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Application of deep learning object classifier to improve e-waste collection planning

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A B S T R A C T

This study investigates an image recognition system for the identification and classification of waste electrical and electronic equipment from photos. Its main purpose is to facilitate information exchange regarding the waste to be collected from individuals or from waste collection points, thereby exploiting the wide acceptance and use of smartphones. To improve waste collection planning, individuals would photograph the waste item and upload the image to the waste collection company server, where it would be recognized and classified automatically. The proposed system can be operated on a server or through a mobile app. A novel method of classification and identification using neural networks is proposed for image analysis: a deep learning convolutional neural network (CNN) was applied to classify the type of e-waste, and a faster region-based convolutional neural network (R-CNN) was used to detect the category and size of the waste equipment in the images. The recognition and classification accuracy of the selected e-waste categories ranged from 90 to 97%. After the size and category of the waste is automatically recognized and classified from the uploaded images, e-waste collection companies can prepare a collection plan by assigning a sufficient number of vehicles and payload capacity for a specific e-waste project.

1. Introduction

The global generation of waste electrical and electronic equipment (WEEE), or e-waste, is estimated to be 30–50 million tons per year (Cucchiella et al., 2015). Although WEEE has a high recycling value, many WEEE items also contain hazardous substances that must be separated from the municipal waste stream (Oguchi et al., 2011). Waste collection companies rely on the involvement of society to properly dispose of e-waste. Different collection methods have been offered, which include collection at supermarkets and electrical and electronic equipment stores, and municipal collection centers (European Commission, 2012). Other methods include mobile collection, such as curbside collection (Saphores et al., 2012) and on-demand collection, where a resident requests that the material be collected from a household (Król et al., 2016). On-demand collection may be suitable for efficiently planned waste collection, especially in city centers.

Efficient collection requires an optimal number of vehicles and optimized routing (Król et al., 2016; Mar-Ortiz et al., 2013) to prevent unnecessary collection costs and a potential decrease in profit (Dat et al., 2012). In addition, a flexible and reliable communication system between residents and the waste collection company may increase the amount of legally collected waste (Chi et al., 2014; Ramos et al., 2014). Internet-based waste collection services have already been investigated in India and China (Agrawal and Mittal, 2017; Cao et al., 2018; Gu et al., 2019), and emerging technologies and e-commerce have become new trends in the area of e-waste recycling. In China, Zhang et al. (2019) investigated the key drivers and barriers involved in residents' choice of e-commerce for e-waste recycling. They found that e-commerce was not universally accepted by residents, but that attitudes, subjective norms, and the perceived convenience of e-commerce were positively correlated with the intention to use e-commerce for e-waste recycling.

Smartphones and mobile applications are ubiquitous, and our "information society" uses numerous applications in everyday life (Chopdar et al., 2018; Kim et al., 2017; Sohn, 2017). These applications can be designed to facilitate the collection of waste (including WEEE), improve communication between residents and collection companies, and enhance the automation of logistics. The mobile applications that currently support waste collection are relatively limited, however; applications are mainly used to either find the location of waste collection points or set reminders related to the collection schedule (Asekol, 2019; ECS e-Waste, 2019; LIFE WEEE

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– RAEE, 2019; SWICO, 2019). Additional features, such as vehicle route planning, were included in a study that used a website-based application for waste collection on demand (Nowakowski et al., 2018). In practice, there is a gap in communication between residents and collection companies. In many cases, the data provided by a resident is not sufficient to precisely plan a route for loading waste equipment. At collection points, if an individual has excessive equipment to be collected, or if the dimensions of the appliance are large, it is difficult or even impossible to load the waste into a collection vehicle. Even if a large item is manageable, the collector must return to the collection company base, unload the item to make room for more waste, and then continue the route, which makes waste collection more expensive and much less efficient.

Fig. 1 outlines the WEEE disposal priorities from the perspective of an individual disposing of end-of-life equipment, and the perspective of a waste collection company. It considers the type, dimensions, and number of pieces of equipment to be collected. These data are integral to the preparation of a waste collection plan that uses vehicles and staff resources, which are the main factors that contribute to the cost of collection and transportation. As on-demand waste collection is mainly used for large- and medium-sized waste items, the routing plan should include vehicle packing optimization (Nowakowski, 2017). Equipment may vary in size, and the loading plan should be optimized to use the full payload capacity of a vehicle.

In this study, we investigated a novel system to facilitate waste collection planning, and to facilitate the communication between the individual requesting waste pickup and the collection company. Its primary purpose is to use vision recognition algorithms to identify the waste equipment type and dimensions.

