Sara Paiva
Sérgio Ivan Lopes
Rafik Zitouni
Nishu Gupta
Sérgio F. Lopes
Takuro Yonezawa (Eds.)

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A Feature-Fusion Transfer Learning Method as a Basis to Support Automated Smartphone Recycling in a Circular Smart City

Nermeen Abou Baker(✉), Paul Szabo-Müller, and Uwe Handmann

Computer Science Institute, Ruhr West University of Applied Sciences, Lützowstrasse 5, 46236 Bottrop, Germany
{nermeen.baker,paul.szabo-mueller,uwe.handmann}@hs-ruhrwest.de

Abstract. In this paper, we present how Artificial Intelligence (AI) could support automated smartphone recycling, hence, act as an enabler for Circular Smart Cities (CSC), where the Smart City paradigm could be linked to the Circular Economy (CE), which is a leading concept of the sustainable economy. While business and society strive to gain benefits from automation, the ongoing rapid digitalization, in turn, accelerates the mass production of Waste Electric and Electronic Equipment (WEEE), often called E-Waste. Therefore, E-Waste is the fastest growing waste stream in the world and comes up with several negative environmental and social impacts. In our research, we show an AI technique (particularly, Transfer Learning) that could become an enabler for the CSC and the CE in general and supporter of automated recycling, specifically. However, research on this topic is emerging only recently, and practical applications are lacking even more. For instance, object recognition has extensive research, whereas smartphone classification nevertheless has rare attention. Our main contribution is a Transfer Learning (TL) approach based on visual-feature extraction to classify smartphones; as a result, it supports automated smartphone recycling independently of brands and even without any ex-ante information about product designs. Our findings show that the main advantages of using TL, are reducing the size of the training-set, computation time, and significant enhancements without designing a completely new network from scratch. This may ease the automated recycling of smartphones as well as other E-Waste, hence, contribute to the development of the CE and CSC.

Keywords: Feature fusion · Transfer learning · Smartphone recycling · Circular economy · Automation systems · Smart city · Sustainability · E-waste management · Circular city

1 Introduction

1.1 Motivation and Challenges

The interplay of emerging digital technologies such as AI, Smart City development, CE opportunities, and challenges associated with E-Waste brings us to our research question

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Fig. 1: How can AI (particularly, TL) be applied in order to enable automated smartphone recycling, hence, contribute to the development of CSC?

In particular, this paper addresses the problem of smartphone recycling and applies a feature-fusion TL method to classify smartphones without any ex-ante information about product designs. In our interdisciplinary research in cooperation with digitalization and sustainability, we embed this deep investigation in the wider framework of Smart City development and CE.

Cities around the world are looking for strategies to become more sustainable places. On one hand, economic prosperity, environmental quality, and social wellbeing should go hand in hand. On the other hand, cities try to cope with global and local challenges, such as; climate change, air pollution, biodiversity loss, social inequality, and resource depletion. These visions of sustainable city convergence with digital technologies, like AI, 3D Printing, Big Data Analysis, and the Internet of Things (IoT) in the smart city concept and almost all areas of life [1–3].

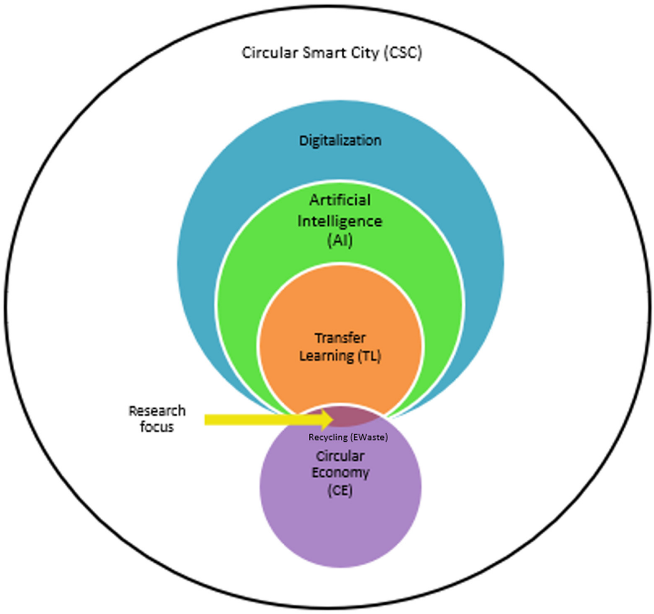

Fig. 1. Our cooperative interdisciplinary research with digitalization and CE in the framework of Smart City

Particularly, AI could become the fundamental driver of CE and CSC. Despite that, the smart city concept faces some challenges concerning the security and privacy issues, and the rising of infrastructure costs, there are still ubiquitous areas of application, such as; enhancing the city's security level by recognizing people' faces [43, 44] to access restricted areas [8–10], improving traffic flows by partly autonomous drones and vehicles [11–13], traffic management and smart tracking, assistance systems [14, 15], predictive maintenance [16, 17], and last but not least, smart waste management, such as [18];

installing sensors on waste bins to enhance the collection, smart disposal segregation, sorting and disassembling, and maximizing materials use.

Some smart city initiatives also aim to become circular cities by picking up elements of the CE, to magnify benefits from smarter use of resources [4]. The CE concept proposes low-emission and resource-saving modes of production and consumption by closing material loops and extending product life-cycles. In the combination of the smart city and the CE concept, we see a kind of new category or focus of action, respectively, which we call a Circular Smart City (CSC).

In general, digital technologies could pull down some existing barriers to the CE, like lacking knowledge about the location and condition of obsolete products or included as well as currently higher costs of their treatment compared to 'non-circular' ones [5, 6]. By doing so, digitalization could support the application of CE strategies, for example, some of the so-called R-Strategies like the redesign, reuse, redistribution, refurbishment and maintenance, repair, remanufacturing, as well as recycling of materials [7].

However, while businesses and society strive to get advantages from the ongoing rapid digitalization, it comes with several side-effects. Figures from the latest Global E-Waste Monitor [19] indicate that digitalization currently accelerates the mass production of E-Waste and will speed up more in the future. E-Waste is the fastest growing waste stream in the world, with an annual growth rate of 3 to 4%. From 2014 to 2019, it grew by 21%. Nonetheless, only 17.4% of global E-Waste was officially documented and properly recycled in 2019. On one hand, this comes up with several negative environmental and social impacts, not only at the end-of-life-phase of those products but along the whole value chain.

