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Wood Species Image Classification Using Two-Dimensional Convolutional Neural Network

Klasifikacija vrsta drva prema slikama uz pomoć dvodimenzionalne konvolucijske neuronske mreže

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ABSTRACT • *The woodworking industry's recognition and classification of timber is essential for trade, production and timber science. Traditional methods of identifying wood types are complex, time-consuming, costly and require expertise in wood science. Traditional techniques have been replaced by convolutional neural networks (CNNs), a deep learning tool to better identify wood species. In contrast to earlier studies that used pre-trained models, a novel architecture designed explicitly for the WOOD-AUTH dataset was proposed in this study to develop a new 2D CNN model. The data collection encompasses high-level visual representations of 12 distinct types of timber. It is aimed to create a simpler and faster model as an alternative to time-consuming and heavy wood classification models. Compared to previous studies, this research worked with a newly structured 2D CNN network based on 12 wood species. High accuracy and fast computation time were achieved using fewer numbers (three layers) of the convolutional neural network. The proposed model achieved 94 % accuracy, 87 % precision, 81 % recall, 80 % F1 score and 112 minutes 27 seconds computation time. The 2D CNN model performed better than the transfer learning models regarding training epochs. The primary benefit of the model is its ability to achieve high accuracy with lower computation time, even at high epochs compared to other models. The introduced 2D CNN model produced satisfactory outcomes for wood species classification.*

KEYWORDS: *2D convolutional neural network; image classification; deep neural network; wood species*

SAŽETAK • *Identifikacija i klasifikacija drva u drvnoj industriji ključna je za trgovinu, proizvodnju i znanost o drvu. Tradicionalne metode identifikacije vrste drva složene su, dugotrajne i skupe te zahtijevaju stručnost s područja znanosti o drvu. Za bolju identifikaciju vrste drva tradicionalne su metode zamijenjene konvolucijskim neuronskim mrežama (CNN), odnosno alatom za duboko učenje. Za razliku od ranijih studija koje su se koristile unaprijed obučenim modelima, u ovoj je studiji predložena nova arhitektura dizajnirana upravo za skup podataka WOOD-AUTH kako bi se razvio novi 2D CNN model. Zbirka podataka obuhvaća vizualne prikaze visoke razluči-*

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vosti 12 različitih vrsta drva. Cilj je bio stvoriti jednostavniji i brži model kao alternativu dugotrajnim i složenim modelima klasifikacije drva. Za razliku od prethodnih istraživanja, u ovom je istraživanju primijenjena nova 2D CNN mreža koja se temelji na 12 vrsta drva. Visoka točnost i brzo vrijeme izračuna postignuti su korištenjem manjeg broja slojeva (tri sloja) konvolucijske neuronske mreže. Predloženim je modelom postignuta točnost od 94 %, preciznost od 87 %, opoziv od 81 %, F1 rezultat od 80 % i vrijeme izračuna od 112 minuta i 27 sekundi. Model 2D CNN pokazao se boljim od modela transfernog učenja u smislu epohe poduke. Primarna prednost modela jest njegova sposobnost postizanja visoke točnosti uz kraće vrijeme izračuna, čak i pri visokim epohama u usporedbi s drugim modelima. Prezentirani 2D CNN model dao je zadovoljavajuće rezultate za klasifikaciju vrste drva.

KLJUČNE RIJEČI: *2D konvolucijska neuronska mreža; klasifikacija slike; duboka neuronska mreža; vrste drva*

1 INTRODUCTION
1. UVOD

Wood has played an important role in human existence over time, fundamentally essential in many respects. With technological advancement, the industrial utilization and application of wood have been further enhanced. In its natural state, wood is an attractive traditional material with numerous advantages that have made it popular compared to other materials (Jones and Brischke, 2017; Nguyen *et al*., 2017; Popescu *et al*., 2011). It is important to possess a comprehensive understanding of its remarkable physical attributes, anatomical structure, mechanical properties, and chemical composition to ensure efficient use of wood. Furthermore, it is equally important to recognize its significant role as an essential prerequisite. (Brauns and Rocens, 2007; Kasal, 2004; Winandy and Rowell, 1984; Zabel and Morrell, 2020). Moreover, it should be noted that some wood species are protected nationally and globally. Therefore, identifying the wood species was important (Kırbaş and Çifci, 2022). The exact identification of wood species forms a pressing issue in different domains, including ecology, construction, furniture manufacturing and restoration, and determining the mechanical and economic properties of wood and wood-based materials. Wood species such as teak, ebony, and mahogany possess unique anatomical, physical, aesthetic, chemical, and mechanical properties (Tou *et al*., 2007; Vacha and Haindl, 2013). Differences in composition and structure vary between wood species and are used in their differentiation (Huang *et al.*, 2020).

