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Analysis of Biodegradable and Non-Biodegradable Materials Using Selected Deep Learning Algorithms

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Abstract

It is possible to divide the materials used in the world into recyclable and nonrecyclable. Biodegradable materials contain elements naturally degraded by microorganisms such as foods, plants, fruits, etc. Waste from this material can be processed into compost. non-biodegradable materials include materials that do not naturally decompose, such as plastics, metals, inorganic elements, etc. Waste from this material can only be reused by converting it into new materials. In this study, the classification of biodegradable and non-biodegradable materials was done using deep learning methods. Convolutional Neural Network (CNN) performs steps such as preprocessing and feature extraction in classification. 5430 images were used for the dataset. 70% of this dataset was used as training data, 15% as validation data, and 15% as test data. Of the Deep Learning methods, the pre-trained neural networks AlexNet, ShuffleNet, SqueezeNet, and GoogleNet were used. For each algorithm, the performances were evaluated by classifying them as biodegradable and non-biodegradable. With this study, we can identify, track, sort, **and** process waste materials by classifying materials.

Keywords: Deep Learning; convolutional neural Networks; biodegradable; non-biodegradable; classification.

1. Introduction

Biodegradable substances are naturally degradable such as bacteria, fungi, ultraviolet rays, ozone, oxygen, water. Decomposition is the breaking down of complex organic materials into simple units [1]. These simple units provide the soil with a variety of nutrients. Biodegradable materials are generally non-toxic and do not heat up in the environment over long periods. Therefore, they are not considered environmental pollutants. Examples of biodegradable materials include anything made from natural materials, such as plants or animals. These biodegradable substances do not harm the ecosystem. Such products include biodegradable plastics, polymers, and household cleaners [2, 3].

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Natural processes cannot degrade Non-biodegradable substances in nature, and therefore, these substances remain in the environment longer without being degraded. Examples of common non-biodegradable materials include plastic, polyethylene, scrap metals, aluminum cans, glass bottles, etc. Since these substances do not disappear in nature for many years, they are also harmful to the ecosystem [1,3]. Many substances, such as non-biodegradable metallic substances pollute natural waters and soils and cause various hazardous problems. The use of non-biodegradable materials harms countries' ecosystems. Developing countries, in particular, are now paying attention to the use of biodegradable materials [2,2,4].

The significance of the study;

- Non-biodegradable materials remain in nature for many years and damage the ecological balance,
- Separation of non-biodegradable materials is essential for recycling,
- Recycling and reusing materials provide crucial economic support for countries,
- The success rates of the algorithms used in the classification study are high, and it will be beneficial to use them in parsing processes,
- With models that can be used in large data sets, it will be much easier to separate non-biodegradable materials.

Convolutional neural networks are a type of multilayer perceptrons. Although it has been used in areas such as image and sound processing, natural language processing, and biomedicine, it has achieved the best results in the field of image processing [5]. In this section, we summarize some of the work in image classification. Cireşan and his colleagues conducted a study for handwriting recognition following the results of this neural network trained with the probabilistic gradient descent method using the Convolutional Neural Network (CNN) approach [6]. Sarıgül and his colleagues also proposed a backpropagation algorithm to minimize the error rate. The backpropagation algorithm considers the activation errors and increases the classification performance without changing filters [7]. Traore and his colleagues presented a convolutional neural network (CNN) for microscopic image identification [8]. Seo and Shin proposed a hierarchical convolutional neural network for image classification. They also used the maximum pooling method in their study [9]. In their study, Cetinic and his colleagues investigated the applicability of a convolutional neural network that showed successful results in visual tasks by analyzing different aspects of image similarity for the classification of images related to art [10]. In their study, Han and his colleagues demonstrated and proposed that it is possible to classify data by representing graphs instead of classifying images [11]. Park and his colleagues used an extreme learning machine (ELM) to train the artificial neural network they created. This study achieved higher accuracy and required less training time using their proposed method [12]. Santos and his colleagues proposed a deep and fast convolutional neural network (CNN) based on an extreme learning machine and a fixed filter bank in their study and it was shown that the model can be used on low-cost computers and is faster than GPU-based models [13]. Coletta and his colleagues also investigated the active learning algorithm and studied this topic. A flexible image classifier was used in the study [14].Yuan and his colleagues also worked with the active learning algorithm and reduced the cost of the manual labeling process in this study. The algorithm used in the study can increase estimation accuracy by adaptively tuning between multiple criteria [15]. Matiz and Barner proposed using an inductive convolutional neural network (CNN) in their study [16].