A closer look at the evolution of the production and use of digital devices, such as; smartphones, which we investigate in deep, support our argumentation. Smartphones play a vital role in our daily life. People and businesses use them for communication, shopping, navigation, entertainment, and many other activities with few screen touches. The continuous consumption of smartphones contributes to a scarcity of non-renewable resources since smartphone manufacturers use Rare Earth Element (REE) and other precious metals. According to [32], only about 1% of smartphones are recycled, and one reason behind this extremely low-rate is the technological complexity to recycle REE. On the other hand, the raw material value of E-Waste offers vast economic opportunities. It is estimated [20] to be 5100 tons of smartphone content of precious and critical metals in units put on the market by 2035 comparing to 1500 tons by 2020.

A periodic table that demonstrates the scarcity of elements used in smartphones was demonstrated in 2019 on the 150th anniversary of the creation of the original periodic table [33]. Modern smartphones contain more than 30 different elements, in which gold, silver, and copper are used for wiring and lithium and cobalt for the battery, and other REE, including yttrium, terbium, and dysprosium. Even though having fractions of grams is considered endangered. Many concerns are raised because about 17 elements needed to manufacture smartphones are finite, and the continuous depletion of these resources is alarming due to limited supplies, lack of recycling, or the location in conflict zones. A study by Yale University [34], tried to find possible replacements. However, they found 12 metals and metalloids, namely rhenium, rhodium, lanthanum, europium, dysprosium, thulium, ytterbium, yttrium, strontium, thallium, magnesium, and manganese, have no replacement at all because the substitution will be inadequate and will decrease the performance.

But how to make use of these resources with the help of digital technologies such as AI? So far this is still an open question [21], but this is a prerequisite for smart(er) smartphone recycling, which is a significant component of smarter E-Waste management.

The remainder of the paper is organized as follows. First, we further elaborate on our motivation and challenges to make AI an enabler to CE in terms of E-Waste Management, we present the state of the art of automated waste management, and to narrow our focus on smartphone recycling. Second, we present a TL method to classify smartphones based on feature extraction. Third, our implementation of the TL is described in detail, followed by demonstrating our experimental results and discussion of optimizing the classification performance. Finally, we draw our conclusion and future work.

1.2 State of the Art of Automated Waste Management and Smartphone Recycling

Waste Management

Traditional waste recycling has many drawbacks: It uses intense manual labor leading to high operation costs, and workers are exposed to these harmful substances through inhalation, skin contact, or ingestion [22]. Moreover, many industrial and household appliances contain hazardous toxic materials like mercury that damages the human brain.

Digital technologies could enhance waste management. It could do so not only the end-of-life-phase of products but it could also extend their life-time and enhance their product-life-cycle. To overcome these barriers and to gain CE benefits, many waste management companies now understand the increasing need for smart Waste Management Systems (WMS) and the automated disassembly of products to maintain sustainability or stimulate eco-design products. Digital solutions are increasingly used to meet the requirements of processing massive waste streams, e.g. identifying waste container loads, tracking vehicle routes, etc. Real-time processing of a large volume of data with the minimum human intervention will certainly support industrial decision-making. Applying AI, including deep learning techniques, will enable building smart WMS. This includes but is not limited to; E-Waste collection, recognizing waste patterns, sorting and evaluating the material status, and estimating the behaviors of waste generators, thereafter to support CE. All in all, we think that AI-enhanced E-Waste Management will contribute to the development of CSC.

Smartphones Recycling

Smartphones are a specific type of E-Waste and there is also potential, but also a need for further research on smart E-Waste management in this area. This is indicated by the fact that the above-mentioned challenges drive leading smartphone manufacturers (Apple, Samsung, and Huawei) to take further measures to adopt a closed-loop system and assess design sustainability, hence to develop and implement CE strategies.

Apple developed two disassembly robots, Liam, followed by Daisy, as a closed-loop supply chain. The company announced that Daisy could recover all the materials like Gold and REE used to manufacture its smartphones [35]. Apple claimed that Daisy can disassemble 15 different iPhone models at 200 devices per hour, which is more efficient than any traditional recycling. They assemble devices by breaking down and separating components to recover materials from iPhones. Daisy can disassemble 2 million devices per year and recycle them automatically.

Samsung announced that the Re+ program has its sustainable promise to support CE. According to [36], the company collected 3.55 million tons of end-of-life products between 2009 and 2018 through this program. It stated that the material compositions of smartphones are: plastic, aluminium, steel, copper, cobalt (the primary resource used in batteries), and gold and other materials, with the percentage of 35.1%, 20.2%, 10.6%, 10.0%, 8.6%, 15.5% respectively. Their new vision is to allow the company to design the devices to be easy to repair, disassemble, and recycle, which will expand the life span of products and improve durability.

Huawei also takes part in supporting CE through its Green Action program. Its service centers took back almost 60 tons of spare parts every month in 2019 and involved its customers in a credit-based recycling program [37]. Furthermore, hundreds of thousands of smartphone batteries were replaced each month of 2019 through the battery replacement program at a fixed price, and they improve their maintenance quality through discounted repair programs and even the EMUI 10.1 system that improves the file fragmentation to prevent phones from freezing up for 18 months. Eventually, the customers can use the product longer with fewer resources in the long term.

These companies can make products from recycled or renewed materials only by using their own product design knowledge as a core prerequisite of recycling. It is worth mentioning that modular phones like ARA by Google, G5 by LG, the Dutch FairPhone, or the German ShiftPhone are examples of modular smartphones. They are considered as best-practice in sustainable design and durability. These phones are easily disassembled, contain less hazardous substances, long time warranty (mostly five years) as well a transparent cost-breakdown [38]. Unfortunately, they fail to take a big market share because of their high costs in relation to lower-technical feasibility compared with conventional smartphones.

