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PICK-UP SERVICE FOR END-OF-LIFE CONSUMER ELECTRONICS USING A CNN-BASED IMAGE RECOGNITION MODEL

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Abstract. *Due to globally diminishing natural resources, the Korean government has been regulating EPR (extended producer's responsibility) practices since 2000 and providing pick-up service for end-of-life (EOL) consumer electronics. Unfortunately, the current system for requesting pick-up service does not identify the actual volume information of the EOL products being collected, so the loading capacity of pick-up vehicles cannot be optimized. This study applies CNN (convolutional neural network)-based image recognition technology to identifying the model numbers of disposed EOL products. The accuracy of the suggested technology is tested through experimentation. Application of the suggested registration method is expected to improve the loading capacity of pick-up vehicles.*
Keywords: CNN, Image recognition, EOL, Consumer electronics, Pick-up service, Loading capacity

1. **Introduction.** Due to continuously diminishing natural resources worldwide, most developed countries have recognized the necessity of recycled materials. The Korean government's response to this issue was to introduce formal regulation of EPR (extended producer's responsibility) practices in 2000.

The convenience of having a special pick-up service for end-of-life (EOL) consumer electronics at desirable disposal locations has resulted in a continually increasing number of collected EOL products over the last 5 years, as shown in Figure 1. The loading capacity of pick-up vehicles is a very important factor for efficiency due to the limited number of pick-up vehicles available.

Currently, a consumer can initiate a collection request by registering specific information at the service company's website, such as type (e.g., large refrigerator) and quantity of EOL consumer electronics. The collection system identifies transportation availability using pre-defined representative information based on candidate product type, i.e., large or small/medium refrigerator. Unfortunately, it is impossible to identify the actual volume of each candidate product because it varies depending on the manufacturer and model number.

The current procedure of pick-up service of EOL consumer electronics is illustrated in Figure 2.

When ambiguous representative information is used to create a collection schedule for pick-up vehicles, the loading capacity of each vehicle cannot be optimized. Thus, more trips are required, resulting in higher operation costs.

The purpose of this study is to improve the loading capacity of pick-up vehicles by obtaining actual EOL product information (volume and weight) through CNN-based image

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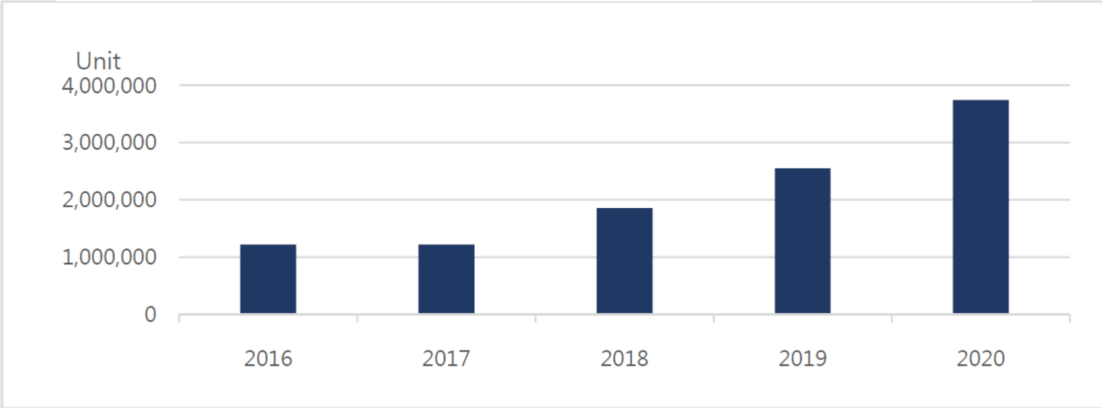