This study classified biodegradable and non-biodegradable materials using the Deep Learning method. The items with visual representations in the dataset were classified using pre-trained networks, and the success criteria were compared. The second part of the study explains the literature review, and the third part explains the materials and methods used. The fourth chapter summarizes the experimental analysis results, and finally, the fifth chapter summarizes the study results.

2. Experimental

In this study, a biodegradable and non-biodegradable image classification study was conducted. Pre-trained convolutional neural networks were used for the study. In this study, information about the dataset is first given. Then, the pre-trained convolutional neural networks are explained, and the mathematical equations of the evaluation metrics are presented. The flowchart of the method used in the study is shown in Figure 1.

2.1. Dataset Description

The dataset consists of 5430 images obtained from the Kaggle open-access database. There are 2794 biodegradable images and 2634 non-biodegradable images. The distribution of biodegradable and non-biodegradable images in the dataset is shown in Figure 2 [17].

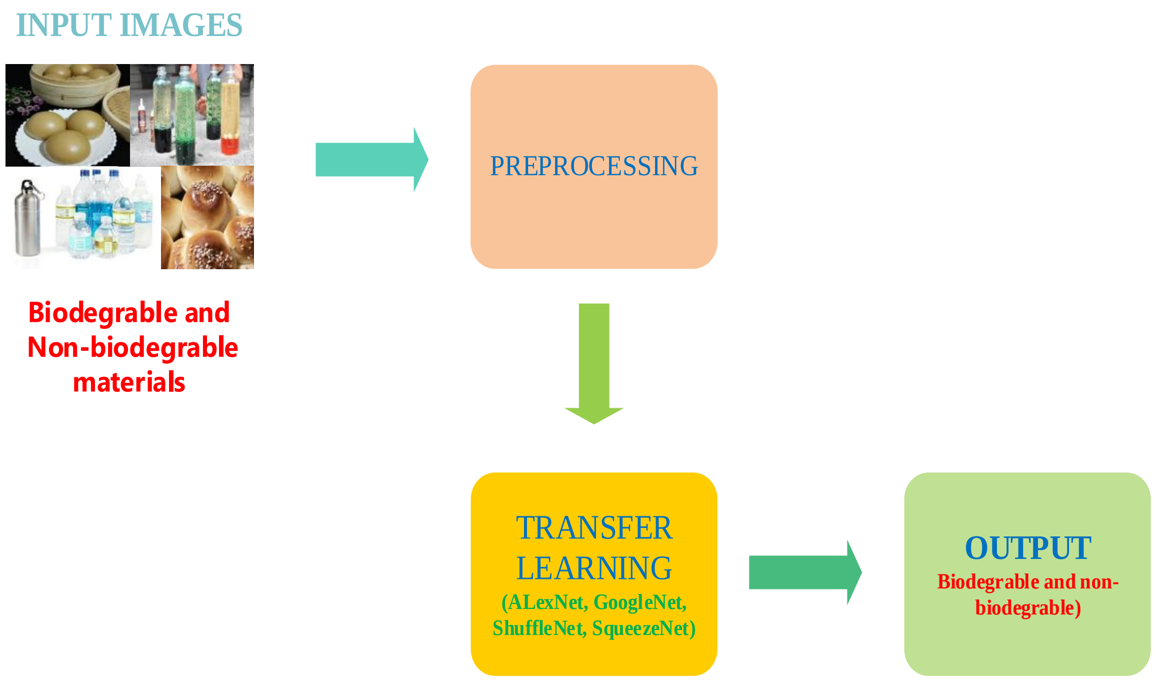

Figure 1: Image classification flowchart.

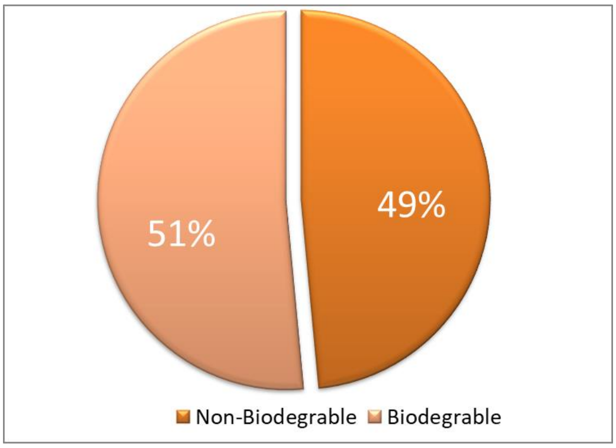

Figure 2: Image distributions within the dataset.

