Transfer learning approach towards a smarter recycling*

Nermeen Abou Baker[1][0000−0002−9683−5920], Jonas Stehr[0000−0002−5332−6616], and Uwe Handmann[1][0000−0003−1230−9446]

Ruhr West University of Applied Sciences, 46236 Bottrop, Germany
nermeen.baker@hs-ruhrwest.de
https://www.hochschule-ruhr-west.de

Abstract. The increasing consumption of electrical and electronic devices is alarming. Therefore, the transition from linear to circular economy becomes essential. The key solution to support this transformation is artificial intelligence. This work presents a transfer learning approach to support the recycling of electrical and electronic waste (Ewaste). We emphasize the use of transfer learning technique, particularly, to classify Ewaste. In this approach, we design a hybrid model of residual nets and inception modules that can classify features of a source domain (smartphones in our case) and leverage this knowledge to another device (electric screwdrivers, as an example). Using our model, we achieve an overall accuracy of 94.27% and 97.22%, respectively. These are comparable to the popular pre-trained models, which use similar network topologies. We use a web crawler program for collecting images from search engines to build the datasets with less efforts. We show that transfer learning is more robust and performs better than training from scratch. It avoids duplication and waste of computational resources. As a result, with the benefits of transfer learning, we can provide detailed information about the devices that need to be recycled. Ultimately, this would greatly support the overall recycling process.

Keywords: Transfer learning · classification · Ewaste · circular economy.

1 Introduction

According to the Organization of Electronic Cooperation and Development (OECD) [5], all products that contain a Printed Circuit Board (PCB) and use electricity are called electrical and electronic devices. When this appliance reaches end-of-life, it is called Ewaste. Middle to high-income countries are more likely to consume more technology that will sooner become Ewaste [18]. This paper is organized as follows: It starts by introducing the motivation and challenges, state of the art of automated Ewaste management, and the reason for

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using smartphones recycling as a case study, in the Introduction in Section 1. Section 2 presents the research gap. Section 3 describes our transfer learning approach, which is designing an Ewaste classifier as an efficient method for Ewaste classification. Finally, the conclusion of the work is given in Section 4.

1.1 1.1 Motivation and challenges

Recently, many initiatives foster the transformation from linear to a circular economy. However, only a few studies mention this transformation of Ewaste. Other studies attempted to recover electrical components (ECs) and materials using conventional methods such as acid burning, melting, and shredding to reduce metal and materials recovery. Informal recovery of lead from PCBs also emits dioxin and other chlorine compounds [5].
A survey of literature reviews [16] conducted from 2004 to 2019, found that there are six fundamental Artificial Intelligence (AI) applications in Solid Waste Management (SWM), which are: waste dumpster level detection, forecasting of waste characteristics, process parameters prediction, process output prediction, vehicle routing, and SWM planning. The field of Ewaste classification for recycling is still emerging.

1.2 State of the art of using artificial intelligence in related works

A review of the state-of-the-art is presented by [15] to dismantle and sort ECs. They found that Convolution Neural Networks (CNN) combined with physical separation and spectroscopy techniques play a vital role in classifying ECs because of their low cost. It shows that machine learning can detect the Tantalum capacitors on PCBs, then scrap them using a robot arm. ECs from a PCB image could be identified using CNN with high accuracy [11].
ZenRobotics Recycler (ZRR) utilizes a combination of AI, robots, and sensors [22]. It is a robot system that features two robot arms with multiple sensors, including High Definition (HD) RGB cameras, Near InfraRed (NIR) sensors, and metal detectors. With the support of deep learning software, it can sort 13 different materials or waste streams. This robot has an average purity 97% for tested waste streams. The study emphasizes the importance of digitalization as an "instrument" for achieving sustainability and future competitiveness efforts. In addition, our review of [4], shows that transfer learning is a promising technology that supports object classification. It has significant advantages in achieving high performance while saving training time, memory, and effort in network design. They also proved that weight freezing is an effective method to reduce network complexity and eliminate overfitting.

