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Ahşap Kusur Tespiti İçin Optimize Edilmiş AlexNet Mimarisi

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ÖZET

Ahşap kusur tespiti ağaç işleri endüstri mühendisliğinde üretim ve kalite planlamada önemli rol oynamaktadır. Bu makale, AlexNet mimarisi kullanılarak kusurlu ve kusursuz ahşap yüzey görüntülerinin sınıflandırılması üzerine odaklanmaktadır. İlk olarak, karışık olan yüzey görüntüleri kusurlu ve kusursuz diye ikiye ayrılmış ve yeniden düzenlenmiştir. Çalışmada kullanılan veri kümesinde 1992 kusursuz, 18 284 kusurlu ahşap yüzey görüntüsü bulunmaktadır. Ahşap yüzey görüntüleri üzerinde toplam 43 000 ahşap kusur bulunmaktadır. AlexNet mimarisi transfer öğrenme yaklaşımı kullanılarak deneyler gerçekleştirilmiştir. Deneylerde, farklı epoch sayıları (25 epoch, 50 epoch) ve veri artırma yöntemi kullanılarak AlexNet modelin eğitimi gerçekleştirilmiş ve sonra test edilmiştir. Ahşap yüzey kusur tespitinde ikili sınıflamada sonuç olarak, AlexNet mimarisi ile kusurlu ve kusursuz ahşap yüzey görüntülerinin sınıflandırılması sonucunda en başarılı sonuçları AlexNet Augmented modelinin 50 epoch sonrasında elde ettiği görülmektedir. Bu modelde, doğruluk değeri 0.9687, AUC değeri 0.9892 olarak hesaplanmıştır. Yaklaşık %97 oranında ahşap kusur tespiti sonucu bu çalışmada elde edilmiştir. Ayrıca, hassasiyet, geri çağırma ve F-skor değerleri de 0.97 olarak belirlenmiştir. Bu sonuçlar, ahşap yüzey kusur tespitinde AlexNet modelinin yüksek bir performans sergilediğini göstermektedir.*

AlexNet Architecture Optimized for Wood Defect Detection

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ABSTRACT

Wood defect detection plays an important role in production and quality planning in woodworking industrial engineering. This paper focuses on the classification of imperfect and perfect wood surface images using AlexNet architecture. First, the mixed surface images are divided into defective and perfect images and reorganized. The dataset used in this study contains 1992 undefective and 18 284 defective wood surface images. There are a total of 43 000 wood defects on this dataset. Experiments are carried out using the AlexNet architecture transfer learning approach. In the experiments, the AlexNet model is trained using different epoch numbers (25 epochs, 50 epochs) and data augmentation method. It is then tested. As a result of binary classification in wood surface defect detection, it is seen that the AlexNet Augmented model obtained the most successful results after 50 epochs as a result of the classification of defective and perfect wood surface images with AlexNet architecture. In this model, the accuracy rate is calculated as 0.9687 and AUC value as 0.9892. Approximately 97% of wood defect detection results are obtained in this study. In addition, the precision, recall and F-score values are determined as 0.97. These results show that the AlexNet model has a high performance in wood surface defect detection.*

1. INTRODUCTION

Woodworking industry resources should be utilised effectively and efficiently. Due to the scarcity of wood resources, the utilisation rate of processed wood should be improved and increased. Wood surface flaw detection has the potential to realise this goal [1-4]. Finding and classifying surface defects in wood material is a very important process. Once these defects are detected, they can be removed from the production line and necessary actions can be taken.

The combination of artificial intelligence algorithms and digital image processing is extensively utilized for the detection and classification of wood knot defects [5]. Fixed feature extraction and classification recognition technology have gained significant

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popularity in this domain [6, 7]. These technologies encompass computer vision, spectral analysis, and other digital image processing methods [8]. By employing statistical or machine learning approaches, effective feature parameters are extracted from the samples through consistent matching and comparison. In particular, deep learning (DL) has emerged as a highly effective technique in the field of artificial intelligence [9]. DL enables automatic learning of feature values from raw data, reducing the need for manual operations and enhancing the feature extraction process [10].

