Kenan Kılıç*[1,2], Uğur Özcan[3], Kazım Kılıç[4,5], İbrahim Alper Doğru[6]

Using Deep Learning Techniques for Anomaly Detection of Wood Surface

Primjena tehnika dubokog učenja za otkrivanje anomalija na površini drva

ORIGINAL SCIENTIFIC PAPER
Izvorni znanstveni rad
Received – prispjelo: 24. 5. 2023.
Accepted – prihvaćeno: 15. 3. 2024.
UDK: 630*85; 674.038
https://doi.org/10.5552/drvind.2024.0114

ABSTRACT • *The study presents a novel computer-aided vision system for the detection of wood defects using deep learning techniques. Our study utilizes a dataset consisting of over 43000 labelled wood surface defects found in a comprehensive collection of 20276 wood images. To enable rapid decision-making on the production line, a binary classification approach was employed, distinguishing between defective and perfect wood samples. Only flawless wood can be used in production. Wood with one or more defects is not used in production and must be removed from the production line. Deep learning-based convolutional neural networks (CNNs) were optimized and used for the detection of defective and perfect wood. Using the transfer learning approach, experiments were performed with VGG-16, MobileNet, ResNet-50, DenseNet-121, Xception and InceptionV3 architectures. To decide the best optimization, the analysis of Adam, RMSprop, Adagrad, SGD and Adadelta optimization algorithms were tested on CNN architectures. In addition, different numbers of neurons, namely 256, 512, 1024 and 2048 neurons, were used and wood defect detection was performed with optimum parameters. As a result of the experiments, it was found that the RMSprop optimization algorithm of the Xception architecture reached 97.57 % accuracy, which is the most successful result with 512 neurons.*

KEYWORDS: *wood defect; anomaly detection; computer vision; transfer learning image classification*

SAŽETAK • *Predstavljen je novi računalno potpomognuti vizualni sustav za detekciju grešaka drva primjenom tehnika dubokog učenja. Ovo se istraživanje koristi skupom podataka koji se sastoji od preko 43 000 označenih grešaka na površini drva pronađenih u opsežnoj zbirci od 20 276 slika drva. Kako bismo omogućili brzo donošenje odluka na proizvodnoj liniji, primijenili smo pristup binarne klasifikacije, razlikujući uzorke drva s greškama i bez njih. U proizvodnji se može upotrebljavati samo drvo bez grešaka. Drvo s jednom ili više grešaka ne rabi se u proizvodnji i mora se ukloniti s proizvodne trake. Konvolucijske neuronske mreže utemeljene na dubokom učenju (CNN) optimizirane su i primijenjene za otkrivanje drva s greškama i bez njih. Primjenom pristupa transfernog učenja eksperimenti su izvedeni uz pomoć arhitektura VGG-16, MobileNet, ResNet-50, DenseNet-121, Xception i InceptionV3. Kako bi se odabrala najbolja metoda optimizacije, analiza optimizacijskih algoritama Adam,*

* Corresponding author
[1] Author is researcher at Gazi University, Graduate School of Natural and Applied Sciences, Department of Wood Products Industrial Engineering, 06500, Ankara, Turkey. https://orcid.org/0000-0003-1607-9545
[2] Author is researcher at Yozgat Bozok University, Yozgat Vocational School, Design Department, Yozgat, Turkey. https://orcid.org/0000-0003-1607-9545
[3] Author is researcher at Gazi University, Faculty of Technology, Department of Wood Products Industrial Engineering, Ankara, Turkey. https://orcid.org/0000-0001-8283-9579
[4] Author is researcher at Gazi University, Graduate School of Natural and Applied Sciences, Department of Computer Engineering, Ankara, Turkey. https://orcid.org/0000-0003-2168-1338
[5] Author is researcher at Yozgat Bozok University, Yozgat Vocational School, Department of Computer Technologies, Yozgat, Turkey. https://orcid.org/0000-0003-2168-1338
[6] Author is researcher at Gazi University, Faculty of Technology, Department of Computer Engineering, Ankara, Turkey. https://orcid.org/0000-0001-9324-7157

RMSprop, Adagrad, SGD i Adadelta testirana je na CNN arhitekturama. Osim toga, korišteni su različiti brojevi neurona (256, 512, 1024 i 2048), a otkrivanje grešaka drva provodilo se optimalnim parametrima. Kao rezultat istraživanja utvrđeno je da je RMSprop optimizacijskim algoritmom arhitekture Xception postignuta 97,57 %-tna točnost, što je najuspješniji rezultat s 512 neurona.

KLJUČNE RIJEČI: *greške drva; otkrivanje anomalija; računalni vid; transferno učenje klasifikacije slika*

1 INTRODUCTION
1. UVOD

Woodworking industry places great importance on examining defects on the product surface during the quality control process. This step ensures consistent product quality and enhances production efficiency. Defective products must be identified and removed from the production line as early as possible. Wood products require particular attention, as defects can significantly affect their commercial value. These defects can be caused by reasons such as poor-quality raw materials and ineffective production processes. In some countries, the use of raw wood materials is declining due to these defects. Today, wood products are manufactured to strict surface treatment specifications and modern wood processing industries require a robust wood defect detection and identification system. Visual quality audits are currently carried out by trained personnel.

Nevertheless, due to the need for the classification of various types of wood defects and inadequacy of human expertise in practical scenarios, the utilization of convolutional neural networks has become imperative for identifying flaws in industrial products. Although these systems may not be feasible for actual industrial applications, the novel approach has been specifically designed to promptly detect and categorize defects as they occur.

In wood production, computer analysis and image recognition are extensively utilized for identifying surface defects on wooden materials. This method is favored for its cost-effectiveness and lack of additional equipment requirements. Moreover, it seamlessly integrates with operator intervention. Nonetheless, the accuracy of this approach relies on the specific design of the image analysis algorithm, particularly in the realm of digital image processing for wood defect detection. The detection process entails various pre-processing steps such as converting to grayscale, equalizing the histogram, applying spatial or frequency domain filtering, and extracting defect features. Subsequently, machine learning algorithms are employed to classify the images. Overall, the utilization of image analysis and machine learning techniques plays a crucial role in the wood defect detection process (Xie, 2013).

Accurate identification outcomes in wood defect detection rely on the extraction of defect characteristics and making decisions based on these characteristics. Wood surface attributes encompass different elements, such as grayscale co-occurrence matrix, color matrix, color histogram, geometric features, and texture features. However, the intricate nature of wood surfaces makes feature extraction challenging, resulting in heightened complexity in decision-making algorithms. To tackle this issue, Principal Component Analysis (PCA) is frequently used to effectively merge the extracted features, leading to enhanced accuracy in defect recognition.