1.3 Case study: Smartphones

Smartphone recycling will be used as a case study because it faces many challenges. Due to their rapid production and low recycling rates, smartphones are the fastest-growing Ewaste stream. Additionally, traditional recycling can be challenging due to the complexity of recycling hazardous substances and contamination with other materials and metals. Moreover, the technical lifespan of the device is short, almost two years [3]. According to Nordmann et al. [1], between $65-80\%$ of smartphones are recyclable. They found that smartphones are made of 60 different substances. Approximately 56% of a smartphone is made of plastic, 28% of metal (of which 15% copper, $0.35g$ silver, $0.034g$ gold, $0.015g$ palladium, and $0.00034g$ platinum) are used for the cables, the contacts, the circuit board, and the battery, 16% of glass and ceramics are used for displays, and 3% are other substances. The major problem with these substances is that they are mined in different countries. The research on automated smart waste management is still in its infancy due to the lack of datasets and the slow move towards AI-based smart waste management.

2 Research gap

AI and robotics can be used to support the transition from linear to smarter Ewaste recycling. This study aims to bridge the gap between Ewaste recycling and AI by emphasizing the role of transfer learning as a promising method to leverage knowledge gained from training a specific device into other devices, rather than training each device from scratch.

3 Our approach

Our goal is to process small and medium-sized electronic devices that need to be recycled. The suggested technique is: designing an artificial intelligence (transfer learning specifically) system. We aim to maximize material recovery rates and to classify objects reliably with the least amount of human intervention. Eventually, this will be a black box classifier for many future devices.

3.1 Design an artificial intelligence system

Besides negative health impacts, human intuition is imprecise when dealing with repeated patterns in waste streams. Hence, intelligent systems are imperative, especially when dealing with complicated tasks with small datasets.

Why artificial intelligence In the waste stream, there are repeated patterns that play a fundamental role in dealing with complicated tasks that have incomplete or uncertain datasets. This makes it impossible for humans to process them precisely. Thus, an intelligent system is essential. Machine learning is a promising method because of its lower cost and distinctive features of ECs. Although research in this domain could be costly at the beginning, it is a smart investment if it is designed to be modular, and extensible in the long term. Since there is a high need to structure, analyze and evaluate a large stream of patterned data,

including AI in waste management is essential.
Using artificial neural networks to mimic human brains is an efficient method to process Ewaste classification with minimal human interventions. In addition, deep learning can be applied to recognize recycling devices in a way that is more accurate than human performance. Theoretically, increasing the number of images per category can boost the accuracy of recognition. On the other hand, this, in turn, increases training time and memory consumption, which are undesirable in the industry. Our approach suggests a trade-off between accuracy, training time, and memory by using the transfer learning technique. It will reduce the computational burden and surpass the accuracy of training from scratch. To ensure this point, in a previous study [2], we used an AlexNet as a pre-trained model to focus on the transfer learning technique as a promising solution for object classification and the benefits of applying previously gained knowledge from a source domain and transferring it to a target domain via deep neural networks.

Creating datasets The web contains a huge amount of data that could enrich the data sources for building a useful dataset. A web crawler is a program or a script that retrieves useful information according to an algorithm. It navigates the web and downloads a document in an automated and methodical way. It fetches the HTML pages, parses them, and extracts the related data [26].
Training CNNs requires huge datasets used as training images. To our knowledge, no previous study has published a public dataset for Ewaste. Therefore, we use a web crawler program that is designed for collecting garbage datasets by [12]. This web crawler is written to capture images from Google images and Baidu images. It is relatively easy to crawl here because it doesn't require a login, authentication, or dynamic load. The only concern is the time between requests should be long enough to prevent floods of queries to the web page that could block the IP requests because the source may consider these requests as malicious or suspicious and cause a denial-of-service attack [23]. We use a keyword-based web crawler as a starting point to collect data from the web. Using keywords, we can construct our dataset for each class, such as "iPhone 6" + "backside". We can also set the maximum number of images that we want to download. The resolution of the images could also be identified.
It is difficult to collect appropriate images from the Internet to train a CNN directly. For example, searching for a specific keyword doesn't just crawl images we want, it also retrieves noisy images. The keyword "iPhone 6" leads to images that are not suitable for learning, such as the charger, the packaging of the device, or non-related photos taken with the device. This happens because it uses keyword-based metadata for the searched image [8]. The dataset should be homogeneous and should not contain anomalous objects. In this case, manual pre-processing is essential to filter the data and focus on the object in the center region-of-interest. Thus, data pre-processing should be completed before training, and removing irrelevant images manually is an important step, as shown in figure 1. After data cleaning, we apply deep learning models to classify smartphones, and