However, the small sample size in wood knot defect detection can lead to over-fitting or under-fitting of the model, limiting the final prediction accuracy [11]. To solve this problem, researchers have used deep convolutional neural network (CNN) models and trained these models with large datasets such as ImageNet and used them to extract features from small datasets in different domains using transfer learning. With these developments, there are many examples in the literature where good results have been achieved.

As an illustration, the work by Thenmozhi et al. (2019) employed the pre-trained AlexNet model to classify insects. The study demonstrated that utilizing transfer learning with the AlexNet model resulted in a 7.65% higher accuracy compared to the original AlexNet model [14]. Similarly, Gao et al. (2019) proposed a method for identifying tree species using transfer learning. Experimental outcomes indicated a significant improvement in accuracy for stem and leaf classification, with increases of 51.38% and 51.69%, respectively [15].

In 2020, Kentsch et al. performed classification and identification experiments on a winter orthomosaic dataset using the ResNet-50 model with transfer learning [16]. The findings revealed that incorporating transfer learning from a general-purpose dataset enhanced the accuracy by 9.78%. Moreover, an additional improvement of 2.7% is observed when applying transfer learning from a dataset that closely resembled the image type.

In this article, the importance of the classification of surface defects in wood material is emphasised. For the efficient use of wood resources, the use of treated wood should be increased. For this purpose, the combination of digital image processing and artificial intelligence algorithms are among the frequently used methods. These technologies include methods such as feature extraction and classification recognition technology. Deep learning is an extremely effective method in this field. These developments show that transfer learning method can also be an effective approach for wood knot defect detection and classification. In this paper, two classifications are made over augmented and non-augmented wood images over the AlexNet architecture. In addition, the potential of the transfer learning method in wood surface defect detection is mentioned.

2. MATERIAL AND METHODS

2.1. DataSet

This study utilizes a dataset derived from extensive databases in the field of woodworking industrial engineering. To ensure the authenticity of the wood images used in the experiment, they were captured in an actual production environment within the woodworking industry. The dataset encompasses a substantial volume of real data obtained from the timber production line. To mitigate challenges arising from the manufacturing process, such as high conveyor belt speeds and intense vibrations, high-resolution wood surface images were collected at a sampling rate of 66 kHz. The used sampling frequency of 66 kHz with the total number of captured pixels resulted in a data transfer speed of 773 MBs^{-1}, which means that we were able to capture 66.4 images per second [17].

The dataset comprises 20 276 original images of sawn timber surfaces. Among these images, 1 992 do not exhibit any surface defects, while the remaining 18 284 images contain various types of surface defects. Typically, these defects manifest in ten common forms on the wood surfaces, with certain images exhibiting multiple defects. The most prevalent defects in the dataset are live knots, which occur in 58.8% of the images, followed by dead knots, which occur in 41.2% of the images. In total, the dataset includes 43 000 instances of wood surface defects across the 20 276 images.

All the wood surface images are stored in BMP format with a resolution of 2800×1024 pixels. The dataset encompasses ten distinct types of wood surface defects, encompassing various forms of knots, cracks, blue stains, resins, and marrows [17]. Figure 1 depicts the ten common defects found in the dataset, while Figure 2 illustrates examples of both flawed and flawless surface images. [17]. 10 common defects of the dataset are given in Figure 1. Imperfect and perfect surface images of the dataset are given in Figure 2.

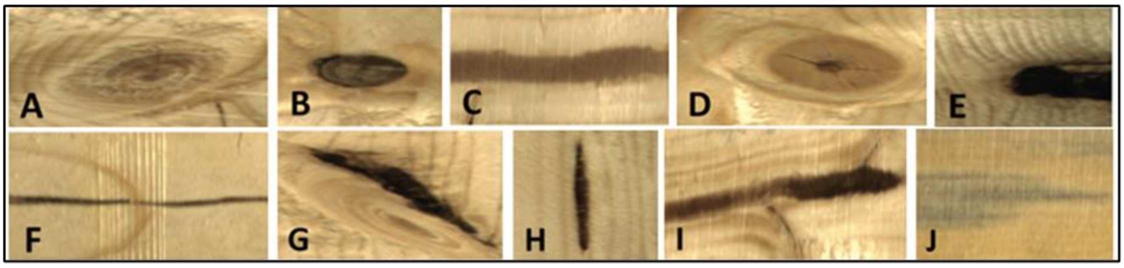


Figure 1. Images of 10 common defect types of the dataset: (A) Live Knot, (B) Dead Knot, (C) Quartzity, (D) Knot with crack, (E) Knot missing, (F) Crack, (G) Overgrown, (H) Resin, (I) Marrow (J) Blue stain.