FIGURE 1. Amount of collected EOL consumer electronics through last 5 years

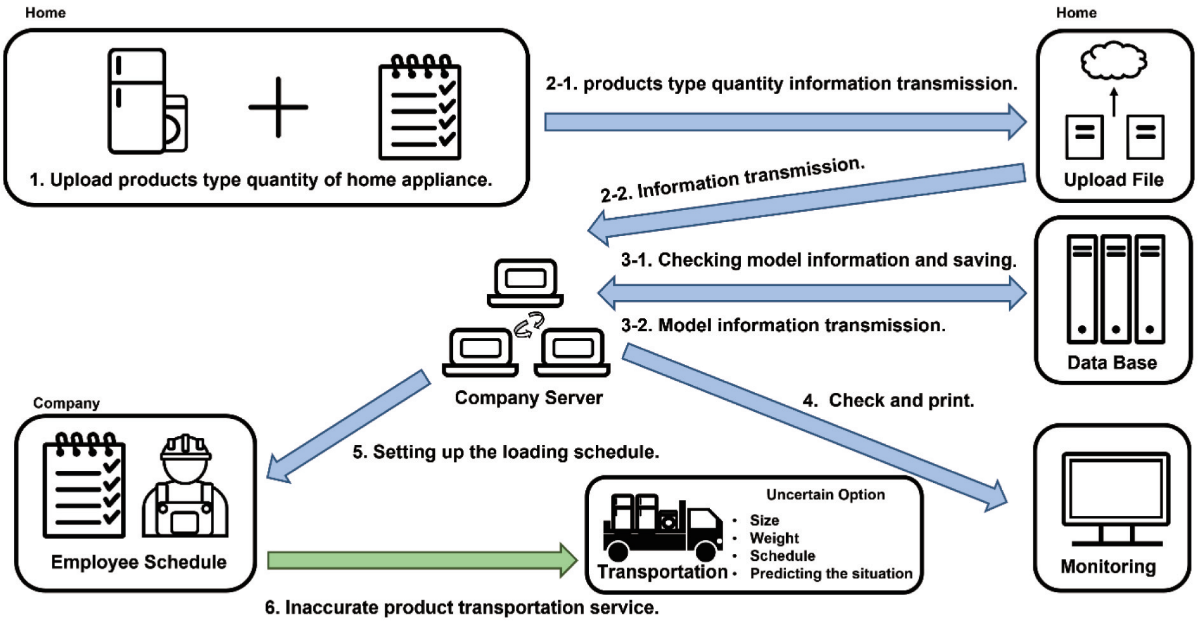

FIGURE 2. Current procedure of pick-up service of EOL consumer electronics (AS-IS)

recognition technology. The proposed system uses pictures of candidate EOL products provided by users during pick-up service registration.

The CNN-based image recognition technology developed in this study identifies relevant information such as model number and manufacturer to improve the collection schedule of pick-up service vehicles. The suggested new pick-up service of EOL products is illustrated in Figure 3.

This paper is organized as follows. Section 2 summarizes the related literature on CNN-based image recognition studies. Section 3 describes the image analysis model developed in the present study. Section 4 details experimental studies conducted on the proposed system. Finally, the study results are presented and discussed in Section 5, and future research topics are identified.

2. **Related Works.** Supervised learning, a type of machine learning, can extract appropriate information by matching new input information with existing supervised learning data [2]. However, supervised learning has limitations. Notably, it only obtains reliable results when well-defined data with appropriate features are introduced in advance [3]. The procedure of general supervised learning is illustrated in Figure 4.