Various methodologies have been used by researchers to extract features for detecting defects on wood surfaces. In a study by Zhang *et al*. (2015), the wavelet transform and Local Binary Patterns (LBP) algorithm were employed to extract image characteristics associated with both deceased and living knots. Another study conducted by Li *et al*. (2021) used the OTSU algorithm and mathematical morphology to extract characteristics of insect eyes, living knots, and deceased knots on wood surfaces. They also used the Sobel operator to extract edge contours of wood surface defects. Additionally, Li *et al*. (2019) improved the precision of wood surface defect classification by constructing correlated histograms of wood surface image elements and conducting feature extraction. These studies collectively emphasize the importance of feature extraction in detecting wood defects and demonstrate the use of various algorithms and techniques to enhance accuracy and efficiency in recognizing defects on wood surfaces.

These studies emphasize the significance of effectively integrating and extracting characteristics for precise identification and categorization of wood defects. In the realm of examining image features for wood defect detection, convolutional neural networks (CNNs) are frequently used. CNNs enhance decision-making efficiency by utilizing nonlinear discriminant functions (Packianather and Drake, 2005). In a study conducted by Luo (2019), various neural network models, including the backpropagation (BP) neural network, support vector machine (SVM) and CNN, were compared in terms of their effectiveness in classifying wood defects. The findings clearly demonstrated that both the CNN and SVM models outperformed the BP neural network model in terms of accuracy in detecting and categorizing wood defects. This indicates that the CNN and SVM models are more suitable and capable of achieving higher classification accuracy, particularly in the field of wood defect detection. In conclusion, the application of CNNs and SVMs in wood defect detection highlights their effectiveness in accurately classifying wood defects based on image features. The enhanced performance of these models underscores the importance of selecting the appropriate neural network architectures to enhance the accuracy of wood defect detection and categorization (Luo, 2019).

With the advancements in deep learning algorithms, researchers have increasingly turned to CNN models for accurately classifying wood surface defects. Wang *et al*. (2021) have developed diverse frameworks based on CNN models for this purpose. Urbonas *et al*. (2019) achieved a detection accuracy of 96.1 % in identifying wood surface defects through the implementation of the R-CNN method. Shi *et al*. (2020) improved both the speed and accuracy of defect detection by combining the mask R-CNN method with the neural architecture search (NAS) technique when dealing with wood veneer defects. In the context of solid wood panel defect detection, Fan (2020) conducted an extensive analysis utilizing models like R-CNN, Fast R-CNN, and Faster R-CNN. They devised a human-computer interactive system for detecting defects in solid wood panels and used SQL Server software tools to create tables containing image information. These studies underscore the growing utilization of deep learning approaches and CNN models in precisely detecting and categorizing wood surface defects. Table 1 provides a summary of machine learning-based studies on wood defect detection.

Computer vision technology used in wood production is a highly effective tool for the detection and classification of defects on wood surfaces. Properly configured and calibrated computerized vision systems can be used to increase productivity and improve product quality in wood production. Using specialized algorithms including pattern recognition, feature extraction and classification, these systems can quickly and accurately detect defects in wood surfaces. This paper will examine how computer vision technology can be used for wood defect detection and why this technology is important for the wood industry. The highlights of this study are as follows:

- This is the first study in the literature on binary classification for this dataset.
- With the help of deep learning architectures for wood defect detection, binary classification is performed as defective and perfect.
- A high level of success is achieved in wood defect detection with 97.57 % accuracy in two classifications as defective and perfect.
- Within the scope of wood defect detection, six different CNN architectures, five different optimization algorithms and four different neuron numbers are used.
- The structure of well-known CNN architectures is updated by adding batch normalization and dropout layers. The training of the new architecture is started with the transfer learning method and fine-tuned by retraining with the images in the data set.
- Existing wood defect detection methods have been found to have certain limitations, particularly in terms of speed and accuracy on the production line. The distinctive characteristics of wood products, along with the presence of multiple defect types, make image segmentation and feature extraction challenging. To address these issues, a novel approach using a fully convolutional neural network (CNN) has been proposed for classifying imperfect and perfect wood. This method surpasses previous techniques and eliminates the need for extensive image pre-processing and feature extraction. Consequently, it enables faster and more precise detection and identification of wood defects.

The rest of the article is organized as follows: In Section 2, the material and dataset are introduced, and pre-processing, CNN architectures and optimization algorithms used in the method are presented. In Section 3, the findings of the study and their comparison with existing studies are presented. Finally, Section 4 provides conclusions and some recommendations.

Table 1 Studies on wood defect detection, accuracy and defect types
Tablica 1. Istraživanja o otkrivanju grešaka drva, točnosti rezultata i vrste grešaka

Rank *Rang*	**Study** / *Istraživanje*	**Identified defect types** *Utvrđene vrste grešaka*	**Accuracy** *Točnost*
1	Ren *et al*., 2017	“Encased knot, leaf knot, edge knot, and sound knot”	91.55 %
2	Zhang *et al*., 2015	“Live knot, dead knot, and crack”	92.00 %
3	Yu *et al*., 2019	“Live knots, dead knots, pinholes, and cracks”	92.00 %
4	Zhang *et al*., 2016	“Live knot, dead knot, and leaf knot”	93.00 %
5	Li *et al*., 2017	“Live knot, dead knot, and crack”	94.00 %
6	Li *et al*., 2019	“Crack and the mineral line”	94.30 %
7	Ding *et al*., 2020	“Live knots, dead knots, and checking”	96.10 %
8	Urbanos *et al*., 2020	“Branch, core, split, and stain defects”	96.10 %
9	Yang *et al*., 2020	“Dead knot, live knot, worm hole, decay”	96.72 %

2 MATERIALS AND METHODS
2. MATERIJALI I METODE

2.1 Dataset
2.1. Skup podataka

To address the limited availability of comprehensive databases in the woodworking industry, a large-scale dataset of wood surface defects was collected for experimentation purposes. The dataset consisted of 20276 instances from sawn timber surfaces. Among these instances, 1992 images were defect-free, while 18284 images exhibited one or more surface defects. The dataset encompassed a total of 10 commonly observed wood surface defects. Fused knots and falling knots were the most prevalent defects, accounting for 58.8 % and 41.2 % of occurrences, respectively. This dataset provides a valuable resource for research and development in the field of wood defect detection and analysis (Kodytek *et al*., 2021a).

The dataset comprises over 43000 annotated wood surface anomalies found in a collection of 20276 wood images. The dataset encompasses ten prevalent defect types, namely fused knots, fallen knots, cracked knots, cracks, resins, piths, ures, missing knots, blue stain, and overgrowth defects. The images have a resolution of 2800 × 1024 pixels and are saved in the BMP format. The data was directly gathered from a wood production line during the manufacturing process (Kodytek *et al*., 2021b). Figure 1 presents typical examples of wood defects in the dataset.

2.2 Data augmentation and data pre-processing
2.2. Pojačanje podataka i prethodna obrada podataka

Data augmentation is the process of adding data to increase and stabilize the number of data to be processed (Purnama *et al*., 2019). High-rate sampling and under sampling methods are widely used on unbalanced datasets. Studies show that data augmentation improves success in classification problems performed with deep learning network architectures (Lopez *et al*., 2017; Ayan and Ünver, 2018). In order to prevent imperfect and perfect class imbalance in the dataset and to increase the performance of the deep learning architecture, the number of images in the dataset is increased by applying techniques such as horizontal and vertical rotations, angle changes up to a maximum of 355 degrees, zooming with a minimum value of 1.1 and a maximum value of 1.5, random contrast and brightness enhancement with a maximum value of 0.2. Wood images are converted from 2800 × 1024 pixels bmp format to 300 × 300 jpeg format.