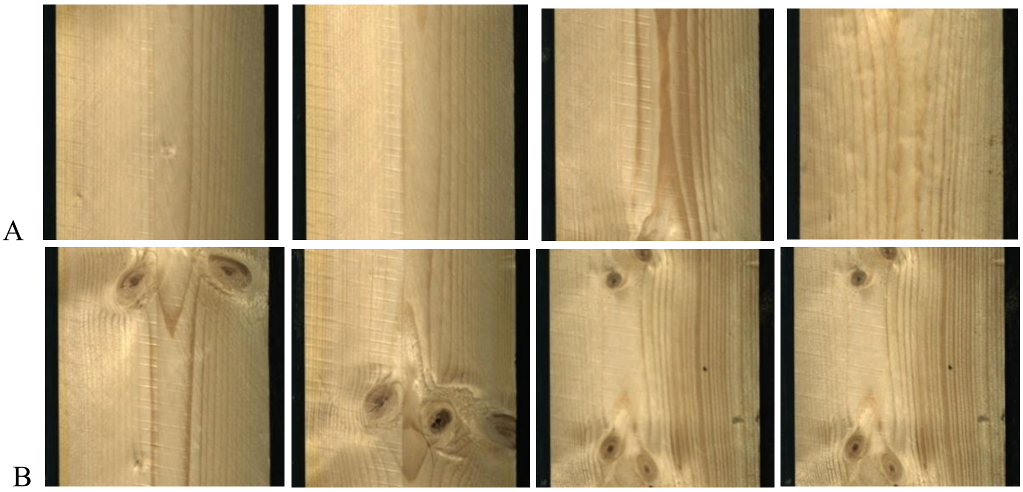


Figure 2. Images of perfect wood surface (A), Images of imperfect wood surface (B).

2.2. Data Augmentation

Augmentation operations are important techniques used in image processing applications. In this study, it is aimed to create diversity in images by using different augmentation methods. Firstly, the flip operation is applied. With this process, the images are rotated symmetrically on the horizontal axis. Then, vertical rotation is applied and the images are rotated symmetrically on the vertical axis. The angle of rotation of the images has also been changed. The maximum rotation angle is set to 355.0 degrees and the images are randomly rotated up to this angle. Zooming is also a method used in the augmentation process. Images are zoomed in or out up to a maximum of 1.5 times. The lighting process allows the lighting characteristics of images to be changed. In this study, a maximum illumination change of 0.3 is applied. The warp operation is used to distort the shapes of the images. The maximum distortion ratio is set to 0.2. Finally, the probability of augmentation operations is also determined. In this study, the probability of realisation of the lighting process is chosen as 75%. These augmentation operations contribute to the expansion of the training dataset by creating diversity in the images.

2.3. Convolutional Neural Network (CNN)

CNN is the most widely preferred deep learning model in image analysis and is a neural network architecture that automatically detects features associated with filtering on pixel matrices [18].

CNN architectures consist of two parts: feature learning and classification. In the feature learning part, there are convolution, activation and pooling layers. The convolution layer uses filters to determine the characteristics of the images. The pooling layer controls weights and reduces weights. The activation layer removes the linearity of the network and allows it to be evaluated with different parameters. The classification part consists of smoothing and fully connected layers. The convolution layer processes the input images with filters. The activation function removes the linearity of the network [19,20].

2.4. AlexNet

AlexNet, a convolutional neural network (CNN) model, was introduced by Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton in 2012. It stands as a significant milestone in the advancement of deep learning. AlexNet garnered considerable recognition for its exceptional performance in the ImageNet competition, solidifying its success in the field. The model contains 60 million parameters and 650,000 neurons as an eight-layer CNN. AlexNet achieved a higher accuracy by using deeper and wider fully connected layers than previous models. Furthermore, the use of the ReLU activation function accelerated the training time and reduced the overfitting problem. AlexNet has formed the basis of many deep learning models that have had a major impact on visual processing tasks such as computer vision and object recognition. This architecture consists of 3 fully connected layers with 5 convolution layers, 2 ReLU activation layers and 3 maximum pooling layers. The softmax function is used for the classification process. The input image size of the network is 227x227x3 and 11x11 convolution filters are used [21]. A schematic representation of the AlexNet architecture is given in Figure 3.

