A Trial of Recognition of Electronic Parts by Deep-Learning for Efficient Recycling

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Abstract. Waste electronic appliances contain a large amount of recyclable materials, but identifying and separating them still requires significant manual labor. To improve material recycling efficiency, we develop a system that utilizes deep learning to recognize and analyze electronic components automatically. Since the inference speed of deep learning models can become a bottleneck in real-time recycling systems, we propose a lightweight neural network specifically designed for the classification of electronic components on wasted electronic boards. Experimental results show that the proposed model achieves approximately 95% accuracy while requiring only about 120 μsec to classify a single component image.

Keywords: electronic wastes, recycling, deep learning, CNN, resource paradox, SDGs

1 Introduction

In recent years, electronic products have brought significant changes to people's lives. The popularization of electronic information devices such as computers and smartphones has made our lives more convenient and secure, rendering them essential. While products continue to become more high-performance, their lifespan has not increased. People choose to buy new products rather than repair them. Consequently, massive quantities of electronic waste are generated annually, consuming vast amounts of resources.

Issues concerning resources and waste are critical matters affecting humanity's future, and countries worldwide are promoting the Sustainable Development Goals (SDGs). However, not a few initiatives to achieve the SDGs involve excessive resource input, which paradoxically worsens environmental conditions. One project of the Ritsumeikan Global Innovation Research Organization (R-GIRO), "Multi-Value Circulation to Solve the Resource Paradox Problem" [1], defines this contradiction as the Resource Paradox Problem [2] and aims to build a truly sustainable society from both environmental and resource perspectives. This research specifically targets the advancement of resource recycling from electronic waste.

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Electronic waste contains relatively high amounts of resources such as gold, copper, paragium, and so on. To improve recycling efficiency, there is a need for systems for automatic and fast classification and analysys of printed circuit boards (PCBs) and components. Building on recent advances in computer vision technology, research and development is progressing on the detection and classification of electronic components using camera images. Laszlo et al. developed a system that detects and classifies electronic components on a conveyor belt by extracting contours [3], while Bassiouny et al. developed a system that detects the positions of electronic components from photoimages of circuit boards [4]. In Japan, the Ministry of the Environment is also advancing demonstration experiments [5].

In object recognition within images, a technology called deep learning [6] has become widespread. When a deep learning classifier is introduced to some issue, an existing general-purpose model is often reused, while it is not necessarily optimal for the target. Unlike the image classification problem for general objects with diverse appearances, the diversity in the appearance of electronic components is small, suggesting that a more lightweight model is sufficient for classification. Furthermore, deep learning requires large amounts of training data, yet to the best of our knowledge, no publicly available image datasets for electronic components exist.

The paper first constructs a training dataset by photographing electronic circuit boards, extracting components, and assigning labels; the dataset is available at [7]. Based on the evaluation of model accuracy and execution time in experiments, the layer configuration, number of nodes, and other parameters are adjusted, and an optimal model is proposed that achieves the best trade-off between inference speed and recognition performance.

2 Training Dataset of Electronic Components

Deep-learning-based image recognition classification requires images as training data. Typical deep learning models require thousands or tens of thousands of training images. As for electronic components themselves, images consist of relatively simple geometric shapes and have stable forms. On the other hand, when considering waste circuit boards flowing on a conveyor belt, factors like shooting angle, lighting and shadows, component occlusion, defocus or motion blur, and dirt must be accounted for. This necessitates a larger number of images on actual wasted boards. We produce a training image dataset for electronic components by photographing wasted boards collected in our laboratory.

The samples are randomly selected from PCs and devices for electronic experiments. The boards are placed on a table and photographed using a smartphone manipulated by hand. Color images are captured at 5120x3840 resolution. Four images from different angles are taken per board: one from right above and three from angled above, rotating approximately 45 degrees horizontally each. An example is shown in Figure 1.