electric screwdrivers, as example, to test transfer learning method. With this crawler, we create the source dataset (smartphones) that contain 8 classes with 150 images per each as, Gigaset GX290_plus, HTC One M8, Huawei P20 Pro, iPhone 6, Samsung Galaxy A20, Sony XA Dual, Sony XZ1, and Xiaomi Redmi Note 8, with a balanced dataset of about 1200 images in total. For the target dataset (electric screwdrivers), it consists of 4 balanced classes as, Bosch_IXO, Hitachi_DS_12DVF3, Makita_DDF481, and Parkside_PAS_3.6_A1 with 240 images in total.

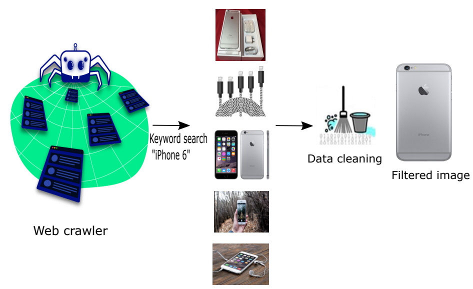


Fig. 1: The web crawler and pre-processing of a smartphone device.

Transfer learning Humans leverage previous knowledge gained from experience and reuse them to tackle new but related problems. CNN tries to mimic the human brain employing a concept called, transfer learning. Transfer learning is the process that uses the information gathered from a previous task to improve the performance of a new but related task [6]. Therefore, transfer learning by definition contains two basic components, which are: the domain and the task, as follows [17]:

– The domain D has two elements, namely, the feature space X, and a marginal probability distribution $P(x)$ i.e. $D = \{X, P(x)\}$, where $x \in X$.
– The task T has two elements, namely, a label source Y and the prediction function $f(\cdot)$ denoted by $T = \{Y, f(\cdot)\}$.

By using the notations of: D_S for source domain, T_S for source task, D_T for target domain, and T_T for target task, where $y \in Y$ and y, is the corresponding label of x in D_T using the knowledge in D_S and T_S, where $D_S \neq D_T$, or $T_S \neq T_T$. Transfer learning could be defined as follows: Transfer learning aims to help improve the learning of the target predictive function that is used to predict the corresponding label, i.e. $f(x) = P(y|x)$, which is the probability distribution.
Choosing the source should be well defined because it should provide two requirements: The source distribution should be similar to the target distribution

i.e. it has similar features, and source data (in our case as images) should provide useful information to classify. Therefore, the source data should have a high accuracy rate.
Transfer learning has four techniques, which are: Model transfer, instance transfer, mapping transfer, and adversarial transfer [21]:

- Model transfer uses the learned knowledge from the base model to predict the target model.
- Instance transfer chooses partial instances from the source domain and assigns suitable weights as supplements to the training set in the target domain. This approach focuses on giving less importance to samples who are irrelevant in the source domain to reduce the distribution difference.
- Mapping transfer maps instances from the source domain and a target domain and creates a new data space that improves the similarity between them.
- Adversarial transfer uses an adversarial method to find the transferable features, which are suitable for the source and target domains.

We apply the model transfer method. It usually uses the same model architecture as a trained model, and it is implemented by tuning the full layers of the model trained on the source domain or fine-tuning the classification layers only. The former approach partially uses the parameters of the trained model, whereas the latter approach takes full parameters that remain fixed to initialize the training process [13].
The similarity of data distribution between source and target domain has a huge impact on the efficiency of transfer learning [24]. In addition, the backpropagation in CNN may decrease when the model becomes very deep. Therefore, the skip-connections approach can overcome this problem by skipping inactive levels and reusing the activation from previous levels. Recently, transfer learning and domain adaptation have gained attention in many applications. Most of recent domain adaptation research focuses on learning the domain invariant features. This is done by mapping the source and target domains in the same latent space or adapting one or more layers in the network structure. Domain adaptation methods such as the Central Moment Discrepancy (CMD) [25], Maximum Mean Discrepancy (MMD) [9], and Residual Transfer Network (RTN) [14] employ residual layers. Therefore, we will use RTN as a method to control domain adaptation. The model transfer design of our approach is shown in figure 2.