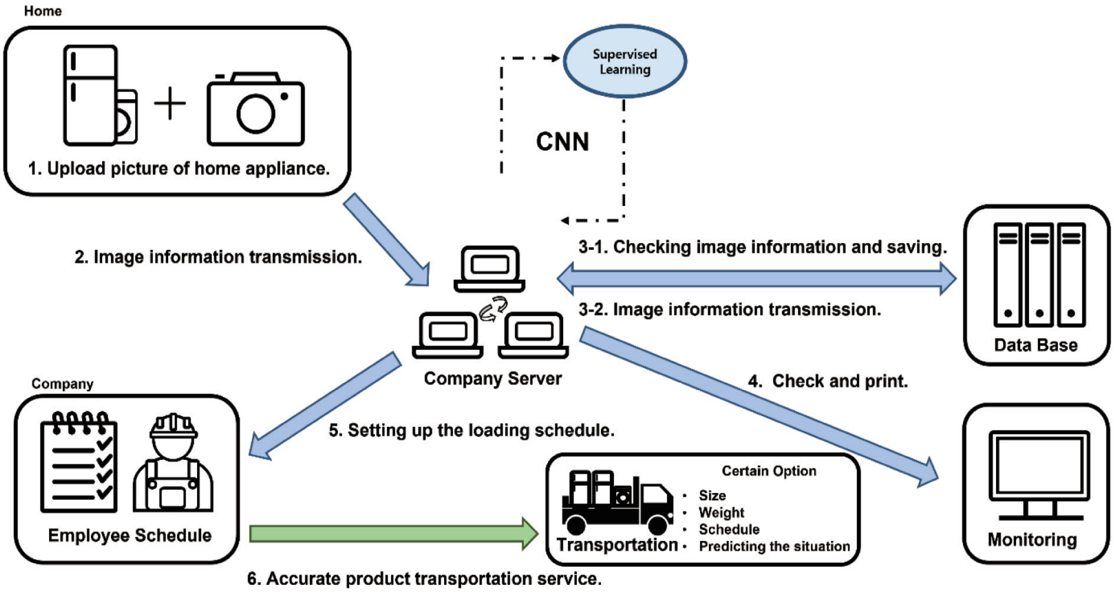

Figure 3. Proposed new pick-up service of EOL consumer electronics (TO-BE)

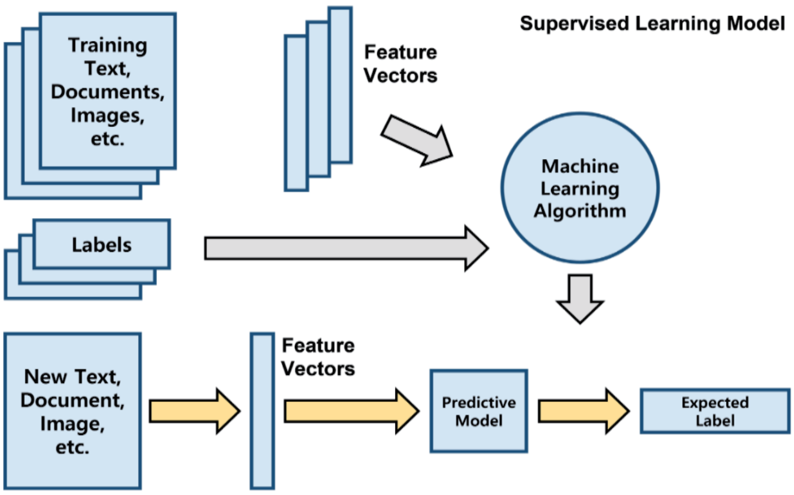

Figure 4. Supervised learning method

CNNs are one of the most widely used algorithms for analyzing visual images by learning specific features from given image data [4]. Particularly, CNNs can be used to classify specific image information (i.e., product model number) by extracting related features from given image data [5]. In addition, CNNs can utilize image data through multiple partitions and extract specific features of partitioned images, even if they are distorted.

CNN-based image recognition technology has enabled several practical applications. For example, in 2021, Han et al. studied deep-learning-based image recognition models to improve the efficiency of beef sirloin classification [6].

Another example addresses customs tax rates based on the specific product type being imported, which is hard to identify by individual business provider alone. In 2020, Lee et al. developed a suggestion model of HS (harmonized commodity description and coding system) code by applying a deep-learning-based CNN and classifying product types from images [7].

In 2020, Choi et al. described a smart closet for the blind utilizing deep-learning and image recognition [8]. Blind people can experience difficulty selecting clothes to wear, so

Choi et al. designed a smart closet that translates clothing image information classified by deep learning and image recognition into audio to help them.

In 2019, Yoon et al. developed an intelligent search model for similar trademarks using a CNN. Searching for similar trademarks is a very difficult and potentially expensive task [9]. Therefore, a CNN was applied to searching for similar trademarks similar to the one proposed in the present study.

In 2020, Tan et al. described D-leaf-based technology based on image recognition [10]. Their automatic identification system of plants utilizes CNN-based image recognition technology. In 2017, Pritt and Chern studied satellite images that provide important information for responding to natural disasters and environmental changes [11]. They developed an artificial neural network that classifies satellite images into 63 classes using deep-learning that achieved 83% accuracy.

Fu et al. developed the image recognition technology by developing GPU-GPU communication for allowing faster and more accurate approaching to the target [12].

ULOS fabric is a traditional product of the Batak tribe in Indonesia. Each ULOS fabric pattern has a unique meaning that is difficult for laypeople to recognize and interpret. In 2021, Siregar and Mauritsius developed an API for classifying ULOS fabrics by applying CNN technology that achieved 87.27% accuracy [13].

