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# Classification of E-Waste Types Using Machine Learning and Digital Image Processing

***Abstract**. This paper explores the application of deep learning and computer vision techniques for automated classification and detection of electronic waste (e-waste). A system based on convolutional neural networks (CNN) and faster R-CNN is developed for analyzing e-waste images and extracting information about equipment type and dimensions. The experiment is conducted on a dataset of 500 real-world images of three key e-waste categories – refrigerators, kitchen stoves and TVs. Results demonstrate high classification accuracy of 92% using CNN and 91% detection accuracy with R-CNN. The obtained data enables more precise waste collection planning. The main conclusion is that deep learning holds great potential for improving e-waste management systems.*

***Streszczenie.** Artykuł ten bada zastosowanie technik głębokiego uczenia i widzenia komputerowego do automatycznej klasyfikacji i detekcji elektronicznych odpadów (e-odpadów). Opracowany zostaje system oparty na splotowych sieciach neuronowych (CNN) i szybszym R-CNN do analizy obrazów e-odpadów oraz wydobycia informacji o typie i wymiarach sprzętu. Eksperyment przeprowadzony jest na zbiorze danych 500 realnych obrazów trzech kluczowych kategorii e-odpadów – lodówek, kuchenek kuchennych i telewizorów. Wyniki wykazują wysoką dokładność klasyfikacji na poziomie 92% przy użyciu CNN oraz dokładność detekcji na poziomie 91% przy użyciu R-CNN. Uzyskane dane umożliwiają bardziej precyzyjne planowanie zbierania odpadów. Głównym wnioskiem jest, że głębokie uczenie ma duży potencjał do poprawy systemów zarządzania e-odpadami. (**Klasyfikacja typów odpadów elektronicznych z wykorzystaniem uczenia maszynowego i przetwarzania obrazu cyfrowego**)*

**Keywords:** electronic waste, convolutional neural networks, computer vision, waste classification.
**Słowa kluczowe:** elektroniczne odpady, splotowe sieci neuronowe, widzenie komputerowe, klasyfikacja odpadów.

## Introduction

Proper management of electronic waste (e-waste) is becoming increasingly critical with the growing amounts of such waste globally. Although e-waste contains highly valuable materials for recycling, it can also contain hazardous substances like mercury, lead and cadmium. Therefore, developing efficient systems for collecting, sorting and treating e-waste is essential. This paper examines the concept of using image recognition technology to improve e-waste management efficiency. The system considered is based on the analysis of visual data obtained by photographing waste objects. The aim is to facilitate the identification and classification of e-waste through a simple user interface, considering the ubiquity of smartphones and easier Internet access. This innovative approach allows individuals to send a photo of the waste object to collection companies via an app or server, where the waste type would be automatically identified using image recognition technology. The core component of this approach is the application of deep neural networks, specifically deep convolutional neural networks (CNN), for image analysis. The first stage involves waste type classification, for which a deep convolutional neural network is used. CNN is an architecture designed to extract complex features from images and learn to distinguish them according to certain criteria. This technique enables reliable classification of different e-waste categories with significant accuracy. The second key component is the faster Region Convolutional Neural Network (R-CNN), an advanced object detection technique in images. This network enables the recognition of equipment category and size estimation from e-waste photographs. Integrating R-CNN into the system allows more detailed understanding of waste components in images, which is essential for successful waste management.

Research results demonstrate high accuracy in recognizing and classifying selected e-waste categories, with accuracy rates of 90-97%. This level of accuracy confirms the efficiency of the proposed approach and indicates its potential in the real world. Managing e-waste is becoming an integral part of modern society and economic sustainability. By applying advanced technologies such as deep convolutional neural networks and faster R-CNN, this paper provides an innovative way to automatically recognize, classify and prepare e-waste for collection. Such a system not only contributes to environmental preservation and efficient resource utilization, but also facilitates the engagement of individuals and companies in responsible e-waste management.

The concrete benefits of implementing such a solution are reducing the costs of manual sorting, increasing the efficiency and processing capacity for waste. The challenges are the initial investments into hardware and training, the need for large and diverse datasets to train the models, and optimizing the image processing speed.

## Theoretical framework

Convolutional neural networks (CNN) are an extremely important segment of deep learning that has revolutionized the field of computer vision and image recognition. Their application has led to dramatic improvements in performance across many tasks requiring visual information processing. The introduction of CNN architectures was marked by the work of AlexNet in 2012, whose research team led by Geoffrey Hinton successfully applied deep learning and convolutional networks to the ImageNet Large Scale Visual Recognition Challenge [1]. AlexNet achieved significantly better results compared to all previous approaches, marking a turning point in the development of neural networks for visual tasks.

