Research Article

Artificial Intelligence in Recycling: Waste Management with Convolutional Neural Networks

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Abstract: The rapid growth of urbanization and economic development has led to a significant increase in household waste, highlighting the necessity for developing sustainable waste management processes. Traditional waste sorting methods are based on manual processes, leading to high labor costs and low efficiency. This makes waste management systems less environmentally and economically sustainable, especially in densely populated areas. Furthermore, these methods reduce the efficiency of recycling processes and waste valuable resources by making it difficult to correctly sort waste by type. The time-consuming nature of manual methods and the risk of human error necessitate technological solutions to improve these processes. In this context, artificial intelligence-based technologies play an important role in waste management processes. Artificial intelligence reduces costs and increases efficiency by minimizing human errors through fast and accurate sorting processes. This study employed a publicly accessible dataset containing 22,564 images classified as recyclable and organic waste to train Convolutional Neural Network (CNN) models. The models' performance was assessed using metrics such as validation accuracy and validation loss. The findings indicate that the Optimized Convolutional Neural Network (OCNN) model achieved superior generalization capacity with a validation accuracy of 90.41%, outperforming the traditional CNN model, which attained 88.26%. This study aims to increase environmental sustainability and improve economic efficiency in waste management by using innovative methods. The proposed approaches are developed to increase the efficiency of waste classification processes, thereby supporting the conservation of natural resources and promoting higher recycling rates.

Keywords: Waste Management, Recycling, Economic Sustainability, Digital Transformation, Artificial Intelligence
Jel Codes: L51, O14, Q55

Geri Dönüşümde Yapay Zekâ: Evrişimli Sinir Ağlarıyla Atık Yönetimi

Öz: Kentleşme ve ekonomik kalkınmadaki hızlı büyüme, evsel atıklarda önemli bir artışa yol açarak sürdürülebilir atık yönetimi süreçlerinin geliştirilmesi gerekliliğini ortaya koymuştur. Geleneksel atık ayrıştırma yöntemleri manuel süreçlere dayanmakta, bu ise yüksek işçilik maliyetlerine ve düşük verimliliğe yol açmaktadır. Bu durum, özellikle yoğun nüfuslu bölgelerde atık yönetim sistemlerini çevresel ve ekonomik açıdan daha az sürdürülebilir kılmaktadır. Ayrıca, bu yöntemler geri dönüşüm süreçlerinin verimliliğini azaltmakta ve atıkların türlerine göre doğru şekilde ayrılmasını zorlaştırarak değerli kaynakları israf etmektedir. Manuel yöntemlerin zaman alıcı doğası ve insan hatası riski, bu süreçleri iyileştirmek için teknolojik çözümler gerektirmektedir. Bu bağlamda, yapay zekâ tabanlı teknolojiler, atık yönetimi süreçlerinde önemli bir rol üstlenmektedir. Yapay zekâ, hızlı ve doğru ayrıştırma süreçleri sayesinde insan hatalarını en aza indirerek maliyetleri düşürmekte ve verimliliği artırmaktadır. Bu çalışmada, Evrişimsel Sinir Ağı (Convolutional Neural Network-CNN) modellerini eğitmek için geri dönüştürülebilir ve organik atık olarak sınıflandırılmış 22.564 görüntü içeren halka açık bir veri kümesi kullanılmıştır. Modellerin performansı, doğrulama doğruluğu ve doğrulama kaybı gibi ölçütler kullanılarak değerlendirilmiştir. Bulgular, Optimize Edilmiş Evrişimsel Sinir Ağı (Optimized Convolutional Neural Network-OCNN) modelinin %90,41'lik bir doğrulama doğruluğu ile üstün genelleme kapasitesi elde ettiğini ve %88,26'ya ulaşan geleneksel CNN modelinden daha iyi performans

Cite: Yenikaya, M. A. (2025). Artificial intelligence in recycling: Waste management with convolutional neural networks. *Fiscaoeconomia, 9*(2), 1225-1236. https://doi.org/10.25295/fsecon.1607759

Submitted: 26.12.2024
Accepted: 06.03.2025

gösterdiğini ortaya koymaktadır. Bu çalışma, yenilikçi yöntemler kullanarak atık yönetiminde çevresel sürdürülebilirliği artırmayı ve ekonomik verimliliği iyileştirmeyi amaçlamaktadır. Önerilen yaklaşımlar, atık sınıflandırma süreçlerinin verimliliğini artırmak, böylece doğal kaynakların korunmasını desteklemek ve daha yüksek geri dönüşüm oranlarını teşvik etmek için geliştirilmiştir.