2.3 Deep learning
2.3. Duboko učenje

Deep learning primarily relies on artificial neural networks as its foundation. These architectures can process vast amounts of data by learning from their representations. Consequently, deep neural networks possess more hidden layers in comparison to traditional neural networks (Deng and Yu, 2014). Within deep neural networks, labelled input values are passed through nonlinear activation functions, applying specific weights, to produce an output (Schmidhuber, 2015). The objective of training a deep neural network is to optimize these weights in order to minimize the error value (Ergün and Kılıç, 2021). This study focuses on presenting the deep learning architectures that have been used.

2.3.1 Convolutional Neural Network (CNN)
2.3.1. Konvolucijska neuronska mreža

CNNs are a class of multilayer perceptrons inspired by the visual processing center in animals. These networks have demonstrated remarkable success in a wide range of domains, including image and sound processing, natural language processing, and biomedicine. Notably, CNNs have achieved particularly impressive outcomes in the field of image processing. Their ability to capture spatial dependencies in data has made them a powerful tool for tasks such as image recognition, object detection, and image segmentation. The versatility and effectiveness of CNNs have contributed to their widespread adoption and continued advancement in various fields of study. Forward propagation algorithms in CNNs employ different error rate minimization algorithms, one of which is the back-

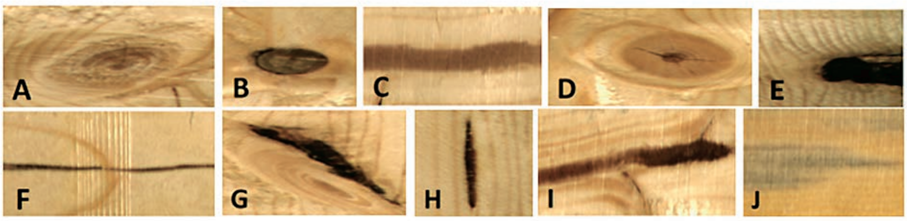

Figure 1 Typical examples of wood defects within the dataset used in the study: (A) Live Knot, (B) Dead Knot, (C) Quartzity, (D) Knot with crack, (E) Knot missing, (F) Crack, (G) Overgrown, (H) Resin, (I) Marrow (J) Blue stain
Slika 1. Tipični primjeri grešaka drva unutar skupa podataka primijenjenih u istraživanju: (A) zdrava kvrga, (B) mrtva kvrga, (C) inkrustacija kvarca, (D) ispucala kvrga, (E) ispala kvrga, (F) pukotina, (G) obrasla kvrga, (H) smolenica, (I) srčika (J) plavilo

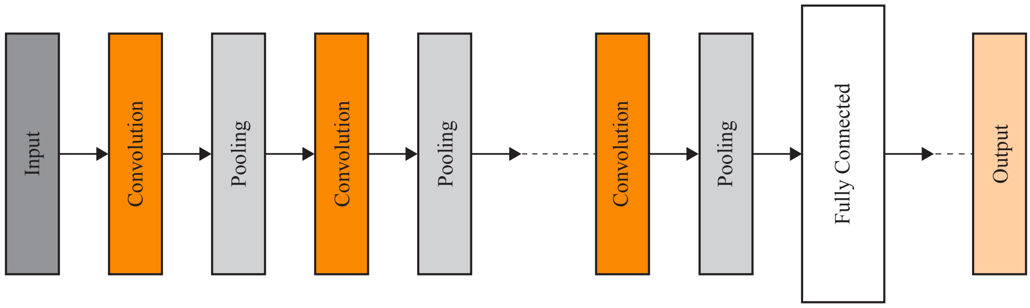

Figure 2 Building block of a typical CNN
Slika 2. Sastav tipičnog CNN-a

propagation algorithm. In the backpropagation algorithm, the error value from the forward propagation stage undergoes derivative operations from the output layer to the input layer, enabling error backpropagation (Tüfekçi and Karpat, 2019). CNNs are deep learning architectures that extract distinctive features from pixel matrices of images, using these features for class prediction (LeCun *et al*., 1998). They have widespread use in computer vision applications including image classification, object detection, image segmentation, voice recognition, text and video processing, and also medical image analysis (Pacal *et al*., 2020).

A CNN is comprised of three primary elements: convolutional layers, pooling layers, and fully connected layers. Figure 2 illustrates the CNN architecture used for image classification. In the convolutional layer, the input image undergoes convolution with kernels or filters to generate feature maps that capture important patterns and features. The pooling layer follows, reducing the size of each feature map to minimize the number of weights, a process also referred to as sub-sampling. Several pooling methods, including general pooling, maximum pooling and average pooling, can be used. As the feature matrix obtained from convolution and pooling layers is typically multidimensional, it is flattened into a one-dimensional vector before being passed to the fully connected layer. The fully connected layer is where the deep neural network is trained using the converted one-dimensional feature vector, enabling classification tasks to be performed (Ergün and Kılıç, 2021).

Convolutional Layer

The convolution layer is a vital component of a CNN and plays a central role in image processing. Since images are usually stationary, the patterns found in one region can also occur in other regions. By taking a small section of a large image and sliding it across the entire image (input), each point can be transformed to a single location (output). These small sections that move over the larger image are referred to as filters or kernels. The filters are constructed using the backpropagation technique. (LeCun and Bengio, 1995).

Sub-sampling or Pooling Layer

Pooling in a CNN refers to the process of downsampling an image. It involves selecting a portion of the output and subsampling it to obtain a single output value. There are different types of pooling techniques, such as maximum pooling, average pooling and mean pooling. Pooling reduces the computational burden by reducing the number of parameters, while also providing the network with the ability to handle variations in shape, size and scale (Atacak *et al*., 2022).

Fully-connected Layer

The final component of the CNN consists of the fully connected layer (FC Layer). In this layer, each neuron connects to all neurons in the previous layer, and neurons in the current layer collectively contribute to production (Sultana *et al*., 2019).

2.3.2 VGG-16
2.3.2. VGG-16

The VGG-16 architecture is composed of a total of 21 layers. Among these layers, 13 are convolutional layers, five are maximum pooling layers, and three are fully connected layers. One notable characteristic of this network is that all layers have a spatial size of 3×3 pixels. The architecture of VGG-16 can be visualized in Figure 2. For input, the VGG-16 architecture expects a vector of dimensions 224×224×3, representing an image with width, height, and three-color channels. The output of the network is a vector with 1000 values, indicating the predicted class to which the image belongs (Simonyan and Zisserman, 2014).

