POLİTEKNİK DERGİSİ

JOURNAL of POLYTECHNIC

ISSN: 1302-0900 (PRINT), ISSN: 2147-9429 (ONLINE)
URL: http://dergipark.org.tr/politeknik

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Using deep learning techniques furniture image classification

Derin öğrenme tekniklerini kullanarak mobilya görüntüsü sınıflandırması

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To cite to this article: Kılıç K., Kılıç K., Özcan U. ve Doğru İ. A., "Using Deep Learning Techniques Furniture İmage Classification", ***Journal of Polytechnic***, *(*): *, (*).

Bu makaleye şu şekilde atıfta bulunabilirsiniz: Kılıç K., Kılıç K., Özcan U. ve Doğru İ. A., "Derin Öğrenme Tekniklerini Kullanarak Mobilya Görüntüsü Sınıflandırması", ***Politeknik Dergisi***, *(*): *, (*).

Erişim linki (To link to this article): http://dergipark.org.tr/politeknik/archive

DOI: 10.2339/politeknik.1315328

Using Deep Learning Techniques Furniture Image Classification

Highlights

- *Five different furniture images are classified as bed, chair, sofa, swivelchair, table.*
- *The transfer learning approach for furniture image classification reduces training time. It achieves higher accuracy in less time. It also solves the weight initialization problem.*
- *An ROC value of 99.99% is obtained with the VGGNet-19 and Resnet-152 architecture.*
- *In furniture image classification, 98.87% classification success is achieved with VGGNet-19 and Resnet-152 architecture.*
- *This study shows that technology has the potential to deliver a smarter and user-centered shopping experience.*

Graphical Abstract

In this study, furniture images are classified using different convolutional neural network architectures. Five different categories of furniture (bed, chair, sofa, swivel chair and table) are classified. Images of the classified furniture are shown in Figure.

Figure. Images of the dataset of furniture images

Aim

The aim of the paper is to solve the problems faced by consumers and furniture industry professionals with the classification of furniture images.

Design & Methodology

Different CNN architectures are used for the classification of furniture images on a 5-class dataset.

Originality

It is a study using different CNN architectures and transfer learning method.

Findings

The best performance in the experiments is found with the VGGNet-19 and ResNet-152 CNN model with 98.87% test accuracy.

Conclusion

Among the architectures used, VGGNet-19 and ResNet-152 architecture gives the highest result with 98.87%. An ROC value of 99.99% was obtained with the VGGNet-19 and Resnet-152 architecture. Furniture image classification VGGNEt-19 and Resnet-152 architectures have shown success with transfer learning method.

Declaration of Ethical Standards

The authors state that the materials and methods employed in this study do not necessitate ethical committee approval and/or special legal permission.

Using Deep Learning Techniques Furniture İmage Classification

Araştırma Makalesi / Research Article

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(Geliş/Received : 15.06.2023 ; Kabul/Accepted : 27.10.2023 ; Erken Görünüm/Early View : 29.12.2023)

ABSTRACT

The furniture sector is developing and progressing rapidly today. The difficulty of choosing among many different designs and styles in the furniture industry poses a problem for consumers and sellers. The aim of the paper is to solve the problems faced by consumers and furniture industry professionals with the classification of furniture images. Based on this objective, this paper addresses the use of artificial intelligence techniques for the classification of furniture images. Machine learning algorithms and neural networks are used to automatically classify furniture images. In this paper, five different convolutional neural network architectures are used for the classification of furniture images: Alexnet, VGGNet-19, DenseNet-201, Squeezenet1.1 and ResNet-152. Using these architectures, VGG-19 and ResNet-152 achieved 98.87% classification accuracy. Five different furniture categories (bed, chair, sofa, swivel chair and table) are classified with VGGNet-19 and ResNet-152 architectures with an ROC (Receiver Operating Characteristic) value of 99.99%. In addition, it is reported that faster and more accurate results are obtained by using the transfer learning approach. SqueezeNet1.1 architectures provided an average classification accuracy of 97.07%, while the Alexnet model (94.15%) achieved the lowest accuracy. By using deep learning algorithms, the features of images are extracted and classified. This study shows that the technology has the potential to deliver a smarter and user-centered shopping experience. It also provides a furniture classification method that can provide a competitive advantage by increasing efficiency in furniture production and sales. The results obtained in the study show that CNN architectures used with transfer learning method are effective in analyzing and classifying furniture images.

Anahtar Kelimeler: Görüntü sınıflandırma, derin öğrenme, bilgisayar görüşü, mobilya görüntüsü, transfer öğrenme.