Anahtar Kelimeler: Atık Yönetimi, Geri Dönüşüm, Ekonomik Sürdürülebilirlik, Dijital Dönüşüm, Yapay Zekâ
Jel Kodları: L51, O14, Q55

1. Introduction

Each year, approximately 2.01 billion tons of waste are generated worldwide, with forecasts suggesting a 70% increase to 3.4 billion tons by 2050 (World Bank, 2018). This situation necessitates the development of new approaches to make waste management processes more efficient and sustainable. According to the United Nations Environment Program (United Nations Environment Programme, 2024), a large proportion of household waste is either landfilled or not managed properly, increasing environmental and economic costs.

Waste sorting processes using traditional methods are insufficient to meet current needs due to both labor requirements and low accuracy rates. Failure to properly sort waste leads to waste of natural resources and also increases greenhouse gas emissions, accelerating climate change (IPCC, 2021). Therefore, the development of smarter and automated waste sorting systems offers significant opportunities not only for environmental sustainability but also for economic efficiency.

In recent years, artificial intelligence and machine learning technologies have emerged as innovative tools providing advanced solutions in the field of waste management. In particular, Convolutional Neural Networks (CNN) stand out with their high accuracy rates in image processing and classification problems. CNN detects features such as edges, patterns and objects in images and incorporates this information into the learning process (Poznyak et al., 2019). This method is used as an effective tool in data classification processes and exhibits the ability to successfully categorize images. However, the success of such models depends on the size and diversity of the data set used. The generalization capability and performance of a model can be adversely affected by insufficient or imbalanced datasets.

The Optimized Convolutional Neural Networks (OCNN) model developed within the scope of the study was compared with the traditional CNN structure and the performance differences were evaluated. The training and test datasets were obtained from a large dataset of organic and recyclable wastes, and detailed analyses were performed on key metrics such as validation accuracy and validation loss of both models.

The study attempted to highlight the necessity of waste management practices for organizations using the framework of resource conservation theory. Resource conservation theory argues that individuals tend to protect limited physical and environmental resources and emphasizes the importance of managing these resources effectively and sustainably (Hobfoll, 2001). This theory, which forms the basis for all approaches and practices that promote environmental sustainability, expresses the necessity of organizing the world's scarce resources in a planned and future-oriented manner to meet the demands and expectations of people. In this respect, the theory of resource conservation reflects the general perspective of recycling operations, which can be defined as the recycling of elements that have lost their meaning and function and have become waste.

In this context, the transformation of resources with a sustainable approach has taken an important dimension in today's world, which is called the digital age, with the use of smart technologies, especially deep learning methods such as CNN. The integration of

CNN into recycling processes has an important role as a solid, functional and effective solution for the effective management and conservation of resources. In waste management, artificial intelligence technology automates the sorting process by accurately identifying waste types through images, thus directly contributing to the goals of efficiency and waste prevention emphasized within the scope of resource conservation theory.

This study aims to make significant contributions to technological innovations in the field of waste management. In particular, by automating the waste sorting process, it is aimed to reduce the high labor costs caused by traditional methods and to contribute to the protection of natural resources by enhancing the effectiveness of recycling processes.

2. Conceptual Framework

The use of artificial intelligence and deep learning approaches in waste management processes has become an important research area in recent years. In this context, Altikat et al. (2021) utilized deep convolutional neural networks (DCNN) with four and five layers to classify waste into categories such as glass, paper, plastic, and organic. In the study, it was reported that five-layer architectures achieved higher accuracy rates, and 83% accuracy was achieved in organic waste classification. The study draws attention to the automation potential of DCNNs in recycling processes and shows that these models can increase efficiency in waste sorting processes (Altikat et al., 2021). Dookhee (2022) evaluated various CNN architectures such as DenseNet and ResNet on a dataset of 15,515 images representing 12 different waste categories. In the study, 89.57% accuracy was achieved when the Xception model was optimized with the Nadam algorithm. This study highlights the important role of model optimization and data augmentation techniques in improving classification performance (Dookhee, 2022). Another study by Wang (2020) used the VGG16 CNN model to classify recyclable, hazardous and kitchen waste categories. In the study, 81.1% accuracy was achieved by applying preprocessing and data enhancement techniques. The study demonstrates the effectiveness and applicability of the VGG16 model in environmental applications (Wang, 2020).