Implementation We propose a hybrid model that is inspired by a combination of two concepts, namely, residual nets and inception module with dimension reductions. This model consists of four parts, and 67 layers, as illustrated in figure 3:

- The input image size is [224 224 3]. It starts with stacking three convolutional layers (followed by a RELU as activation function and channel normalization layer). These layers are as follows; the first convolutional layer has a 7×7 filter

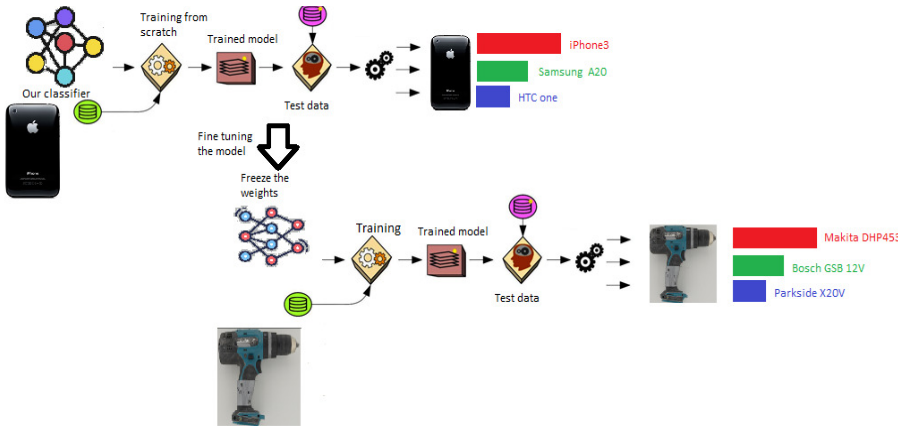


Fig. 2: The model transfer design of our approach.

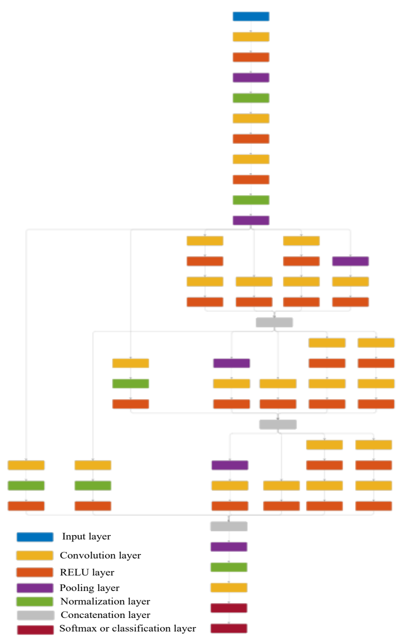


Fig. 3: Our classifier model.

size to reduce the input image directly without losing spatial information. Then two consecutive convolution layers are added with 1×1 and 3×3 filter sizes to generate a large number of feature maps. These layers are used to enable the model to learn global features.
- Stacking three inception modules on top of each other. Inception blocks with dimension reductions play a major role in reducing computation costs. This module has four branches that are 1×1, 3×3, and 5×5 convolutional kernels size in parallel, with one branch that has a max-pooling layer. It is used to down-sample the input when it is fed-forward through the network, which is achieved through the reduction of the dimension of input data. The convolution is used to compute the reductions. We increase the number of filters when going deeper in the network to extract more complex features. These blocks are connected through a concatenation layer.
- Using RTN as residual connections between each inception block. There are three connections between each inception module to increase feature reuse and avoid vanishing gradients, as mentioned before.
- It ends with output task-specific layers. An average pooling layer is added to calculate the mean of all feature maps of the last inception module. This is followed by a dropout layer with 0.4 to enhance regularization and flatten the layers. Then a fully connected layer is added to correspond to the number of classes in the domain dataset, which is 4 in our case. Finally, a softmax layer is utilized to calculate the probability distribution of the prediction vector.