Derin Öğrenme Tekniklerini Kullanarak Mobilya Görüntüsü Sınıflandırması

ÖZ

Mobilya sektörü günümüzde hızla gelişmekte ve ilerlemektedir. Mobilya sektöründe birçok farklı tasarım ve tarz arasından seçim yapmanın zorluğu, tüketiciler ve satıcılar için bir sorun oluşturmaktadır. Makalenin amacı, mobilya görüntülerinin sınıflandırılmasıyla tüketicilerin ve mobilya endüstrisi profesyonellerinin karşılaştığı sorunları çözmektir. Bu amaca dayanarak bu çalışma, mobilya görüntülerinin sınıflandırılması konusunda yapay zeka tekniklerinin kullanılmasını ele almaktadır. Makine öğrenimi algoritmaları ve sinir ağları, mobilya görüntülerini otomatik olarak sınıflandırma sürecinde kullanılmaktadır. Makalede, mobilya görüntülerinin sınıflandırılması için beş farklı evrişimli sinir ağı mimarisi kullanılmıştır: Alexnet, VGGNet-19, DenseNet-201, Squeezenet1.1 ve ResNet-152. Bu mimarilerin kullanımıyla VGG-19 ve ResNet-152 %98.87 doğruluk ile sınıflandırma başarısı elde edilmiştir. Beş farklı mobilya kategorisi (yatak, sandalye, kanepe, döner koltuk ve masa) sınıflandırılmış VGGNet-19 ve ResNet-152 mimarisiyle %99.99 ROC (Receiver Operating Characteristic) değeri elde edilmiştir. Ayrıca, transfer öğrenme yaklaşımının kullanılmasıyla daha hızlı ve doğru sonuçlar elde edildiği belirtilmiştir. SqueezeNet1.1 mimarileri %97.07 ortalama sınıflandırma doğruluğu sağlarken, en düşük doğruluğu Alexnet modeli (%94.15) gerçekleştirmiştir. Derin öğrenme algoritmalarının kullanılmasıyla görüntülerin özellikleri çıkarılmakta ve sınıflandırılmaktadır. Bu çalışma, teknolojinin daha akıllı ve kullanıcı odaklı bir alışveriş deneyimi sunma potansiyeline sahip olduğunu göstermektedir. Aynı zamanda, mobilya üretim ve satışında verimliliği artırarak rekabet avantajı sağlayabilecek bir mobilya sınıflandırma yöntemi sunmaktadır. Çalışmada elde edilen sonuçlar, mobilya görüntülerinin analizi ve sınıflandırılmasında transfer öğrenme yöntemi ile kullanılan CNN mimarilerinin etkili olduğu göstermiştir.

Keywords: Image Classification, deep learning, computer vision, furniture image, transfer learning.

1. INTRODUCTION

Currently, the furniture sector is witnessing swift expansion and progress. Furniture plays a significant role in embellishing our residences, workplaces, and commercial areas. Nevertheless, consumers often encounter the challenge of selecting from a wide array of furniture options. This also presents a dilemma for furniture vendors and manufacturers. At this juncture,

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machine learning and artificial intelligence techniques come into play, presenting solutions in the realm of furniture image categorization. Furniture image categorization involves analyzing an image to ascertain the specific furniture type it encompasses. This process necessitates the utilization of computer-based artificial intelligence algorithms for the automatic recognition of intricate and diverse furniture designs. These algorithms encompass methodologies such as deep learning and neural networks, and acquire knowledge by leveraging a substantial dataset of images for training purposes.

Furniture constitutes an essential aspect of our daily lives. At present, the furniture industry is experiencing significant growth and advancement. In addition to serving functional purposes, furniture often serves as a reflection of a family's aesthetic preferences and carries cultural and symbolic values. As a result, furniture style has emerged as a critical factor in furniture design and selection. In recent times, the rise and swift progress of social media platforms have contributed to the growing recognition and popularity of online furniture sourcing [1]. The rapid advancements in internet technology and big data have closely intertwined with the rapid development of e-commerce platforms. Within this vast landscape of transactions, furniture images have become the primary medium for conveying product information. The automated identification of furniture among numerous products has become an essential requirement in the realm of e-commerce [2]. Advancements in this technology can assist businesses in automatically recognizing uploaded furniture images based on their color and style. This, in turn, can lead to reduced labor consumption, enable users to efficiently search for their desired furniture on websites, and aid businesses in providing more accurate furniture recommendations to enhance sales. Currently, a majority of research in furniture image recognition focuses on the classification of furniture according to its type, particularly tables, chairs, beds, and so on, amidst complex backgrounds [3,4]. Traditional approaches to image classification primarily involve extracting image features such as texture and color, followed by applying a suitable classifier to categorize these features. Due to advancements in computer hardware and the rapid evolution of big data technology, deep learning (DL) has garnered substantial interest in both scientific research and real-world applications [5]. (CNNs) have emerged as a prominent choice for image classification tasks in both academic and industrial domains [6,7]. Researchers are currently exploring the application of DL methods in classifying furniture images. CNNs utilize convolution and pooling layers to extract meaningful features from images and reduce their dimensions, eliminating the requirement for intricate feature extraction methods. This advantageously simplifies the overall process of extracting relevant information from images. Classification is then performed using fully connected layers. For instance, Zhu Bin et al. developed a CNN-based model specifically for product image recognition to assess the emotional intentions of chairs [8]. Wang et al. proposed the use of a metric learning algorithm combined with CNN to refine the furniture image database by removing redundancies and irrelevant images [9]. Zhu et al. employed expert evaluation and cluster analysis to categorize chairs into different furniture styles, such as Eastern, Western, modern, and new technology, achieving high recognition accuracy using the classical ResNet-50 model [10]. Ye et al. utilized a deep group over-parameterized convolution (DGOVGGNet-16) model, which combines an enhanced VGGNet-16 architecture, for automatic furniture image classification, achieving an accuracy of 95.51% [11].