2 Method: Transfer Learning Approach - Extraction of Information Based on Visual Features

While describing the potentials of AI for smart E-Waste Management is easy, the development of the respective solutions is a rather sophisticated task. Concerning the technical challenges that face AI solutions, building an entire Neural Network (NN) is a challenge even to AI experts. Therefore, rather than reinventing the wheel, we used AlexNet [24] as a pre-trained model on a large-scale dataset, fine-tuned the model on a new, relatively small training-set of smartphone images, and transferred the learned characteristics to classify smartphones.

Challenges for smartphone classification emerge as their designs look similar recently in terms of shape and size, especially when keypads, big antennas, buttons, screen flips, and slides are abdicated. Instead, big touchscreens, all-glass front, multi-cameras, and adjusted size to fit in hands became the typical design, in order to satisfy users' preferences.

The extraction of information based on visual features is often solved based on NN [39]. Convolutional Neural Networks (CNN) application has significant success in object recognition and classification [40]. Therefore, our method is designed to extract information based on visual features.

2.1 Transfer Learning Method

It is labor-intensive to train NN from scratch because a huge data set is needed. Alternatively, an approach like TL could help to solve classification problems, e.g. different smartphone models. Bear in mind that TL is considered as a supplement but not a replacement to learning techniques. To successfully implement TL, why, how, and when to transfer should be clear beforehand.

Why Transfer Learning

In AI, new knowledge could be obtained by starting from scratch, but it needs a tremendous amount of training data. The TL technique has verified its efficacy against the scratch method's training to tackle this problem. TL is a relatively new topic in the AI domain. It is used when the source and target datasets have different features, and it works efficiently when the target dataset has a small amount of data. The main concept is to reuse specific parts of source samples into target samples to improve the attained learning in a new task. Thus, our method is based on extracting features using a TL approach that seeks good feature representation in the source and leads to better smartphone classification accuracy and less error. Later in the implementation, we will test the advantages of TL.

How to Transfer and Why AlexNet is Used?

Image classification is one domain area in the field of deep learning [15]. Using TL techniques (Fine-tuning AlexNet, specifically) have impressive success in many fields that underpin modern AI-enabled technology, to name but a few; biometrics [25], medical images [26], fault diagnosis in the industry [27], natural language processing [28]. However, smartphone classification received less attention.

Performing TL means choosing a pre-trained model that leverages the required task as a starting point and then fine-tune it to achieve the desired results. AlexNet has been used intensively in many applications as a leading model that uses TL for the following reasons:

- First, it is considered a deep NN because it has many hidden layers of non-linear feature extractors, as we will describe them further in the network structure section.
- Second, it outperformed the other Non-deep learning method in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2012 [26].

- Third, it has a high-performance trade-off between accuracy and speed, thanks to Rectified Linear Units (ReLU) that accelerates the convergence of the NN than using saturation function like Tanh or Sigmoid [41].

Therefore, we used AlexNet in our approach, and we will describe the architecture in Sect. 3.1.

When to Transfer?

Even though TL has superior benefits, it is not merely a plug-and-play model. To decide what features are maintained in the network is an open challenge. The pre-trained model should be well understood before proceeding with any modifications.

3 Implementation

3.1 Classifying Smartphones

In the implementation, we pass the training data to the network, and setting the options of the training algorithm; then, we will train the network and optimize the performance. Figure 2, shows the system flowchart of the total implementation. The computing environment was Matlab since it has a suitable deep learning toolbox, which allows us to comprehensively customize solutions by creating, editing, visualizing, and analyzing the CNN, on a core i5 Intel laptop with 16 GB RAM. An Allied GigE camera is used for real-time testing.

We used the TL concept to classify 14 models of smartphones from different brands. We start by building our dataset; then, we fine-tune the traditional AlexNet structure to fit with our target output. Next, we set the training options to trigger the early stop. After training the network, we monitor the performance, and we suggest to perform controlling the error rate and data augmentation to enhance the generalization capabilities. A technical description of the procedure is delivered in the following section.

Network Architecture

In this paper, we suggest a fine-tuning of the pre-trained model of AlexNet. First, the standard AlexNet is analyzed here. It has eight learned layers, as follows:

- Five convolutional layers (conv1–conv5), which are basically used to extract features. The information extracted from (conv1–conv3) represents the generic features with different colors, texture, and intensity. Whereas, the next layers (conv4–conv5) extract the more refined features (or local patterns) like those with different sizes and shapes.
- Three pooling layers, usually to downsample the features to implement faster computation.
- Three Fully Connected (FC) layers: (FC6–FC7) who are mainly used for features that are more task-specific and prevent the model from overfitting while training, (FC8) combines the previous features to present the output 1000 labels.