2. Literature review

The purpose of object detection based on image recognition is to identify whether specific objects appear in an image. After the object is identified, the next step is to determine its location and size using a special adjustable frame. Object detection and identification have been widely used in artificial intelligence systems for robotics, electronics, road safety, autonomous driving, intelligent transportation systems, and content identification (Pamuła, 2018). Deep learning techniques have enabled advanced feature recognition directly from image data, leading to considerable progress in general image detection and object classification. In 2012, Alex Krizhevsky proposed a deep learning convolutional neural network (CNN) called AlexNet (Krizhevsky et al., 2017), which demonstrated exceptional image classification precision in the Large-Scale Visual Recognition Challenge (Russakovsky et al., 2015). Additional applications have since been introduced for visual and voice recognition systems, image processing, and the analysis of medical data (Krizhevsky et al., 2017; LeCun et al., 2015).

There are several techniques for detecting objects using deep machine learning, a technique in which the aspects of an image that are required for detection tasks are automatically learned. Recent studies have focused on using deep learning CNNs to detect specific objects, such as faces (Li et al., 2015), pedestrians (Howard et al., 2017), vehicles (Zhou et al., 2016), and road signs (Zhu et al., 2016). The ability to detect and track vehicles is required from many autonomous driving applications, such as collision warning, adaptive cruise control, and automatic lane maintenance. Other deep learning CNNs have focused on general image recognition (Girshick et al., 2014; Ren et al., 2017).

Several image processing and recognition techniques have been used in waste management and waste processing applications. Image processing is widely used in sorting objects with specific shapes and transparencies (Gundupalli et al., 2017; Wang et al., 2019b). Waste collection schedules based on the image processing of waste containers have been discussed (Aziz et al., 2015; Bin Aziz et al., 2018). The proposed methods located containers in the image, and determined the level of waste in each container using four masks and a set of support vector machine (SVM) classifiers. Vertical containers can be empty, partly full, or full of waste of various shapes and sizes. Hannan et al. (2016) proposed a content-based image retrieval (CBIR) system to explore the possibility of detecting the fill level of solid waste containers from the texture extracted from the images. In the system, various methods for determining similarity distance were used to calculate and compare the distance between images. The accuracy of the proposed feature extraction techniques was tested on a set of 250 container images, and the results showed that the earth movers' distance was highly accurate for measuring the similarity of objects, and provided better performance than other distances. In an overview of information and communication technologies (ICTs) and their use in solid waste management (SWM) and monitoring, Hannan et al. (2015) stated that in the context of rapid development, ICTs have become an integral part of the planning and design of SWM systems. To better plan, monitor, collect, and manage solid waste, four ICT categories have been proposed: spatial, identification, data collection, and data transfer. Imaging technologies in SWM applications focus on container-level measurement and waste sorting, and the results of the study by Hannan et al. detail several obstacles to the introduction of large-scale systems, such as insufficient data, costly network structures, lack of real-time information, and lack of dynamic planning and routing.

In this paper, we propose a novel approach for the identification and classification of waste equipment. The proposed algorithm uses neural networks with a deep learning feature. A deep learning

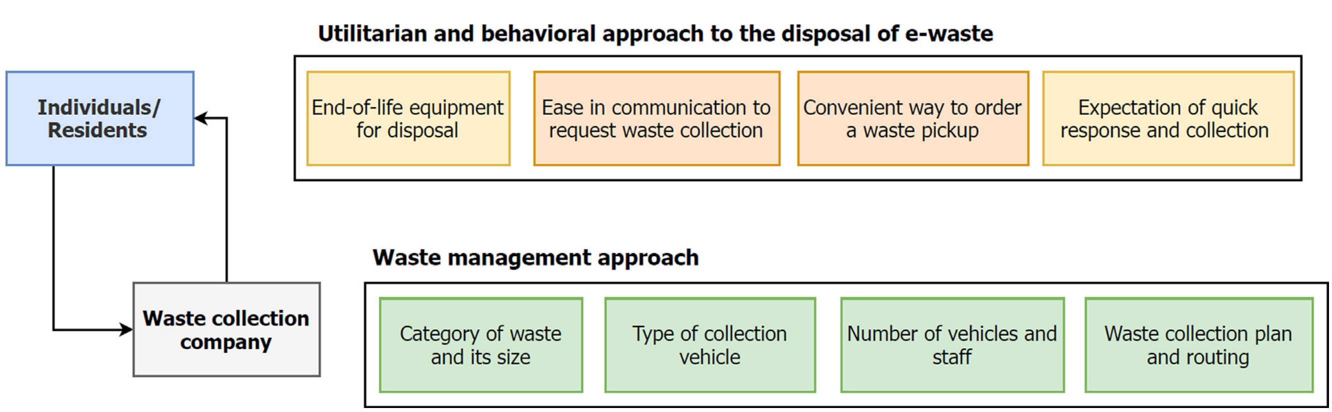


Fig. 1. Resident and waste company priorities for WEEE collection.