Regenerate responseThe key highlights and advantages of this study are given:

- 5 different CNN architectures (Alexnet, VGGNet-19, DenseNet-201, Squeezenet1.1, ResNet-152) are employed.
- The ResNet-152 architecture achieved a classification success rate of 98.87% in furniture image classification. This value is more successful than the studies in the literature.
- Transfer learning approach provided faster and more accurate results with fewer parameters.
- Furniture classification performance of well-known CNN architectures is measured and the results were presented comparatively.

The objective of this article is to classify furniture images and address the challenges faced by consumers and professionals in the furniture industry. By utilizing CNN architectures and transfer learning, deep learning algorithms extract and classify image features. Transfer learning, utilizing pre-trained CNN models, accelerates the training process and enhances accuracy. This study has the potential to enhance the shopping experience by providing a smarter and more user-centered approach. Simultaneously, classifying furniture images can improve efficiency and confer a competitive advantage in furniture production and sales. The materials and methods section of the paper offers insights into the dataset used and the deep learning techniques employed.

2. MATERIAL AND METHOD

2.1. Dataset

The furniture image dataset used in this study is derived from an open dataset obtained from the Kaggle competition by a data science engineer named Nikhil Akki. The dataset is first published in 2018 in Mumbai, India [12]. Furniture images belong to five categories of data: bed, chair, sofa, swivel armchair and table furniture images. The backgrounds of furniture images are quite complex and contain different visual information that has nothing to do with the furniture. For example, such as, outdoor environment, walls, curtains, people, windows, etc. are available in the dataset images. The dataset

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contains 1000 images of beds, 1000 images of chairs, 1000 images of sofas, 1000 images of swivelchairs and 447 images of tables. There are 4447 furniture images in total. Images of the dataset are given in Figure 1.

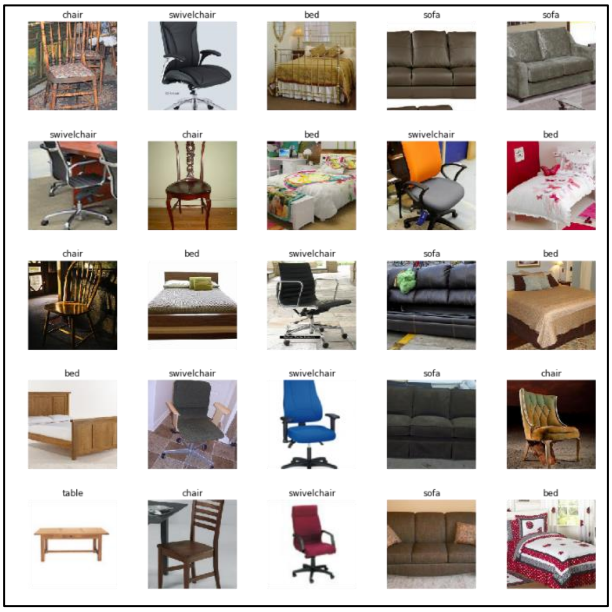

Figure 1. Images of the dataset of furniture images

2.2. Deep Learning

Deep learning is a method based on artificial neural networks. These structures have the ability to handle large amounts of data by learning from their representation. For this reason, deep neural networks are used, which contain more hidden layers compared to traditional neural networks [13]. In deep neural networks, labeled input values are passed through nonlinear activation functions with specific weights to produce an output [14]. The goal of deep neural network training is to optimize these weights to minimize the error value [15].

2.2.1. Convolutional neural network

CNN is a deep learning model known for its excellence in tasks such as image processing and recognition. CNNs can successfully analyze image data, especially with their structures based on convolution and pooling operations. CNNs have achieved great success in many application areas. For example, it is used in areas such as object recognition, face recognition, object detection, image classification, image restoration, automated driving and medical image analysis. The success of CNNs is based on their hierarchical learning of features in the data thanks to their multi-layered structure and convolutional layers. CNN architectures create feature maps by applying filters to the input data with convolutional layers. In addition, pooling layers reduce the data size, while fully connected layers perform the classification process. In this way, CNN architectures can be effectively used in tasks such as image processing and classification without the need for complex feature extraction methods. Sampling layers reduce and summarize feature maps. Fully linked layers obtain results by linking feature maps to classes or output labels [16].

The initial layer in every CNN is called the "input layer," and its purpose is to receive the images, resize them, and pass them to subsequent layers for feature extraction.