Brintha et al. (2019) developed a system using a deep learning algorithm to classify solid waste as non-biodegradable and biodegradable. The study aims to increase recycling rates by automating waste sorting processes. The research has shown that deep learning techniques are an effective tool for sorting biodegradable waste (Brintha et al., 2019). Ramsurrun et al. (2021) proposed a deep learning-based model to classify waste into five main categories. These categories include metal, plastic, paper, cardboard, and glass. In the study, the VGG19 model was used together with the SoftMax classifier to achieve 88% accuracy. This study demonstrated that deep learning-based models can be successfully applied to sort different types of waste (Ramsurrun et al., 2021).

Pandey et al. (2023) compared CNN and Support Vector Machine (SVM) algorithms to classify waste such as plastic, paper and metal. In the study, CNNs achieved 83% accuracy with hyperparameter optimization. The study shows that CNN models have the potential to achieve higher levels of accuracy with the right tuning (Pandey et al., 2023). Faria et al. (2021) studied a dataset containing organic and three different solid waste classes using the VGG16 architecture. As a result of the research, an accuracy rate of 88.42% was achieved and these results emphasize the usefulness of CNN-based models in waste management. This study revealed that deep learning models are particularly effective in the classification of organic waste (Faria et al., 2021).

In the study of Zhang et al. (2021), firstly waste classification was performed with AlexNet, DenseNet169, VGG16 and GoogleNet models, then transfer learning-based DenseNet169 model was used, and it was reported that this approach was more successful than other methods with an accuracy rate of 82.8% (Zhang et al., 2021).

In the study of Wang et al. (2021), a system was developed in which a deep learning-based classifier was integrated with the cloud computing technique, and in this system, waste was divided into six categories. In the study, it was reported that the classifier based on the Mobilenetv3 architecture achieved a high success rate by reaching 94.24% accuracy rate (Wang et al., 2021).

In the study by Nowakowski & Pamuła (2020), a CNN-based classification method was utilized, and in addition, the R-CNN model was employed to determine object sizes. The developed system was reported to achieve accuracy rates ranging from 90% to 96.7%, demonstrating successful results (Nowakowski & Pamuła, 2020).

In the study by Tatke et al. (2021), the existing approaches and methods used in waste classification were examined in detail. In the study, the performances of various methods such as simple CNN, VGG16, ResNet50 and HOG+SVM were compared. It was stated that the ResNet50 model in particular exhibited superior performance with a high accuracy rate, while the VGG16 network gave successful results at a level that would meet daily usage requirements (Tatke et al., 2021).

Wu et al. (2021) developed a visual scene understanding-based method for garbage detection and classification in the home environment. In this study, objects in the scene are modeled using knowledge graphs with multiple modalities such as images, videos, and text. In addition, the Efficient Spatial Attention (ESA) mechanism is added to the backbone of the YOLOv5 network to form the YOLOv5-Attention-KG model. This model is designed to provide real-time detection capabilities to service robots. Test results show that the proposed model has higher detection and classification accuracy compared to the original YOLOv5 model, and its real-time performance meets the practical use requirements (Wu et al., 2021).

The study by Yenikaya et al. (2024) examined the use of artificial intelligence-based deep learning models in the field of health and compared the performances of ResNet101, AlexNet, GoogLeNet and Xception models in detecting COVID-19 and viral pneumonia through chest X-ray images; As a result of experiments conducted on 1,680 images, it was revealed that the ResNet101 model achieved the highest success with an accuracy rate of 96.3% and emphasized that artificial intelligence-supported diagnostic methods can speed up the diagnostic process by reducing the workload of healthcare professionals (Yenikaya et al., 2024).

In this study, based on the approaches presented in the literature, an OCNN model is developed with an innovative approach for the classification of organic and recyclable wastes. The developed model aims to prevent overlearning and increase generalization capacity by using modern optimization techniques and differs from the separation approaches used in the literature in this respect. Thus, this study aims to make an innovative contribution to literature and overcome the limitations of existing methods.

3. Material and Method

This study focuses on the classification of waste into two primary categories, recyclable and organic, using image-based data. The primary objective is to develop an effective model that distinguishes between these waste types. The general workflow diagram of the research including data collection, pre-processing, model implementation, model training and performance evaluation stages is presented in Figure 1.

