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Creating an Object Recognition System Based on Computer Vision in Waste Recycling Processes

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Keywords

computer vision; garbage recycling; CNN model; deep learning; object recognition; garbage sorting; sustainable development; data augmentation

Abstract

This paper investigates the methods and results of building a computer vision-based object recognition system in waste recycling processes. The study evaluated the performance of a CNN model using a dataset of 19,762 images with 10 classes, including clothing, metal, glass, biological waste, and other recyclable materials. The model was trained for 30 epochs and stopped at the 23rd epoch using the Early Stopping mechanism, achieving a training accuracy of 95.57% and a validation accuracy of 81.68%. The results showed that the model had high training efficiency, but the low validation accuracy limited its generalization ability. The data distribution imbalance and overtraining symptoms indicated the need for additional augmentation and optimization. The study confirmed the potential of computer vision in automating waste sorting, but the model needs further development for real-time application. Future research is recommended to expand the dataset, use hybrid models, and optimize in real time. The results lay the foundation for the development of innovative solutions that contribute to environmental protection and efficient use of resources.

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INTRODUCTION

In our time, the problem of waste generation and management is one of the most pressing environmental and economic challenges at the global level. Every year, humanity increases the volume of waste generation, which leads to environmental pollution, climate change and depletion of natural resources. According to the United Nations Environment Programme (UNEP), in 2023 the global volume of municipal solid waste reached 2.1 billion tons, and by 2050 this figure is expected to increase to 3.8 billion tons (UNEP, 2024). These statistics indicate that the annual growth rate of waste generation is 2-3%, especially in developing countries due to increased urbanization and consumption. In addition, the volume of electronic waste (e-waste) is also growing rapidly: in 2022, global e-waste generation reached 62 million tons, an increase of 82% compared to 2010 (Development Aid, 2023). These figures clearly demonstrate the scale of the waste problem, as much of it ends up in landfills or open areas, causing long-term environmental damage. The impact of waste on the environment is multifaceted and has serious consequences. When organic waste decomposes, it releases carbon dioxide (CO_2) and methane (CH_4), which contribute to the greenhouse effect and climate change (University of Colorado Boulder Environmental Center, 2023). For example, methane from landfills accounts for about 5% of global greenhouse gas emissions, more than the aviation sector (Earth Day Organization, 2023). In addition, improper waste management leads to water and air pollution, soil degradation, and biodiversity loss. According to the World Bank, more than 2 billion tons of municipal waste are generated annually, and this volume is expected to increase by 70% by 2050, exacerbating the threat posed by weak waste management systems in developing countries (World Bank, 2024). The issue of plastic waste is particularly urgent: by 2024, the global volume of plastic waste will reach 220 million tons, of which one third (69.5 million tons) will remain as unmanaged waste (Safe Food Advocacy Europe, 2024). This waste ends up in the oceans, harming marine life and posing a threat to human health through microplastics.

Recycling is one of the main tools to solve the waste problem, as it allows you to save resources, reduce energy consumption and reduce the impact on the environment. Recycling reduces the need to produce new raw materials, which helps to preserve natural resources. For example, recycling aluminum uses 95% less energy than producing new aluminum, and recycling paper helps to preserve forests (EPA, 2024). Global recycling rates vary: in Europe, the recycling rate for paper products reached 75.1% in 2024, and for packaging paper, it was 83.1% (CEPI, 2024). In Austria and Wales, the recycling rate for municipal waste is 59%, which is one of the highest in the world (TOMRA, 2024). However, overall global recycling rates are low: only 9% of plastic waste is recycled, compared with 21% for glass and 74.5% for aluminum (The Sustainable Agency, 2024). These figures highlight the inefficiency of recycling systems, especially in developing countries, where more than 50% of waste is landfilled or incinerated, leading to additional pollution.