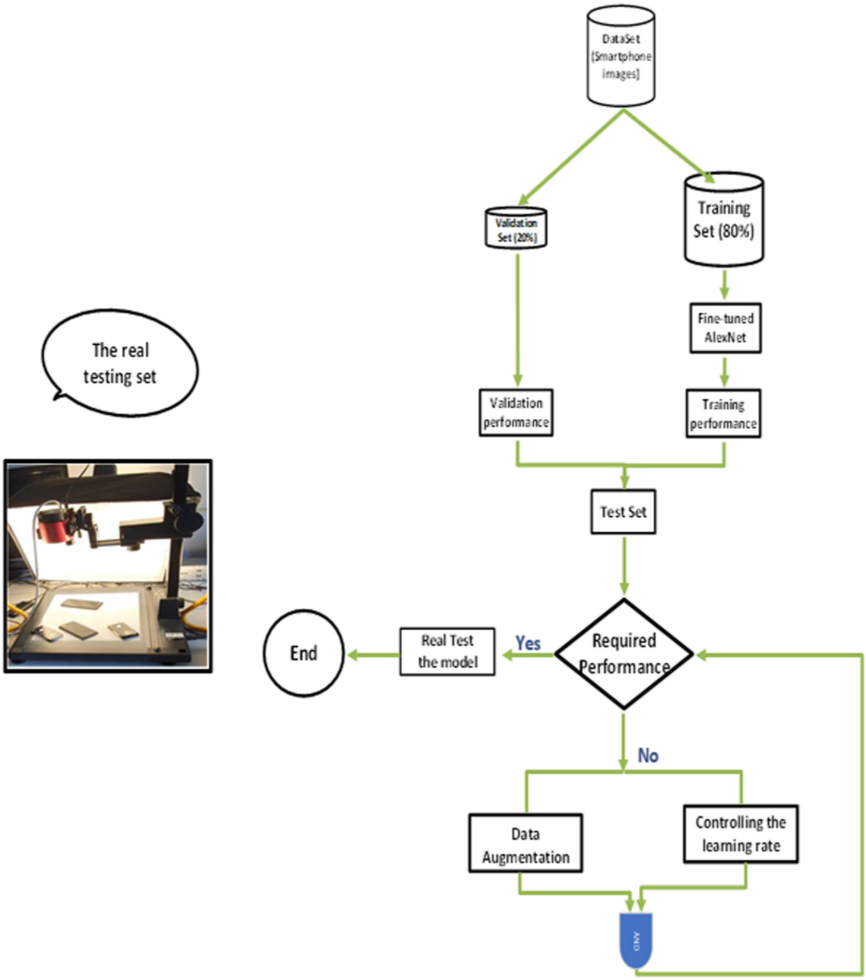

Fig. 2. The system workflow of implementing smartphone classification with TL

AlexNet is a large CNN that has successfully classified 1.2 million images with 1000 object labels, so this abundant data is rich with a wide variety of feature representations. In the original pre-trained AlexNet architecture, the last third layer is configured to map the extracted features from the previous layers to 1000 output classes; then, the softmax layer acts as a normalization step to turn the raw values of the 1000 classes into a probability distribution of the image belongs to that class; thus, the sum of all elements in this vector is equal to 1. Finally, the last layer takes the most probability and returns the most likely class as a network output. We propose a network modification by freezing

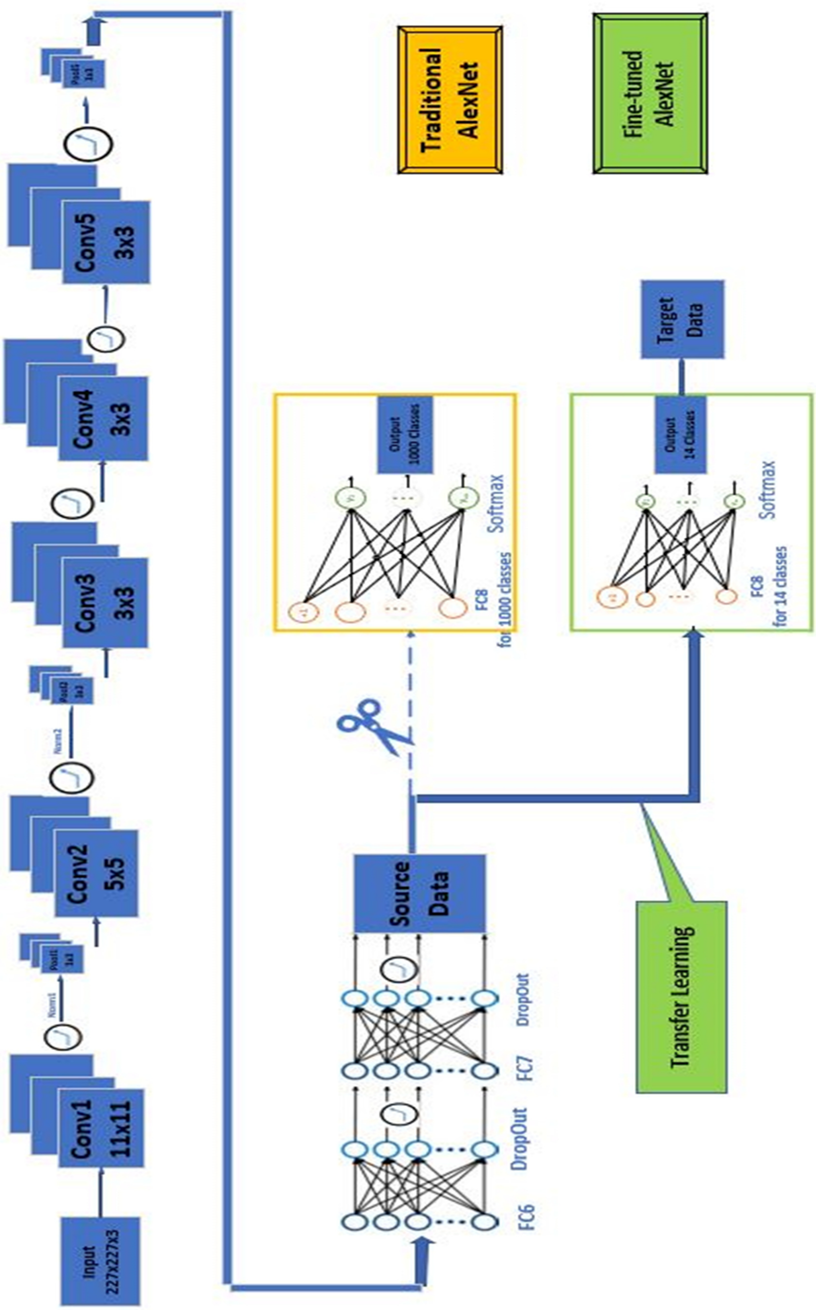

Fig. 3. Transfer learning approach by fine-tuning AlexNet structure

the last three layers, replace them with (an FC layer, a softmax layer, a classification output layer) to suit the new training-set, then retrain them, as illustrated in Fig. 3.

Training Algorithm

We control the behavior of the training algorithms to gain better training performance. We split the dataset as 80% (320 images) for the training-set and 20% (80 images) for the validation. We used the Stochastic Gradient Descent with Momentum (SGDM) method as a training algorithm because it converges faster towards lower minima, and it oscillates less. We set the mini-batch size to 20 and we found that the accuracy and loss factor stabilize when the max epoch is equal to 20, where in each iteration one mini-batch is trained and the number of epochs represents the number of times that the network sees the entire dataset. We control the early stop when the validation error no more improves to set a trade-off between the training time and accuracy. Following the training, we evaluate the network performance using the validation-set during training. It is an important step to check overfitting.