Indeed, the traditional method of wood species identification based on macroscopic and microscopic characteristics has limitations, such as being time-consuming, impractical, and expensive. Moreover, the accuracy of this method may depend on the expertise of the professionals involved, which may vary. Hence, using machine learning and computer vision methodologies to automate processes holds immense potential for delivering expedited, efficient, and cost-effective solutions of wood species identification (Mohan *et al*., 2014; Rajagopal, 2019). The wood industry faces a significant hurdle in swiftly identifying a substantial timber volume. To address this issue, leveraging machine learning techniques and approaches can substantially enhance the speed and precision of wood species identification methods (Kırbaş and Çifci, 2022). Researchers have been striving to improve efficiency in recent years by shifting towards computer algorithms for wood image recognition methods instead of relying solely on human labour. One commonly utilized technique for recognizing wood species and their classification is to employ surface recognition models based on texture features. Most computer-based identification methods consist of two significant stages: feature extraction and classification. Boundary detection algorithms play an essential role in feature extraction methods. These methods include the Gray Level Co-occurrence Matrix (GLCM) (Manik *et al*., 2020; Santosa, 2019) for extracting grey colour matrices, the colour history statistical method (Zhao, 2013), and classification methods such as Support Vector Machine (SVM) (Sun, 2015; Souza *et al*., 2020), k-nearest neighbour algorithm (KNN) (Gani and Limam, 2013; Kobayashi *et al*., 2015; Fuentealba *et al*., 2014), and neural networks (Ravindran *et al*., 2018; Yinglai *et al*., 2020; Yang *et al*., 2019). Huayu *et al*. (2017) employed the structural covariance networks and mean squared error (SCN-MSE) technique to enhance the characteristics of digital images depicting Mongolian timber. Zhao (2013) devised a reliable approach for classifying wood species based on coloured wood surface images that effectively differentiate between intra-species and inter-species colour variations. Wang *et al*. (2013) successfully detected eight wood species in their experiments, achieving an accuracy rate of 86 %. Using the Fisher-Tree method, they extracted features from Mask Matching Images (MMI) and employed support vector machines (SVM) for species classification. Hafemann *et al.* (2014) conducted a comparative analysis, evaluating the performance of traditional classifiers against convolutional neural networks (CNNs). The first dataset comprised macroscopic images of 41 species, while the second dataset contained microscopic images of 112 species. The study found that the accuracy of CNN for the dataset of microscopic images was 97.32 %, while for the dataset of macroscopic images, it was

95.77 %. Kwon *et al*. (2017) introduced a CNN-based automatic identification system for wood species, while Huang *et al.* (2020) evaluated the performance of various CNN models for wood species recognition. The study reported that the LeNet3 model achieved the highest accuracy of 99.3 %. In addition, combining deep learning and machine learning techniques resulted in a recognition accuracy of 93.07 %. Tang *et al.* (2018) utilized the SqueezeNet architecture to develop a wood identification system for rapidly and reliably identifying wood species. Their research was focused on 100 frequently traded wood species in Malaysia, and their CNN-based model achieved top 1 and top 2 accuracies of 77.52 % and 87.29 %, respectively. Geus *et al*. (2020) conducted a study to evaluate the performance of four newly proposed CNN architectures for the classification of microscope images of wood. They compared the results with a pre-existing attribute method. Among the newly proposed architectures, the DenseNet model was found to achieve the highest accuracy of 98.75 %, indicating its effectiveness in wood species recognition. Lopes *et al*. (2020) assessed the performance of InceptionV4 and ResNetV2 architectures on North American hardwoods and obtained an accuracy of 92.60 %. Sun *et al*. (2021) used transfer learning with ResNet50 for wood species identification and achieved a high accuracy of 99.60 %. Fabijańska *et al*. (2021) employed a residual CNN architecture to recognize 14 European coniferous and flowering wood types in Europe. Their method achieved 93 % and 98.7 % accuracy rates for wood image patches and core images, respectively.