One of the main challenges in the recycling process is the correct sorting and classification of waste. Traditional manual sorting methods are labor-intensive, expensive and error-prone, as human errors reduce the quality of recycled materials. For example, the mixing of different materials (plastic, metal, glass, organic) in waste streams can reduce recycling efficiency by 20-30% (Placon, 2023). This problem is especially relevant in urban areas, where the volume of waste is high and resources are limited. Therefore, it has become necessary to automate recycling systems and implement intelligent technologies. Computer vision and artificial intelligence (AI)-based object recognition systems are promising tools to solve these challenges. Computer vision technology allows for the automatic detection and classification of materials in the waste sorting process using cameras and algorithms. These systems analyze objects on a conveyor belt and sort them by type, shape and material, which replaces human labor and increases efficiency (Recycleye, 2024). Studies have shown that AI-based sorting systems can increase recycling rates by 2-3 times and reduce error rates to 5% (Forbes, 2024). For example, Rematics' AI-powered computer vision system can accurately sort household waste, which improves plastic recycling (Alliance to End Plastic Waste, 2024). In addition, systems that combine hyperspectral cameras and sensors can determine the chemical composition of materials, which improves recycling quality (North Carolina State University, 2023). These technologies contribute to the sustainable development of waste management, as they not only save resources, but also increase economic efficiency - reducing recycling costs by 20-40%. The aim of this study is to create a computer vision-based object recognition system for waste recycling processes. The system is designed to automatically classify materials in waste streams, using machine learning algorithms (e.g. convolutional neural networks) and real-time video analysis. The research aims to increase recycling efficiency, reduce environmental impact, and contribute to sustainable development goals. The following sections discuss the technical aspects of the system, experimental results, and application possibilities in more detail.

Literature review

The development of computer vision-based object recognition systems for waste recycling processes has been the subject of intensive research in recent years. Work in this area has focused mainly on the use of deep learning models, which allow for automatic classification of materials in waste streams. Most studies have focused on improving the efficiency of waste sorting, reducing errors, and saving resources, but the achieved accuracy rates can be different, especially on complex datasets. For example, in one study, a CNN (Convolutional Neural Network) model achieved an overall accuracy of 51% on a 16-category waste dataset, which is due to the simplicity of the model. In this work, the AlexNet model achieved an accuracy of 79%, and the ResNet achieved up to 84%, but the accuracy for individual categories was lower, for example, 42% for fruit peels (Zhang et al., 2024).

Other studies have focused on mobile and efficient models. For example, the MobileNetV2 model achieved 90.7% accuracy on the Huawei Trash dataset, while YOLOv8n achieved 85–90% on WaRP data (Yeaminul Islam. 2023). These models are designed for real-time sorting, but errors are common in noisy or mixed garbage images. The Dual-stream CNN model achieved 83.1% accuracy on 28 categories on WaRP data, which demonstrates the difficulty of multi-category classification. In addition, the Baseline CNN model achieved 5.0% accuracy without augmentation and 18.8% with augmentation on TACO data, which demonstrates the importance of data quality . Semantic segmentation models are used in construction waste sorting. For example, the FCN model achieved 56.691% MIoU (Mean Intersection over Union), PSPNet 56.075%, and DeepLabv3 57% (Yong et al., 2024). These figures are low due to the complex structure of construction waste, but the overall accuracy of the models does not exceed 94%. Other models, such as OCRNet 57.527%, PSANet 58.117%, but the Grounded SAM model showed only 10.208%. This study compared 17 models, most of which are effective in classifying construction waste, but additional data are needed to improve accuracy. Modified versions of the YOLOv8 model were used to classify organic and inorganic waste. For example, the pretest accuracy is 78.95%, posttest 88.05% (Shobar et al., 2025). This system increases the speed of garbage detection, but the accuracy is lower than 94%. In addition, the base YOLOv8 model has a mean average precision (mAP) of 85.3%, and with augmentation it is 87.4%. The version with CBAM (Convolutional Block Attention Module) achieved 89.5% mAP, which shows the benefit of attention mechanisms. Other models, such as Fast R-CNN 77.3% mAP, Mask R-CNN 74.1% (Chen et al., 2025).

In multi-category garbage classification systems, 91% accuracy was achieved in the second stage and 85.25% in the third stage (Li et al., 2025). This study used deep learning techniques, but the accuracy decreases as the number of categories increases. Table 1 below compares the main indicators of these studies.