Next, images of electronic components are trimmed from the circuit board image using Windows 10 Screenshot and the Sketch tools. The extracted images are saved as JPG files. An example of the trimming process is shown in Figure 2.

The extracted component images are manually classified and saved in the corresponding directory for each category. The targets in this paper are resistors, capacitors, and semiconductor

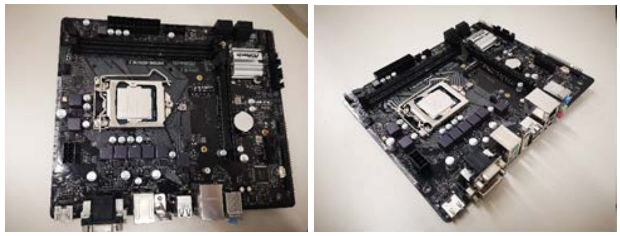

Fig. 1. an example of a photographed wasted circuit board

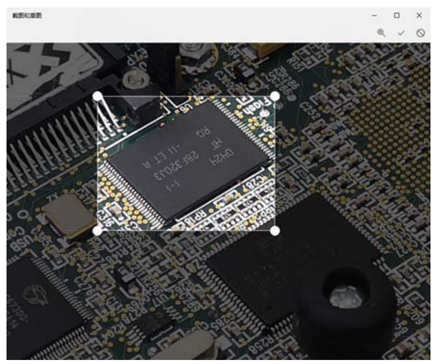

Fig. 2. trimming process of components from board images

components. Based on component shape, components are classified into six categories: chip capacitors, cylindrical capacitors, integrated circuits, transistors, chip resistors, and others. Example images of the categorized components are shown in Figure 3.

Classified images are normalized to 50×50 pixels in shape and saved as a $50 \times 50 \times 3$ numpy array in the Python code. Data augmentation is then performed. The ImageDataGenerator class from the Keras API is used for data augmentation. Parameters are set to random rotation ± 20 degrees, horizontal shift ± 0.2, vertical shift ± 0.2, and random horizontal flipping. Nine images are generated from each original image, and the dataset is created by combining these with the original image. The dataset breakdown is shown in Table 1.

3 Network Model

In deep-learning-based image recognition, recognition and classification are performed using a network model called a convolutional neural network (CNN). A CNN consists of convolutional layers that extract spatial features from images, pooling layers that spatially reduce the distribution of features, and fully connected layers primarily responsible for classification and decision-making.

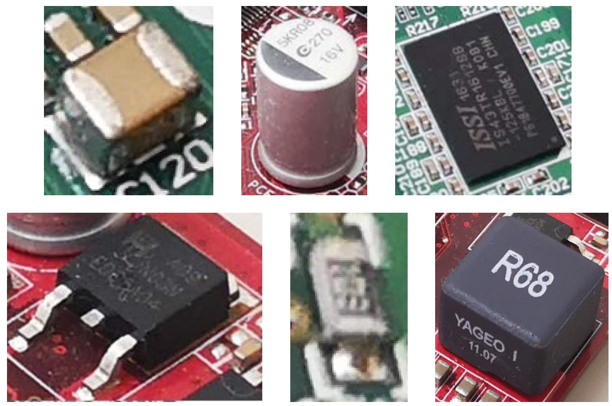

Fig. 3. Examples of part images: Chip Capacitor, Cylindrical Capacitor, Integrated Circuit, Transistor, Chip Resistor, and Other (from left-top to rightward)

Table 1: Breakdown of the Electronic-Part Dataset

Category	Number
Chip Capacitor	3,070
Cylindrical Capacitor	2,170
Integrated Circuit	3,060
Transistor	1,820
Chip Resistor	1,370
Other	230

They are defined by the number of layers and their order, the size and number of convolutions, the pooling method, the type of activation function, and the number of nodes.

Considering that electronic components have a relatively simple, geometric appearance, this paper references the comparatively small-scale VGGNet[8]. Although VGGNet demonstrates excellent classification performance, it is a general-purpose model designed for 1000-category classification tasks. Consequently, it remains over-engineered for our specific purpose and incurs a correspondingly high computational load. Therefore, we reduce the number of layers and nodes based on VGGNet16 and adjust parameters for electronic components, that is, our target.