Following the input layer, there are multiple "Convolution layers" that function as filters for the images. These layers extract features from the images and also play a role in calculating matching feature points during testing.

After extracting the feature sets, they are subsequently forwarded to the "pooling layer." This layer downscales the large images, while maintaining the essential information contained within them. It preserves the most significant details by retaining the maximum value within each window, thereby safeguarding the optimal representations of each feature.

After the pooling layer, the Rectified Linear Unit (ReLU) layer comes into play. This layer replaces the negative values generated by the pooling layer with 0. This nonlinear activation function adds nonlinearity to the network, increasing its capacity to learn complex patterns and representations. This process ensures the stability of the convolutional neural network (CNN) by maintaining the mathematical stability resulting from the learned values being close to 0 or close to infinity.

The last layer of the model is called the (Fully Connected layer). This layer connects all neurons from the previous layer to each neuron in the current layer, thus integrating information and making predictions based on the learned features. It plays a crucial role in the classification or regression task by aggregating the learned representations and producing the final output of the model. These layers take the highest-level filtered images and transform them into distinct categories, typically through the utilization of tags or labels [17].

The overall architecture of the CNN, as described above, can be visualized in Figure 2.

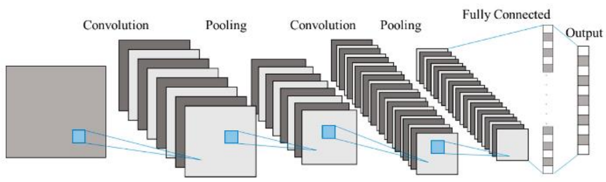

Figure 2. Schematic expression of a CNN

AlexNet

AlexNet is a convolutional neural network (CNN) model renowned for its exceptional performance in visual recognition and classification tasks. The architecture of AlexNet comprises eight layers and encompasses a staggering 60 million parameters. The initial two layers of the model employ convolution and pooling operations to extract low-level features from the input images.

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Subsequently, the subsequent three layers are designed to capture higher-level features. The final three layers consist of fully connected layers that are specifically utilized for the classification task. Notably, one of the pivotal advancements introduced by AlexNet is the utilization of the "ReLU" (Rectified Linear Unit) activation function, which significantly expedites the pre-training phase of deep learning models. Additionally, a technique called "dropout" is employed during model training to mitigate the risk of overfitting [18].

VGGNet-19

VGGNet-19 is an image classification model with 19 layers. It is developed by the Visual Geometry Group at the University of Oxford.

The use of "bn" (batch normalization) in the model indicates that batch normalization is used. VGGNet-19, consisting of convolution and fully connected layers, enhances the ability to learn deep features through iterative convolution operations using filters in the 3x3 dimension. Batch normalization accelerates the training process and enhances the network's ability to learn consistently. By normalizing the input data within each mini-batch during training, batch normalization reduces the internal covariate shift and helps stabilize the learning process. This, in turn, leads to faster convergence and improved overall training performance [19].

DenseNet-201

DenseNet-201 is a 201-layer dense CNN model. It is designed to reduce over-compliance and improve information flow. Unlike traditional CNN structures, the outputs of previous layers are directly linked to the layers that follow. This allows better transfer of low-level features. DenseNet-201 has been trained on the ImageNet dataset and can be used in a variety of visual tasks. The model is popular and widely used in computer vision and artificial intelligence [20].

Squeezenet1.1

SqueezeNet 1.1 is an updated version of the original SqueezeNet model. This deep learning model provides high accuracy using fewer parameters and operates at smaller sizes. SqueezeNet 1.1 reduces weight matrices and model size through compression strategies while maintaining classification accuracy. This model is suitable for resource-constrained devices and applications. SqueezeNet 1.1 performs well on the ImageNet dataset and runs lighter and faster [21].

ResNet-152

ResNet-152 is a deep neural network architecture that has made significant advancements in the realm of deep learning and has demonstrated exceptional performance on extensive datasets like ImageNet. Comprising 152 layers, this model possesses a highly intricate structure. ResNet-152 employs residual blocks, a specific configuration, to effectively address the issue of gradient loss. This model performs exceptionally well in a variety of computer vision tasks such as object detection, image classification and image segmentation. Its capabilities extend to accurately identifying objects, classifying images, and accurately segmenting regions of interest within images. [22].

2.3. Transfer Learning

A technique used in deep learning. In this method, the learned features of the model trained on one task are used for another task. In this way, a model trained on a larger and general dataset is expected to perform better on a smaller or customized dataset. Transfer learning requires less data, provides faster training and increases the ability to generalize. This method is useful with limited data sets or when fast model iterations are required [23].