The literature review summarizes the drawbacks of previous research as listed below in bullet points:

- Conventional wood recognition is laborious, expensive, unfeasible, intricate, and arduous.
- The conventional techniques necessitate significant data processing, labour, and proficient expertise in selecting and extracting features.
- While deep learning methods have shown promise in many areas of image classification, the disadvantage is that the architectures employed are resource-intensive and time-consuming.
- It can be seen that the transfer learning models developed by (Haefmann *et al*., 2014), (Kwon *et al*., 2017), (Lopes *et al*., 2020) and (Su *et al*., 2021) provide accuracy higher than the proposed 2D CNN model. However, these applications require higher hardware systems for the model training, such as Tesla C2050 GPU with high numbers of epochs and XEON CPU with 64 GB RAM capacity computer specifications. In contrast to the high transfer learning models, the proposed 2D CNN model provided 94 % accuracy with NVIDIA GeForce RTX 2070 with 16 GB RAM capacity with shorter computation time. The previous transfer learning applications are not only expensive for the hardware system but also expensive for the computation time.

As an alternative version, this paper aims to address the limitations of existing studies and develop an efficient 2-dimensional convolutional neural network (2D CNN) model that can quickly and accurately identify wood species. The proposed model is designed specifically for the WOOD-AUTH (Barmpoutis, 2017; Barmpoutis *et al*., 2018) dataset and aims to improve classification accuracy compared to previous work that used popular pre-trained models. Therefore, it is desired to develop a more straightforward and faster model as an alternative to time-consuming and heavy wood classification models.

This paper is organized as follows: Section 2 details the dataset employed in the study. Section 3 outlines the methodology adopted in the research. Section 4 introduces the proposed 2D CNN model and discusses its implementation. Section 5 presents the findings and corresponding discussions. Lastly, Section 6 concludes the paper with a summary of the conclusions.

2 DATA SET
2. SKUP PODATAKA

The proposed model was developed using the WOOD-AUTH Laboratory of Wood Technology of Forestry and Natural Environment School of the Aristotle University of Thessaloniki, Greece (Barmpoutis, 2017; Barmpoutis *et al*., 2018) dataset. The dataset consists of 12 wood species; the total data contain 8160 images. Table 1 illustrates each wood species class with a number of image datasets. The different number of datasets for Walnut wood is less than for other wood types because of pre-defined data. The dataset can be called imbalanced due to the wood sample size.

The images were cropped to 200 × 200 pixels with 96 dots per inch (dpi). The 200 × 200 is low for some deep-learning applications but still efficient for wood classification. The WOOD-AUTH was prepared with 400 × 400 pixels (Barmpoutis, 2017; Barmpoutis *et al*., 2018) in the original data. However, the image resolution is decided based on the specific task, hardware, software and artificial intelligence model computation time. The 200 × 200 images were arranged for the proposed deep learning model to avoid the high computational time, memory requirement and processing power.

Figure 1 demonstrates the image samples from each class in the WOOD-AUTH. These sections indicate distinct features of the wood to provide detailed information for identifying the wood species. Considering various sections, the WOOD-AUTH dataset has different characteristics and variations.

Table 1 WOOD-AUTH dataset details the Latin name, type of species, category and number of images in each class
Tablica 1. Skup podataka WOOD-AUTH detaljno opisuje latinski naziv, vrstu drva, kategoriju i broj podataka u svakoj klasi

Class index *Indeks klase*	**Latin name** *Latinsko ime*	**Species** / *Vrste drva*	**Category** *Kategorija*	**Number of images** *Broj slika*
Wood-1.	*Fagus sylvatica*	European beech *drvo bukve*	Diffuse-porous hardwood *difuzno porozna listača*	1223
Wood-2.	*Juglans regia*	Walnut *drvo oraha*	Semi-diffuse-porous hardwood *semi-difuzno porozna listača*	289
Wood-3.	*Castanea sativa*	Sweet chestnut *drvo pitomog kestena*	Ring-porous hardwood *prstenasto porozna listača*	1532
Wood-4.	*Quercus cerris*	Turkey oak *drvo turskog oraha*	Ring-porous hardwood *prstenasto porozna listača*	600
Wood-5.	*Alnusglutinosa*	Alder *drvo johe*	Diffuse-porous hardwood *difuzno porozna listača*	696
Wood-6.	*Fraxinusornus*	Manna ash *drvo crnog jasena*	Ring-porous hardwood *prstenasto porozna listača*	648
Wood-7.	*Picea abies*	Norway spruce *drvo obične smreke*	Softwood *četinjača*	460
Wood-8.	*Pinus sylvestris*	Scots pine *drvo bijelog bora*	Softwood *četinjača*	332
Wood-9.	*Ailanthus altissima*	Tree-of-heaven *nebesko drvo*	Ring-porous hardwood *prstenasto porozna listača*	332
Wood-10.	*Robiniapseudoacacia*	Black locust *drvo bagrema*	Ring-porous hardwood *prstenasto porozna listača*	440
Wood-11.	*Cupressus sempervirens*	Mediterranean cypress *drvo sredozemnog čempresa*	Softwood *četinjača*	552
Wood-12.	*Platanus orientalis*	Old world sycamore *drvo azijske platane*	Diffuse-porous hardwood *difuzno porozna listača*	1056
	Total / *Ukupno*			8160