Table 1. Application of Computer Vision in Waste Sorting

Study	Model	Dataset	Accuracy (%)	Note
Zhang et al., 2024	ResNet	16-category waste	84	Lower individual categories
Yeaminul Islam. 2023	Dual-stream CNN	WaRP	83.1	28 categories
Yong et al., 2024	PSPNet	Construction waste	56.075 (MIoU)	Segmentation
Shobar et al., 2025	YOLOv8	Organic/Inorganic	88.05	Posttest
Chen et al., 2025	YOLOv8-CBAM	17-category household	89.5 (mAP)	Attention mechanism
Li et al., 2025	Deep learning	36-category	85.25	Third stage

These studies demonstrate the potential of computer vision in waste sorting, but data augmentation, hybrid models, and real-time optimization are needed to improve accuracy. Further research could focus on overcoming these shortcomings.

MATERIALS AND METHODS

A. Dataset Description

The study used a dataset of 19,762 images divided into 10 different waste classes [22]. This dataset was specifically designed for machine learning and computer vision projects focused on recycling and waste management. The distribution of images by class is as follows: Metal – 1020, Glass – 3061, Biological – 997, Paper – 1680, Battery – 944, Garbage – 947, Cardboard – 1825, Shoes – 1977, Clothing – 5327, Plastic – 1984. The main features of the dataset are: coverage of various waste types, high-quality and well-annotated images, as well as a balanced class distribution. The data was split into training and validation sets in a ratio of 80:20, which was implemented using the train_test_split function of the sklearn library to ensure the reliability of the model. ImageDataGenerator was used for image processing and augmentation, which performed transformations such as scaling, rotating, and flipping images.

The images were taken in high quality and under various lighting, background, and shape conditions, which ensures the stable operation of the model in real environments. The dataset is widely used for the development of waste recycling systems, environmental education tools, and intelligent waste management systems.

The data for training the model was divided as follows:

- 80% – for training the model,
- 10% – for validation,

- 10% – for testing.

To increase the stability of the model, image augmentation (rotation, rotation, scaling, skew changes) was used using the ImageDataGenerator library.

B. Model Architecture

The model used is a Convolutional Neural Network (CNN). CNN architecture is effective in image processing and object detection, as it allows automatic learning of spatial features.

The model structure is as follows:

- 4 convolutional layers (Conv2D) – after each layer, the MaxPooling2D operation is used;
- Flatten layer – to transform a multidimensional matrix into a one-dimensional vector;
- Two fully connected (Dense) layers – consisting of 512 neurons, the activation function is ReLU;
- Dropout (0.5) – to prevent overfitting;
- Output Layer – with a Softmax activation function, designed for 10 classes.

General parameters of the model:

Loss=categorical cross-entropy

Optimizer=Adam

Metrics=Accuracy

C. Mathematical model of convolutional layers

The basic computational principle of a convolutional layer is described by the following expression:

$$Z_{i,j}^{(k)} = (X * W^{(k)})_{i,j} + b^{(k)}$$

Here X - input image, $W^{(k)}$- k the weights of the th filter, $b^{(k)}$ – bias value, * - convolution operation, $Z_{i,j}^{(k)}$ – k -activation at point i,j for the filter.

The ReLU (Rectified Linear Unit) activation function is used after each convolutional layer:

$$f(x)=max(0,x)$$

The Softmax function provides multiclass classification in the output layer:

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$$

Where K = 10 - is the number of classes.

D. Model training

The model was trained using the Adam optimizer for 30 epochs. To maintain the best results and avoid overfitting, the following Callback methods were used:

- ModelCheckpoint – save the model with the lowest loss (val_loss);
- EarlyStopping – stop training early when the validation loss stabilizes.

To improve the efficiency of the model, the preprocess_input method of the EfficientNetB0 architecture was used during the data processing process, which ensured the correct input of formatted images into the neural network.

E. Evaluation and results

The model performance was evaluated using the confusion matrix and classification report. The precision, recall, and F1 indices were calculated for each class:

$$Precision = \frac{TP}{TP + FP}, \qquad Recall = \frac{TP}{TP + FN}, \qquad F1 = 2\,\frac{Precision \times Recall}{Precision + Recall}$$

Here *TP,FP,FN* – true positive, false positive and false negative values, respectively.