CNN was used to classify the waste equipment detected in images, and faster regions with a convolutional neural network (R-CNN) were used to automate the identification and size of the waste equipment.

3. Materials and methods

3.1. The main concept of e-waste image recognition

A novel proposal for a WEEE collection planning system, including the identification and classification of waste appliances, is shown in Fig. 2. Individual photographs are taken of the equipment intended for disposal, and the photo is then uploaded to a server running image recognition software that identifies the equipment. Depending on smartphone capability, this system could also work as a mobile application. After the identification and classification of the e-waste, the collection company prepares a plan for efficient retrieval based on the size and category of the waste items. The planning process could be further supported by artificial intelligence algorithms to optimize collection vehicle routes. The main model for image recognition is based on a deep learning object detector, faster R-CNN.

3.2. Deep learning methods for waste identification from images

Deep learning is a field of machine learning that teaches computers to learn from experience. Machine learning algorithms use computational methods to "learn" information directly from data without relying on a predetermined equation as a model. The proposed waste identification model uses a deep learning CNN convolutional classifier, as shown in Fig. 3.

The model inputs were images containing selected categories of e-waste. In this study, we selected three types of electrical and electronic equipment from households that are commonly disposed of: refrigerators, washing machines, and monitors or TV sets. Each of the objects had some distinctive features that were utilized in the learning procedure. Further development of the system would include additional categories of waste equipment. The output of the model was information about three classes of objects represented by the images. A deep learning CNN can be divided into two main functional modules: the feature-learning module and the classification module. The feature-learning module is mainly composed of alternating convolutional layers and pooling layers. The convolution layer conducted a 2D convolution on the input $h \times w \times c$ image $\boldsymbol{x}$, with m distinct filters. The output was a feature map $\boldsymbol{y}$ (given in (1)) of c channels.

$$\mathbf{y} = [y_{i,j,q}] = [b_k + \sum_{i'=1}^{k_h} \sum_{j'=1}^{k_w} \sum_{p=1}^{c} (w_{i',j',p,q} \times x_{i+i',j+j',p})] \quad (1)$$

where b_k is the bias, $w_{i,j,p,q}$ is the specific weight of the q-th convolutional filter of size $k_h \times k_w$, $i = 1,2,\ldots,h$, $j = 1,2,\ldots, w$, $p = 1,2,\ldots, c$, and $q = 1,2,\ldots, m$.

A 2D convolutional layer applies the sliding convolutional filters to the input. The layer convolves the input by moving the filters along the input vertically and horizontally, computing the dot product of the weights and the input, and then adding a bias term. The pooling layer is mainly responsible for spatial sub-sampling; it conducts a special 2D convolution with a stride larger than 1 that usually equals the filter size. Max pooling was used, as shown in Eq. (2).

$$\boldsymbol{y} = [y_{i,j,q}] = \max_{1 \le i' \le w_p, 1 \le j' \le h_p} (x_{i+i',j+j',q}) \quad (2)$$

where x is the $\boldsymbol{h}' \times \boldsymbol{w}' \times \boldsymbol{m}$ input feature map, $\boldsymbol{y}$ is the pooling result of size $h_p \times w_p$, $i = 1,2,\ldots,h_p$, $j = 1,2,\ldots,w_p$, and $q = 1,2,\ldots,m$.

Each layer in the feature-learning module uses the output of the previous layer as input, thus forming a hierarchical feature mapping that transforms the raw pixel data into multilevel feature vectors. The classification module is composed of fully connected layers. It utilizes the highest-level feature vector and functions as a single hidden layer feedforward neural network classifier. For classification tasks, the input size is usually the size of the training images. The images used were of RGB format and 128 × 128 pixels in size.

3.3. Classification results using the deep learning convolutional network

A set of photos of waste electrical equipment was collected for identification. The set included photographs of refrigerators, washing machines, and television sets of different models. Some of the photos are presented in Fig. 4. Large home appliances are