2.4. Experimental Setup

The dataset used for this research is divided into five categories. These classes are five categories: bed, chair, sofa, swivelchair and table. No data augmentation is made in the study. The images in the dataset are composed of pixels of different widths and sizes and are not standardized. Images are resized to 200x200 pixels before the experiments. 10% test images are removed from the dataset. After the test images are scattered, 15% validation is reserved and training is performed. A total of 4447 furniture images are used for classification. The subset size (batch-size) of the classified images are used as 64. The number of training epochs for the models using the transfer learning approach is set to 20 epochs. The experiments are conducted in the Kaggle kernels cloud environment using Google infrastructure, using an Nvidia Tesla P100 graphics card. Python programming language is used for the software of the application.

During the training of CNN networks, the Adam function used as the optimizer and ReLU is used for the activation. The Learning Rate Finder function is used to determine the learning rates of the networks and the learning rate is halved after every 5 unsuccessful epochs. For models that did not develop for 10 epochs, training is stopped. Thus, precautions were taken to memorize the network. In addition, CNN architectures have dropout and normalization layers to prevent overfitting.

2.4. Evaluation Metrics

Confusion matrix is used for performance measurement of machine learning classification tasks. According to the confusion matrix, TP represents true positive, TN true negative, FP false positive, and FN false negative.

Accuracy: The ratio of correctly classified samples to the total number of samples, indicating the overall correctness of predictions.

AUROC: Measures the overall performance of a model by calculating the area under the ROC curve. Higher values indicate better performance.

Error Rate: The proportion of misclassified samples out of the total number of samples, reflecting the model's tendency for incorrect predictions.

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Precision: The accuracy of positive predictions made by the model, calculated as the ratio of correct positive predictions to the total number of positive predictions.

Recall: The model's ability to correctly identify positive instances, measured as the proportion of correctly identified positive samples out of the total number of true positive examples.

F1-score: A balanced metric combining precision and recall, providing an overall assessment of the model's performance, especially in imbalanced datasets. The evaluation metrics are given in Table 1.

Table 1. Evaluation metrcis formula

Metric	Formula
Accuracy	(TP + TN) / (TP + FP + TN + FN)
Error Rate	(FP + FN) / (TP + FP + TN + FN)
Precision	TP / (TP + FP)
Recall	TP / (TP + FN)
F1-score	2 * Precision * Recall / (Precision + Recall)

3. RESULTS AND DISCUSSION

The performance values found as a result of classifying furniture images with CNN architectures are given in Table 2. This table shows the precisson, recall, F1-score, ROC, time, error rate and accuracy values of Alexnet, VGGNet-19, Densenet-201, Resnet-152, Squeezenet1.1 and Resnet-152 CNN models after 20 epochs. The 152-layer ResNet-152 CNN model showed the highest success with 98.87% test accuracy. Table 3 shows the most successful values obtained after 50 epochs

Table 2. The most successful values obtained by deep learning architectures in furniture image classification after 20 epoch

CNN Model	Precision	Recall	F1-score	ROC	Time	Error rate	Accuracy
AlexNet	0.94	0.94	0.94	0.99	00:25 s	0.035	0.9415
VGGNet-19	0.97	0.97	0.97	0.99	00:37 s	0.015	0.9707
DenseNet-201	0.99	0.99	0.99	0.99	00:40 s	0.003	0.9865
SqueezeNet1.1	0.97	0.97	0.97	0.99	00:27 s	0.021	0.9707
ResNet-152	0.99	0.99	0.99	0.99	00:43 s	0.006	0.9887

Table 3. The most successful values obtained by deep learning architectures in furniture image classification after 50 epoch

CNN Model	Precision	Recall	F1-score	ROC	Time	Error rate	Accuracy
AlexNet	0.94	0.94	0.94	0.99	00:29 s	0.043	0.9415
VGGNet-19	0.99	0.99	0.99	0.99	00:41 s	0.018	0.9887
DenseNet-201	0.98	0.98	0.98	0.99	00:43 s	0.005	0.9797
SqueezeNet1.1	0.95	0.95	0.95	0.99	00:30 s	0.020	0.9505
ResNet-152	0.99	0.99	0.99	0.99	00:47 s	0.021	0.9887

Alexnet CNN model in Phase 15, VGGNet-19 model in Phase 17, Densenet-201 model in Phase 16, Squeezenet1.1 model in Phase 16 and Resnet-152 in Phase 15 provided the most successful results. In terms of F1-score, AlexNet model gives 94%, VGGNet-19 model 97%, DenseNet-201 model 99%, SqueezeNet1.1 model 97%, Resnet-152 model 99%. The number of correctly and incorrectly identified furniture as a result of the classification process of AlexNet, VGGNet-19, DenseNet-201, SqueezeNet1.1 and ResNet-152 deep learning architectures is shown in Figure 3. AlexNet, Sensitivity, recall and F1 score values are high and the ROC curve looks quite good. Training time and processing time are short and accuracy is high. VGGNet-19, precision recall and F1 score are quite high and the ROC curve also shows a very good performance. Training time and processing time seem to be slightly longer than other models. DenseNet-201, Sensitivity, recall and F1 score values are still high and the ROC curve looks good. The training time and processing time may be slightly longer, but the error rate is very low. The SqueezeNet1.1 model has slightly lower sensitivity and recall values compared to other models, but still performs well. Training time and processing time are similar to the others. ResNet-152, sensitivity, recall, F1 score and ROC curve appear to be quite good. The training time and processing time seems to be a bit longer than the other models, but still the high accuracy and low error rate are remarkable.