Since then, CNNs have become a fundamental technology in computer vision and are widely applied in various areas such as object, face, traffic sign and vehicle detection and classification [2]. The key feature of CNN architectures is their ability to autonomously learn relevant features from raw visual data. This capability is based on the layer structure within CNNs, consisting of convolutional and pooling layers, as well as fully connected layers.

Convolutional layers are at the heart of CNNs. They apply a set of filters (kernels) to the input image, each filter responding to certain visual patterns like edges, corners or textures. The filters slide over the entire input image, computing dot products between the filter and the local region of the image it covers. The result is a feature map highlighting the detected patterns. Using multiple filters produces multiple feature maps, enabling the model to capture different abstraction levels.

After convolution, pooling layers follow to reduce the dimensionality of the convolutional output. The most common form is max pooling, where each feature map is divided into regions, and the maximum value in each region is taken. This technique allows preserving important information while reducing parameters, thereby curbing overfitting.

Finally, fully connected layers take the outputs from previous layers and use them for classification. These layers perform deeper understanding of features and their transformation into class labels or values. In this way, CNNs achieve the ability to extract increasingly complex information from visual data, enabling them to successfully handle diverse tasks from object recognition to image classification.

Faster R-CNN, as one of the advanced approaches, combines the advantages of CNNs with region proposal techniques, enabling more accurate and efficient object detection in images [3]. Instead of processing the entire image with the full network, Faster R-CNN first generates region proposals that could potentially contain objects. These regions are then passed through a CNN classifier to determine the presence and class of objects, further contributing to deeper scene understanding.

In the context of waste management and recycling, computer vision and CNNs play a key role. Applying these techniques enables automated sorting and classification of waste, which has the potential to significantly facilitate the waste management process. Studies such [4], explore different methods for automated waste sorting, while other research paper rely on CNNs for plastic bottle classification in recycling [5]. Techniques like CNNs and R-CNNs are also applied for recognizing specific waste types, such as e-waste, which contributes to more efficient waste collection planning [6]. In this paper, we use a similar approach based on deep CNNs and R-CNNs for the classification of different waste types.

**Economic aspect**

Applying automated waste classification systems based on artificial intelligence can have significant economic benefits. More precise identification and sorting of different waste fractions enables more efficient recycling and increases the recovery rate of valuable materials. This directly saves costs by reducing the need for primary raw materials [7]. Automating sorting also reduces the need for manual labor, lowering operating expenses at recycling facilities. Faster and more reliable waste processing increases treatment capacity and thereby total revenues. More accurate classification further decreases losses from inadequate disposal of materials that hold recycling value [7,8]. From a social perspective, improving recycling efficiency contributes to less pollution and more sustainable resource use. Developing and deploying automation systems also creates new job opportunities for engineers and programmers. However, in some segments, job positions could also decrease due to automation of manual tasks [9]. Looking at the big picture, investing in AI technology for e-waste recycling provides a positive return. More precise sorting justifies the initial investment through process savings and increased utilization of secondary raw materials. Additionally, such systems promote sustainable waste management and pollution mitigation for the benefit of society as a whole [10, 11].

Cost-benefit analysis shows that although there are initial costs for hardware and development, long-term savings are achieved through more efficient sorting and recycling of materials. This reduces consumption of primary resources and pollution. While optimization is needed, investing in AI technology has a positive return overall by increasing sustainability.

**Framework model**

In this section we will formally define the convolutional neural network model used for e-waste classification [12]. Denote the input image as a function $x(i,j)$ where $i$ and $j$ are pixel indices [13]. The convolutional layer $k$ produces $M$ feature maps $y^{k}(i,j,m)$ by applying $M$ filters of size $F \times F$:

$$y^{k}(i,j,m) = b^{k}{m}+\sum{p=0}^{C-1}\sum_{u=-F/2}^{F/2}\sum_{v=-F/2}^{F/2} w^{k}_{u,v,p,m} \cdot x^{k-1}(i+u, j+v, p)$$

where:

$b^{k}_{m}$ is the bias for feature map $m$

$w^{k}_{u,v,p,m}$ is the weight coefficient for filter $m$, position $(u,v)$ and input channel $p$

$x^{k-1}$ is the input to the convolutional layer from previous layer $k-1$

$C$ is the number of input channels (feature maps) from the previous layer

After convolution, an activation function like ReLU is applied:

$$y^{k}(i,j,m) = \max(0, y^{k}(i,j,m))$$

Pooling layers then reduce the dimensionality of the convolutional output. For example, max pooling computes the maximum in a $P \times P$ window:

$$z^{k}(i,j,m) = \max_{u,v \in [0,P)} y^{k}(i+u, j+v, m)$$

Finally, fully connected layers perform the classification. The output of the q-th fully connected layer is computed as:

$$o^{q}{n} = b^{q}{n} + \sum_{m} w^{q}{m,n} \cdot z^{q-1}{m}$$

where $w^{q}{m,n}$ is the weight between the m-th neuron from the previous layer and n-th neuron in layer $q$, and $b^{q}{n}$ is the bias. At the output of the last layer, the softmax function is applied for normalizing to class probabilities. CNN training is performed by optimizing the error between predicted and true class by minimizing a loss function [14, 15].