3.2 Training the Network

After preparing the three previous components, we are ready to train our network. We demonstrate different metrics to evaluate the classification efficiency; accuracy, and loss function. Besides that, the confusion matrix of validation testing and real-time testing will be conducted later to test the model performance. The accuracy represents the percentage of the correctly classified trained images during an iteration to the number of the entire dataset, which calculates the Root-Mean-Squared-Error (RMSE) in the model gradients function. The error between the predictions and the true known class is called the loss function. It defines the extent to which the actual outputs are correctly predicted; practically, it represents the mini-batch loss. In the NN we aim to minimize the loss function (see Fig. 4).

4 Results and Discussion

After training the network, we found that the validation accuracy is equal to 86.4%, and it is stabilizing to be less than the training accuracy, which is not adequate. We recommend the following steps to modify some training options to gain a better performance.

4.1 Controlling the Learning Rate

Choosing the learning rate is one of the challenging tasks in learning a CNN. In our method, we schedule the learning rate by reducing updating the weights by slowing down the learning rate initially to maintain the useful features, but then we speed up the learning features. We set the dropout factor as 0.5 to obtain maximum regularization [42]. We found that the validation accuracy is 88.7%, but the model is underfitting (Fig. 5).

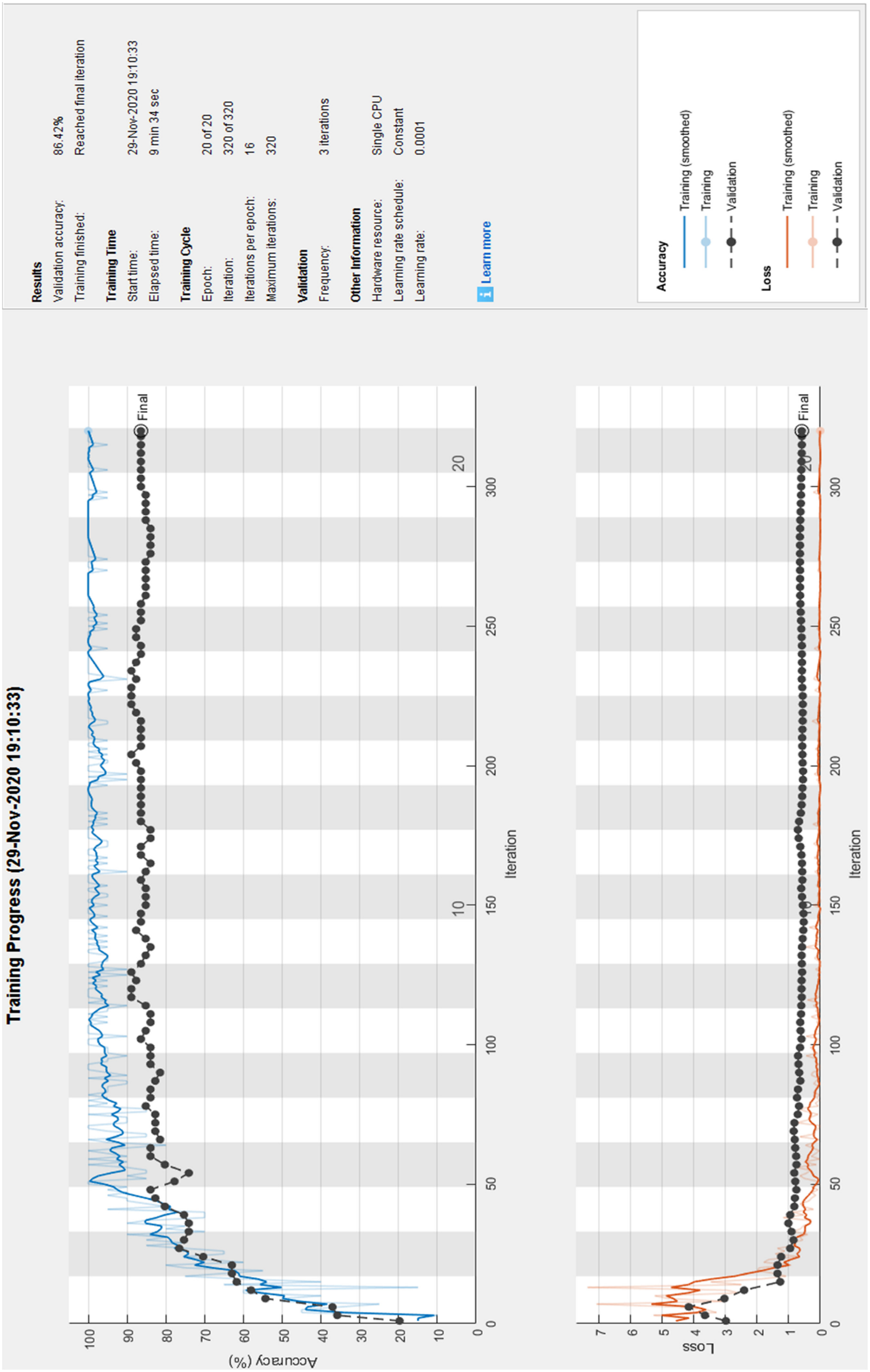

Fig. 4. The network performance before improvement

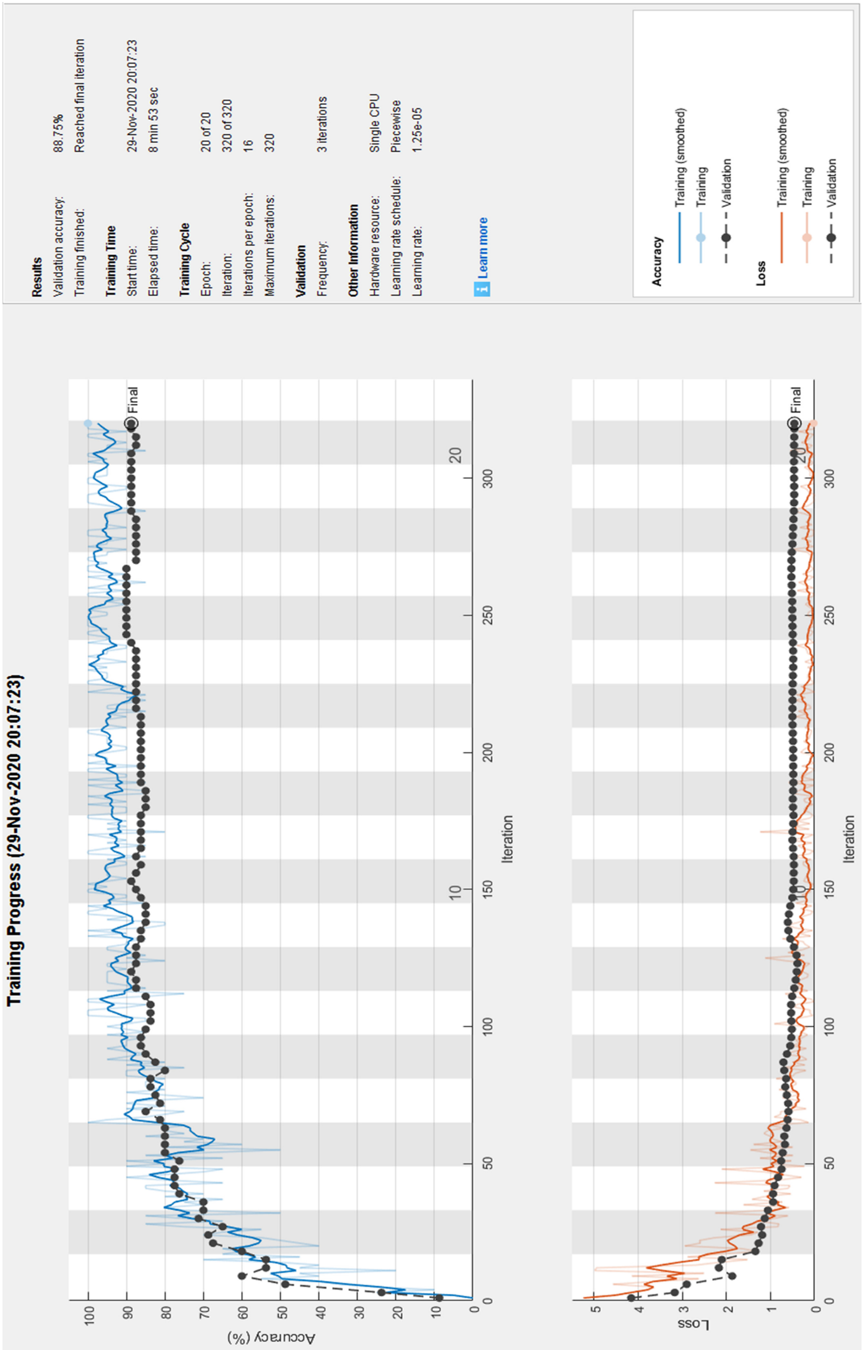

Fig. 5. The network performance with controlled learning rate

4.2 Data Augmentation

Data augmentation is an automatically pre-processing stage during the training phase, to cope with the imperfect images in terms of different angles, substandard lightings, or not well-cropped or framed. This, in turn, prevents the overfitting problem by showing the network, different variations of the same image, such as; rotation, reflection, translation, shear, and scaling during the training phase. Subsequently, it leads to effortless adding multiple viewpoints of the same class of the non-altered data-set hence, teaching the network that minor shifting, mirroring, or cropping of images does not affect the prediction, but enhancing the classification accuracy. Consequently, it solves the problem of having a few training data.