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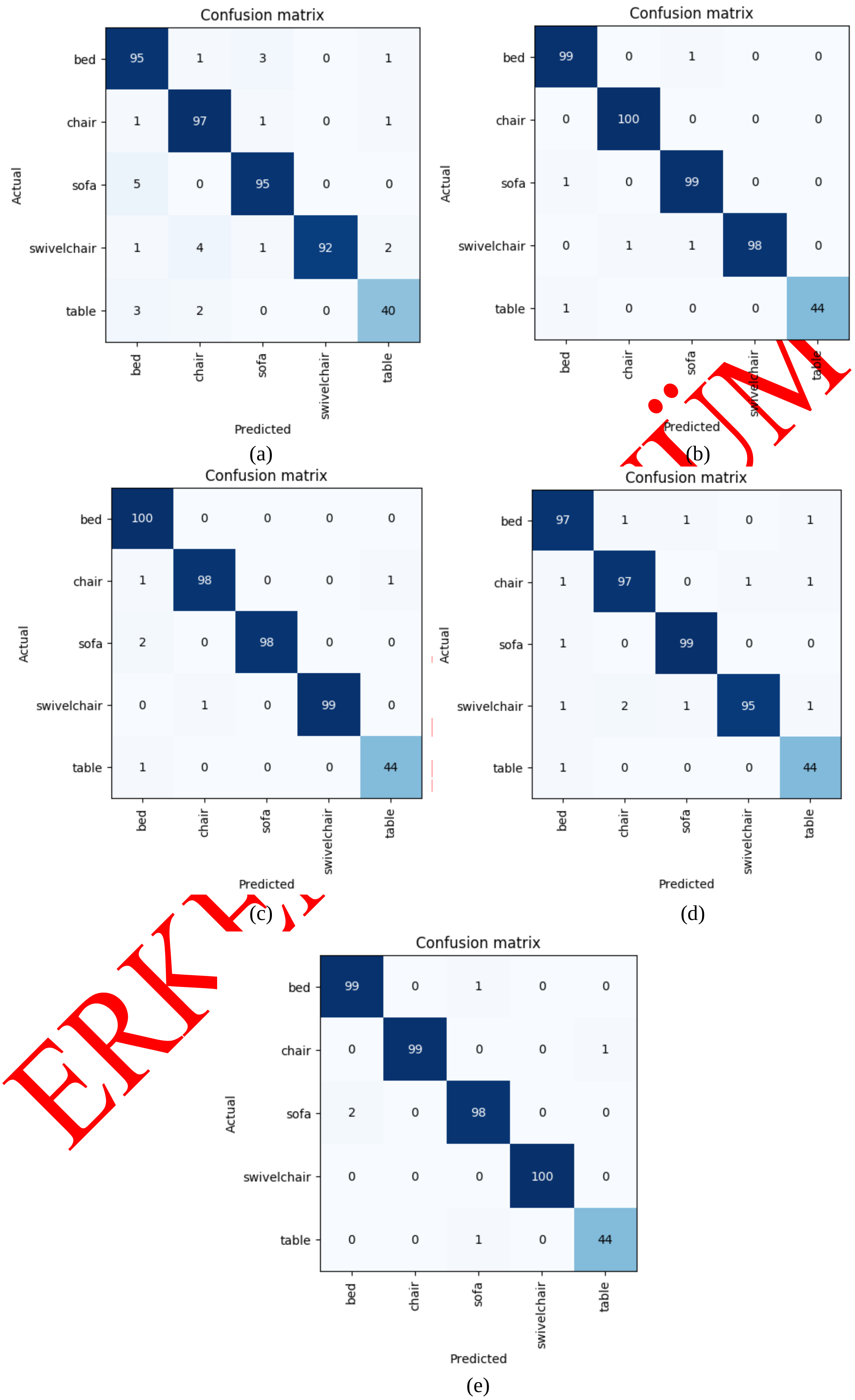

Figure 3. Confusion matrices of the most successful results (a) AlexNet (b) VGGNet-19 (c) DenseNet-201 (d) SqueezeNet1.1 (e) ResNet-152

The ROC curve graph showing the classification performance of the deep learning architectures used in furniture classification is given in Figure 4.