AlexNet is a structure that popularised the DL (Deep Learning) model as it is used as the underlying architecture. Different architectures such as ZFNet and Google Net are used in classification, but in this study we focus on the architecture of AlexNet. AlexNet's achievements are evidenced by its first place in the ImageNet competitions.

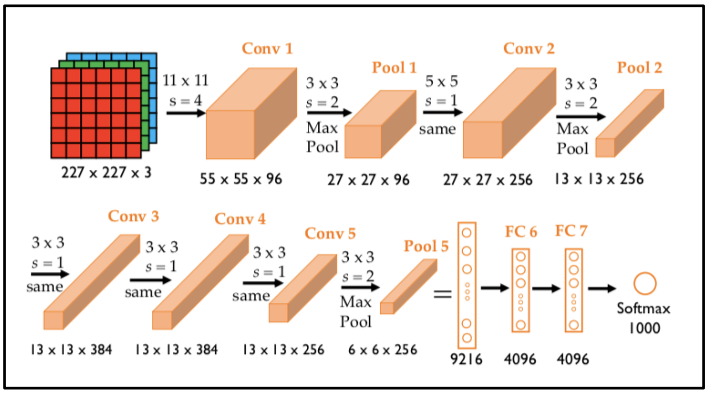


Figure 3. Schematic representation of the AlexNet architecture [21].

2.5. Transfer Learning

Transfer learning is the technique of using the previously learnt knowledge of deep learning models in other tasks. This approach aims to achieve better results by speeding up the training process for smaller datasets or different tasks. Transfer learning can be implemented by methods such as transferring weights or using feature extractors. In this way, better performance with less data can be achieved by sharing common features and representations [22].

2.6. Experimental Setup

In this study, there are a total of 20 276 images in two classes, 1992 perfect wood surface images and 18 284 imperfect wood surface images. Resised from the actual image dimensions. The reason for the resize operation is that the architecture has an input of 227x227x3. Images are converted from BMP format to JPEG format. These wood surface images are divided into two classes: imperfect and perfect. These classes are divided into 70% train, 15% validation and 15% test. Two different variables are used in the experiments, 25 and 50 epochs. In addition, experiments are carried out in two different variables, with and without data augmentation. Batch size is used as 64. ReLU is used for activation and Adam is used for optimization. Python programming language is used in the applications. NumPy, Pandas, Matplotlib and Fast.ai libraries and features are used in the experiments. Experiments are carried out on Nvidia T4 x 2 video card as a video card.

2.7. Evaluation Metrics

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN) \quad (1)$$

AUC is the area under the Receiver Operating Characteristic (ROC) curve of a classification model.

$$\text{Precision} = TP / (TP + FP) \quad (2)$$

$$\text{Recall} = TP / (TP + FN) \quad (3)$$

The F-score represents the harmonic mean of precision and recall, considering both the accuracy and comprehensiveness of the model.

$$\text{F-score} = 2 * ((\text{Precision} * \text{Recall}) / (\text{Precision} + \text{Recall})) \quad (4)$$

$$\text{Error rate} = (FP + FN) / (TP + TN + FP + FN) \quad (5)$$

These equations exemplify frequently employed metrics for assessing the efficacy of classification models. TP (True Positive), TN (True Negative), FP (False Positive), and FN (False Negative) pertain to the concurrences and disparities between the actual class labels and the prognostications made by the classification model.

3. RESULTS AND DISCUSSION

The results obtained from the experiments with and without data augmentation for wood surface defect classification, and the results obtained from the experimental results at 25 and 50 epochs are given in this section. The most successful values obtained by the AlexNet architecture after 25 and 50 epochs are given in Table 1.

Table 1. The most successful values obtained by the AlexNet architecture after 25 and 50 epochs.