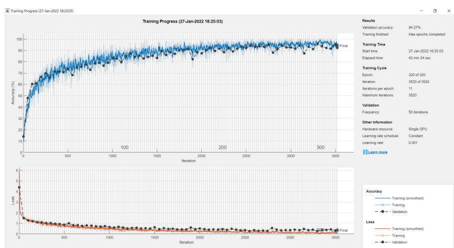
The implementation environment is MATLAB, and the following training options are chosen, as follows: The batch size is 64, and the maximum epochs is 320, and Stochastic Gradient Descent with Momentum (SGDM) optimizer. To accelerate the training, we use NVIDIA Quadro P4000. The learning rate is 10^-3 for the source domain and we scheduled the learning rate for the task domain, with a decay factor of 0.5 for each 20 epoch to detect local features. This technique maintains the global features at the beginning and drops the learning rate to detect the local features. We split the labels as 80% for training and 20% for validation sets.

Results and discussion We train the model on the training set and test it on the validation set. We train this base model from scratch for the source domain (the smartphones dataset), and we got the accuracy of 94.27% with generalization, as shown in figure 4a. An example of the tested images of the source dataset is shown in figure 4b.

Then, training a small target dataset using fine-tuning the base model. First, it freezes the network parameters for the whole base model except the task-specific layers. This means preserving (not changing) the model parameters, including weights and biases for every neuron, rather than training using random initialization. This process is implemented by setting the learning rate to zero for the frozen layers. Next, training the result by backpropagation the network parameters instead of random initialization. We fine-tune this model for the target domain (the electric screwdriver dataset), hence, we get the accuracy of

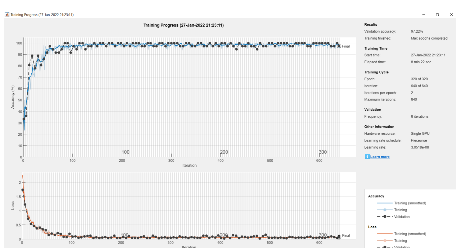
97.22% with generalization. Although it is achieved with about 75 epochs, we unify the testing for fair evaluation, with very short training time compared to training the source domain, as shown in figure 4c.

An example of the tested images of the target dataset is shown in figure 4d.



(a) Example of accuracy performance for testing source domain (smartphones dataset).

(b) Example of accuracy performance for testing source domain (smartphones dataset).



(c) Model performance for target domain (electric screwdriver dataset).

(d) Example of accuracy performance for testing target domain (electric screwdriver dataset).

Fig. 4: The performance of the suggested model

We evaluate our classifier with three popular trained models that use similar design methods, such as GoogLeNet [19] and Inception-V3 [20] that use the inception module concept, and ResNet-18 that uses the residual method [7]. From the confusion matrix, the diagonal elements represent the samples that were correctly classified. To calculate the overall accuracy, is the percentage of the correctly classified samples over the total number of samples. Table 1 shows the overall accuracy values of the tested models.

We find that, our suggested model approaches the popular pre-trained models with the advantage that training the network can leverage features related to Ewaste rather than images like ImageNet (a benchmark dataset that is used for training the popular models). These results are also confirmed by [10], that pre-training on ImageNet provides fewer benefits and does not transfer well to small

Table 1: Evaluation of our approach

Tested Models	**Tested datasets**	
	Smartphones	***Electric screwdriver***
GoogLeNet	94.3%	93.33%
Inception-V3	96.11%	95.52%
ResNet-18	94.97%	94.59%
Our Transfer Model	**(Source)** 94.27%	**(Target)** 97.22%

fine-grained tasks. Therefore, training off-the-shelf models, like GoogLeNet, Inception-V3, and ResNet-18, in our case, can be a starting point to extract features, but transferring weights from related source tasks can learn better adaptable features. Figures 4a and 4c proves the transfer learning benefits of speeding up the training time and overcoming the small-scale related target dataset.

4 Conclusion

Deep learning is data-hungry. In other words, when data is scarce, the model will perform poorly. Therefore, transfer learning is a strategy that overcomes this limitation. In our approach, we focused on using transfer learning as a core technique for object classification. Our model is used as a base, then transferred to another task. This would save time and effort than training from scratch. We proved that our model achieves high accuracy, and it approaches popular pre-trained models that are applied to train ImageNet. We used web crawling to extract images automatically from web pages to build our datasets. We show that web crawling is a powerful tool for retrieving any information from a seed URL, usually from search engines. Finally, we can transfer all the detailed information to the next phase of material processing to support the overall recycling process with minimum human intervention, but with higher accuracy. A more extensive comparison with other object classification models (e.g. other artificial neural networks topologies) can be performed as a future work.

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