2.3.3 MobileNet
2.3.3. MobileNet

MobileNet, a compact and highly efficient deep CNN model, is renowned for its outstanding performance and smaller size compared to other popular models. Its exceptional efficiency is achieved by utilizing depth-wise separable convolutions, a technique where a single filter is applied to each input channel, followed by 1×1 point-wise convolutions that merge the outputs of the depth-based layers. This strategy significantly reduces both the model's size and computational requirements. In MobileNet, every layer is accompanied by batch normalization and ReLU activation, except for the fully connected layer, which connects to the softmax layer responsible for classification tasks. MobileNet consists of a total of 28 layers, excluding the depth and point convolutions (Howard *et al*., 2017).

2.3.4 ResNet50
2.3.4. ResNet50

Unlike previous CNN architectures, the ResNet architecture uses residual blocks. In residual blocks, input x passes through the convolution layers to produce the result $F(x)$. This result is added to the input x to obtain the output $H(x) = F(x) + x$. This method ensures that residual values from the previous layer are not ignored. Residual blocks are an important feature that distinguishes the ResNet architecture from others. ResNet is available in versions with different depths, 18-34-50-101 and a maximum of 152 layers, and has a very low error rate (He *et al*., 2016). In this study, a 50-layer architecture is used.

2.3.5 DenseNet121
2.3.5. DenseNet121

DenseNet, a network architecture, is designed to enhance the information flow among layers, allowing each layer to receive supplementary inputs from preceding layers and transmit its feature maps to the subsequent layer. This architecture offers a notable advantage by promoting feature propagation, which facilitates the reuse of learned features and reduces the overall number of network parameters. Specifically, the DenseNet architecture comprises 121 layers, dense blocks, and three transition layers. There are various versions of DenseNet, differing in the number of layers, such as DenseNet121, DenseNet169, and DenseNet201 (Huang *et al*., 2017).

2.3.6 Inception-V3
2.3.6. Inception-V3

The model has undergone training by a top-tier hardware expert in the industry and boasts over 20 million parameters. It comprises both symmetric and asymmetric building blocks, with each block incorporating diverse components like convolutional layers, average and maximum pooling, merging operations, dropout layers, and fully connected layers. Additionally, batch normalization is implemented on the activation layer, and Softmax is used for classification purposes (Ali *et al*., 2021).

2.3.7 Xception
2.3.7. Xception

Xception is a CNN model based on the Inception-V3 architecture. It introduces several improvements to reduce time and space complexity. The model uses a linear stack of depth-wise separable convolution layers and incorporates residual connections. The key feature of Xception is the deeply separable convolution, which separates the learning of channel-based and spatial-based features. This helps capture complex patterns while reducing computational complexity. Additionally, Xception employs residual connectivity to address issues of vanishing gradients and representational bottlenecks by creating shortcuts within the network. Overall, Xception offers improved efficiency and performance compared to Inception-V3, making it a popular choice for various computer vision tasks (He *et al*., 2016).

2.4 Optimization algorithms
2.4. Optimizacijski algoritmi

Optimization techniques are used to minimize errors that can arise during program execution. These techniques are commonly referred to as gradient descent. Optimization methods involve a systematic approach that consists of multiple steps. The number of steps performed during this process is known as the learning rate. It is crucial to select an appropriate value for the learning rate. Choosing a small learning rate extends the solution process, while a large learning rate can result in overshooting the minimum point. SGD, Adagrad, RMSProp, Adadelta and Adam algorithms are among the most widely used optimization methods (Bosch *et al*., 2007; Frome *et al*., 2007; Seyyarer and Aydın, 2017; Cebeci, 2020).

In this study, Adam, Adagrad, Adadelta, SGD and RMSprop algorithms are used.

2.5 Transfer learning
2.5. Transferno učenje

When there is not enough data in image analysis studies, a transfer learning approach is usually preferred for studies with CNN architectures. This approach is to use the parameters of a network that has already been trained on a similar task in the new task. The CNN trained for the new task is initialized using the weights of the pre-trained network, and the parameters are updated by retraining a set number of times (Weiss *et al*., 2016; Fırıldak and Talu, 2019). In this study, six different architectures of the selected CNN, five different optimization algorithms and four different neuron numbers (256, 512, 1024, 2048) were tested. In order to determine the best optimization algorithm compatible with CNN architectures, 30 (6×5) experiments were performed with 256 neurons. Then, after determining the optimization algorithm that gave the best result, 24 (6×4) experiments were performed using 256, 512, 1024 and 2048 neurons. In total, 54 experiments were performed.

2.6 Experimental installation
2.6. Postavljanje eksperimenta

The dataset used for this research was divided into two categories: imperfect and perfect wood images. Due to the limited number of perfect wooden images in the dataset used, the number of images in the training set was increased in order to balance the data distribution and increase the performance of the network. With this increase, the number of perfect wooden images becomes equal to the number of defective wooden images. However, data augmentation is performed only on the training set. The dataset consisted of a total of 20276 images, including 1992 perfect wood images and 18284 defective wood images. The dataset was randomly divided into three subsets: 70 % for training, 15 % for validation, and 15 % for testing.

6 different well-known CNN architectures (VGGNet, ResNet50, MobileNet, DenseNet121, Xception and InceptionV3) were trained for wood defect detection using images. Each of the architectures was trained using the same hyperparameters. Instead of starting education from scratch, the transfer learning method was preferred. With this method, it is aimed to prevent overfitting, save time and increase accuracy. ImageNet weights were used for the weights of the network. Well-known transfer learning architectures have feature extractor layers and an additional classifier softmax layer. It also uses the "adam" activation function for activation within the network. For the experiments, first the batch normalization layer, the fully connected layer and the dropout layers with a ratio of 0.25 were added to the softmax layer of these architectures. The purpose of this is to prevent overfitting of the network.

In order to provide comparative and comprehensive analysis, different optimizers such as Adam, RMSprop, Adadelta, Adagrad and SGD were used in the experiments. At the same time, for the most successful optimizer, 256, 512, 1024 and 2048 neurons are added to each of the architectures and their performances are measured separately.

The learning rates of the networks at the beginning of the training were determined as standard 0.0001, and the validation loss was checked in each training cycle, and if the loss did not decrease for 5 epochs, the learning rate was reduced by 50 %. Thus, it is aimed to use dynamic learning rate. Since the study involved many experiments and comparative analysis, the number of epochs was determined as 20, considering the training times. Batch size was set to 64, considering the ram and graphics card capacity and data size.

Experiments were carried out in the Kaggle kernels cloud environment using Google. The infrastructure is on the Nvidia Tesla P100 graphics card. Python programming language was used in the application software.

2.7 Evaluation metrics
2.7. Mjerni podatci za ocjenjivanje

Accuracy

Chicco and Jurman (2020) presented that the accuracy metric is a ratio between correctly estimated data points and all the data points in the dataset. Eq. 1 expresses the formula of accuracy metrics.

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

TP, TN, FP, and FN are abbreviations that represent the terms true positive, true negative, false positive, and false negative.

Precision

The precision score is expressed as a score between true positive and all the predicted number of samples which are presented as positive (Power, 2020). Eq. 2 indicates that precision score.

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

Recall

Power (2020) defined the recall score which is a ratio between true positive instances and the actual number of samples represented as positive. Eq. 3 illustrates the recall score.

$$recall = \frac{2}{TP + FP} \quad (3)$$

F1 Score

According to Chicco and Jurman (2020), the F1 score is a metric that calculates the harmonic mean of precision and recall, as described in Eq. 4.