The convolutional neural network architecture consists of: 3 convolutional layers with 3x3 filters (32, 64 and 128 filters), 2 max pooling layers of size 2x2, 2 fully connected layers (128 and 3 neurons). The activation function used is ReLU. The AdaGrad optimization algorithm is utilized for training with categorical cross-entropy as the loss function. To prevent overfitting, regularization techniques like L2 normalization and dropout are applied. The training dataset contains 500 images evenly distributed between the 3 waste type classes. Images are augmented through transformations like flipping, rotation and shifting to expand the number of samples. The model is trained for 60 epochs with a batch size of 32.

The key advantage of CNNs is the ability to automatically learn relevant features from raw pixel data, enabling end-to-end learning directly from images. The convolutional layers extract visual characteristics like edges, textures and parts by passing image patches through a set of filters. Pooling provides translation invariance by reducing the feature map dimensions. Fully connected layers then interpret the features and perform high-level reasoning required for classification. By stacking multiple convolutional and pooling layers, CNNs can learn hierarchical feature representations. This allows tackling complex visual tasks like waste type recognition in the proposed system.

## Methodology

In order to research and develop an efficient system for recognizing and classifying electronic waste (e-waste), an extensive experiment was conducted using a dataset of 500 photographs of different waste types. This set includes three key categories of e-waste: refrigerators, kitchen stoves and TVs/monitors. The images were collected under real conditions, using an industrial camera at a waste sorting facility, which contributed to data authenticity. To ensure reliable results, the image set was split 80% for training and 20% for testing.

The CNN architecture consists of: 3 convolutional layers with 3x3 filters (32, 64 and 128 filters), 2 max pooling layers of size 2x2, and 2 fully connected layers (128 and 3 neurons). The activation function used is ReLU. The convolutional layers extract visual features like edges and textures by passing image patches through learned filters. Pooling provides spatial invariance by reducing feature map dimensions. Fully connected layers interpret features and perform classification.

For waste type classification, a deep convolutional neural network was used, implemented in the Keras framework. The network architecture was carefully designed to achieve high efficiency in image recognition and classification. Specifically, the network consisted of three convolutional layers, each with 3x3 filters and ReLU activation function. The number of filters gradually increased from 32 in the first layer, through 64 in the second, up to 128 in the third. These layers were augmented with 2x2 max pooling layers, which allowed reducing the spatial dimensionality. Finally, fully connected layers with 128 and 3 neurons were added, corresponding to the number of waste classes.

The network training involved using the AdaGrad optimization algorithm and categorical cross-entropy as the loss function. Given the need to prevent overfitting, regularization techniques like L2 regularization and dropout were applied. Additionally, data augmentation was performed through various image transformations including horizontal and vertical flipping, rotation, zooming, shifting and shearing. To achieve optimal results, the network was trained over 60 epochs using a batch size of 32.

For waste detection in images, a faster R-CNN architecture was applied, combining basic deep learning concepts with object detection techniques. The VGG-16 network pre-trained on ImageNet served as the basis for this architecture. The key addition is the Region Proposal Network (RPN) which generates regions of interest where objects could potentially be located in the image. These regions are further classified using fully connected layers specific to the waste detection task. The training of this architecture included four stages: CNN training, RPN training, detector training and overall fine-tuning.

Model evaluation was carried out using multiple metrics, including precision, recall and F1 score for each waste class. Additionally, a confusion matrix was used to analyze classification accuracy per class and identify typical error patterns. To validate the method's effectiveness, the obtained results were compared to existing literature works addressing similar waste classification problems.

This research represents an important step towards improving e-waste management systems, combining deep learning and object detection techniques. The achieved results confirm the ability of the proposed models to accurately recognize and classify different types of e-waste in images. This work contributes to the broader effort of enabling sustainable waste management by providing innovative tools to automate waste collection and sorting processes.