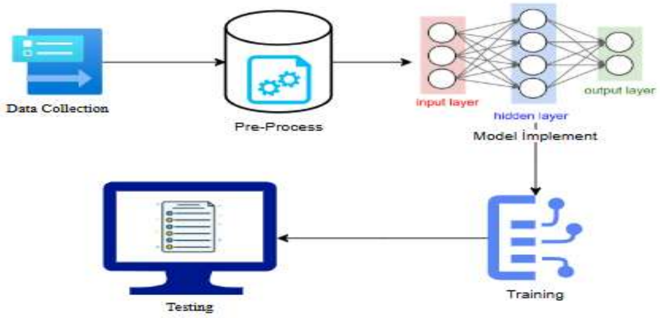

Figure 1. Workflow diagram

3.1. Data Collection

In this study, an open-source dataset obtained from the Kaggle website (Kaggle, 2024) was used for training CNN models. The data set consists of two primary categories, recyclable and organic waste. Images in each category were placed into subfolders to ensure accurate and consistent labeling. Figure 2 shows the distribution of the images of both classes in detail.

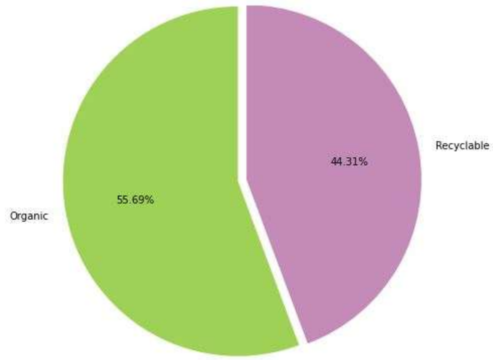

Figure 2. Image distribution of organic and recyclable waste

In the training phase of the study, a total of 22,564 images, including 9,999 recyclable waste and 12,565 organic waste images, were used. In the testing phase, a total of 25,112 images, consisting of 14,001 organic waste and 11,112 recyclable waste images, were used to evaluate the performance of the model. This comprehensive dataset formed the basis for testing the model's classification ability under different conditions and evaluating its generalization capacity. Figure 3 presents sample images from the dataset.

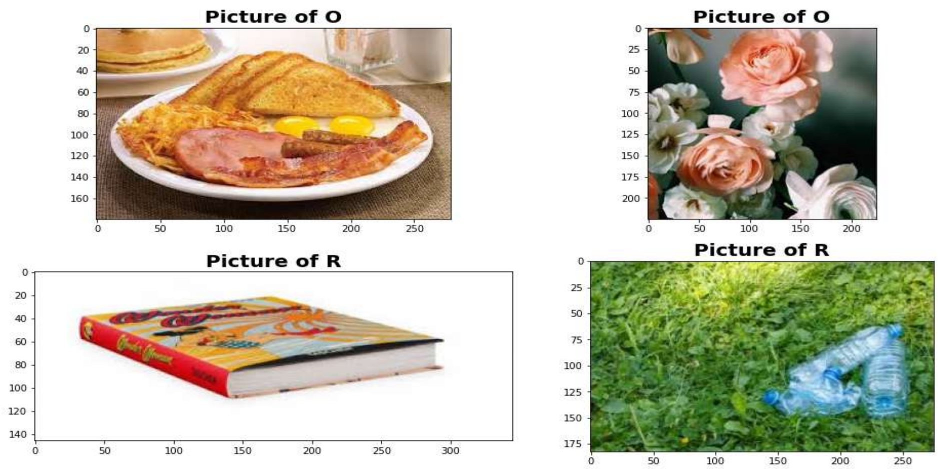

Figure 3. Example images extracted from the dataset (O-Organic, R-Recyclable)

This dataset used in this study is structured in a way that is compatible with the class labels of the images. This structure allowed the CNN model to proceed consistently in the data learning phase and increase the classification accuracy.

3.2. Data Preprocessing

During the data preprocessing phase, several steps were taken to enhance the performance of the waste classification model. Initially, the dataset images were resized to 224x224 pixels to align with the model's input requirements. Following this, the images were normalized by scaling their pixel values to a range of [0, 1]. This normalization process improved the model's training efficiency and stability while ensuring consistent performance across images with varying lighting conditions.

3.3. Model Implementation

The training and testing of the models developed to perform the classification was performed using the Google Colab platform. In this environment, traditional CNN and OCNN architectures were applied, and the performance of the model was tested for classifying waste into two different classes: recyclable and organic. Thanks to the high processing power provided by Google Colab, the training process of the model was accelerated, and efficient learning was performed on large data sets.