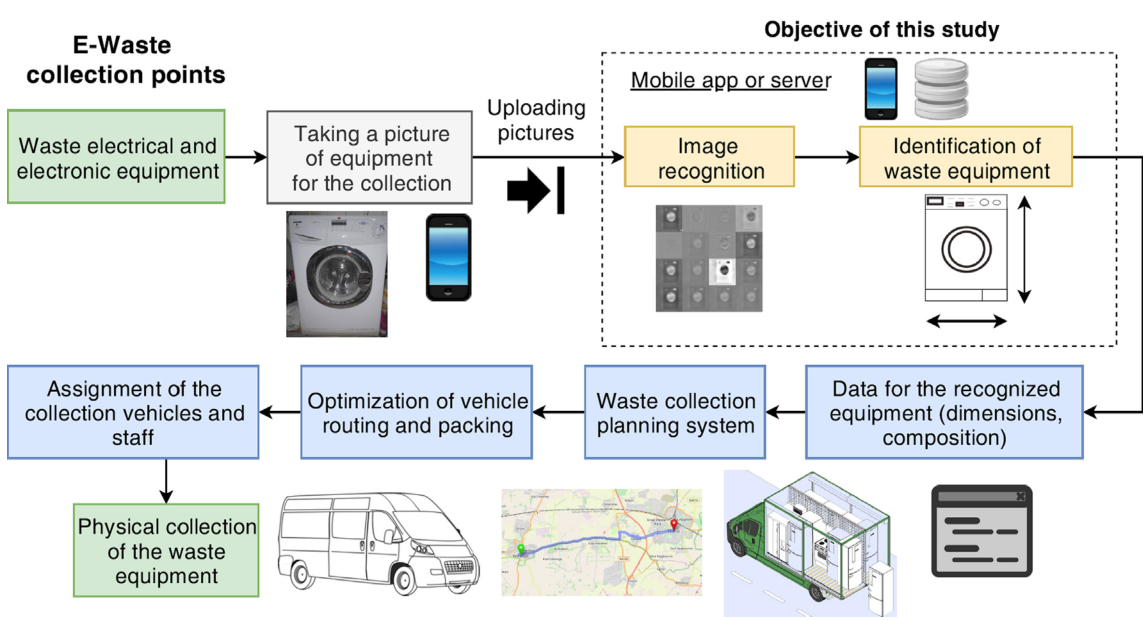


Fig. 2. E-waste collection using image recognition and visual classification of waste equipment.

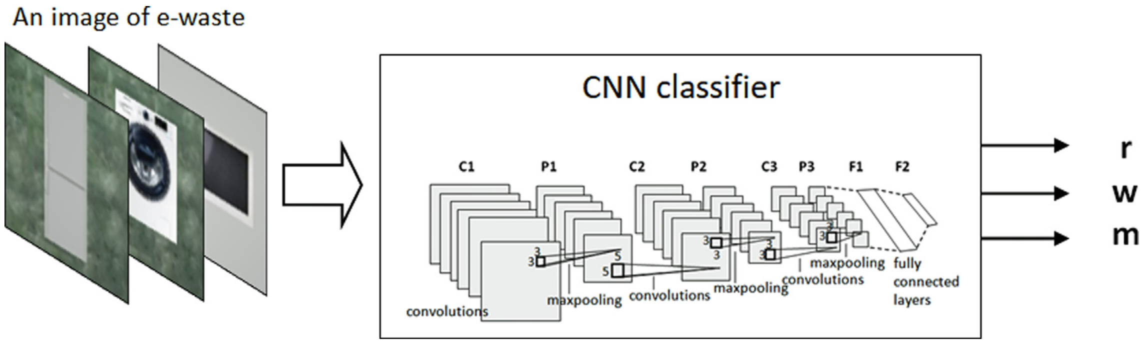


Fig. 3. Deep learning convolutional neural network classifier (r = refrigerator, w = washing machine, m = monitor or TV set).

Fig. 4. Examples of pictures from a learning set.

commonly removed from a household as they approach the end of their life, thus the equipment was not deformed or significantly damaged.

The proposed network was trained using 180 training images (60 for each class) and was then tested on 30 test images (10 for each class). The test images were not part of the training set. For training and testing, square images cropped from the photographs of waste equipment were used. Each image contained one waste item (a refrigerator, a washing machine, or a TV set/monitor), and the images were scaled to 128 × 128 pixels. Various configurations of the convolutional network were applied. The tested deep learning network architectures contained three CNN layers. The network accuracy was determined by the number of correctly recognized equipment images. Modifications to the deep learning CNN layer organization were conducted in three areas: the number of filters, the size of the filters, and the method of scanning inputs. A systematic approach was used to determine the required filter sizes, which were 7 × 7, 9 × 9, and 11 × 11 for the first layer (C1), 7 × 7, 5 × 5, and 3 × 3 for the second layer (C2), and 3 × 3 for the third convolutional layer (C3). The filter size was gradually changed, and each new configuration was trained. The number of filters was chosen from the set {16, 32}, and the stride size was varied from 1 to 4. The training was repeated five times, and the results of the estimation were evaluated. The set of filters with the best performance was selected.

4. Results

4.1. Classification results for selected categories of e-waste

The initial configuration of the CNN network was determined using MATLAB software and examples provided by the software developer. The details of the two selected configurations are presented in Table 1.