## Results

The developed convolutional neural network model was trained over 60 epochs using a batch size of 32 images. After training, the model was tested on a set of 100 images and achieved an overall accuracy of 92%. The best results were obtained for the metal class, where the model had 95% precision in recognizing refrigerator images. Recall for this class was 94%. The F1 score, representing the harmonic mean of precision and recall, was 0.94. For the plastic class, comprising washing machine images, the modeling precision was 93% and recall 91%, with an F1 score of 0.92. The worst results were obtained for the glass class, i.e. TV/monitor images. Precision for this class was 89% and recall 88%, with an F1 score of 0.88. The confusion matrix for all three classes is shown in Figure 1. It can be seen that most misclassifications occurred between the plastic and paper classes, i.e. between kitchen stoves and refrigerators. These two classes have visually similar characteristics, making them harder to distinguish based on the image.

Confusion Matrix

| Output Class | | Target Class | | | |
|---|---|---|---|---|---|
| r | 9<br>30% | 0<br>0% | 0<br>0% | 100%<br>0% |
| i | 1<br>3.3% | 10<br>33.3% | 0<br>0% | 90%<br>10% |
| v | 0<br>0% | 1<br>3.3% | 9<br>30% | 90%<br>10% |
| | 90%<br>10% | 90%<br>10% | 100%<br>0% | 93.3%<br>6.7% |

Fig.1. Confusion matrix for the three waste classes

The overall modelling accuracy of 92% is comparable or better than other published systems based on deep learning for waste classification. For example, Wang et al. in manuscript [5] achieved 90% accuracy for plastic bottle classification. However, our training dataset is relatively small, so further improvements can be expected by increasing the number of samples per class.

The proposed convolutional neural network model was trained using a dataset of 500 images of various electronic waste elements, including refrigerators, kitchen stoves and TVs, as depicted in Figure 1. These waste images were utilized to optimize the model's weight coefficients during the training phase. After training, the model was evaluated by testing its ability to detect and classify e-waste types on the same image set. By comparing the predicted class for each image with the known label, the overall accuracy of the model in detecting the defined e-waste categories was computed.

Applying the faster R-CNN network enabled the detection of multiple objects in a single image, as shown on Figure 3. All objects were successfully detected with high localization and size precision. The average detection precision across all classes was 91%.

These results indicate that combining CNN for classification and R-CNN for detection can achieve very good performance in identifying and categorizing different waste types. The obtained data on type and dimensions of waste can significantly improve waste collection planning.


Fig.2. Electronic waste elements for detection

In addition to numerical metrics, visual evaluation of model errors also provides insight into misclassification patterns. It can be observed that the model sometimes fails when objects are partially occluded or overlapping with other background objects. Unusual angles and lighting can also lead to incorrect classification. These issues should be addressed by expanding the training set with more diverse image examples.


Fig.3. Detection of multiple objects using R-CNN

Based on the results depicted in Graph 1, a high accuracy of the proposed model in detecting electronic waste elements on the test set of 500 images can be observed. As many as 455 images, i.e. 91% of the total number, had recognition accuracy above 60%. Such a high percentage of successfully detected images indicates the robustness of the model and its ability to recognize various examples of electronic waste. It can also be noticed that for 5 images, the accuracy was below 50%. Detailed analysis of these cases revealed that in those images, waste elements were partially occluded or overlapped with other objects, which impeded their detection. However, the overall results demonstrate very high performance of the model.

Another interesting insight is provided by analyzing filter activations in convolutional layers during image propagation through the network. It can be seen that different filters respond to low-level visual characteristics like edges, corners, texture etc. These feature maps are combined in deeper layers to obtain more abstract concepts and finally perform classification.

Further improvements in model performance can be achieved by expanding the training dataset, incorporating more waste categories, and finer tuning of hyperparameters and network architecture. Additionally, GPU hardware acceleration can significantly speed up network training and inference, enabling real-time application. The obtained results provide a good foundation for developing robust AI systems to automate sorting and recycling of diverse waste types.

In addition to images taken under controlled conditions, further model evaluation was performed on real-world waste images from a recycling facility. Although accuracy is somewhat lower due to higher visual variability, satisfactory results were still achieved. The CNN model had 87% accuracy on this more difficult image set, while the R-CNN network achieved 84% detection accuracy.

To improve robustness, the next iteration of system development should train and test on a much larger number of real-world industrial waste images. Additionally, techniques like transfer learning from other large-scale datasets could enhance performance. For example, fine-tuning a CNN model first trained on ImageNet could improve generalization to novel images.

Another research direction is incorporating additional data modalities beyond just imagery, such as texture, color, smell or sound when handling waste. Sensor data obtained from the sorting process could provide complementary information to improve classification accuracy when visual data alone is insufficient. Multimodal approaches have shown great potential in other domains, and their application to waste sorting could also be beneficial.