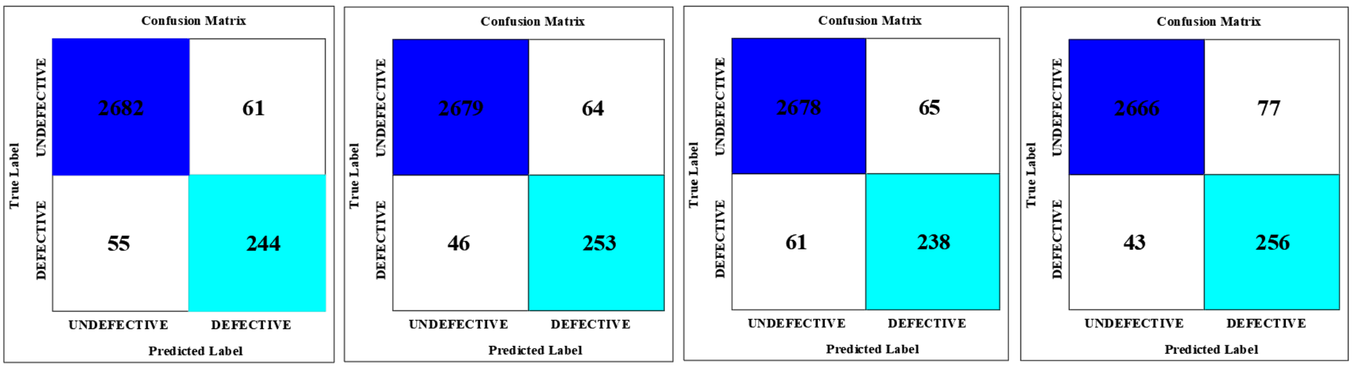
Algorithm	Epoch count	Accuracy	AUC	Precison	Recall	F-score	Error rate
AlexNet Not Augmented	25	0.9608	0.9862	0.96	0.96	0.96	0.0381
AlexNet Not Augmented	50	0.9621	0.9852	0.96	0.96	0.96	0.0361
AlexNet Augmented	25	0.9602	0.9859	0.96	0.96	0.96	0.0414
AlexNet Augmented*	50	0.9687	0.9892	0.97	0.97	0.97	0.0394

Two classification performances of the AlexNet model for wood surface defect detection are evaluated. When we look at the results obtained without data augmentation, we see that the accuracy rate for 25 epochs is 0.9608 and the AUC is 0.9862. In addition, precision, recall, F-score and error rate vary approximately between 0.96 and 0.0381. When the number of epochs is increased to 50, there is a slight increase in the accuracy rate and AUC value, but the other performance metrics remain almost the same.

In the experiments performed with data augmentation, the accuracy rate for 25 epochs is calculated as 0.9602, the AUC value is calculated as 0.9859, and the precision, recall, F-score and error rate values ranged between approximately 0.96 and 0.0414. When the number of epochs is increased to 50, an increase in the accuracy rate and AUC value is observed, while other performance metrics are also improved.

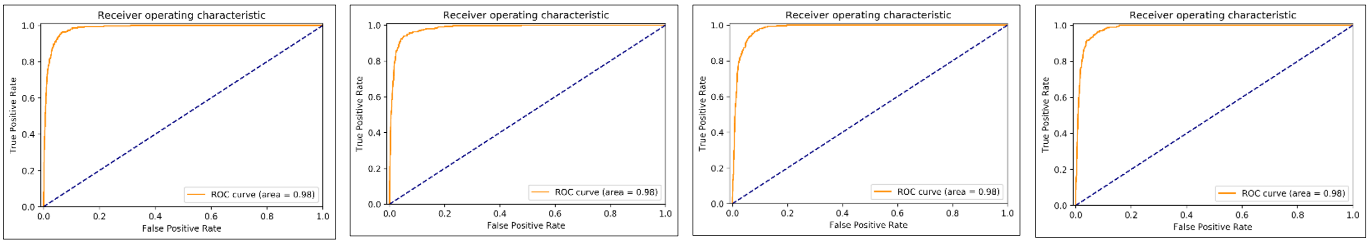
Based on these results, it seems that increasing the data improves the performance of the AlexNet model. The results obtained both without and with data augmentation show that the model has very high accuracy and AUC values. It is also observed that the performance generally improves with increasing the number of epochs.