In our method, we use AlexNet that expects the input images' size as $227 \times 227 \times 3$, so the training-set should be first resized to feed the first layer. Besides that, additional randomly vertically flipping and vertically and horizontally translating the images are performed to prevent the model from memorizing the training-set.

We perform reflection and translation on the X and Y axis, so our dataset was augmented by 4 leading to 1680 images. We also shuffle the data before each epoch to avoid discarding it every epoch. We found that the model is generalized, but the activation accuracy is 86.25% (Fig. 6).

Previously, we found that applying data augmentation or having a constant learning rate leads to non-adequate network performance. We found that the model generalized well without over or underfit, and the accuracy is enhanced to become 96.25% by scheduling the learning rate, and we augment the dataset, as illustrated in Fig. 7. By testing the (80 images) in the validation-set, a confusion matrix is demonstrated in Fig. 8. It is a numeric matrix that is used to measure the performance of the network by creating a matrix from the true class and the predicted class. It shows how many observations in every cell, where the diagonal of the matrix shows the correctly classified objects.

The normalized row and column (on the side of the matrix) display the percentage of correctly classified class (highlighted in blue color) and the incorrectly classified class (highlighted in orange color). We found that most of the smartphones are correctly classified since the activation accuracy reached to 96.25%.

Apparently, from the confusion matrix we can calculate the loss function of the validation-set, as the following equation:

$$\text{Error rate of the ValidationSet} = (\text{The number of incorrectly classified objects in the validationSet})/(\text{The total number of validationSet}) \tag{1}$$

This means that the error rate here is equal to 0.0375 (3/80), which is very acceptable. It also confirms the loss function value that is shown in Fig. 7.