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

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

AUC

The Area Under the Curve (AUC) quantifies the extent of discrimination ability of a classification architecture by measuring the area beneath the ROC Curve. It provides a measure of how well the architecture can differentiate between positive and negative examples. As the AUC value increases, indicating a larger area under the curve, the discrimination ability of the architecture improves (Adegun and Viriri, 2020).

Error Rate

Error Rate indicates the ratio of the absolute difference between the true value and the value obtained by the classifier (Ergün and Kılıç, 2021).

3 RESULTS AND DISCUSSION
3. REZULTATI I RASPRAVA

This section contains wood defect classification results of 6 different transfer learning architectures. Experimental results are performed with different

Table 2 The best results of CNN architectures and optimization algorithms after 20 epochs
Tablica 2. Najbolji rezultati CNN arhitekturâ i optimizacijskih algoritama nakon 20 epoha

CNN model *CNN model*	**Optimization algorithm** *Optimizacijski algoritam*	**Precision** *Preciznost*	**Recall** *Opoziv*	**F1-score**	**ROC**	**Time** *Vrijeme*	**Accuracy** *Točnost*
VGG16	Adam	0.9706	0.9698	0.9701	0.9884	309.44 s	0.9698
VGG16	RMSprop*	0.9754	0.9747	0.9750	0.9914	309.19 s	0.9747*
VGG16	Adagrad	0.9705	0.9711	0.9707	0.9918	309.92 s	0.9711
VGG16	SGD	0.9549	0.9566	0.9530	0.9885	308.92 s	0.9566
VGG16	Adadelta	0.9616	0.9586	0.9597	0.9833	312.30 s	0.9586
MobileNet	Adam	0.9720	0.9701	0.9708	0.9866	148.97 s	0.9701
MobileNet	RMSprop*	0.9749	0.9737	0.9742	0.9880	156.01 s	0.9737*
MobileNet	Adagrad	0.9633	0.9612	0.9620	0.9840	146.99 s	0.9612
MobileNet	SGD	0.9542	0.9533	0.9537	0.9781	145.91 s	0.9533
MobileNet	Adadelta	0.9316	0.9316	0.9316	0.9565	145.02 s	0.9316
ResNet50	Adam	0.9709	0.9684	0.9693	0.9899	260.55 s	0.9684
ResNet50	RMSprop*	0.9740	0.9734	0.9736	0.9920	258.28 s	0.9734*
ResNet50	Adagrad	0.9715	0.9701	0.9706	0.9851	259.85 s	0.9701
ResNet50	SGD	0.9695	0.9635	0.9653	0.9880	264.58 s	0.9635
ResNet50	Adadelta	0.9567	0.9556	0.9561	0.9817	260.07 s	0.9556
DenseNet121	Adam*	0.9715	0.9714	0.9715	0.9911	268.23 s	0.9714*
DenseNet121	RMSprop	0.9653	0.9648	0.9651	0.9878	267.61 s	0.9648
DenseNet121	Adagrad	0.9689	0.9668	0.9676	0.9868	266.89 s	0.9668
DenseNet121	SGD	0.9692	0.9665	0.9665	0.9882	266.62 s	0.9665
DenseNet121	Adadelta	0.9580	0.9536	0.9553	0.9797	267.39 s	0.9536
XCeption	Adam	0.9711	0.9678	0.9689	0.9892	389.93 s	0.9678
XCeption	RMSprop*	0.9756	0.9756	0.9734	0.9911	383.37 s	0.9724*
XCeption	Adagrad	0.9662	0.9635	0.9645	0.9823	384.23 s	0.9635
XCeption	SGD	0.9626	0.9579	0.9596	0.9828	383.87 s	0.9579
XCeption	Adadelta	0.9585	0.9464	0.9501	0.9774	385.66 s	0.9464
InceptionV3	Adam	0.9699	0.9691	0.9695	0.9887	200.64 s	0.9691
InceptionV3	RMSprop*	0.9732	0.9717	0.9723	0.9915	198.71 s	0.9717*
InceptionV3	Adagrad	0.9649	0.9619	0.9630	0.9873	199.61 s	0.9619
InceptionV3	SGD	0.9643	0.9615	0.9626	0.9852	199.06 s	0.9615
InceptionV3	Adadelta	0.9444	0.9352	0.9386	0.9676	199.59 s	0.9352

numbers of fully connected layer neurons and different optimization algorithms added to the architectures, and the results are presented comparatively. First, architectures were trained with optimization algorithms and the most successful optimizer was determined. In the next stage, experiments were carried out by combining the most successful optimizer with different fully connected layer neurons. The performance of the architectures used to classify imperfect and perfect timbers is shown in Table 2. Experiments are performed with the augmented and balanced dataset.

Table 2 shows that the most successful results of the different architectures used for the experiments were obtained with the RMSprop optimizer. The most successful result was obtained as 97.47 % with the VGGNet-16 architecture with 256 neurons. The results show that SGD and Adadelta optimizers produce lower results and fail more than others. Adagrad is the optimizer that provides results closest to RMSprop in all architectures. Although Adam provided the most successful performance in large-scale image classification competitions such as ImageNet, it fell behind RMSprop and Adagrad in this study for the detection of wood defects.

Experiments were conducted with four different variables, 256, 512, 1024 and 2048 neurons, with the RMSprop optimization algorithm that gives the best result as shown in Table 3.

In the experiments conducted with different neuron numbers using the RMSprop algorithm, the following accuracy was found: VGG16 1024 neurons - 97.50 %, Mobilenet 256 - neurons 97.37 %, Resnet50 256 - neurons 97.34 %, DenseNet121 2048 neurons - 97.34 %, Inceptionv3 2048 neurons - 97.24 %. Increasing the ResNet50 architecture with 256 neurons did not improve accuracy. The Xception architecture achieved the highest accuracy at 512 neurons. In Densenet121 and InceptionV3 architectures, the highest accuracy was achieved at 2048 neurons. Among all experiments, the Xception architecture RMSprop optimization algorithm gave the highest accuracy result of 97.57 % with 512 neurons.