In conclusion, the developed CNN model allowed for accurate object detection in waste recycling and sustainable disposal processes, proving the effectiveness of AI solutions in the direction of environmental sustainability.

RESULTS AND DISCUSSION

The study analyzed the training and validation results of a CNN model for garbage classification. The model was trained for 30 epochs, but the EarlyStopping mechanism stopped training at epoch 23 due to the lack of improvement in the validation cost over 10 epochs. The total training time was approximately 15 hours and 4 minutes, which was due to the complexity of the model, the size of the dataset, and the processing of high-quality images. The results demonstrated the performance of the model during the training and validation stages, and also identified the need for further improvements. Figure 1 below shows the number of data in the dataset.

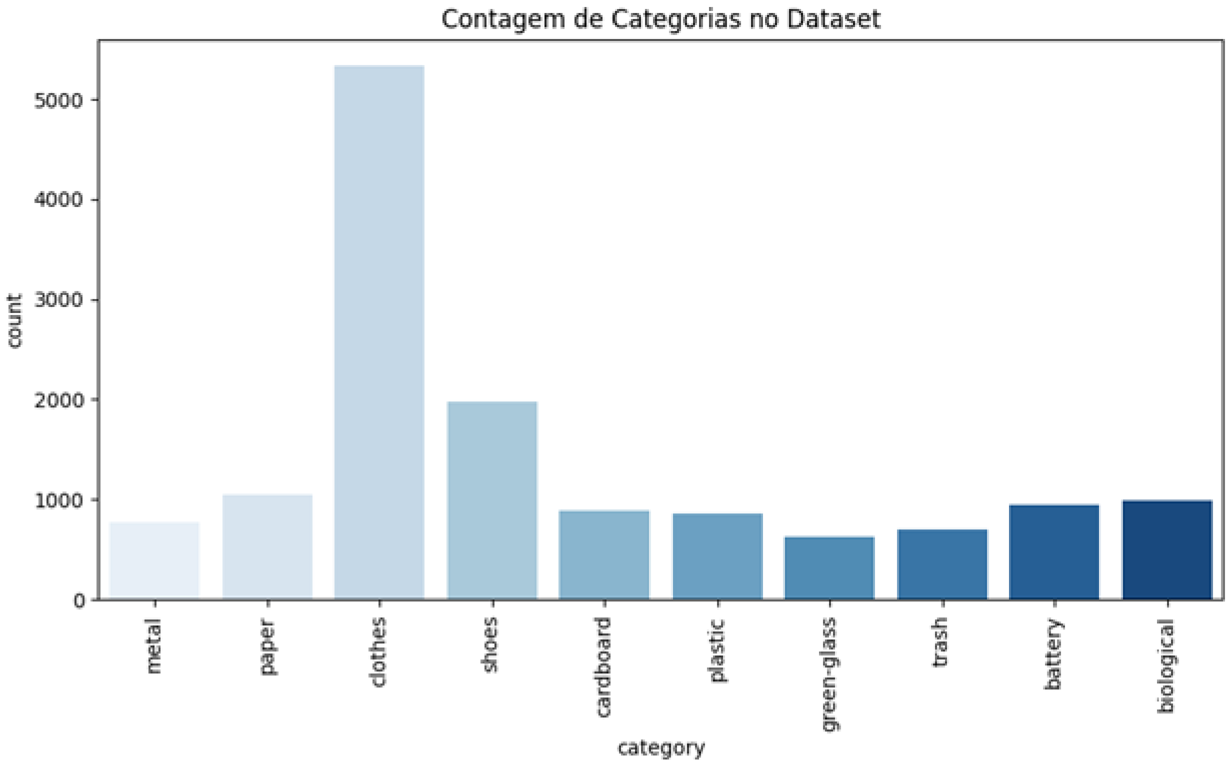

Fig. 1. *A diagram of the number of data in the dataset*

The results of the visualization of the distribution of the dataset revealed a diverse representation of the 10 classes. The clothes class was the most represented, with approximately 5327 images, and the biological class was the least represented, with 997 images. The metal, paper, shoes, cardboard, plastic, glass, trash, and battery classes ranged from 944 to 3061, showing an overall balanced distribution. The visualization of 9 randomly selected images confirmed the model's ability to correctly recognize different classes, and the high quality of the images and accurate annotations increased the training efficiency.