2.2. Convolutional Neural Network (CNN)

Convolutional Neural Networks are also a type of multilayer perceptron inspired by the visual center of animals [18]. CNN is widely used in image classification, image recognition, and object tracking and has high-performance values. In a convolutional layer, the feature maps of the previous layer become learning kernels, and the activation function is used to generate the output feature map. Each output map can combine convolutions with multiple input maps. In general, the CNN is formulated as in Equation 1 [19][20].

$$x_j^e = f\left(\sum_{i\epsilon M_j} x_i^{e-1} * k_{ij}^e + b_j^e\right) \qquad (1)$$

Here, Mj represents a selection of the input map. If the output map j and map k are collected on the input map i, the kernels applied to map i will differ for output maps j and k. The convolutional architectures used in the study are listed below [21, 22].

AlexNet; this is a deep learning algorithm proposed by Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton. This deep convolutional neural network consisting of 25 layers consists of 5 convolutional layers, three max pool layers, two dropout layers, three fully connected layers, seven relu layers, two normalization layers, softmax layers, input and classification layers (output). The image processing in the input layer is 227x227x3. In the last layer, the classification is done, and the value of the classification number is given in the input image. The layers of AlexNet are shown in Figure 3

The GoogleNet algorithm consists of 144 layers: the convolutional layer, the max-pooling layer, the softmax layer, the fully linked layer, the relay layer, the input layer, and the output layer. The image to be included in the input layer is 224x224x3. 1x1, 3x3, and 5x5 filters are used in the convolution layer. Pooling of size 3x3 is used. Linear activation is used for activation. The filter structures used are shown in Figure 4 [13, 15, 15].

The architecture of SqueezeNet consists of an independent convolutional layer (con1), eight fire modules (fire2-9), and a final convolutional layer (con10). The graphical representation of SqueezeNet can be found in Figure 5 [23,24,25].

ShuffleNet has less complexity and fewer parameters compared to other CNN architectures. Moreover, it is suitable for low-power mobile devices because deep convolution is applied only in the feature map with the bottleneck. The ShuffleNet architecture is shown in Figure 6 [15, 26, 27].

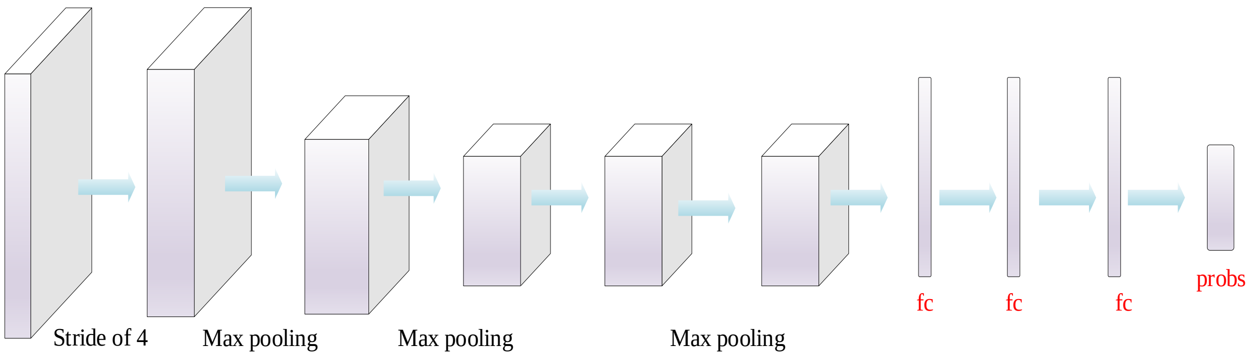

Figure 3: AlexNet architecture [28].