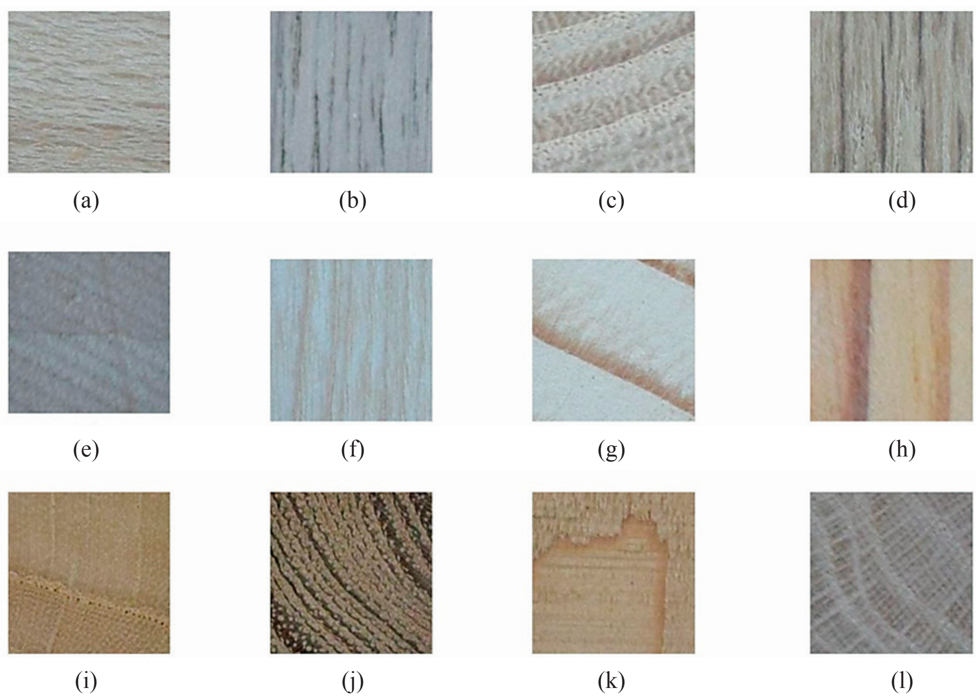

Figure 1 Images display samples of twelve wood species. (a) European Beech, (b) Common Walnut, (c) Sweet Chestnut, (d) Turkey Oak, (e) Common Alder, (f) Manna Ash, (g) Norway Spruce, (h) Scots Pine, (i) Tree of Heaven, (j) Black Locust, (k) Mediterranean Cypress, (l) Oriental Plane
Slika 1. Slike prikazuju uzorke dvanaest vrsta drva: (a) drvo bukve, (b) drvo običnog oraha, (c) drvo pitomog kestena, (d) drvo turskog hrasta, (e) drvo obične johe, (f) drvo crnog jasena, (g) drvo obične smreke, (h) drvo bijelog bora, (i) nebesko drvo, (j) drvo bagrema, (k) drvo sredozemnog čempresa, (l) drvo azijske platane

The 8160-image data was split into the train (80 %) and test (20 %). 6528 images were used for the model training, and 1632 were used for the model test evaluation. The two-dimensional (2D) convolution neural network (CNN), model evaluation metrics and the proposed model are explained in detail in Section 3 and Section 4, respectively.

3 METHODOLOGY
3. METODOLOGIJA

Employing the MATLAB software neural network toolbox, the proposed 2D CNN was configurated from scratch based on the different number of epochs. First, minor epochs were implemented to check model progress with low accuracy. The number of epochs has been increased to 30 and 50; it should be noted that those numbers were decided by trial and error. The best results were obtained with 50 epochs. The 2D CNN classifier consists of the ReLU activation and softmax output function with Adam optimizer and cross-entropy loss. The hyperparameters are elaborated on in Section 4. The model was interpreted by performing accuracy, precision, recall and F1 score indicators and compared to some transfer learning models in TensorFlow Hub.