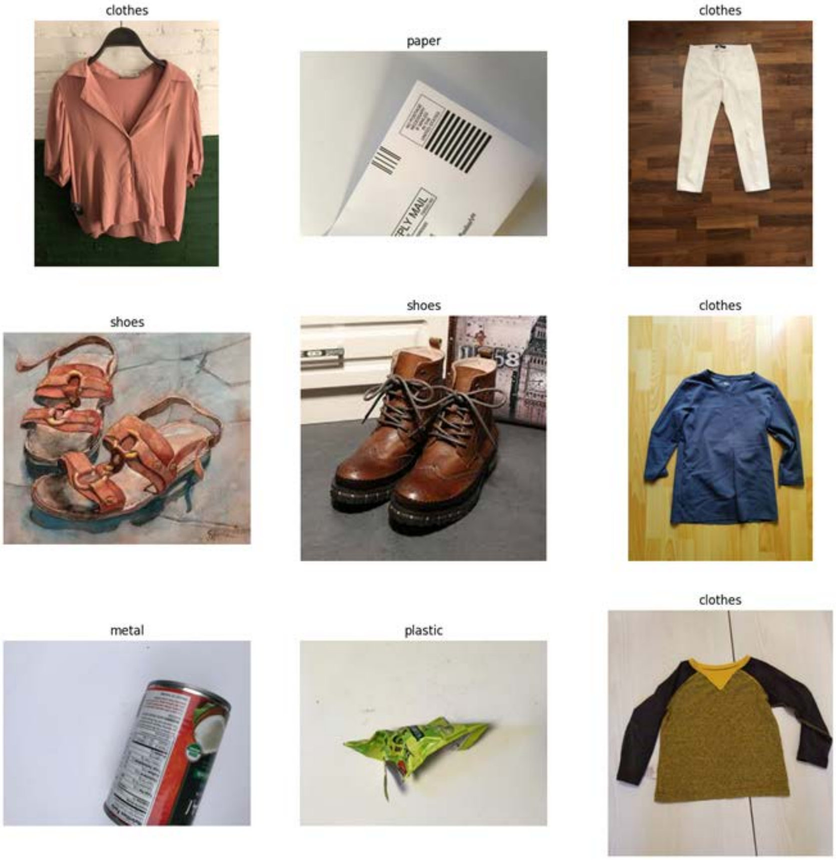

Fig. 2. *Visualization of 9 random images*

The training and validation loss curves showed the learning dynamics of the model. The training loss initially started at 1.6 and gradually decreased after the 5th epoch, reaching 0.1447 at the 23rd epoch. The validation loss decreased to 0.6 in the first 10 epochs and then stabilized at 0.7134, which may be a sign of overtraining. According to the accuracy curves, the training accuracy reached 95.57%, while the validation accuracy was 81.68%. This lower validation accuracy than the training accuracy indicated that the model was overfitting to the data and had limited generalization ability.