3.3.1. Convolutional Neural Networks (CNN)

The Convolutional Neural Network (CNN) architecture illustrated in Figure 4 represents a deep learning framework widely utilized for tasks such as classification, object detection, and segmentation by extracting features from image data (LeCun et al., 1998). This architecture is composed of sequential layers, including convolutional (Conv2D) layers, activation functions (commonly ReLU), and pooling layers. Convolutional layers use learnable filters to identify low-level features such as edges and textures, as well as high-level features like shapes and objects. Pooling layers, on the other hand, reduce the dimensions of the feature maps, thereby decreasing computational complexity (Krizhevsky et al., 2012).

Following feature extraction, the two-dimensional feature maps are flattened into a one-dimensional vector using the Flatten layer. This vector is then passed to fully connected (Dense) layers, where the classification process occurs. For multiclass classification tasks, softmax activation functions are typically employed, while sigmoid activation functions are utilized for binary classification problems. This structured approach allows the model to effectively process and analyze image data for a variety of applications.

Although traditional CNN architectures can successfully learn low-level features, they may run the risk of overfitting due to the increased number of parameters in large-scale and complex datasets (Szegedy et al., 2015).

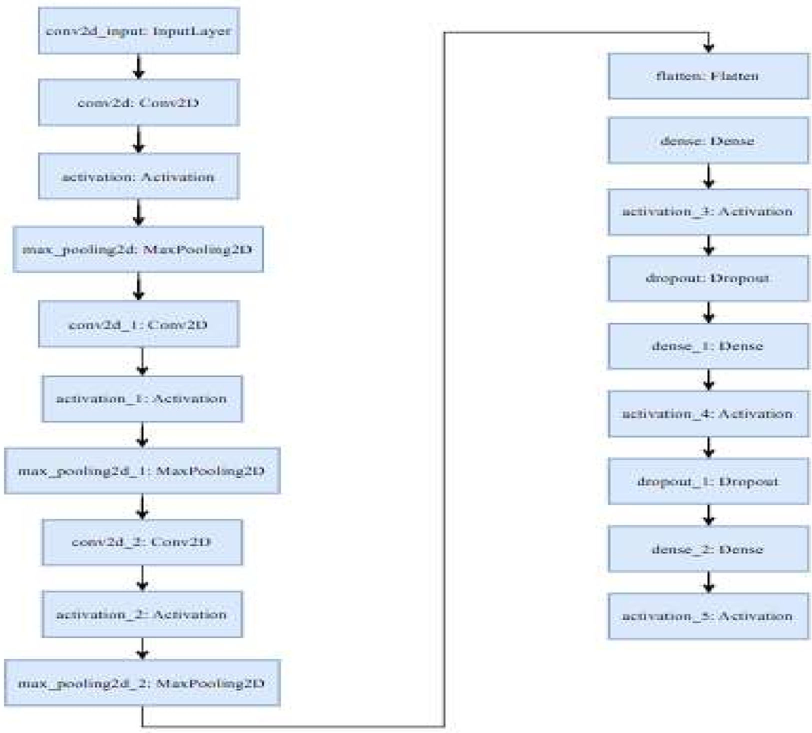

Figure 4. CNN architecture

3.3.2. Optimized Convolutional Neural Networks (OCNN)

The Optimized Convolutional Neural Network (OCNN) model, whose architecture is shown in Figure 5, overcomes the limitations of traditional CNN architecture and applies modern optimization techniques such as Dropout, Batch normalization and Global Average Pooling (GAP) to improve the generalization performance of the model. These techniques both increase the stability of the model in the training process and improve the validation performance by reducing the risk of overfitting.