3.1 Explanation of CNN
3.1. Objašnjenje CNN-a

O'Shea and R. Nash (2015) explained the introduction of the CNN algorithm. (CNNs) resemble traditional Artificial Neural Networks (ANNs) because they consist of neurons that undergo self-optimization through learning. Each neuron receives input and performs operations, such as a scalar product followed by a non-linear function, similar to many other ANNs. The entire network, from the input raw image vectors to the final output of the class score, can still be expressed as a single perceptive score function (the weight). The network last layer contains loss functions associated with the classes, and the usual tips and tricks developed for traditional ANNs are still applicable. CNNs differ from traditional ANNs in their primary use for image pattern recognition. This distinction allows the encoding of image-specific features into the architecture, which is essential when establishing CNN models. The convolutional layer is the first layer of CNN and works for feature extraction from the input image. The pooling layer reduces the number of parameters but does not have any function. The fully connected layer (last layer) is flattening the previous output layer in a vector. Kilic *et al.* (2022) explained the 1D CNN application for a regression analysis to predict machine-based datasets. Dhillon and Verma (2020) indicated that CNN consists of neurons with a learnable weight and bias. Sinaice *et al.* (2022) presented deep neural network image mapping and automatic recognition. Jannat *et al.* (2021) showed that CNN architecture has convolutional, pooling, and fully connected layers. In summary, CNN-based architectures are widely used in the literature for image classification; thus, 2D CNN was preferred to classify the WOOD-AUTH dataset. Section 3 demonstrates the model evaluation metrics, and Section 4 elaborates on the proposed model with hyperparameters.

3.2 Evaluation metrics
3.2. Mjerila evaluacije

3.2.1 Accuracy
3.2.1. Točnost

According to Powers (2020), the accuracy measure refers to the ratio of correctly predicted data points to all data points in the dataset. Eq. 1 expresses the formula of accuracy metrics.

$$accuracy = \frac{TP - TN}{n^{+} + n^{-}} = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

TP as a correctly identified positive instance, TN as a correctly identified negative instance, FP as a mistakenly identified positive instance, and FN as a mistakenly identified negative instance.

3.2.2 Precision
3.2.2. Preciznost

The precision score is a measure of the accuracy between the total number of true positive samples and the total number of predicted samples defined as positive (Power, 2020). Eq. 2 illustrates the calculation for the precision score.

$$precision = \frac{TP}{TP + FN} \tag{2}$$

3.2.3 Recall
3.2.3. Opoziv

The recall score was defined as a metric that compares true positive samples to the total number of true positive samples (Power, 2020).

$$precision = \frac{TP}{TP + FN} \tag{3}$$

3.2.4 F1 Score
3.2.4. F1 rezultat

The F1 score is a harmonic mean of the precision and recall shown in Eq. 4

$$F1score = \frac{2 \cdot TP}{2 \cdot TP + FP + FN} = 2 \cdot \frac{precision \cdot recall}{precision + recall} \tag{4}$$

The worst value is 0 for all evaluation metrics, whereas the best is 1.

4 PROPOSED 2D CNN CLASSIFICATION MODEL FOR WOOD SPECIES
4. PREDLOŽENI 2D CNN MODEL ZA KLASIFIKACIJU VRSTA DRVA

The 2D CNN models are preferred for image recognition and classification for different tasks, such as the wood industry, medical science, and interdisciplinary engineering fields. Therefore, 2D CNN was selected to classify the wood species based on their texture. The image dataset was normalized using zero-centre normalization. Afterwards, the proposed model was designed based on the explanation of (Simonyan and Zisserman, 2015) using 3 and 5 kernels with ReLU activation function and 400 fully connected layers to reduce training time. The filter size was selected. The filter size range between 32 and 1024 as the power of two, and a large filter size can provide a powerful model. However, the large filter size was not selected to create the proposed model in case of overfitting. Therefore, the proposed model worked with 20, 40 and 50 filter sizes. Due to the multiple classes, the output function was decided to work with the softmax function with cross-entropy (Zhang and Sabuncu, 2018). The Adam optimizer was implemented in the convolutional network for gradient descent optimization. Compared to the previous studies, the proposed model included three convolutional layers. Figure 2 illustrates the proposed model structure with the values of each parameter.