An example of processed test images (a washing machine, a refrigerator, and a computer monitor) after using layers C1, C2, and C3 for the selected 16 feature maps (FM) is shown in Fig. 5. A similar procedure was applied to the other images of waste equipment.

This method was used for the detection and classification of three types of e-waste equipment, with an average accuracy of 90–96.7% depending on the configuration and number of training sessions. Examples of classification results using the convolutional network are presented in Fig. 6.

In the confusion matrix plots (Fig. 6), the rows correspond to the predicted class (Output Class), and the columns correspond to the true class (Target Class). The diagonal cells correspond to observations that were correctly classified, and the off-diagonal cells correspond to incorrectly classified observations. Both the number of observations and the percentage of total observations are shown in each cell. The column on the far right of the plot shows the percentages of all tested images predicted to belong to each class that were correctly (green/upper value) and incorrectly (red/bottom value) classified. The row at the bottom of the plot shows the percentages of all the images belonging to each class that were correctly and incorrectly classified. The cell in the bottom right of the plot shows the overall accuracy. Although the number of images in the training and test series was not large, high accuracy was obtained—on average, >90%. For images that contained many additional elements, e.g., furniture or other devices, the learning sequence should include many additional examples of electronic devices. The method presented above allows for the recognition of only one object in an image. It also does not allow object dimension specifications.

Table 1
Classification results for two deep learning convolutional neural network configurations.

Configuration number	Deep learning CNN configuration						Accuracy on test images
	Input	**C1**	**C2**	**C3**	**F1**	**Output (F2)**	
CNN1	16,384 (128x128)	32 FM FS 9x9 MS 60x60	32 FM FS 7x7 MS 25x25	16 FM FS 3x3 MS 12x12	256	3	93.3%
CNN2	16,384 (128x128)	32 FM FS 11x11 MS 30x30 Stride = 4	32 FM FS 5x5 MS 12x12 Stride = 1	16 FM FS 3x3 MS 5x5 Stride = 1	256	3	96.7%

Padding: 0, 1, 1 for convolutional layers, respectively;
FS = Filter size, FM = Feature map, MS = Feature map size, max pooling with 3 × 3 filter.