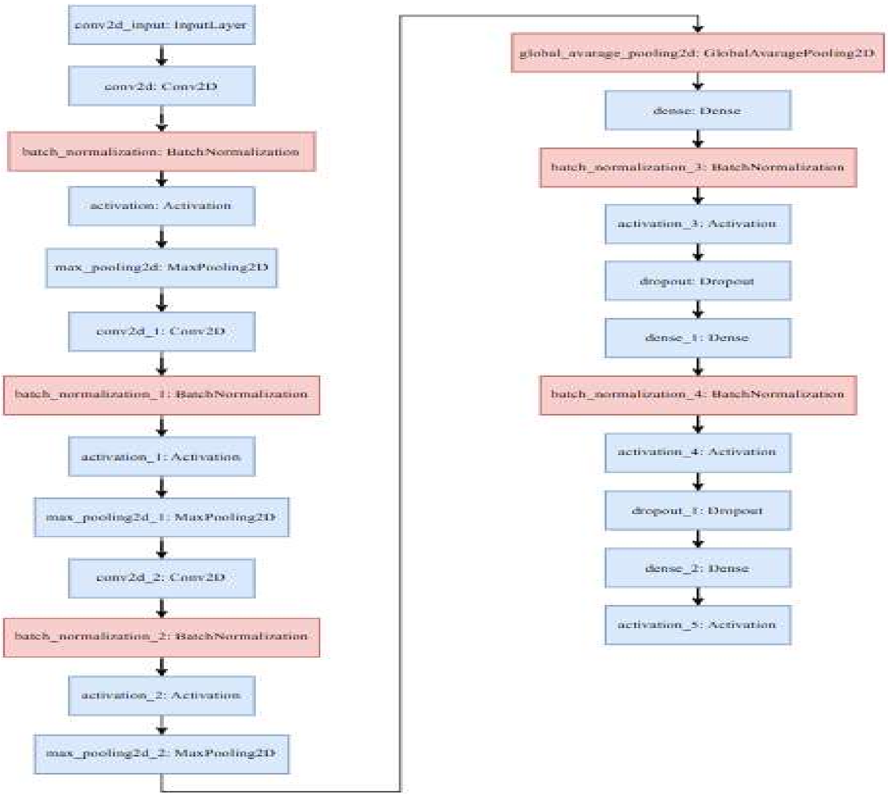

Figure 5. OCNN architecture

Batch normalization makes the learning process faster and more stable by normalizing the inputs in the model layers after each mini-batch data processing. This method contributes to faster convergence of the model, especially by reducing the effect of differences in the range of values of the weights and prevents overlearning by reducing the sensitivity of the parameters.

Dropout is applied as a regularization technique that reduces the risk of overlearning by disabling random neurons during the training of the model. This technique helps the model to achieve a more generalizable structure by keeping different neurons active at each training step. For example, Dropout applied in fully connected layers improves the performance of the model on the validation dataset and prevents the memorization problem that may occur during training.

GAP is an alternative to traditional Flatten layers that reduces the output size by averaging all values in the feature maps. This approach significantly reduces the number of parameters, making the model lighter and reducing the risk of over-learning. Moreover, GAP allows the model to learn the key features more efficiently and provides strong performance in the classification task.

By integrating these optimization techniques into the model architecture, a model with stronger generalization capacity and superior validation performance compared to traditional CNN structures has been developed. In this way, the model not only provides successful results on complex data sets but also operates in a lighter structure.

3.4. Training and Testing

In the training and performance evaluation phases of the study, training and testing datasets structured as folders in the dataset were used. During the training of the models, Adam optimizer was preferred as the optimization algorithm and categorical cross-entropy, which is appropriate to the nature of the classification problem, was applied as the loss function. In the training process, the traditional CNN model was trained with a batch size of 256 and the OCNN model was trained with a batch size of 64, and the training time for both models was set as 10 epochs.

Model performance was analyzed based on key metrics such as validation accuracy (val_accuracy) and validation loss (val_loss). Validation accuracy represents the correct prediction rate on the validation dataset that the model has not seen before and is considered as an important indicator in evaluating the generalization ability of the model. Validation loss measures the model's prediction errors on the validation dataset, and low loss values indicate that the model's errors on the validation data are minimized. This evaluation process allowed us to compare the performance of the models on the validation data and determine their overall performance.

4. Findings

This study utilized a dataset sourced from Kaggle to compare the performances of CNN and OCNN models. Both models were trained over 10 epochs, and their performance was assessed using the metrics of training accuracy (Accuracy), training loss (Loss), validation accuracy (Val_Accuracy), and validation loss (Val_Loss). The results of this comparative analysis are summarized in Table 1.

Table 1. Results obtained from the analysis

Epoch	CNN: Loss	CNN: Accuracy	CNN: Val_Loss	CNN: Val_accuracy	OCNN: Loss	OCNN: Accuracy	OCNN: Val_Loss	OCNN: Val_Accuracy
1	0,5918	0,7423	0,3428	0,8782	1,0623	0,7212	0,9611	0,7672
2	0,4119	0,8305	0,313	0,8798	0,8975	0,8162	0,7962	0,8484
3	0,3579	0,8531	0,3111	0,8802	0,8369	0,8346	0,7663	0,8496
4	0,344	0,8625	0,2783	0,8977	0,7857	0,8486	0,6785	0,8961
5	0,3034	0,8808	0,2956	0,889	0,7546	0,8551	0,6577	0,8969
6	0,281	0,8897	0,2832	0,8957	0,731	0,8561	0,6406	0,8866
7	0,2452	0,9036	0,3212	0,8882	0,6981	0,8647	0,6442	0,8747
8	0,1982	0,9246	0,3421	0,889	0,6673	0,8662	0,5984	0,889
9	0,1687	0,9379	0,3596	0,8886	0,6422	0,8713	0,6834	0,8587
10	0,1463	0,9464	0,4082	0,8826	0,6248	0,8684	0,5433	0,9041