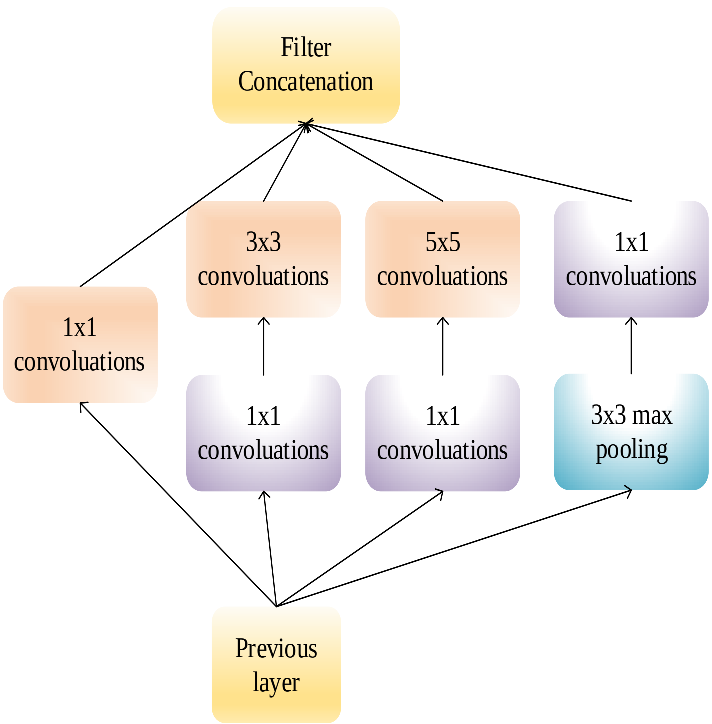

Figure 4: GoogleNet architecture [28].

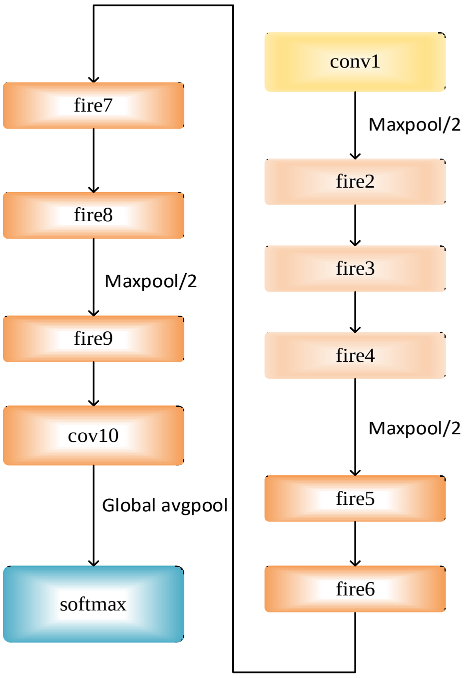

Figure 5: SqueezeNet architecture [13].

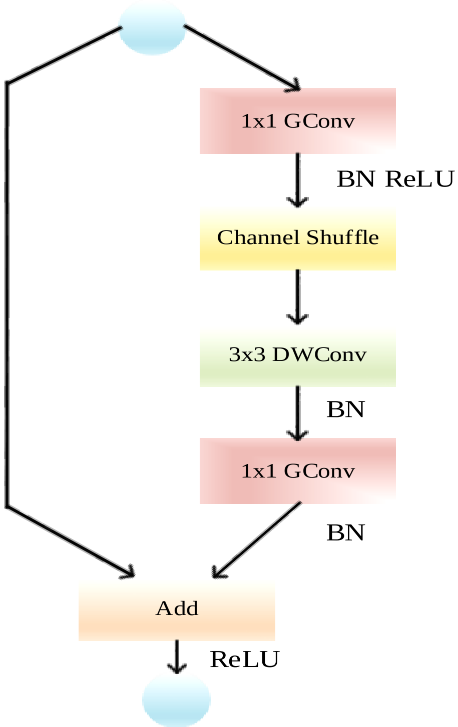

Figure 6: ShuffleNet architecture [28].

2.3 Evaluation Metrics

The basic concepts used in evaluating model performance are error rate, precision, sensitivity, and F-measure. The explanations and mathematical equations for these concepts can be found in Table 1. The model's success is related to the number of samples assigned to the correct class and the number assigned to the wrong class. The information about the performance of the results obtained by the test can be expressed with the confusion matrix. In the confusion matrix, the rows represent the real numbers of samples in the test set, and the columns represent the estimation of the model, as shown in Figure 7 [13, 19, 23, 28].

		Predicted Label	
		Positive	Negative
Actual Label	Positive	True Positive TP	False Negative FN
	Negative	False Positive FP	True Negative TN

Figure 7: Example of the confusion matrix.

Table 1: Basic concepts and equations used in model performance evaluation.