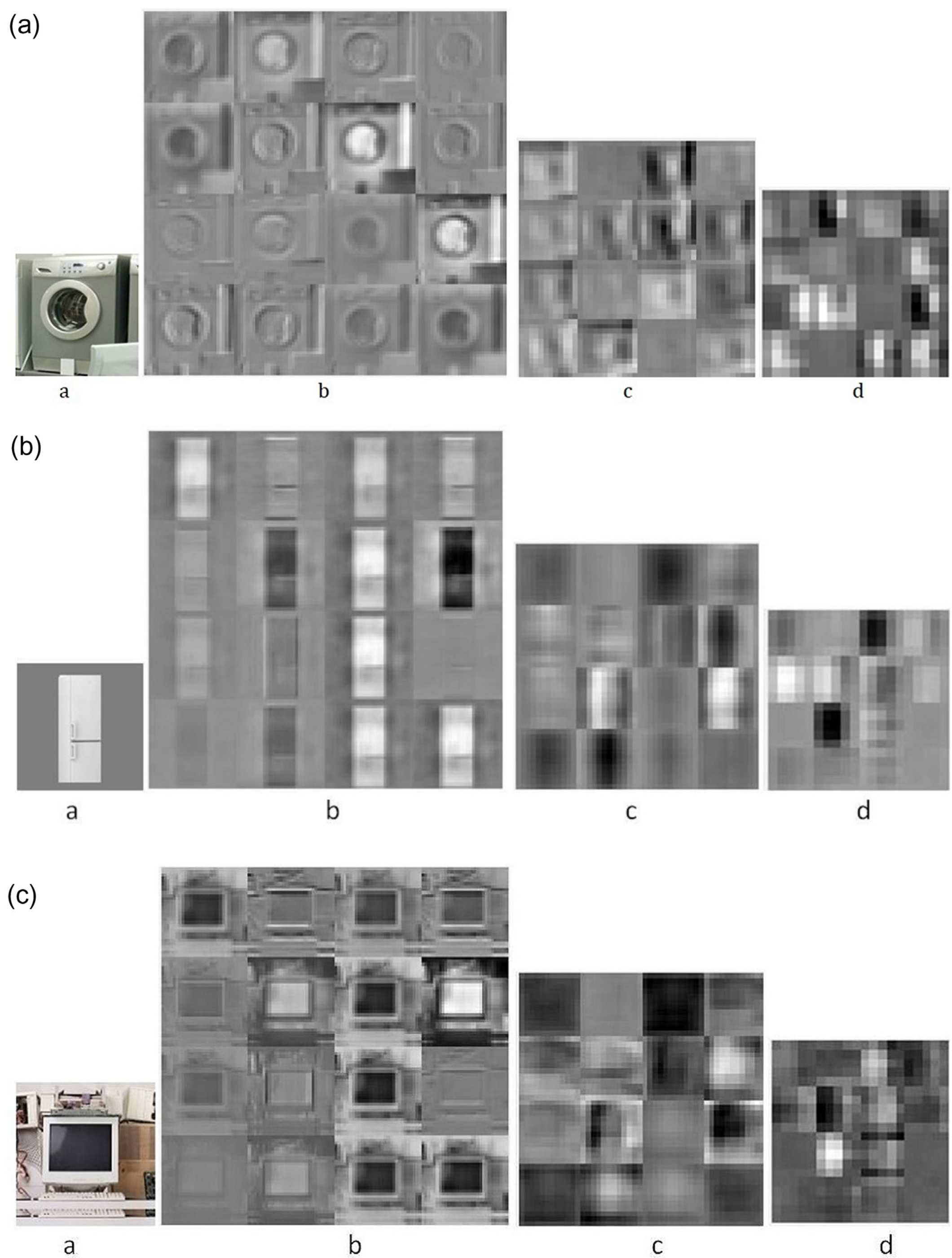
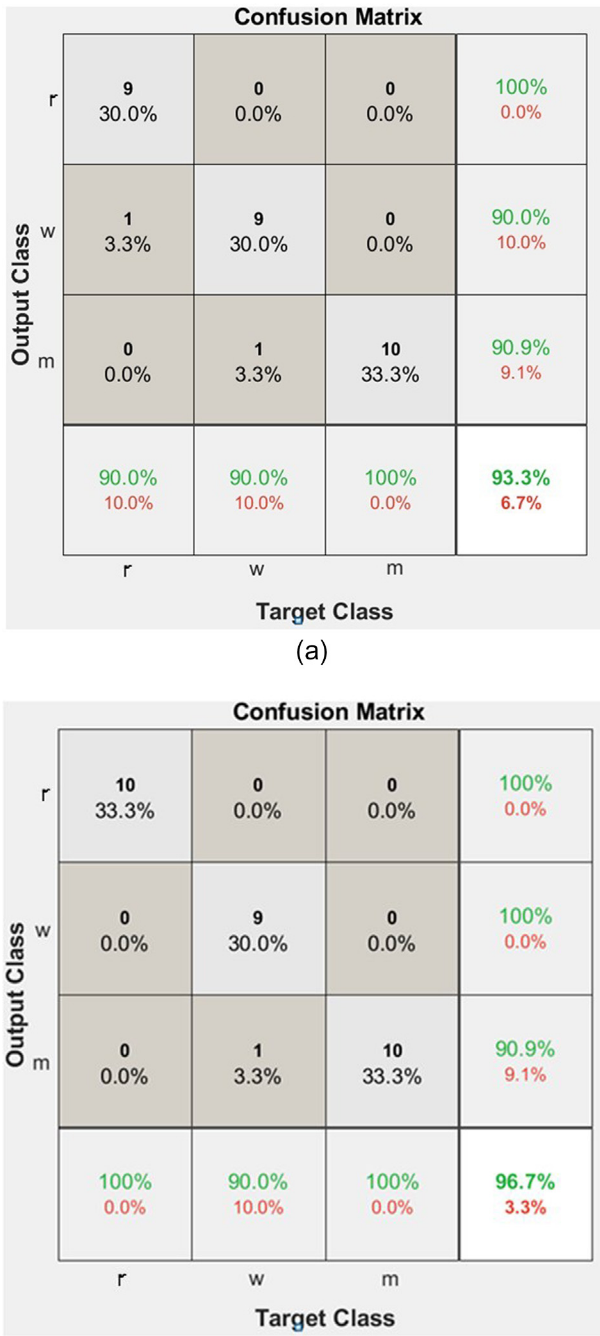


Fig. 5. Feature maps of the test images for the configuration of CNN2. (a) Test images 128 × 128; (b) 16 FM 30 × 30 pixels; (c) 16 FM 12 × 12 pixels; and (d) 16 FM 5 × 5 pixels.



(b)

Fig. 6. Classification results of three types of waste using the convolutional networks CNN1 and CNN2.