The complexity matrices obtained as a result of the validation are given in Figure 4. ROC curves generated as a result of the validation are given in Figure 5.



(a) (b) (c) (d)

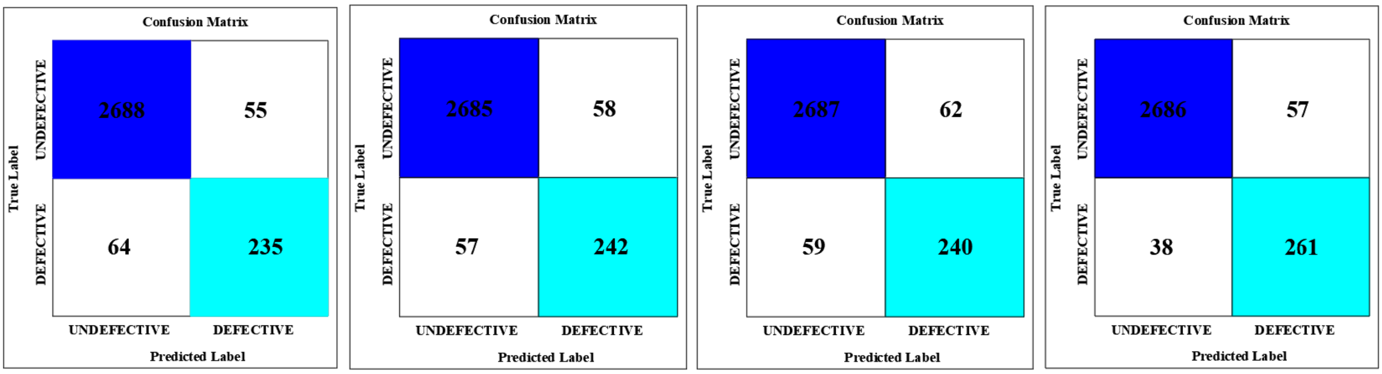
Figure 4. Confusion matrices obtained after validation: (a) Alexnet Not Augmented 25 Epoch, (b), Alexnet Not Augmented 50 Epoch, (c) AlexNet Augmented 25 Epoch, (d) AlexNet Augmented 50 Epoch.



(a) (b) (c) (d)

Figure 5. ROC curves obtained after validation: (a) Alexnet Not Augmented 25 Epoch, (b), Alexnet Not Augmented 50 Epoch, (c) AlexNet Augmented 25 Epoch, (d) AlexNet Augmented 50 Epoch.

Confusion matrices obtained after the test are given in Figure 6. ROC curves generated as a result of the test are given in Figure 7.



(a) (b) (c) (d)

Figure 6. Confusion matrices obtained as a result of the test: (a) Alexnet Not Augmented 25 Epoch, (b), Alexnet Not Augmented 50 Epoch, (c) AlexNet Augmented 25 Epoch, (d) AlexNet Augmented 50 Epoch.

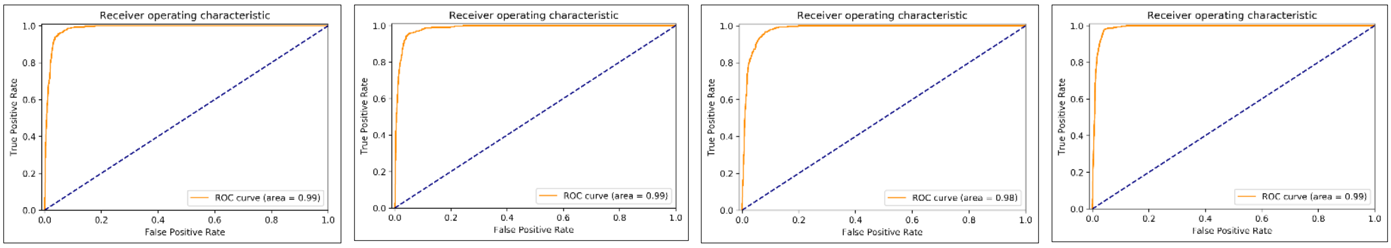


Figure 7. ROC curves obtained as a result of the test: (a) Alexnet Not Augmented 25 Epoch, (b), Alexnet Not Augmented 50 Epoch, (c) AlexNet Augmented 25 Epoch, (d) AlexNet Augmented 50 Epoch.