4.1 ReLU activation function
4.1. ReLU aktivacijska funkcija

According to Albawi *et al.* (2017) and Ajit *et al.* (2020), the ReLU function is implemented as an activation function. It converts negative values to zero and does not influence volume and hyperparameters. Compared to the sigmoid and tanh activation functions, the ReLU function is unaffected by vanishing gradient descent related to the deeper neural networks. Therefore, the ReLU has been preferred over the sigmoid and tanh activation functions. Eq. 5 shows the ReLU function equation.

$$ReLU(x) = \max(0, x)$$
$$\frac{d}{dx}(x) = \{1 if\ x > 0; 0\ otherwise\} \tag{5}$$

4.2 Softmax output layer
4.2. Softmax izlazni sloj

According to Maharjan *et al.* (2020) and Bridle, (1989), the softmax output activation function effectively classifies multiple classes apart from the binary classification. The WOOD-AUTH dataset has 12 classes and is called various classes. Therefore, the softmax activation function has been selected as the output function. Abd-Ellah *et al.* (2018) presented the softmax function formula in Eq. 6.

$$softmax = \frac{\exp(a_r)}{\sum_{j=1}^{k} \exp(a_j)} \tag{6}$$

Where a is the input vector with k dimensions, and y is the output vector with k dimensions.

4.3 Cross-entropy
4.3. Unakrsna entropija

The cross-entropy was used as a loss function of the model for the multi-classification. (Zhang and Sabuncu, 2018) The cross-entropy loss function was defined as a loss training process in the final layer. The multi-classification of the loss (error) function is presented in Eq. 7.

$$cross-entropy = -\sum_{i=1}^{n}\sum_{j=1}^{k} t_{ij} ln y_j(x_i, \theta) \tag{7}$$

Where θ is the parameter vector, t_{ij} is the index that i sample related to j class, and $y_j(x_i, \theta)$ is the output.

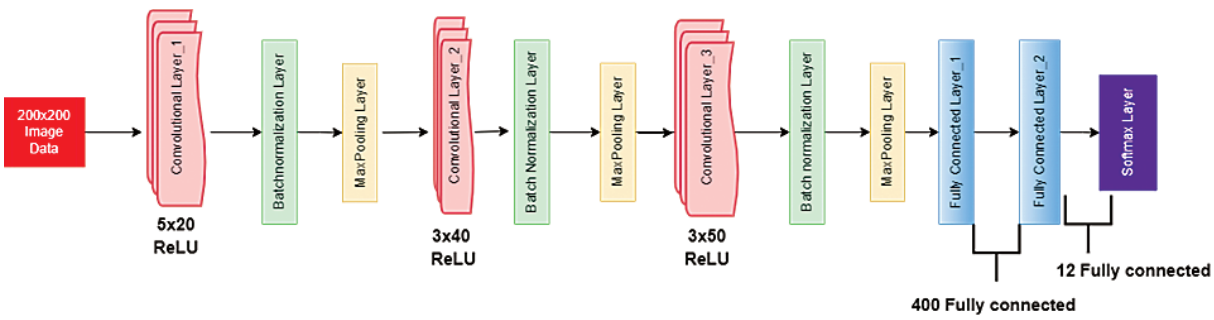

Figure 2 Proposed 2D CNN model structure. Red colour rectangular shape refers to input dataset, pink layered rectangular shape corresponds to convolutional layers, green rectangular shape refers to batch normalization layers, yellow rectangular shape presents max-pooling layers, and the last blue rectangular shape is fully connected layer. The last layer is the output softmax layer. 2D CNN model hyperparameters are detailed in Sections 4.1 – 4.4.

Slika 2. Predložena struktura 2D CNN modela. Crveni pravokutni oblik odnosi se na ulazni skup podataka, ružičasti slojeviti pravokutni oblik odgovara konvolucijskim slojevima, zeleni pravokutnik odnosi se na seriju normalizacijskih slojeva, žuti pravokutni oblik predočuje slojeve maksimalnog udruživanja, a posljednji plavi pravokutni oblik odnosi se na potpuno povezani sloj. Zadnji sloj je izlazni softmax sloj. Hiperparametri 2D CNN modela detaljno su opisani u poglavljima 4.1. – 4.4.

4.4 Adam optimizer
4.4. Adamov optimizator

According to Bock *et al*. (2018), the Adam (adaptive moment estimation) optimizer is a well-known algorithm in gradient descent optimization. The Adam optimizer is distinguished in terms of faster optimization in the deep neural network. The optimizer can converge much faster for deeper networks and convolutional neural networks.

5 RESULTS AND DISCUSSION
5. REZULTATI I RASPRAVA

The model was created based on the WOOD-AUTH to classify the 12 wood species. This model accomplished the task successfully. Apart from the proposed model, some popular transfer learning models have been applied to the dataset to show the strength of the proposed model. The 2D CNN model was outperformed in terms of accuracy and computation time compared to the Efficient B3 and Mobile Net transfer learning models. On the other hand, the outcomes of the proposed model can be compared to the previous applications in the literature. The proposed model performance was evaluated using accuracy metric, precision, recall, F1 score and computation time. Figure 3 demonstrates the confusion matrix of the 12 wood species distribution regarding the predicted and real classes. The 2D CNN model had an accuracy of 94 %, precision of 87 %, recall of 81 % and F1 score of 80 %. The metrics have been explained in Section 3.2. Table 2 demonstrates that the model outcomes are based on the metrics. Figure 3 illustrates the model training and loss relationship. It can be seen that the model worked properly with 50 epochs.

