOOD-AUTH database as shown earlier in Fig. 1 using the proposed Mask RCNN-ResNet approach and Mask R-CNN respectively.

Based on Fig. 1, the proposed model was able to classify individual wood at species level in terms of scores more accurate than Mask R-CNN as follows: (a) Picea abies (Norway spruce or European spruce), (b) Pinus sylvestris (Scots pine (UK), Scotch pine (US) or Baltic pine), (c) Ailanthus altissima (Tree of heaven), (d) Robinia pseudoacacia (Black locust), (e) Cupressus sempervirens (Mediterranean cypress or Italian cypress), (f) Platanus orientalis (Oriental plane tree or oriental sycamore). Moreover, the proposed method in this study performs better than what is obtained in Barmpoutis (2017) and Barmpoutis et al. (2018) on the same wood species from WOOD-AUTH database. Fig. 7 shows the comparison of Mask RCNN-ResNet method and Mask RCNN method on the same wood species from WOOD-AUTH database.

Table 1

Mean average precision (mAP) results for wood identification

Method	mAP
Mask R-CNN	0.90
Mask RCNN-ResNet	0.92

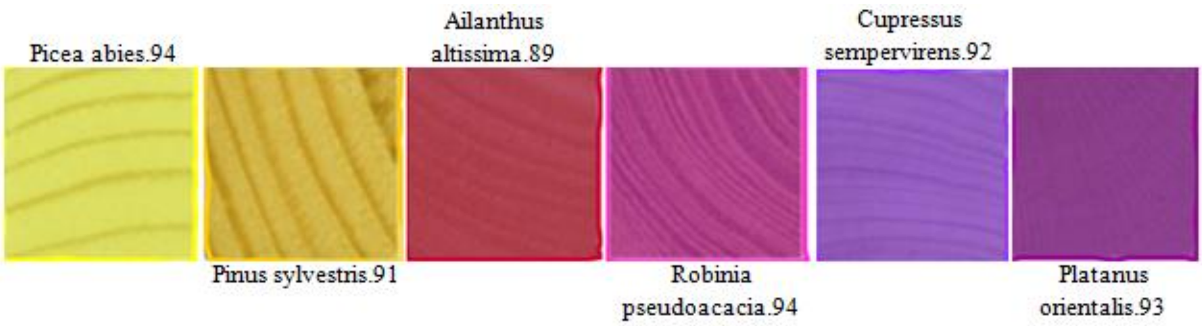

Fig. 5.
Identification of the six different samples of wood species from WOOD-AUTH database as shown in Fig. 1 using Mask RCNN-ResNet approach.

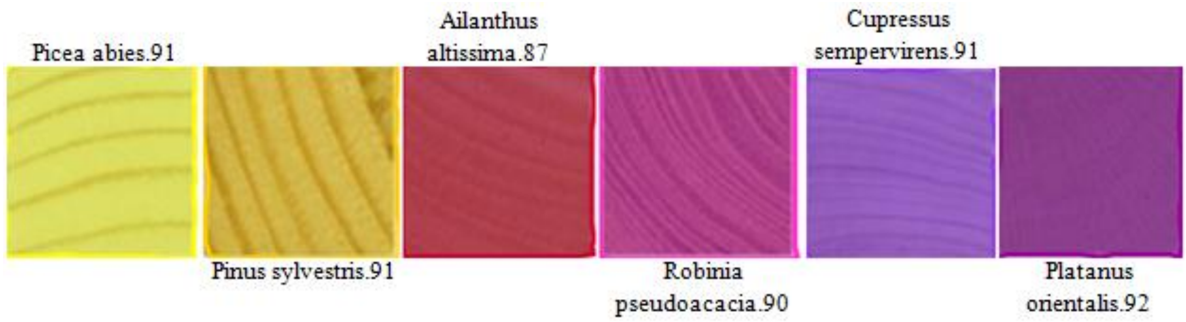

Fig. 6.
Identification of the six different samples of wood species from WOOD-AUTH database as shown in Fig. 1 using Mask R-CNN approach.

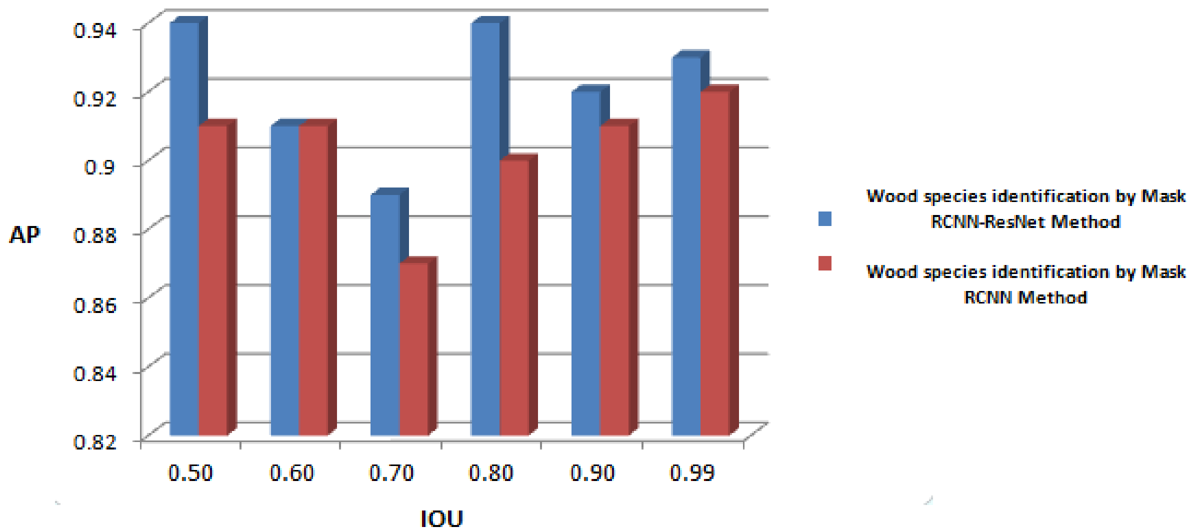

Fig. 7.
Comparison of Mask RCNN-ResNet method and Mask RCNN method on the same wood species.

CONCLUSIONS

Identification of wood at species level using Mask RCNN-ResNet method was proposed in this study that could give assistance to forestry and cultural heritage. The framework of the proposed Mask RCNN-ResNet for wood species identification is a hybrid model of Mask R-CNN and a modified ResNet network (modified model of residual network). This approach reduced the number of training parameters, thereby leading to an increased efficiency during computation. By making use of a deep network that comprises a set of blocks fit enough for solving the issues of gradient vanishing, the performance of ResNet was greatly improved for the overall performance of the proposed method. Six different samples of wood species from WOOD-AUTH database comprising 4272 images were used to evaluate the proposed method efficiency. The proposed Mask RCNN-ResNet method achieved a 0.92 mAP, which is little higher than the 0.90 mAP achieved by the Mask R-CNN method. In the future, further experiments could be conducted on identical wood species of the same taxonomic group for identification at species level.

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