3. Image Analysis Model Description.

3.1. Procedure. The goal of this study is to automatically sort product types using CNN-based image recognition technology and ultimately generate the exact volume and weight of candidate EOL consumer electronics by identifying their model numbers. Customers upload an image of their EOL consumer electronics when registering for a pick-up request, and the classification model applies CNN-based image recognition technology to classifying the actual model number and product type of the EOL product. The experimental procedures are illustrated in Figure 5.

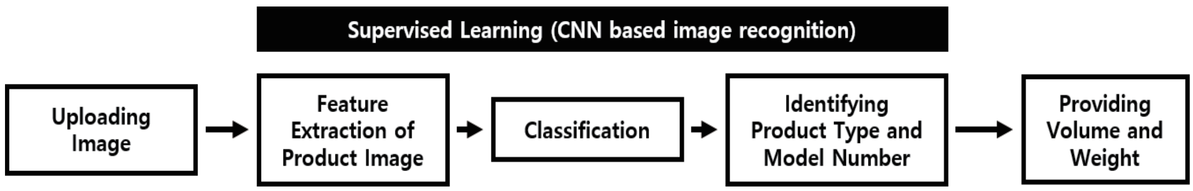

Figure 5. Experimental procedures

Three distinct types of consumer electronics, namely, air purifiers, water purifiers, and computer monitors, were selected as candidate products for this study. A total of 100 images (pictures) of each product were provided in advance to develop a database for supervised learning.

3.2. Developing a classification model. The classification model was developed in Python, and the program was designed using the Keras library, which uses tensor flow as a back-end [14].

To capture the features of each candidate product, a four-stage convolutional layer was constructed, and a two-stage fully connected neural network was then applied to classifying candidate products based on their features. The convolutional layer is composed of Conv2D and MaxPooling2D, with the pool size of MaxPooling2D set to 2×2 for controlling the increased data volume of Conv2D. Multi-dimensional features were extracted from four-stage convolutional layer and transformed into one dimensional feature useful for classifying products by incorporating a flattening layer.

The two-stage fully connected neural network is composed of two different dense layers, and each parameter unit and activation function were set to (512, reLU) and (softmax, 10), respectively. The unit value of the last dense layer was set to 3 because three types of consumer electronics were used in the study experiment.

In the future, more products can be used and the unit value of the density can be adjusted accordingly. To prevent overloading between two different dense layers, a dropout layer was applied with the ratio of 0.5.

Categorical cross entropy was applied as a loss function for multiple classifications, and the image learning process used rmsprop as an optimization tool. The procedures are illustrated in Figure 6.

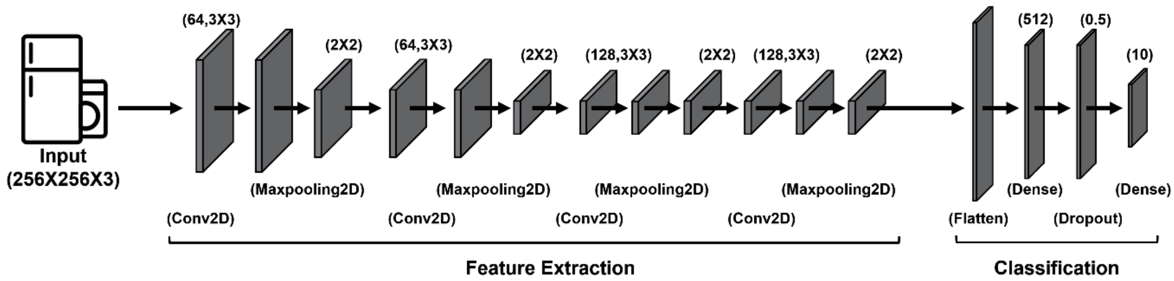

FIGURE 6. CNN model for classifying consumer electronics (Reproduced from [15])

4. **Experimentation.**

4.1. **Training data.** We selected three distinct types of consumer electronics (air purifiers, water purifiers, and computer monitors) for testing the proposed supervised learning method. Each image was adjusted to 256×256 pixels at the pre-processing stage. Three different colors were used for describing a 1-byte image channel because the color of each product was required to sort the product types. Therefore, each consumer electronics image has $256 \times 256 \times 3$ sizes.

CNN-based image learning data was generated by acquiring 100 images of each consumer electronic product type. To test the performance of the designated product model, 80 images were used as training data and the remaining 20 were used as test data.