The proposed model training and cross-entropy loss function can be seen in Figure 4. Figure 4 illustrates the model behaviour with the loss function.

It can be noticed that the model was not exposed to overfitting, and the number of datasets was enough to train the model. In addition to Figure 4, Table 2 presents and compares the proposed model outcomes to other popular transfer learning models.

5.1 Model comparison
5.1. Usporedba modela

The comparison indicates that the proposed model provided fast computation (112 min 27 sec) while obtaining high accuracy (94 %). The transfer learning model Xception accuracy is slightly higher than that of the proposed model; however, its computation time is higher than that of the offered model (the proposed model is 41.07 % faster than the Xception). The 2D CNN model is stronger than the VGG19 transfer learning in evaluation metrics and computation. The proposed model provided a reasonable result for the classification of wood species. This research created a new 2D CNN to classify the WOOD-AUTH dataset. In addition to the proposed model, some popular transfer

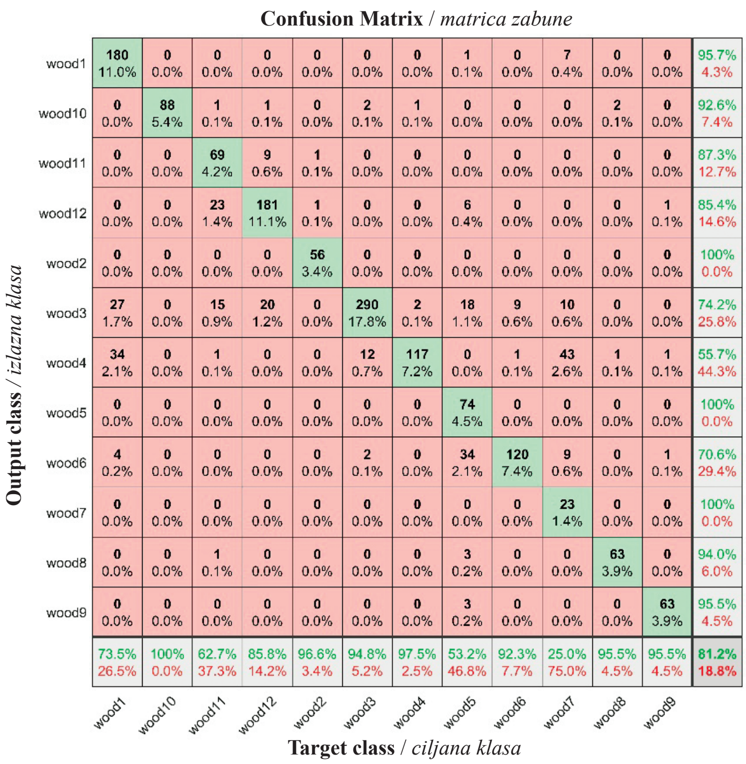

Figure 3 Confusion matrix of 12 wood species with accuracy metrics
Slika 3. Matrica zabune za 12 vrsta drva s metrikom točnosti