The most successful AlexNet classification report obtained in the experiment with data incremental and at the end of 50 epochs is given in Table 2.

Table 2. AlexNet architecture classification report, which is the most successful in wood surface defect classification.

	Precision	Recall	F1-score	Support
Defective	0.99	0.98	0.98	2743
Undefective	0.82	0.87	0.85	299
Micro avg	0.97	0.97	0.97	3042
Macro avg	0.90	0.93	0.91	3042
Weighted avg	0.97	0.97	0.97	3042

There is no existing study in the literature on binary classification of the dataset used in this study. However, an overall assessment can be made by analysing the results of previous research in the field of wood defect classification. The results obtained show the success rates for different types of defects used in different studies.

According to these studies, various methods have been used to accurately classify different types of defects in wood defect classification and high success rates have been obtained. In the study by Ren et al. (2017), "Encased knot, leaf knot, edge knot and sound knot" defect types are classified with a success rate of 91.55% [23]. In the studies of Zhang et al. (2015) and Yu et al. (2019), 92.00% success rate is obtained for defect types such as live knots, dead knots, pinholes and cracks [24,25]. In addition, Zhang et al. (2016) classified the defect types "live knot, dead knot and leaf knot" with a success rate of 93.00% [26].

These results show that the methods developed for the classification of different defect types are effective and provide a high accuracy rate. In conclusion, studies in the field of wood surface defect classification show that successful methods have been developed for the accurate classification of various defect types.

4. CONCLUSIONS

In this paper, the performance of the AlexNet model in binary classification for wood surface defect detection is evaluated. Two different variable scenarios are analysed: without data augmentation and with data augmentation. Data augmentation may help the model to gain more diversity and generalisation ability. According to the findings, it is seen that the performance of the model is better in the experiments with data augmentation.

Firstly, looking at the results of the experiment without data augmentation, it is observed that the accuracy is approximately the same for 25 and 50 epochs. In addition, a slight increase in AUC values is also reported. However, the other performance metrics (precision, recall, F-score and error rate) remained almost the same despite the increase in the number of epochs. This indicates that the model reaches saturation at a certain point and no significant improvement in performance is achieved with more epochs.

On the other hand, when the results of the experiment with data augmentation are examined, it is seen that the accuracy rate and AUC value for 25 epochs are almost the same as the results obtained without data augmentation. However, after 50 epochs, there is a significant increase in the accuracy rate and AUC value. At the same time, other performance metrics also improved. This shows that data augmentation improves the performance of the model and further improvement is achieved by increasing the number of epochs.

When the confusion matrices and ROC curves are analysed, it is seen that the most successful results are obtained by increasing the data and at the end of 50 epochs. These results show that the model can accurately classify defective and non-defective wood surfaces. When precision, recall, F-score and other metrics are analysed, it is seen that the model has a high performance in general.

It is seen that the AlexNet Augmented* model obtained the most successful results after 50 epochs. In this model, the accuracy rate is calculated as 0.9687 and AUC value as 0.9892. Approximately 97% of wood defect detection results are obtained in this study. In addition, the precision, recall and F-score values are determined as 0.97. These results show that the AlexNet model has a high performance in wood surface defect detection.

In conclusion, the experiments and findings in this paper show that the AlexNet model performs successfully in binary classification for wood surface defect detection. It has been determined that increasing the data improves the performance of the model and further improvement is achieved by increasing the number of epochs. These findings show that the AlexNet model is an effective option for wood surface defect detection in industrial applications. However, the general validity of these findings and the performance of the model on different datasets should also be taken into account. Different studies show that defect types can be classified with high accuracy rates and progress has been made in this field. These studies are an important step in terms of quality control and defect detection in the wood industry. Future work could focus on recognising more complex defect types and achieving higher classification performance.

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AUTHOR CONTRIBUTIONS

Kenan KILIÇ: Carried out experiments, reviewed the literature, wrote code, wrote articles.
Uğur ÖZCAN: Designed experiments, analysed the results and wrote articles.

CONFLICT OF INTEREST

There is no conflict of interest between the authors of this article, Kenan KILIÇ and Uğur ÖZCAN.

ETHICS

There are no ethical issues in the publication of this article.

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