Metric	Calculation	
Accuracy	$\frac{TP+TN}{TP+FP+FN+TN}$	The most popular and most straightforward method of measuring model performance is the accuracy rate of the model [15].
Specificity	$\frac{TN}{FP+TN}$	The metric indicates how well the model predicts negative situations [15].
Sensitivity or Recall	$\frac{TP}{TP+FN}$	The number of correctly classified positive samples is the ratio to the total number of positive samples [15].
Precision	$\frac{TP}{FP+TP}$	Precision is the ratio of true-positive samples predicted as class 1 to the number of samples predicted as class 1 [26].
F-Score	$\frac{2*Precision*Recall}{Precision+Recall}$	The measures of precision and sensitivity alone are not sufficient to provide a meaningful comparative result. The evaluation of both criteria together provides more accurate results. For this purpose, the f-measure is defined. The F-measure, the harmonic of precision and sensitivity, is the mean value [19].

3. Results

In this study, the classification of biodegradable and non-biodegradable materials was performed using the Deep Learning method. There are 5432 images in the database. Although the material images are 1600x1200 in size, they were resized to 224x224 and 227x227 for deep learning algorithms. 70% of these images were used for training, 15% for validation, and 15% for testing. The training and testing images were randomly selected. The computer system used has hardware with i7-10750 H CPU @2.60 GHz, NVIDIA Quadro P620 GPU, and 16 GB RAM. Matlab deep learning algorithms were used for the application. The sample images used for classification are shown in Figure 8. AlexNet, GoogleNet, ShuffleNet, and SqueezeNet deep learning algorithms were used for the classification study. The parameters used during training and testing with the CNN models can be seen in Table 2.

Figure 8: Classified images of the data set.

Table 2: Training parameters used in the CNN models.

Parameter	Value
Mini ensemble size	16
Maximum period	100
Initial learning rate	1 to-3
Optimization method	sgdm

When the training times of the analyzes are also examined, as shown in Figure 9, the fastest training was the AlexNet analysis at 55 minutes. After that, SqueezeNet completed the training in 58 minutes and ShuffleNet in 68 minutes. The longest training was GoogleNet at 263 minutes. As the number of iterations increases, the training process becomes longer and takes much more time. The performance results of the CNN models can be found in Table 3.

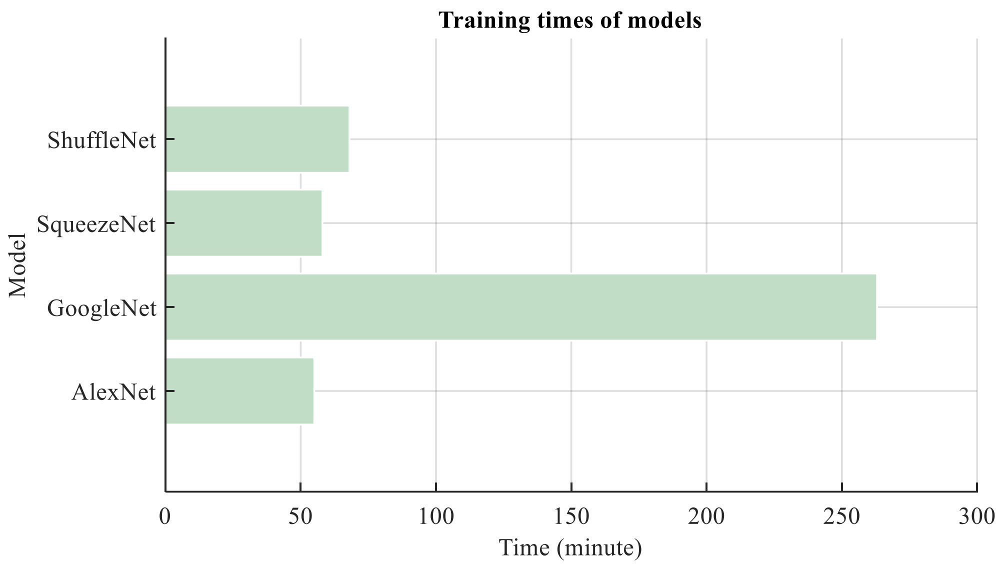

Figure 9: Analysis times of the models.

When examining the performance results of the CNN models, it can be seen that AlexNet has the lowest classification rate of 96.33% and the ShuffleNet model provides the most effective classification accuracy of 98.73%. Looking at the accuracy scores, the ShuffleNet architecture has the highest, and the AlexNet architecture has the lowest. In terms of specificity, GoogleNet has the highest value of 0.9924, while AlexNet has the lowest value of 0.9570. In terms of precision, GoogleNet achieves the highest value with 0.9923. ShuffleNet follows it with 0.980, SqueezeNet with 0.9750, and AlexNet with 0.9575 Figure 10 shows the classification confusion matrices of the analysis results of AlexNet, GoogleNet, ShuffleNet, and SqueezeNet. When the complexity matrices were examined, the CNN models' ability to discriminate between biodegradable and non-biodegradable materials was close.