Although the Xception architecture reaches 97.57 % accuracy, the training and testing time is more than 2 times that of the MobileNet architecture. MobileNet architecture reaches 97.37 % accuracy, which is close to the highest result in the shortest time. At the same time,

Table 3 CNN architectures, RMSprop optimizer and neuron count performances
Tablica 3. CNN arhitekture, RMSprop optimizator i performanse brojenja neurona

CNN model *CNC model*	**Optimization algorithm / number of neurons** *Optimizacijski algoritam / broj neurona*	**Precision** *Preciznost*	**Recall** *Opoziv*	**F1-score** *F1-rezultat*	**ROC**	**Time** *Vrijeme*	**Accuracy** *Točnost*
VGG16	RMSprop / 256	0.9754	0.9747	0.9750	0.9914	309.19 s	0.9747
VGG16	RMSprop / 512	0.9730	0.9730	0.9730	0.9905	308.68 s	0.9730
VGG16	RMSprop / 1024*	0.9754	0.9750	0.9752	0.9920	309.74 s	0.9750*
VGG16	RMSprop / 2048	0.9729	0.9724	0.9726	0.9906	308.78 s	0.9724
MobileNet	RMSprop / 256*	0.9749	0.9737	0.9742	0.9880	156.01 s	0.9737*
MobileNet	RMSprop / 512	0.9704	0.9698	0.9700	0.9813	145.78 s	0.9698
MobileNet	RMSprop / 1024	0.9722	0.9704	0.9711	0.9883	145.86 s	0.9704
MobileNet	RMSprop / 2048	0.9751	0.9734	0.9740	0.9910	147.48 s	0.9734
ResNet50	RMSprop / 256*	0.9740	0.9734	0.9736	0.9920	258.28 s	0.9734
ResNet50	RMSprop / 512	0.9628	0.9632	0.9630	0.9885	258.92 s	0.9632
ResNet50	RMSprop / 1024	0.9741	0.9724	0.9730	0.9910	259.27 s	0.9724
ResNet50	RMSprop / 2048	0.9726	0.9717	0.9721	0.9906	259.00 s	0.9717
DenseNet121	RMSprop / 256	0.9653	0.9648	0.9651	0.9878	267.61 s	0.9648
DenseNet121	RMSprop / 512	0.9697	0.9684	0.9689	0.9893	266.79 s	0.9684
DenseNet121	RMSprop / 1024	0.9734	0.9724	0.9728	0.9909	267.34 s	0.9724
DenseNet121	RMSprop / 2048*	0.9748	0.9734	0.9739	0.9915	267.08 s	0.9734*
XCeption	RMSprop / 256	0.9756	0.9756	0.9734	0.9911	383.37 s	0.9724
XCeption	RMSprop / 512*	0.9769	0.9757	0.9761	0.9870	383.81 s	0.9757*
XCeption	RMSprop / 1024	0.9755	0.9753	0.9754	0.9923	383.54 s	0.9753
XCeption	RMSprop / 2048	0.9636	0.9642	0.9639	0.9737	383.84 s	0.9642
InceptionV3	RMSprop / 256	0.9732	0.9717	0.9723	0.9915	198.71 s	0.9717
InceptionV3	RMSprop / 512	0.9737	0.9714	0.9722	0.9928	198.73 s	0.9714
InceptionV3	RMSprop / 1024	0.9706	0.9691	0.9697	0.9871	198.59 s	0.9691
InceptionV3	RMSprop / 2048*	0.9720	0.9724	0.9721	0.9901	199.45 s	0.9724*

the InceptionV3 architecture, which is low in terms of time, reaches 97.24 % accuracy with 2048 neurons.

The confusion matrix of the test set of the Xception architecture, which achieved the most successful accuracy rate according to the experiments, is shown in Figure 3.

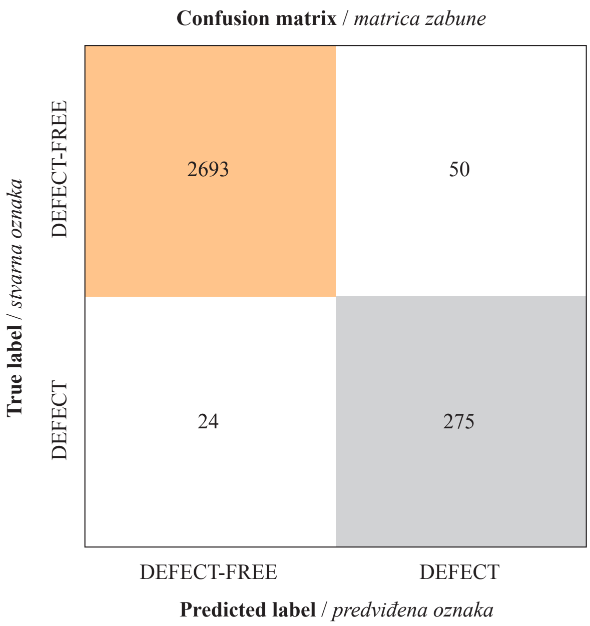

Figure 3 Confusion matrix of the most successful Xception architecture
Slika 3. Matrica zabune najuspješnije Xception arhitekture

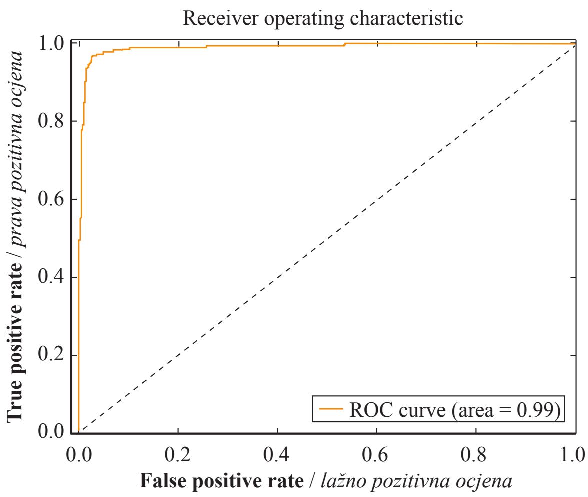

Figure 4 ROC curve showing discernment ability of Xception architecture
Slika 4. ROC krivulja koja pokazuje sposobnost razlučivanja Xception arhitekture

The ROC curve shows how well classifiers separate positive and negative examples. One side of the ROC curve gives the true positive rate, and the other side gives the false positive rate. The area under the curve shows the AUC score. The ROC curve showing the discrimination ability of the Xception architecture, which achieved the most successful results, is shown in Figure 4.

4 CONCLUSIONS
4. ZAKLJUČAK

Wood defect detection is an important issue in quality and production processes in the woodworking industry worldwide. In this study, deep learning-based classification is performed for the detection of imperfect and perfect wood images, and the performance of the architectures used for classification is compared. Deep learning architectures are classified by learning features from the representation of the data. The size and diversity of the data set increases the classification performance. For this reason, the data is divided into 70 % training, 15 % validation and 15 % testing. In the dataset set, 12798 imperfect and 12798 perfect wood images are separated for training. 25596 images are allocated for training. For validation, 2473 images are separated into 15 % of the defective wood images. For validation, 299 images are reserved as 15 % of the perfect wood images. For the test, 2473 images are allocated as 15% of the defective wood images. For testing, 299 images are allocated as 15 % of perfect wood images. Data balancing is done only in training. Data augmentation is done to equalize the number of perfect wood images to the number of imperfect wood images to make the data balanced. Horizontal and vertical flips, angle changes, zooming, random contrast and brightness enhancement techniques are used in the training phase to improve the performance of the classification architecture and prevent overfitting.

VGG-16, MobileNet, DenseNet-121, ResNet-50, Xception, InceptionV3 architectures are used for the experiments. To determine the best optimization algorithm for the architectures, Adam, RMSprop, Adagrad, SGD, Adadelta are used. Experiments are performed with 256, 512, 1024, 2048 neurons to determine the performance of the architecture and optimization algorithms.