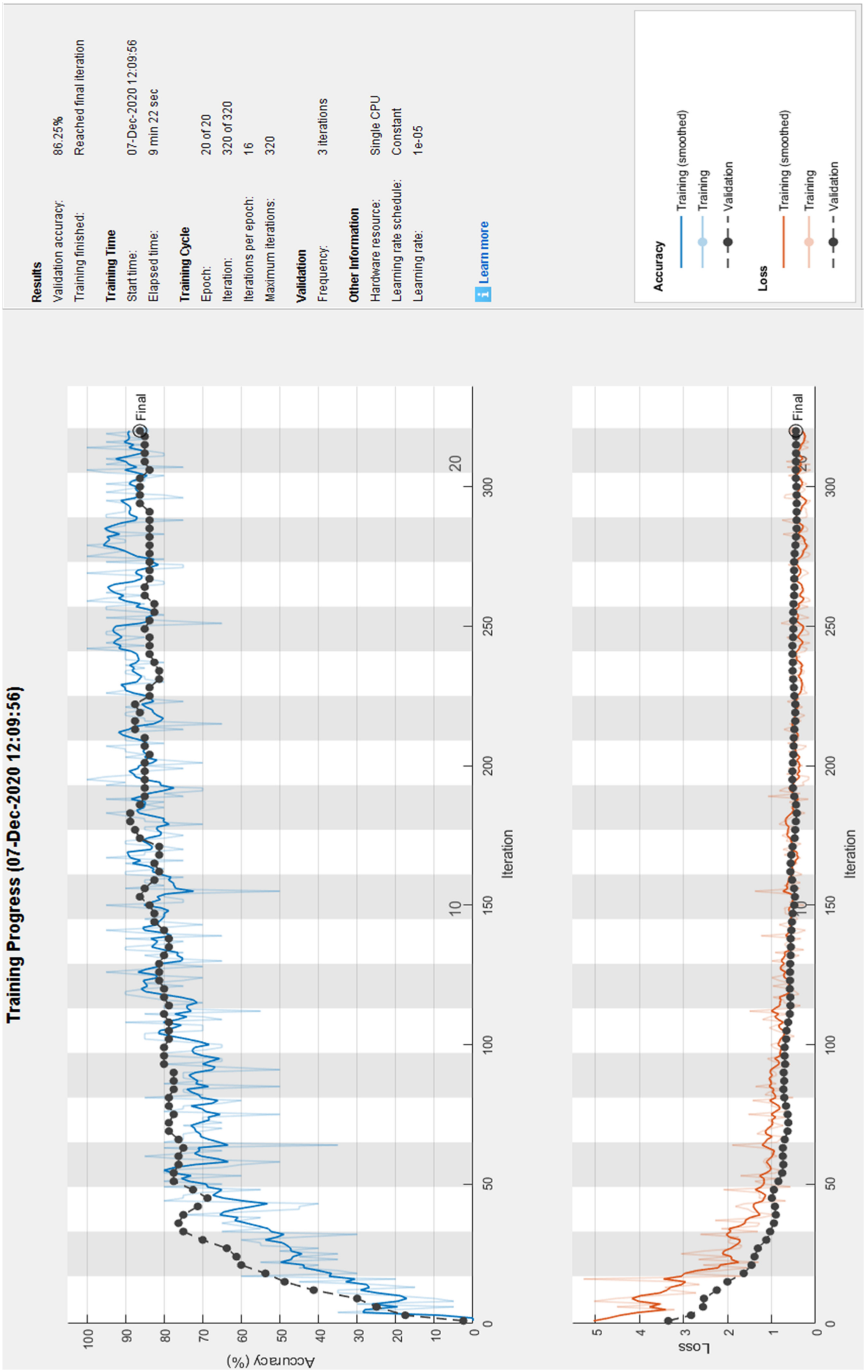

Fig. 6. The network performance with data augmentation

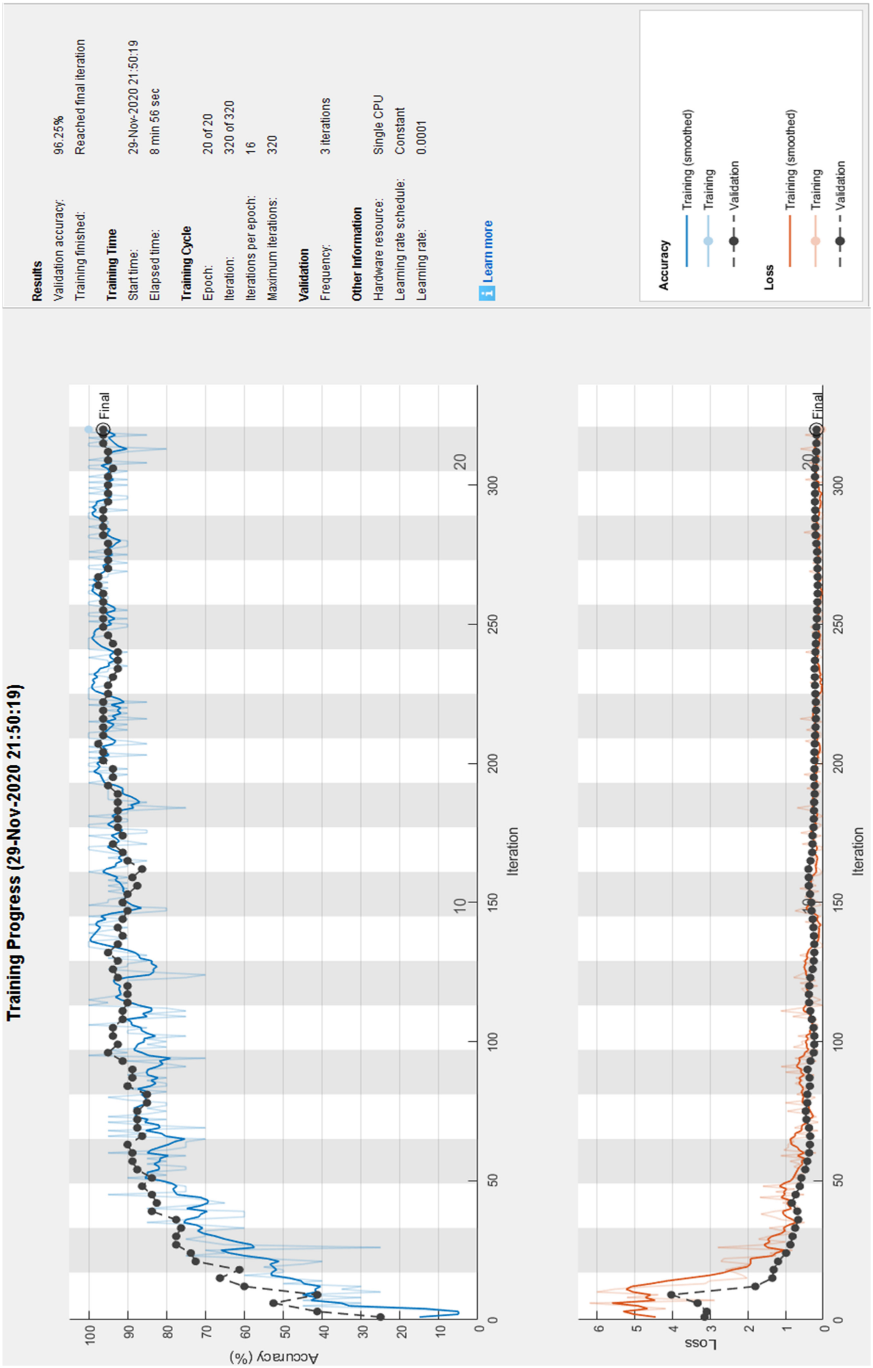

Fig. 7. The network performance including improvements

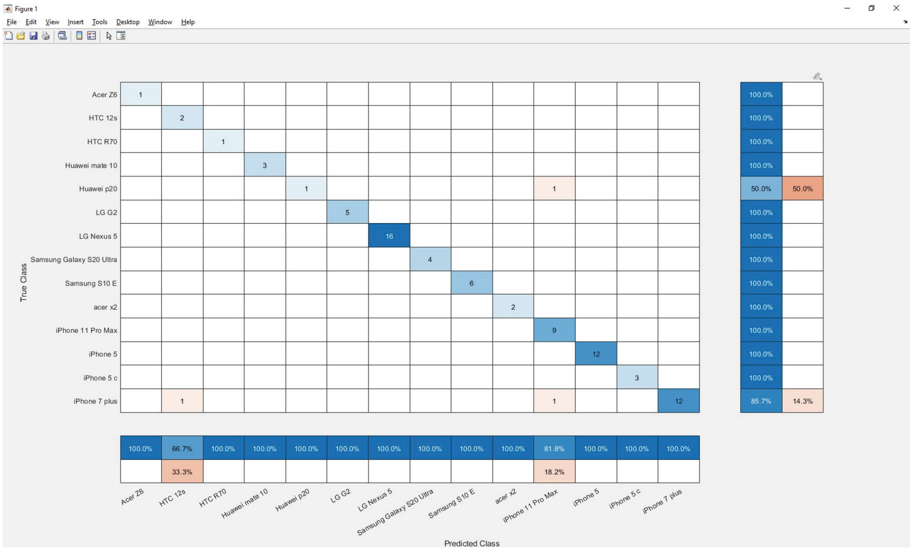

Fig. 8. Confusion matrix of the validation set (Color figure online)

4.3 Real-Time Smartphone Classification

By using the real-testing set, illustrated in Fig. 2, we conducted a real-time smartphone classification, by using the Allied GigE Camera and four examples of smartphone models. Figure 9, shows that a high testing accuracy has been achieved based on visual features only, with our proposed TL approach.

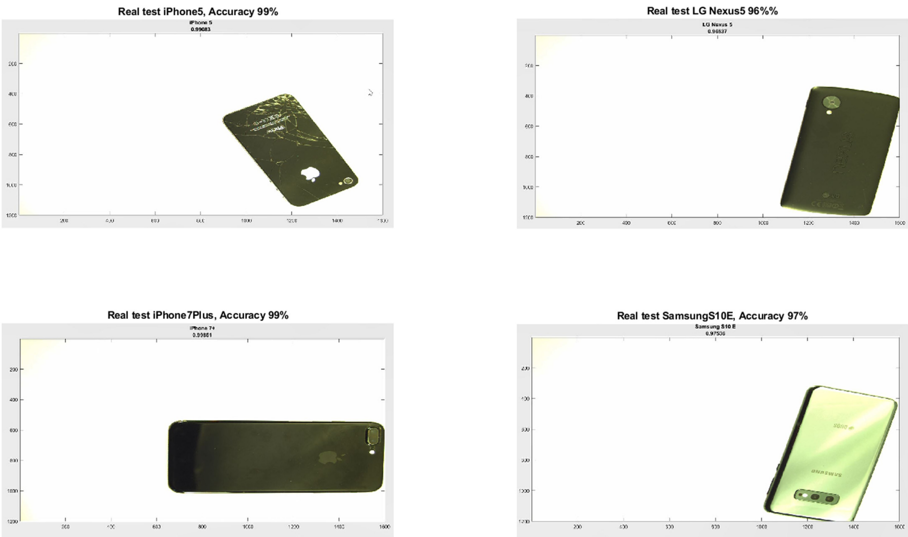

Fig. 9. Real testing on four smartphone models

We found that the model leads to considerable results. Furthermore, this confirmed our investigation that the TL does not require a massive dataset to get high accuracy, even though the dataset is small. Besides that, TL is far easier than building the network from scratch, and the training time is greatly reduced.

The results show that despite having no information about the smartphone design, the model achieves good feasibility of the smartphone classification based on feature fusion by using a TL technique.

5 Conclusion

In this paper, we present how AI could support automated smartphone recycling, hence, act as an enabler for CSC. We investigate a feature-based extraction of smartphones to support CE. Currently, smartphone manufacturers start to endeavor to recycle their own products, however, their recycling programs are designed to fit their own products only, which may limit high recycling quotes. Therefore, we develop a feature-based TL approach that works without having any information about the design of the products. We use the TL technique, by choosing AlexNet as a pre-trained model, to perform our test, and to gain the advantages of TL techniques, as easier and faster way than training the NN from scratch, which we prove in our results.

In consequence, we conclude that AI and CE could conjointly be applied to achieve smart sustainability successfully. As we find that AI can help in transforming the E-Waste management infrastructure into a closed-loop system, we conclude that AI can pave the way towards CSC.

However, further research is needed. Smartphone recognition still faces more challenges even with state-of-the-art image classification methods, especially for the recent smartphone models due to the high similarity in visual characteristics.

Future research will address these shortcomings. We suggest conducting non-destructive testing outside the visible light to detect the internal smartphone components, e.g. the battery, camera, ID sensors, that helps in material recognition, by using a fusion of sensors in different wavelengths to support automated recycling, hence the CE.

Last but not least, we argue that a fully-sustainable system would require rethinking and changing behaviors of customers and smartphone manufacturers, respectively. This would include, for instance, avoiding the replacement of smartphones every couple of years unless they need maintenance and thinking in maintaining raw materials needed by eco-design of future products.

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