Table 3: Performance results of the CNN models.

Model	Accuracy	Specificity	Sensitivity	Precision	F-Score
AlexNet	0.9633	0.9570	0.9696	0.9575	0.9635
GoogleNet	0.9848	0.9924	0.9772	0.9923	0.9847
ShuffleNet	0.9873	0.9797	0.9949	0.9800	0.9874
SqueezeNet	0.9810	0.9747	0.9873	0.9750	0.9811

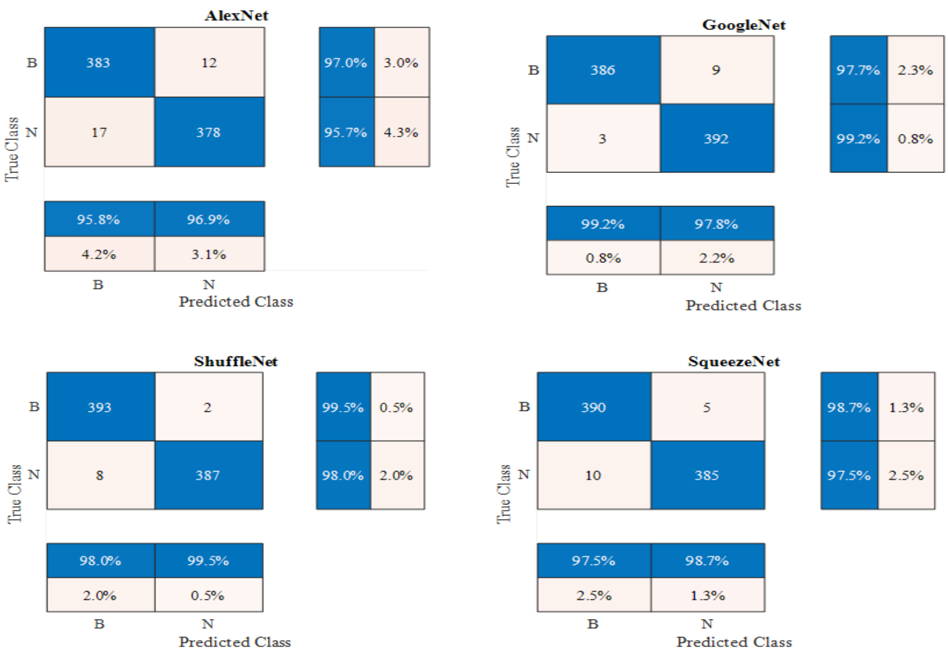

Figure 10: Complexity matrices of the trained neural network models.

4. Discussions

The present study compares the performance of several previous studies in the field of image classification with the proposed study. The methods and classification success rates used in these studies are summarized in Table 4.

Table 4: Comparison of image classification studies and performance results with pre-trained models.

Reference	Model/Algoritma	Accuracy (%)
(Toğaçar and his colleagues)	ESA ve özellik seçimini kullanmıştır	91.10%
[30]	AlexNet and SqueezeNet	95.65%
[31]	CNN	95.75%
[32]	AlexNEt, ResNet, VGG-16, DenseNet	96.60%
This study	**AlexNet, GoogleNet, ShuffleNet, SqueezeNet ve ResNet-18**	**98.74%**

In the table literature, there are many studies on image classification. When the accuracy values presented in the

Table are compared to the other studies in the performance comparison, the success rate obtained with the study is higher.

5. Conclusion

This study used different Deep Learning-based classification approaches to classify biodegradable and non-biodegradable materials. The prediction performance is comparatively analyzed. It was found that the application of CNN-based architectures for classification leads to effective results. The results obtained were architectures with a high accuracy rate. For example, the CNN models AlexNet, GoogleNet, ShuffleNet, and SqueezeNet achieved 96.3%, 98.5%, 98.7%, and 98.1% performance values, respectively, in the classification of biodegradable and non-biodegradable materials. As can be seen from the performance values of the CNN models, the best classification result was obtained with the ShuffleNet CNN model. After that, the SqueezeNet, GoogleNet, and AlexNet models were the best performers. The image classification studies will be investigated in more detail in future studies. We aim to investigate the literature studies in-depth and present a new CNN model in this context.

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