Experiments on the dataset used Xception architecture - RMSprop algorithm - 512 neurons with 97.57 % classification accuracy and 99.11 % ROC score. The most unsuccessful result was achieved by the MobileNet architecture - Adadelta optimization algorithm - 93.16 % classification accuracy with 256 neurons. These results could not be compared since no binary classification has ever been done in the literature for this dataset. In the light of the results, it can be said that a very successful performance was obtained for defect detection in wood with heterogeneous and 10 different defects. In future studies, it is aimed to increase the classification success by automatically segmenting the defect region due to the noise in the images to be used in wood defect detection, enabling deep learning architectures to better see distinctive features and improving the classifier hyper-parameters.

Acknowledgements – Zahvala

This study was prepared within the scope of the doctoral dissertation titled “A Computer Vision Based Machine Learning Approach for Wood Defect Detection” by Kenan KILIÇ in Gazi University, Graduate School of Natural and Applied Sciences, Department of Woodworking Industrial Engineering.

5 REFERENCES
5. LITERATURA

1. Adegun, A. A.; Viriri, S., 2020: FCN-based DenseNet framework for automated detection and classification of skin lesions in dermoscopy images. IEEE Access, 8: 150377-150396. https://doi.org/10.1109/ACCESS.2020.3016651
2. Ali, L.; Alnajjar, F.; Jassmi, H. A.; Gocho, M.; Khan, W.; Serhani, M. A., 2021: Performance evaluation of deep CNN-based crack detection and localization techniques for concrete structures. Sensors, 21 (5): 1688. https://doi.org/10.3390/s21051688
3. Althubiti, S. A.; Alenezi, F.; Shitharth, S.; Reddy, C. V. S., 2022: Circuit manufacturing defect detection using vgg16 convolutional neural networks. Wireless Communications and Mobile Computing, 2022. https://doi.org/10.1155/2022/1070405
4. Atacak, İ.; Kılıç, K.; Doğru, İ. A., 2022: Android malware detection using hybrid ANFIS architecture with low computational cost convolutional layers. PeerJ Computer Science, 8: e1092. https://doi.org/10.7717/peerj-cs.1092
5. Ayan, E.; Ünver, H. M., 2018, April: Data augmentation importance for classification of skin lesions via deep learning. In: Proceedings of Electric Electronics, Computer Science, Biomedical Engineerings' Meeting (EBBT), IEEE, pp. 1-4. https://doi.org/10.1109/EBBT.2018.8391469
6. Bosch, A.; Zisserman, A.; Munoz, X., 2007, October: Image classification using random forests and ferns. In: Proceedings of 11th international conference on computer vision IEEE, pp. 1-8. https://doi.org/10.1109/ICCV.2007.4409066
7. Chicco, D.; Jurman, G., 2020: Machine learning can predict survival of patients with heart failure from serum creatinine and ejection fraction alone. BMC Medical Informatics and Decision Making, 20 (1): 1-16. https://doi.org/10.1186/s12911-020-1023-5
8. Chollet, F., 2017: Xception: Deep learning with depthwise separable convolutions. In: Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 1251-1258. https://doi.org/10.1109/CVPR.2017.195
9. Deng, L.; Yu, D., 2014: Deep learning: methods and applications. Foundations and Trends® in Signal Processing, 7 (3-4): 197-387. http://dx.doi.org/10.1561/2000000039
10. Ding, F.; Zhuang, Z.; Liu, Y.; Jiang, D.; Yan, X.; Wang, Z., 2020: Detecting defects on solid wood panels based on an improved SSD algorithm. Sensors, 20 (18): 5315. https://doi.org/10.3390/s20185315