When the table is analyzed, the verification accuracy of the CNN model was initially recorded as 87.82%, and as the training process progressed, this value reached a maximum of 89.77%. However, this value decreased to 88.26% at epoch 10. The training loss decreased continuously (0.5918 - 0.1463) and the training accuracy increased from 74.23% to 94.64%. On the other hand, the validation loss tended to increase after epoch 4, from 0.2783 to 0.4082, indicating that the model was overfitting. The learning curve of the CNN model after training is given in Figure 6.

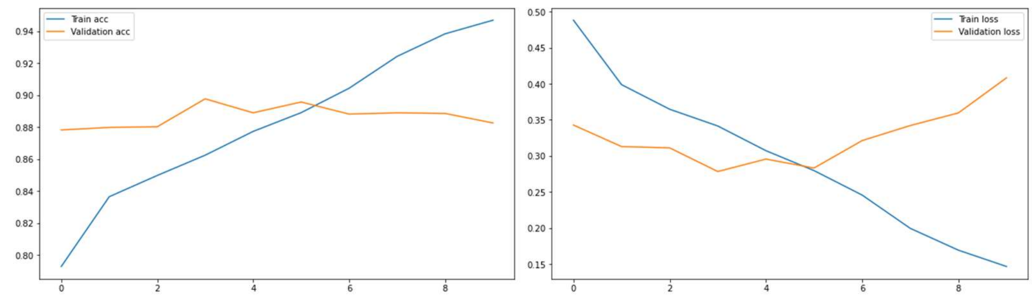

Figure 6. CNN learning curve

In the OCNN model, while the validation accuracy was 76.72% at the beginning, it increased consistently as the training process progressed and reached 90.41% at the end of the 10th epoch. The training loss decreased from 1.0623 to 0.6248 while the training accuracy increased from 72.12% to 86.84%. Moreover, the verification loss reached its lowest level at epoch 8 with a value of 0.5984 and was observed to be 0.5433 in the last epoch. This shows that OCNN shows a stronger generalization ability and greatly reduces the tendency of overlearning. The learning curve of the trained OCNN model is shown in Figure 7.

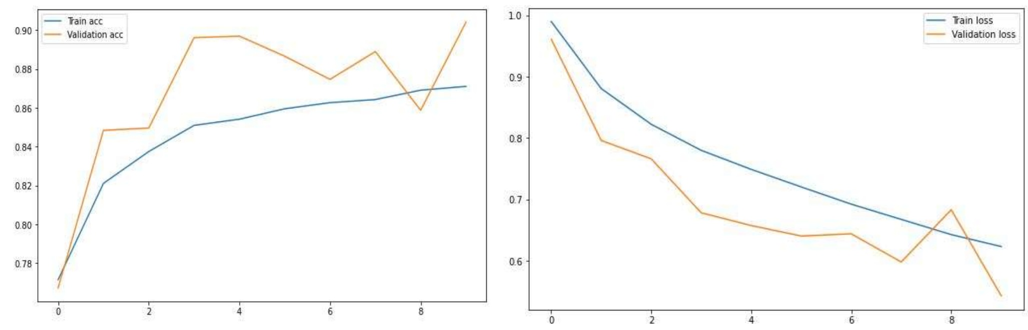

Figure 7. OCNN learning curve

The advanced techniques employed in the OCNN model effectively managed the validation loss while enhancing the validation accuracy. The traditional CNN models, on the other hand, achieved faster accuracy improvement, but showed unstable performance on the validation set. This analysis reveals that the OCNN model provides more stable and successful results, especially on complex datasets. In Figure 8, the sample images from the test dataset and the labels predicted by the OCNN model for these images clearly demonstrate this success.