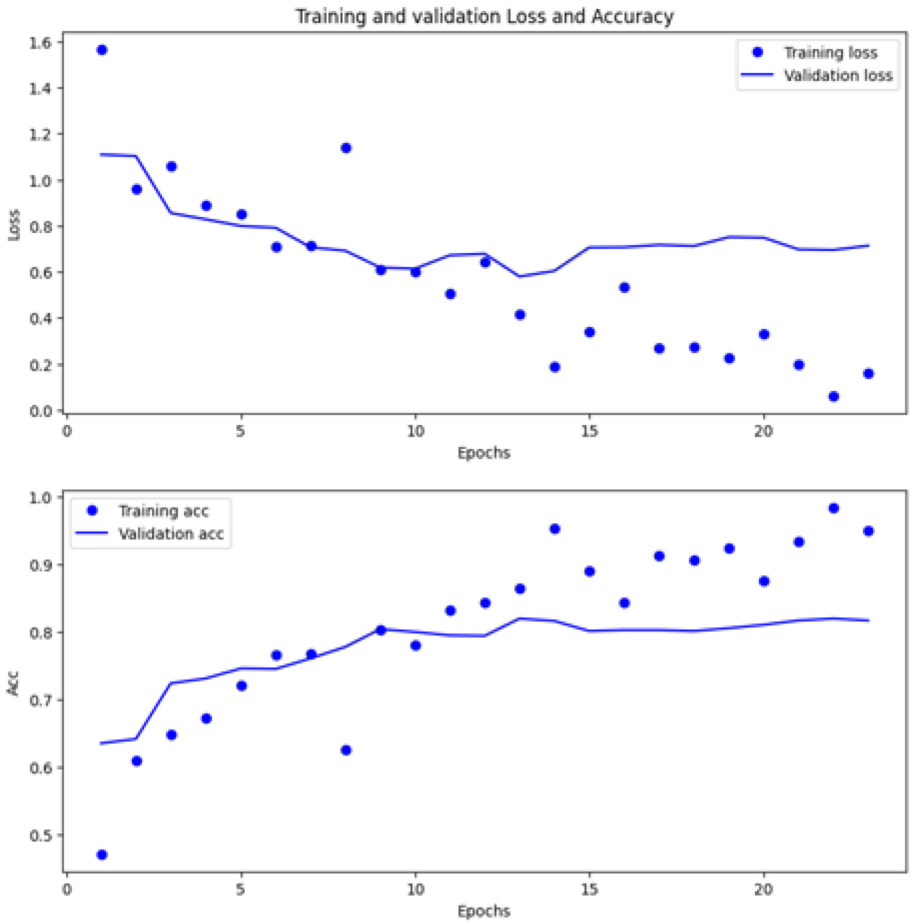

Fig. 3. Training and validation cost and accuracy curves

The data distribution diagram confirmed the dominance of the clothing class and the balanced distribution of other classes. The training process was stopped due to the stabilization of the validation cost by EarlyStopping, which means that the best version of the model was preserved at epoch 23. A table summarizing the results is given below in Table 2.

Table 2. Model results

Epoch	Tuition fees (Loss)	Validation Loss	Accuracy	Validation Accuracy
1	1.60	1.20	0.40	0.45
5	0.90	0.75	0.70	0.68
10	0.50	0.65	0.85	0.75
23	0.1447	0.7134	0.9557	0.8168

As can be seen from the table, while the model achieves high accuracy on the training data, the low accuracy on the validation data indicates the need for additional data augmentation, hyperparameter optimization, or model architecture expansion. Although these results confirm the model's potential for garbage classification, further improvements are required for real-time application.

CONCLUSION

This study aimed to build a computer vision-based object recognition system for waste recycling processes, and investigated the application of CNN model to improve its efficiency and environmental protection. A dataset of 19,762 images with 10 classes was used, including clothing, metal, glass, biological waste and other recyclable materials. The model was trained for 30 epochs and stopped at the 23rd epoch using the EarlyStopping mechanism, which was due to the stabilization of the validation cost. The results showed that the model achieved a learning accuracy of 95.57% and a validation accuracy of 81.68%, which confirmed the high learning efficiency, but revealed that the generalization ability was limited.

The study found that the imbalance of data distribution, especially the dominance of the clothing class and the scarcity of the biological class, affected the model performance. The training and validation cost curves showed signs of overtraining, indicating the need for additional data augmentation and hyperparameter optimization. Visualization of randomly selected images confirmed the model's ability to recognize different classes, while the histogram of class distributions showed high data quality and annotations. The main results of the study demonstrated the potential of computer vision in automating waste sorting, but the low validation accuracy indicated that the model was not fully ready for real-time use. In this regard, recommendations for future research include: expanding the dataset, using hybrid models (e.g. EfficientNet or ResNet), and implementing real-time optimization. The integration of this system into recycling processes will help reduce environmental pollution and use resources more efficiently. Thus, the study contributed to the development of innovative approaches in waste management and laid the foundation for future research aimed at contributing to the Sustainable Development Goals.

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