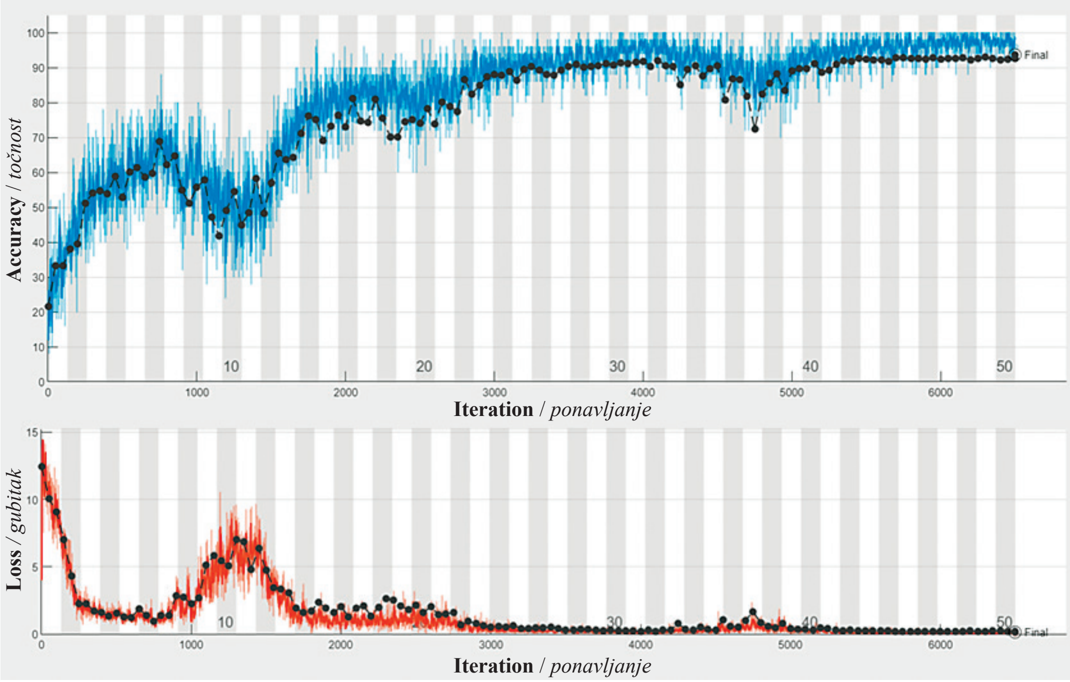

Figure 4 Model training and loss relationship in 50 epochs. Blue line refers to training accuracy, and black line corresponds to test accuracy. Orange bottom line refers to training loss, while black line refers to test loss
Slika 4. Model treninga i odnosa gubitka u 50 epoha. Plava se linija odnosi na točnost treninga, a crna odgovara točnosti testa. Narančasta donja crta odnosi se na gubitak treninga, a donja crna crta predočuje gubitak testa

learning models (Kumar, 2023) have been implemented to show the performance of the newly configurated 2D CNN model. In that case, Efficient B3 and Mobile Net transfer learning models were applied using Tensorflow Hub information.

On the one hand, Xception, Inception V3, ResNet50 and VGG19 (Kırbaş and Çiftçi, 2022) published in the literature were compared to the proposed model. The model's strength is its faster computation time, higher evaluation metrics and fewer convolutional layers. In contrast to the proposed model, the major shortcomings of the transfer learning models is the need for high memory size and slow training; their network architecture weights are exceptionally high.

6 LIMITATIONS
6. OGRANIČENJA

Even though the proposed model is superior to the previous studies, it has some limitations; trial and error hyperparameter tuning and demanding training required to obtain the proper results, compared to the pre-trained models. The data augmentation can be applied to see the model performance on the balanced dataset. In the future, the model will be saved and applied to different wood species datasets. The model can be converted to an application using deep learning deployment techniques used by non-technical, model accomplished, users.

Table 2 Model comparison
Tablica 2. Usporedba modela

Model name *Naziv modela*	**Accuracy, %** *Točnost, %*	**Precision, %** *Preciznost, %*	**Recall, %** *Opoziv, %*	**F1 Score, %** *F1 rezultat, %*	**Computation time** *Vrijeme izračuna*
The proposed 2D CNN model *predloženi 2D CNN model*	94	87	81	80	112 min 27 sec
Efficient B3	82	87	77	81	3 h 24 min
Mobile Net	72	79	66	72	5 h 35 min
Transfer learning models in literature (Kırbaş and Çiftçi, 2022) *Transferni modeli učenja u literaturi* (Kırbaş i Çiftçi, 2022.)					
Xception	95	95	95	95	2 h 38 min 6 s
Inception V3	88	87	87	86	2 h 23 min 34s
ResNet50	37	58	56	57	2 h 6 m 13s
VGG19	61	20	31	23	7 h 30 m 45s

7 CONCLUSIONS
7. ZAKLJUČAK

This research used the new 2D CNN model to employ the WOOD-AUTH dataset with multiple classes (12 wood species classes). The new 2D CNN model required less computation time with 8160 image datasets than the heavy pre-trained transfer learning models. Therefore, the study aims to release a new alternative to deep learning for future classification tasks.

The main conclusions of this research are:

Compared to previous studies, this research worked with the newly configurated 2D CNN network based on 12 wood species. High accuracy and fast computation time were acquired using fewer numbers (three layers) of the convolutional neural network.

The proposed model achieved 94 % accuracy, 87 % precision, 81 % recall, 80 % F1 score and 112 min 27 sec computation time.

Compared to the transfer learning models, the 2D CNN model worked with fewer epochs in training.

The model does not require a high memory size due to the lightweight network structure. Otherwise, transfer learning models need a high memory size, e.g. VGG19 requires 549 megabytes (M.B.) (Keras, 2022).

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