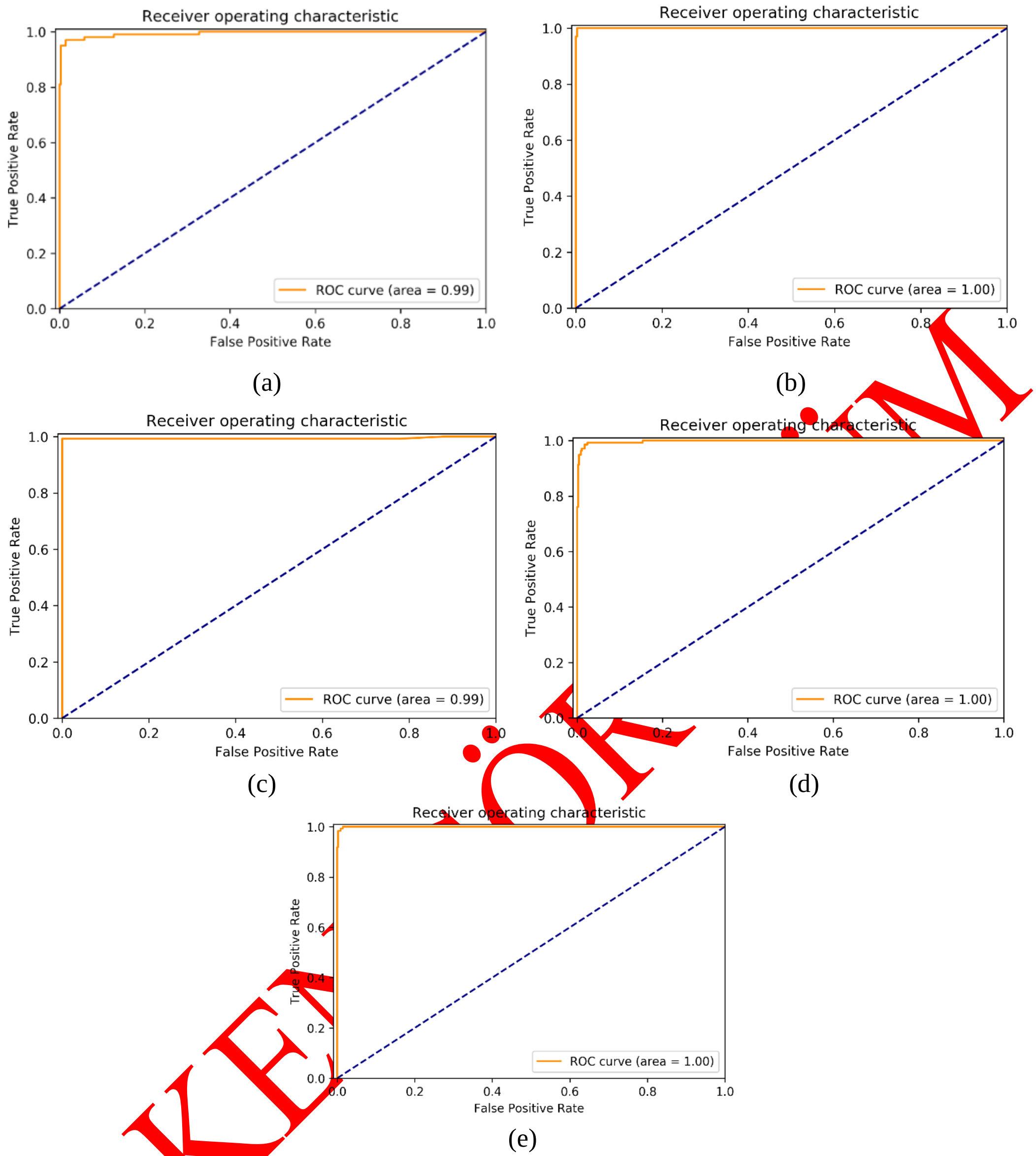

Figure 4. ROC curve plots showing the best classification performance of deep learning architectures used in furniture classification (a) AlexNet (b) VGGNet-19 (c) DenseNet-201 (d) SqueezeNet1.1 (e) ResNet-152

Figure 5 presents a comparison of classification accuracy for various models on the furniture dataset. VGGNet-19 and achieved the ResNet-152 CNN model with 98.87% test accuracy. SqueezeNet1.1 gave an average classification accuracy of 97.07%. The Alexnet CNN model lowest classification accuracy of 94.15%. Successful performance is found with the Table 3 shows the classification report table of the best architecture.

The table presents performance metrics obtained by a classification model for different classes. Here is the interpretation of the table:

Table 3. Resnet-152 architecture classification report table

Class	Precision	Recall	F1-Score	Support
Bed	0.98	0.99	0.99	100
Chair	1.00	0.99	0.99	100
Sofa	0.98	0.98	0.98	100
Swivelchair	1.00	1.00	1.00	100
Table	0.98	0.98	0.98	45
Micro Avg	0.99	0.99	0.99	445
Macro Avg	0.99	0.99	0.99	445
Weighted Avg	0.99	0.99	0.99	445