Table 2 shows the layer structures of our seven candidate network models A to G. conv indicates a convolutional layer with a filter size of 3×3, and conv8,16,32 indicate 8, 16, and 32 filters, respectively. The activation function used is ReLU. maxis a pooling layer, using 2×2 max pooling with a stride of 2 and zero padding. full indicates a fully connected layer, with full64 and full128 representing 64 and 128 nodes, respectively. Dropout is applied immediately after the pooling and fully connected layers, with dropout rates of 0.25 and 0.5, respectively. The output is normalized using the softmax function.

Table 2: Candidate Layer Structures of the Network Model

<table>
<tr><th>A</th><th>B</th><th>C</th><th>D</th><th>E</th><th>F</th><th>G</th></tr>
<tr><td colspan="7">input</td></tr>
<tr><td>conv8
conv8</td><td>conv8
conv8</td><td>conv8</td><td>conv16</td><td>conv8</td><td>conv8
conv8</td><td>conv8
conv8</td></tr>
<tr><td colspan="7">max</td></tr>
<tr><td>conv16
conv16</td><td>conv16
conv16</td><td>conv16</td><td>conv32</td><td>conv16</td><td>conv16
conv16</td><td>conv16
conv16</td></tr>
<tr><td colspan="7">max</td></tr>
<tr><td></td><td></td><td></td><td></td><td>conv32</td><td>conv32
conv32</td><td>conv32
conv32
conv32</td></tr>
<tr><td colspan="4"></td><td colspan="3">max</td></tr>
<tr><td>full64</td><td>full128
full128</td><td>full64</td><td>full64</td><td>full64</td><td>full64</td><td>full64</td></tr>
<tr><td colspan="7">smax</td></tr>
</table>

Model A is a simple architecture based on a typical design widely used in image classification. Model B features two fully connected layers compared to A, doubling the number of nodes. Models C and D reduces the two convolutional layers for each section to one, while increasing the number of filters instead. Models E, F, and G add one more section of convolutional layers, while also increasing the number of convolutional layers in a section.

4 Experiments and Evaluation

We evaluate the computational load and classification accuracy for our candidate network models. TensorFlow[9] and Keras[10] are used for constructing network models and performing training and inference. TensorFlow is an open-source machine learning framework developed by Google. Keras is a machine learning library that provides a high-level API using TensorFlow as its backend. The computational environment used for the experiments is as follows: Intel core i9-9900X processor (10C/20T, 3.5GHz, 19.25MB), 64GB DDR-4 memory, NVIDIA GeForce RTX2080Ti GPU (11GB), Ubuntu 18.04, Cuda 11.4, Cudnn 8.2.4, Python 3.8, and Tensorflow 2.6.

For each candidate model, training is performed using the dataset presented in Section 2. 80% of the component images are used for training, and 20% for testing. For training, the mini-batch size is set to 32, the number of epochs to 200, and the learning rate to 0.01. The loss function is cross-entropy, and the optimization method is stochastic gradient descent (SGD).

4.1 Computational Load and Accuracy

The computational load is evaluated by processing time per image calculated by execution time for test (classification). The processing time and accuracy for each candidate model are shown in Table 3, and their scatter plot is shown in Figure 4.