4.2. Recognition of several objects in an image

To recognize several objects simultaneously in one image, faster R-CNN was used. Faster R-CNN is an object detection technique (Ren et al., 2017) that selects regions to process and determines how those regions are classified. Faster R-CNN allows for the detection of multiple object classes and determines the dimensions within the image. Specifying the dimensions of objects (width and height in pixels) makes it possible to calculate proportions, and thereby the size of the devices. Fig. 7 shows the results of faster R-CNN for an image containing two washing machines, one refrigerator, and one monitor. The CNN used as the basis of the faster R-CNN object detection contained three convolution layers with filters 5×5, 3×3, and 3×3, and other elements of the configuration (number of filters, number of layers, number of neurons in fully connected layers, max epochs) were adjusted to achieve the best result. The condition for learning completion was 10 epochs in each of the four steps of network training.

The same set of images was used to train the R-CNN and deep learning CNN, although the faster R-CNN did not require images of the same size in the training string. The application of faster R-CNN enables the recognition of objects and their size in images. Knowledge of equipment size (overall dimensions, height, and width) is important for waste collection planning. The selected equipment belongs to a category of WEEE that is relatively heavy and varied in size (especially refrigerators and TV sets). An image of waste equipment can contain one, two, or three types of e-waste, and several pieces of the same equipment, or equipment in the same category. Recognition of the type of equipment is the preliminary step in e-waste collection planning, and determining the size of objects is critical. A WEEE collection plan requires the assignment of a vehicle that is capable of loading all waste equipment for which disposal is requested by the customer. An automated system for e-waste reporting is convenient both for customers, who must take and send photos, and for the collection company server, where all the pictures can be recognized and classified by category and size. More examples of images with recognized objects are shown in Fig. 8. The accuracy of the method was, on average, 90%, with 100% image recognition for washing machines and 80% image recognition for refrigerators. The CNN network recognized objects more accurately than the R-CNN network. The advantage of R-CNN is its ability to specify the size of the recognized object.

For a neural network, the training time depends on the network configuration, the length of the training set, and the computer speed. The CNN1 and CNN2 network learning time with MATLAB software on a PC running an Intel® Core™ i5 CPU at 2.5 GHz with 8 GB RAM was approximately 5 min, and for the R-CNN, it was approximately 15 min. However, after training, the networks operated very quickly and could be used successfully in real time.

5. Discussion

The expectations of a circular economy impose significant efficiency requirements on the collection of waste, including WEEE. Improvements in waste management efficiency may arise from a growing interest in on-demand waste collection, as one of the key elements for the future of this type of collection is the exchange of information between customers and collection companies. New internet-based collection methods in India and China, and the results of several recent studies demonstrate the potential of online waste collection services. Furthermore, Xue et al. (2019) argued that a new collection model is required to keep pace with the advent of ICTs in waste management. Numerous emerging companies are engaged in intelligent recyclable collection, in which human–human and human–machine interactions are crucial elements. The concept of intelligent collection proposes that waste or recyclables are collected with the assistance of ICTs and the Internet of Things. This collection model offers advantages for organization, logistics, and data collection (Xue et al., 2019). Esmaeilian et al. (2018) discussed the development of an infrastructural framework to enable the proper collection of product lifecycle data and to better understand product lifecycles. This framework includes new business models that rely on product lifecycle data, and intelligent sensor-based systems for upstream waste separation and on-time collection.

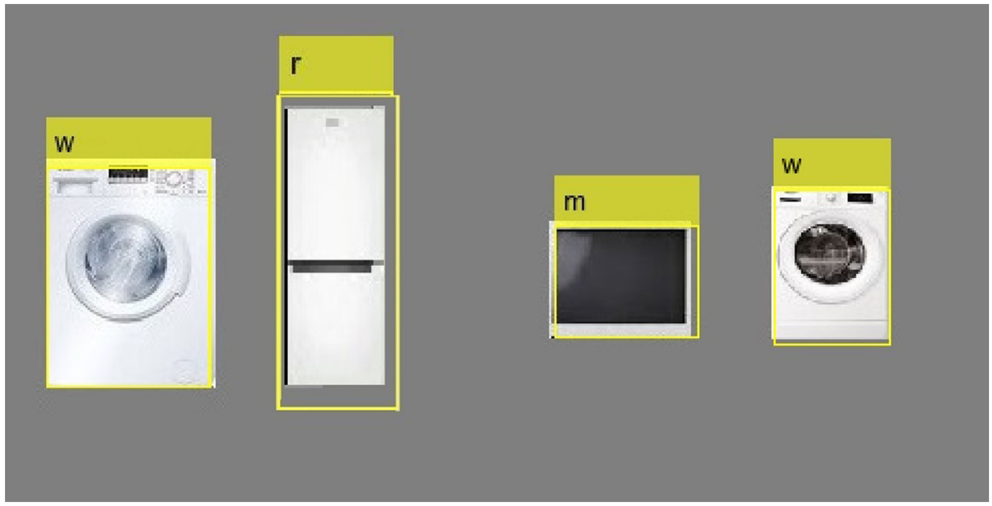


Fig. 7. Detected and labeled objects on the image using the faster R-CNN detection.