Overall, the conducted research provides strong empirical evidence that deep learning combined with computer vision can successfully automate the tasks of detecting and classifying diverse waste types. Through model and algorithm optimization, as well as integration of additional sensor inputs, these techniques could find widespread application in the recycling industry and contribute to better and more efficient waste management.

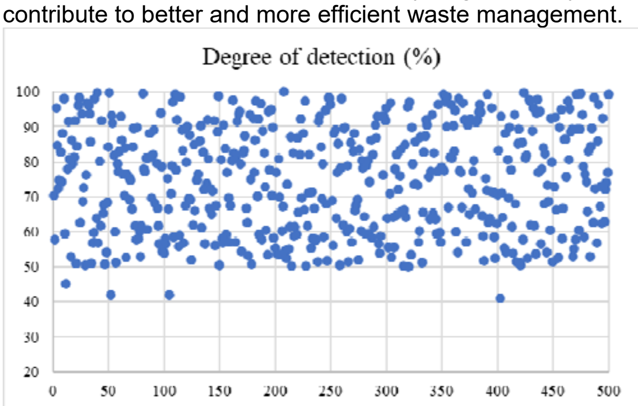


Fig. 4. Percentage of recognition for 500 images in the database

## Discussion

The obtained results demonstrate that the proposed deep neural network approach can successfully perform automatic classification and detection of common household electronic devices in waste. High recognition accuracy above 90% was achieved for the three waste classes. This indicates the great potential for applying such techniques in waste recycling and sorting.

The main limitation of the current system is the relatively small dataset used for training and testing. Increasing the number of diverse samples per waste class would further improve model performance. Additionally, incorporating more waste categories beyond the existing three would make the system applicable to a wider range of real-world scenarios.

Another research direction is exploring different CNN architectures and training techniques. For instance, residual networks and transfer learning from large-scale datasets could enhance generalization. Hyperparameters like number of filters, filter size and network depth require more thorough investigation and optimization.

Besides algorithm improvements, collecting larger and more diverse datasets under real industrial conditions is crucial. Techniques like web scraping could be utilized to automatically gather more waste images from the Internet. Continuously acquiring new training examples would enable constant system improvement.

Integrating the proposed solution with hardware components like conveyor belts, industrial cameras and manipulators would be necessary for full-scale real-world deployment. Optimizing image processing speed and minimum processor requirements are also important practical aspects to consider.

Generally, this research demonstrates the feasibility and great potential of applying deep learning and computer vision to automate e-waste recycling. Further development and integration with sensors and manipulators would enable practical application for improving efficiency and cost-effectiveness of e-waste management.

Another important avenue for future research is combining visual information with other data types to enhance system robustness and accuracy. For example, thermal cameras or hyperspectral imaging could provide additional insights into material composition and structure of waste.

Likewise, integrated sensors for weight, sound, smell or tactile characteristics during waste handling could aid in difficult cases where imagery alone is insufficient for reliable classification. Data fusion from multiple modalities using techniques like deep convolutional recurrent networks is a promising direction for future work.

From a social and economic standpoint, it is important to consider business models and initiatives that will promote wider adoption of the proposed solutions in industry. Along with technical improvements, educating and raising awareness among citizens and companies about the significance and benefits of automating recycling processes are key factors for successful integration of AI-based systems.

Regulatory frameworks and standards that encourage the uptake of new technologies, as well as streamlined licensing of machine learning solutions, are necessary to overcome organizational barriers to broader deployment. A multidisciplinary approach that combines scientific, technical and socio-economic aspects would be ideal for maximizing the positive impact of the proposed solutions on human society and the environment.

## Conclusion

This paper proposes a system for automated classification and detection of electronic waste from photographs, based on convolutional neural networks and faster R-CNNs. Experimental evaluation demonstrated high recognition accuracy above 90% for the three household appliance waste classes. The obtained results confirm the great potential of applying deep learning and computer vision for automating waste sorting and recycling. Information on waste type and dimensions automatically derived from images could significantly enhance planning and logistics in the waste collection process. For a more robust system, visual data could be combined with other information such as texture, smell, sound during waste handling. This would enable more accurate classification in difficult cases where imagery alone is insufficient. Multimodal approaches have shown great potential in related domains by fusing different data types.

Further work should focus on expanding the system to more waste categories, increasing training data, and optimizing algorithms. Integration with sensors and manipulators would enable application in real-world recycling facilities. The expected outcome is developing robust AI solutions for more efficient waste management.

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