11. Ergün, E.; Kılıç, K., 2021: Skin Cancer Detection via Augmented Image Set with Deep Learning. Black Sea Journal of Engineering and Science, 4 (4): 192-200 (in Turkish). https://doi.org/10.34248/bsengineering.938520
12. Fan, J.; Liu, Y.; Yang, Y.; Gou, B., 2020: Research progress in the application of machine vision to wood defect detection. World Forestry Research, 33 (3): 32-37. https://doi.org/10.13348/j.cnki.sjlyyj.2020.0020.y
13. Fırıldak, K.; Talu, M. F., 2019: Examination of Transfer Learning Approaches Used in Convolutional Neural Networks. Computer Science, 4 (2): 88-95 (in Turkish). https://dergipark.org.tr/tr/pub/bbd/issue/49546/527863
14. Frome, A.; Singer, Y.; Malik, J., 2006: Image retrieval and classification using local distance functions. In: Advances in neural information processing systems. https://doi.org/10.7551/mitpress%2F7503.003.0057
15. Huang, G.; Liu, Z.; Van Der Maaten, L.; Weinberger, K. Q., 2017: Densely connected convolutional networks. In: Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 4700-4708. https://doi.org/10.48550/arXiv.1608.06993
16. Gholamalinezhad, H.; Khosravi, H., 2020: Pooling methods in deep neural networks, a review. arXiv preprint arXiv:2009.07485. https://doi.org/10.48550/arXiv.2009.07485
17. He, K.; Zhang, X.; Ren, S.; Sun, J., 2016: Deep residual learning for image recognition. In: Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 770-778. https://doi.org/10.1109/CVPR.2016.90
18. He, K.; Zhang, X.; Ren, S.; Sun, J., 2016: Deep residual learning for image recognition. In: Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 770-778. https://doi.org/10.1109/CVPR.2016.90
19. Howard, A. G.; Zhu, M.; Chen, B.; Kalenichenko, D.; Wang, W.; Weyand, T.; Andreetto, M.; Adam, H., 2017: MobileNets: Efficient convolutional neural networks for mobile vision applications. arXiv:1704.04861. https://doi.org/10.48550/arXiv.1704.04861
20. Huang, G.; Liu, Z.; Van Der Maaten, L.; Weinberger, K. Q., 2017: Densely connected convolutional networks. In: Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 4700-4708. https://doi.org/10.1109/CVPR.2017.243
21. Kodytek, P.; Bodzas, A.; Bilik, P., 2021: Supporting data for Deep Learning and Machine Vision based approaches for automated wood defect detection and quality control. [Data set] Zenodo. https://doi.org/10.5281/zenodo.4694695
22. LeCun, Y.; Bengio, Y., 1995: Convolutional networks for images, speech, and time series. In: The handbook of brain theory and neural networks, 3361 (10): 1995.
23. LeCun, Y.; Bottou, L.; Bengio, Y.; Haffner, P., 1998: Gradient-based learning applied to document recognition. In: Proceedings of the IEEE, 86 (11): 2278-2324. https://doi.org/10.1109/5.726791
24. Li, C.; Zhang, Y.; Tu, W.; Jun, C.; Liang, H.; Yu, H., 2017: Soft measurement of wood defects based on LDA feature fusion and compressed sensor images. Journal of Forestry Research, 28 (6): 1285-1292. https://doi.org/10.1007/s11676-017-0395-6
25. Li, S.; Li, D.; Yuan, W., 2019: Wood defect classification based on two-dimensional histogram constituted by LBP and local binary differential excitation pattern. IEEE Access, 7, 145829-145842. https://doi.org/10.1109/ACCESS.2019.2945355
26. Li, Y. G.; Yang, J.; Dong, C. L., 2021: Research on feature extraction algorithm of wood surface defects. Journal of Northwest Forestry University, 36 (04): 204-208, 281. https://doi.org/10.3969/j.issn.1001-7461.2021.04.29
27. Lopez, A. R.; Giro-i-Nieto, X.; Burdick, J.; Marques, O., 2017, February: Skin lesion classification from dermoscopic images using deep learning techniques. In: Proceedings of 13th IASTED International Conference on Biomedical Engineering (BioMed), IEEE, pp. 49-54. https://doi.org/10.2316/P.2017.852-053
28. Luo, W., 2019: Research on wood classification and sorting algorithms based on ımage multi-feature pattern recognition. PhD Thesis, Northeast Forestry University, Haerbin, China.
29. Pacal, I.; Karaboga, D., Basturk, A.; Akay, B.; Nalbantoglu, U., 2020: A comprehensive review of deep learning in colon cancer. Computers in Biology and Medicine, 126: 104003. https://doi.org/10.1016/j.compbiomed.2020.104003
30. Packianather, M. S.; Drake, P. R., 2005: Comparison of neural and minimum distance classifiers in wood veneer defect identification. In: Proceedings of the Institution of Mechanical Engineers, Part B. Journal of Engineering Manufacture, 219 (11): 831-841. https://doi.org/10.1243/095440505X32823
31. Powers, D. M., 2020: Evaluation: from precision, recall and F-measure to ROC, informedness, markedness and correlation. arXiv preprint arXiv:2010.16061. https://doi.org/10.48550/arXiv.2010.16061
32. Purnama, I. K. E.; Hernanda, A. K.; Ratna, A. A. P.; Nurtanio, I.; Hidayati, A. N.; Purnomo, M. H.; Nugroho, S. M. S.; Rachmadi, R. F., 2019, November: Disease classification based on dermoscopic skin images using convolutional neural network in teledermatology system. In: Proceedings of International Conference on Computer Engineering, Network, and Intelligent Multimedia (CENIM), IEEE, pp. 1-5. https://doi.org/10.1109/CENIM48368.2019.8973303
33. Ren, R.; Hung, T.; Tan, K. C., 2017: A generic deep-learning-based approach for automated surface inspection. IEEE Transactions on Cybernetics, 48 (3): 929-940. https://doi.org/10.1109/TCYB.2017.2668395
34. Schmidhuber, J., 2015: Deep learning in neural networks: An overview. Neural Networks, 61: 85-117. https://doi.org/10.1016/j.neunet.2014.09.003
35. Seyyarer, A.; Aydın, T., 2017: Comparison of Content-Based Image Retrieval System and Image Classification Methods Using Invariant Moments. Anatolian Science – Bilgisayar Bilimleri Dergisi, 2 (1): 1-9 (in Turkish). https://dergipark.org.tr/tr/pub/bbd/issue/57870/752132
36. Seyyarer, E.; Ayata, F.; Uçkan, T.; Karci, A., 2020: Application and comparison of optimization algorithms used in deep learning. Computer Science, 5 (2): 90-98 (inTurkish). https://dergipark.org.tr/tr/pub/bbd/issue/57870/752132
37. Shi, J.; Li, Z.; Zhu, T.; Wang, D.; Ni, C., 2020: Defect detection of industry wood veneer based on NAS and multi-channel mask R-CNN. Sensors, 20 (16): 4398. https://doi.org/10.3390/s20164398
38. Simonyan, K.; Zisserman, A., 2014: Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556. https://doi.org/10.48550/arXiv.1409.1556
39. Sultana, F.; Sufian, A.; Dutta, P., 2018, November: Advancements in image classification using convolutional neural network. In: Proceedings of Fourth International

Conference on Research in Computational Intelligence and Communication Networks (ICRCICN), IEEE, pp. 122-129. https://doi.org/10.1109/ICRCICN.2018.8718718
40. Tüfekçi, M.; Karpat, F., 2019: A Review for Investigation Studies That are Done for Improving Image Processing Classification Based on Convolutional Neural Network (CNN) That is Architectural of Deep Learning. In: Proceedings of International Conference on Human-Computer Interaction. Optimization and Robotic Applications, pp. 28-31. https://doi.org/10.36287/setsci.4.5.007
41. Urbonas, A.; Raudonis, V.; Maskeliūnas, R.; Damaševičius, R., 2019: Automated identification of wood veneer surface defects using faster region-based convolutional neural network with data augmentation and transfer learning. Applied Sciences, 9 (22): 4898. https://doi.org/10.3390/app9224898
42. Weiss, K.; Khoshgoftaar, T. M.; Wang, D., 2016: A survey of transfer learning. Journal of Big Data, 3 (1): 1-40. https://doi.org/10.1186/s40537-016-0043-6
43. Wang, M. L.; Wang, J.; Li, Q. X.; Wang, X. S.; Cao, Q., 2021: Design and implementation of a non-contact ultrasonic wood defect detection system. Shanxi Electronic Technology, 6: 16-19. https://doi.org/10.3969/j.issn.1674-4578.2021.06.005
44. Xie, D. Y., 2013: Analysis to situation and countermeasure of wood manufacture industry of our country. Forest Investigation Design, 3: 85-92. https://doi.org/10.3969/j.issn.1673-4505.2013.03.038
45. Yang, Y.; Zhou, X.; Liu, Y.; Hu, Z.; Ding, F., 2020: Wood defect detection based on depth extreme learning machine. Applied Sciences, 10 (21): 7488. https://doi.org/10.3390/app10217488
46. Yu, H.; Liang, Y.; Liang, H.; Zhang, Y., 2019: Recognition of wood surface defects with near infrared spectroscopy and machine vision. Journal of Forestry Research, 30 (6): 2379-2386. https://doi.org/10.1007/s11676-018-00874-w
47. Zhang, Y. X., 2017: Wood surface defect recognition based on wavelet transform and LBP. MSc Thesis, Nanjing Forestry University, Nanjing, China.
48. Zhang, Y. X.; Zhao, Y. Q.; Liu, Y.; Jiang, L. Q.; Chen, Z. W., 2016, July: Identification of wood defects based on LBP features. In: Proceedings of 35th Chinese Control Conference (CCC), IEEE, pp. 4202-4205. https://doi.org/10.1109/ChiCC.2016.7554010
49. Zhang, Y.; Xu, C.; Li, C.; Yu, H.; Cao, J., 2015: Wood defect detection method with PCA feature fusion and compressed sensing. Journal of Forestry Research, 26: 745-751. https://doi.org/10.1007/s11676-015-0066-4

Corresponding address:

KENAN KILIÇ

Gazi University, Graduate School of Natural and Applied Sciences, Department of Wood Products Industrial Engineering, 06500, Ankara, TURKEY, e-mail: kenan.kilic@gazi.edu.tr