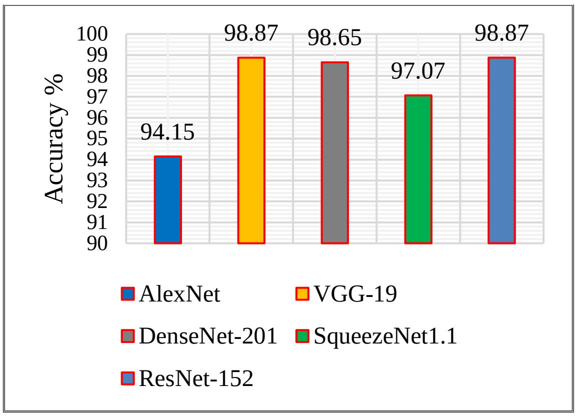

Figure 5. Classification accuracy comparison table for different CNN architectures on furniture images dataset

For the "Bed" class, the model correctly predicted 98% of the positive examples out of 100, and it accurately classified 99% of the true positives. The F1-Score for this class is 99%.

In the "Chair" class, the model correctly predicted all 100 examples as positive, and it accurately classified 99% of the true positives. The F1-Score for this class is 99%.

For the "Sofa" class, the model correctly predicted 98% of the positive examples out of 100, and it accurately classified 98% of the true positives. The F1-Score for this class is 98%.

In the "Swivelchair" class, the model correctly predicted all 100 examples as positive, and it accurately classified 100% of the true positives. The F1-Score for this class is 100%.

For the "Table" class, the model correctly predicted 98% of the positive examples out of 45, and it accurately classified 98% of the true positives. The F1-Score for this class is 98%.

The micro average treats all categories as one category and computes the precision, recall, and F1-Score accordingly. In this scenario, they all stand at 99%.

The macro average calculates the performance metrics for each category separately and then calculates the average. According to this information, precision, recall and F1 Score are all 99%. The weighted average calculates performance metrics taking into account the support (number of instances) for each category. In this study, the precision, recall and F1 Score for the ResNet-152 architecture are all 99%.

In general, the table suggests that the classification model performs admirably by accurately classifying the various categories. The precision, recall, and F1-Score values are consistently close to each other, indicating a well-balanced classification by the model. Moreover, since the support values are similar, it can be inferred that each category has a comparable impact on the model's performance.

In recent years, significant advancements have been made in various fields as a result of the remarkable progress in artificial intelligence. The furniture industry is one of the areas affected by these developments. The use of AI technologies in the furniture industry provides significant advantages for furniture producers and consumers. AI-based image classification has many applications in the furniture industry. For example, a furniture manufacturer could have a large database and analyze this data with AI algorithms to automatically classify different types of furniture. This can help the manufacturer to optimize production processes and minimize errors. In addition, artificial intelligence furniture image classification technology is also used in e-commerce platforms. Many online furniture stores use artificial intelligence algorithms to automatically classify furniture images in order to offer customers the right products. In this way, customers can find the furniture in the style they want more quickly and accurately.

In a study similar to this one, conducted by Du (2021), on furniture style classification, a model based on FISC: Gram transform is utilized. A dataset containing furniture image style attribute tags is created to ensure the objectivity and relevance of the experiment. The test accuracy achieved is 94% [24].

There is one study in the literature with this dataset. In the aforementioned work, a VGGNet-16 model is developed that is combined with the depth group over-parameterized convolution (DGOVGGNet-16) model to perform furniture classification. An average accuracy of 95.51% reported for furniture image classification. Comparing the work in the literature with the work done by us, the success rate can be considered quite successful with an average accuracy of 98.87%.

5. CONCLUSION

Despite the advantages of AI furniture image classification technology, there are also some challenges. First of all, the quality and diversity of the data set is of great importance. In order to obtain good acceptable results, a sufficient and representative data set is needed. In addition, the accuracy and speed performance of the algorithm used are also very important factors. For real-time applications, it is important to achieve fast and accurate results. In this study, furniture images classified using AlexNet VGGNet-19 DenseNet-201 SqueezeNet1.1 ResNet-152 CNN architectures.

- Among the architectures used, ResNet-152 architecture gives the highest result with 98.87%.
- An ROC value of 99.96% is obtained with the Resnet-152 architecture.
- Each epoch of Resnet-152 architecture lasted on average 44 seconds.
- The transfer learning approach provides fast and accurate results with fewer parameter settings.

For future studies, hybrid architectures and different deep learning architectures can be used together with CNN in the classification of furniture images. With this method,

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it is thought that more successful results can be obtained in the classification of furniture images.

DECLARATION OF ETHICAL STANDARDS

The authors of this article affirm that the materials and methodologies employed in their study do not require ethical committee approval or any specific legal permissions.

AUTHORS' CONTRIBUTIONS

Kenan KILIÇ: Identified the problem, reviewed the literature, found a data set, conducted the experiments, wrote the paper.

Uğur ÖZCAN: Interpreted experiments, planned evaluation metrics, analyzed results.

Kazım KILIÇ: He has done code writing, problem identification and article writing.

İbrahim Alper DOĞRU: Evaluated the results and edited the manuscript.

CONFLICT OF INTEREST

This article declares that there are no conflicts of interest or disagreements between the authors.

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