Table 3: Processing Time and Accuracy for Models

Model	A	B	C	D	E	F	G
Processing Time [μs]	94.4	94.6	93.8	93.0	95.2	97.3	97.2
Accuracy [%]	137	132	114	110	125	150	152

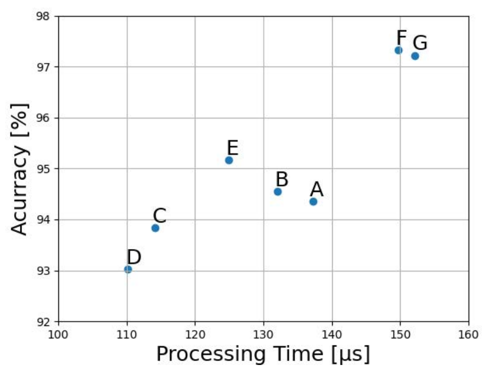

Fig. 4. Scatter Plot of Processing Time and Accuracy

The proposed models require approximately 100 [μs] to classify a single image. They are significantly faster than general-purpose models such as VGGNet. The comparison of the models reveals that the number of layers has a greater impact on the execution time than the number of filters or nodes. Comparing C and D, even though the number of filters in the convolutional layer doubled, the execution time does not change significantly. Figure 4 shows the trade-off between computational load and accuracy. Models D, C, E, and F, located in the upper left of the graph, are considered promising models with a good balance.

4.2 FC Nodes, CNV Filters and Accuracy

Model E exhibits a relatively good balance, so we investigate its relationship with accuracy by further fine-tuning the parameters. Results are shown in Table 4. Each column fc indicates the number of nodes in the fully connected layer, each row cnv indicates the number of filters in the first convolutional layer, and the values represent accuracy. Note that the number of filters in the second and subsequent convolutional layers is doubled from the previous layer. For example, if the

Table 4: fc Nodes, cnv filters v.s. Accuracy [%]

cnv \ fc	16	32	64	128
8	91.8	92.3	95.2	97.0
16	95.8	97.3	96.3	95.5
32	**97.6**	97.2	95.2	96.6
64	96.9	96.9	97.5	96.9

first layer has 8 filters, the second layer has 16, and the third layer has 32. The results show that increasing the number of nodes or filters does not necessarily lead to better performance.

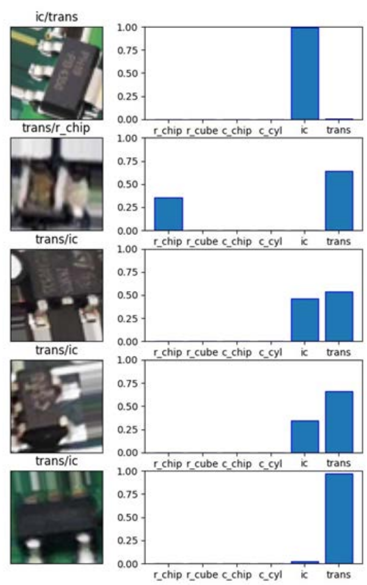

Fig. 5. Examples of Misclassified Images

4.3 Misclassified Images

Figure 5 shows examples of misclassified images. The classification result and the correct answer are marked above the target images. The bar graphs show the softmax outputs of the classification model, indicating the likelihood of belonging to each category. Classifying transistors and integrated circuits frequently results in errors. These two types of components are very similar in shape, differing only in the number of pins, making them prone to confusion.

5 Conclusion

This study attempted to classify electronic waste using camera images automatically. First, electronic wastes are collected, photographed, cropped, and labeled to create a training dataset of electronic components. Deep learning models tuned for electronic component images are proposed. Experimental evaluations assessed computational time and accuracy. Model E, utilizing three convolutional layers, was found to be most suitable for the electronic component classification task. Further parameter tuning of the model achieved even higher accuracy rates. Additionally, images misclassified by the model were reviewed and analyzed.

Future challenges include advancing research on classifying components with highly similar shapes, such as transistors and integrated circuits, and expanding the range of classifiable component types. Concurrently, we are advancing research on a character recognition system for boards and components, aiming to develop a classification method that integrates component shapes and character strings. Furthermore, aiming for systems installed at waste processing facilities, we will proceed with prototyping and evaluation as embedded systems.

Additionally, considering composition analysis and recycling methods, it is desired to establish analysis and classification methods for electronic waste, including determining resource content ratios and value assessments based on recovery processing techniques.

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Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

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