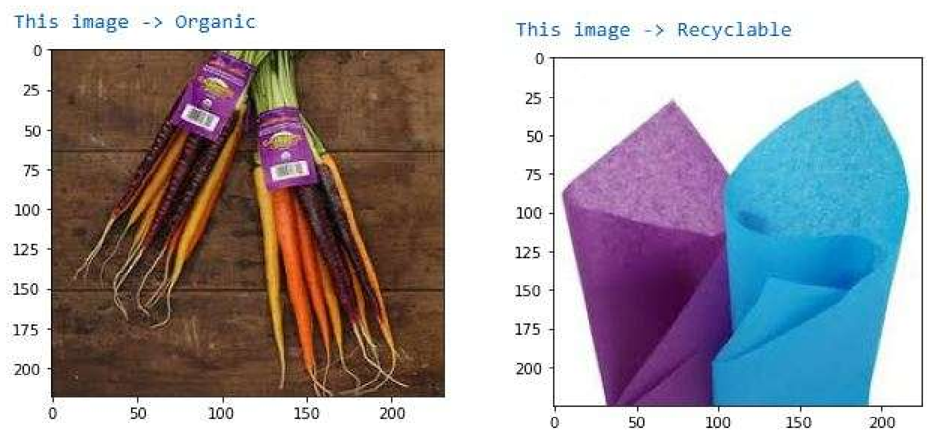

Figure 8. Example images for predicted classes from the test dataset

5. Conclusion

The increasing amount of waste worldwide continues to pose a serious threat to the environment and nature. For waste management processes to be more effective, it is of great importance to classify waste correctly. In this study, an artificial intelligence-based solution was developed to reduce the environmental and economic threats of increasing waste amounts, and waste was categorized into two categories: organic and recyclable. Using an open-source dataset containing a total of 22,564 images, an Optimized Convolutional Neural Network (OCNN) was developed to improve the waste classification process. Within the scope of the study, traditional Convolutional Neural Network (CNN) and OCNN models were trained and compared.

According to the findings of the analysis conducted within the scope of the research, the OCNN model exceeded the 88.26% validation accuracy rate of the traditional CNN model with a validation accuracy rate of 90.41%, and thus it was found to be a more efficient model. The fact that the verification loss of the traditional CNN model tends to increase during the training process indicates that the model tends to overlearn. On the other hand, the OCNN model provides a steady increase in verification accuracy and minimizes the verification loss, which leads to a higher generalization capacity of this model. This finding confirms that modern optimization techniques such as Batch Normalization, Dropout and Global Average Pooling are critical in improving CNN performance. The findings are in line with similar studies in literature. At this point, Ramsurrun et al. (2021) achieved similarly high accuracy rates with the VGG19 model but could not completely avoid the risk of overlearning. Again, Pandey et al. (2023) pointed out the importance of hyperparameter optimization in CNN models to improve accuracy, and the value obtained by the OCNN architecture used in this study supports this suggestion.

In terms of theoretical infrastructure, this study has been evaluated in the light of the theory of conservation of resources. While the theory argues that limited resources should be managed sustainably, the OCNN model developed in this study falls within the scope of the theory with its ability to provide a technological solution to ensure the protection of natural resources. Artificial intelligence-based waste management systems not only increase environmental sustainability but also provide economic and social benefits. Automating waste classification reduces the high labor costs caused by traditional methods, provides economic efficiency to businesses, is widely accepted by society due to its practical and effective nature, and moreover creates a more positive future projection in terms of sustainability.

The developed OCNN model has the potential to form a basis for industrial applications beyond improving waste management processes. The model can be integrated into robotic systems by waste management companies or used in local waste separation facilities. In particular, the high accuracy rate during the separation of organic and recyclable waste indicates that these systems can increase their efficiency in practical applications.

The findings also provide important guidance to policy makers in making waste management policies more efficient and sustainable. In this context, local governments and municipalities can promote smart waste management practices by popularizing artificial intelligence-based systems in recycling facilities. In addition, recycling can be encouraged to become more economically sustainable by ensuring the adoption of automation processes in waste separation through state support and tax incentives. In line with the perspective of protecting natural resources emphasized in the study, it is seen that the developed model overlaps with global sustainability goals. Implementation of policies such as increasing recycling rates and evaluating organic waste in biogas or compost production can contribute to strengthening environmental sustainability.

There are also some limitations to this study. The study focused on only two waste categories, and it could not be evaluated how the performance would change if a larger dataset including other waste types was modeled. In addition, the dataset used in the study is publicly available and it is recommended to test the generalization capacity of the model more comprehensively with waste images obtained from different geographies. It is very important for future studies to investigate the applicability of the OCNN model on different datasets and waste categories, and also to include economic analyses of such systems, both for the development of academic literature and for the formation of practical applications.

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Conflict of Interest: None
Funding: None
Ethical Approval: None
Author Contributions: Muhammed Akif YENİKAYA (100%)

Çıkar Çatışması: Yoktur.
Finansal Destek: Yoktur.
Etik Onay: Yoktur.
Yazar Katkısı: Muhammed Akif YENİKAYA (%100)