Fig. 8. Examples of objects in images detected and labeled using faster R-CNN detection.

Our study proposes a novel application with a deep learning CNN and faster R-CNN for the identification of waste equipment in household collection. This concept would use digital image sharing to facilitate the exchange of information between a collection company and an individual requesting waste retrieval. An additional advantage of such a system is the widespread use and social acceptance of online solutions and smartphone applications. Automated visual waste recognition would benefit both the waste collection companies (by the valorization of waste and recognition of the collection dimensions) and the residents who could conveniently request retrieval by merely sending a photo of the waste equipment. The algorithm and application could be operated on a server or through a mobile application.

The proposed system of e-waste image recognition and classification illustrates a progression from pre-existing applications with potential for automated and robotic waste management systems. Robotic platforms that could be deployed in the automation of nuclear waste material processing were proposed by Shaukat, who investigated the use of robust and rapid systems to visually classify waste and proposed a novel machine vision system for autonomous identification. In this proposal, rotation and scale-invariant moments were used to describe object shape, and a random forest learning algorithm performed object classification with a mean true positive rate of 0.98 (Shaukat et al., 2016).

To identify nails and screws in construction waste, Wang et al. (2019a) proposed a recycling robot. Using neural network technology to assist a robot patrol in an unknown work environment, a faster R-CNN was employed to find nails and screws in real time. Computer vision technology and a path-planning algorithm were applied, and the results indicated that the model's mean average precision for the identification of nails and screws was 0.891. Other applications of visual waste bin level recognition have demonstrated high accuracy: in one study, container or bin detection and waste level classification achieved 90–96.7% accuracy. The

CBIR system identified 97% of the containers correctly by using the k-nearest neighbor classifier (Hannan et al., 2016). Our results suggested that 90–96.7% accuracy could be obtained, and accuracy was affected by the sufficiency of images in the learning and test sets, and by the CNN configuration.

Collection company managers complain that the waste equipment retrieved often differs from that described by the customer. This causes problems for vehicle loading, especially if the dimensions of the waste appliances are larger than expected. The waste collection industry is unique in that, while standardized shipment units such as cardboard boxes, pallets, and other logistic units are used in supply chains, each unit in the collection and loading of e-waste is randomly disposed of—and is thus randomly-sized—when it breaks or otherwise reaches the end of its product life. Furthermore, when they communicate with a collection company, customers are unlikely to know the dimensions of their waste; their priority is to remove an unnecessary object from their household. Similar situations may occur when more than one item requires disposal. To avoid any significant collection problems, a company needs to determine through resident communication how many items are to be collected so that the company can deploy the correct vehicle and assign sufficient staff. Visually identifying waste is one of the easiest ways for residents to communicate with the collection company. The primary practical purpose of the proposed method is to classify and estimate the size of the waste equipment to be retrieved. In essence, size recognition does not need to be highly precise (in millimeters), but just precise enough to determine the dimension requirements of the collection vehicles (centimeters or decimeters). Requesting waste equipment retrieval and planning the collection process are currently not automated. As a result, the cost of mobile collection is high and negatively affects the assessment of this method by collection companies. The accuracy of image recognition and classification through automated algorithms results in efficient categorization by type and estimation of size, and the automation allows for the valorization of waste and reliable load planning.

6. Conclusions

This research presents a novel approach to photographic identification and categorization of e-waste by using CNN to classify the type of e-waste, and using R-CNN to detect the category and size of waste equipment in images. The classification and detection algorithms utilized showed high identification efficiency. Recognition accuracy could be increased further by increasing the number of images in the learning set to several hundred or even several thousand. The application of deep learning CNN and faster R-CNN resulted in waste equipment identification with an accuracy of 90–96.7%. On average, the R-CNN network provided lower accuracy (90%) than the best CNN, but allowed for the identification and determination of the size of the object in the image.

This new method for identifying waste enables the development of a ready-made digital solution to recognize the equipment reported for collection based on customer images. As an essential tool for collection planning, it allows for the potential valorization of the secondary raw material content. It also takes advantage of the widespread use of smartphones and the commonplace ability to take and upload photos, which was an unrealistic expectation until recently. The proposed system of taking, uploading, and recognizing pictures to prepare a waste collection plan can also be utilized in municipal collection centers or in electronic marketplaces where e-waste is stored. In such cases, more waste equipment could be identified using faster R-CNN, as shown in this study.

Further research should consider other categories of equipment submitted for collection to verify the effectiveness of the classification and detection. This method could also be applied to other bulky waste categories for which similar challenges are encountered in waste collection.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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