The RGB coefficient is composed of 0 to 255 numbers at the common learning rate, but this input value can be very high when programming a model efficiently. Therefore, the range was scaled to 1/255 to change the coefficient value range to be 0 to 1. In addition, image data generation was applied to preventing distortion of the learning model results, which can be interpreted as speed acceleration and larger channel numbers [16].

Finally, in order to obtain reasonable results, the proposed learning model was repeated for 100 rounds for each component of the experiments, which determined the repeating numbers (epoch) and mini-batch size in advance. Table 1 summarizes the recognition accuracy and associated run times associated with various numbers of epochs with given mini-batch sizes.

In Table 1, the highest accuracy (93.33%) uses an epoch of 100 with mini-batch size 10. The mini-batch size was varied between 10, 20, and 30 units with a fixed epoch of 100 to optimize the classification model. In Table 2, the repeating number (epoch) and mini-batch size are determined to be 100 and 10, respectively, for further experimentation.

4.2. **Experimental results.** By applying CNN-based image recognition technology, our classification model provides specific target information such as product type and model number, as well as valuable information (volume and weight) regarding the candidate EOL products. Figure 7 illustrates the output of this model.

TABLE 1. The recognition accuracy according to the different epochs (given 10 mini-batch size)

Epoch	Mini-batch size	Accuracy	Time (s)
10	10	46.67%	120.4
50	10	66.67%	608.8
100	10	93.33%	1281.1
150	10	80.0%	1761.4
200	10	80.0%	2472.8

TABLE 2. The recognition accuracy according to the different mini-batch sizes (epoch of 100)

Epoch	Mini-batch size	Accuracy	Time (s)
100	10	93.33%	1281.1
100	20	80.0%	823.3
100	30	86.67%	760.0

Product Image	**Product Type**	Water purifier
	**Model Number**	WD302AP
	Volume (cm^3)	$(170*396*520)cm^3$
	Weight (kg)	8kg

FIGURE 7. Output of the classification model

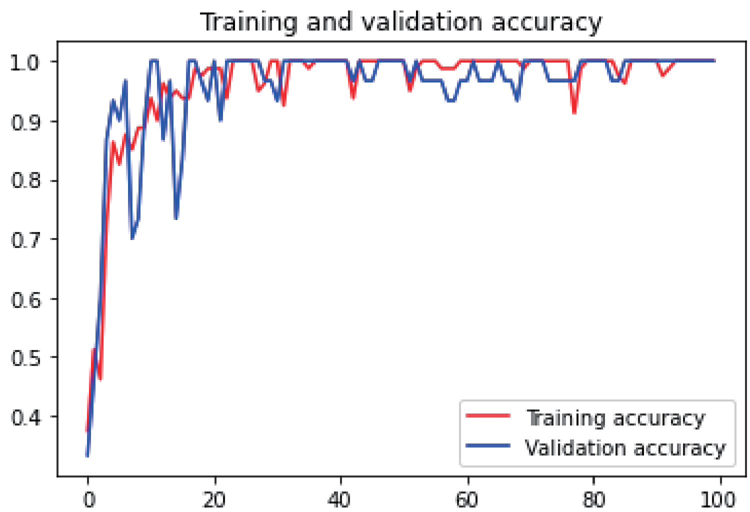

FIGURE 8. The accuracy of the suggested model

The developed classification model is validated based on the accuracy of its image recognition capacity, as shown in Figure 8. The accuracy of the experimental results improved with repeated learning rounds, and the classification accuracy stabilized after 25 rounds. After a total 100 rounds, the classification accuracy of the suggested model was 93.33%.

5. **Conclusions.** Currently, when using the homepage of the Korean EPR service company's website to request pick-up of EOL consumer electronics, the only information the consumer inputs is the product's general type and size (e.g., large or small/medium refrigerator). For example, if the candidate EOL product is a large refrigerator, the current system uses pre-defined representative information of large refrigerators to create a loading schedule and assign pick-up vehicle(s).

Currently, a continuously increasing number of requests for collecting disposed EOL products makes it important to maximize the loading capacity of pick-up vehicles. However, the actual volume of consumer electronics varies depending on the manufacturer and model number, even amongst identical product types. Therefore, the loading capacity of a pick-up vehicle cannot be optimized if it only uses pre-defined representative information.

To overcome the current limitations of using only basic representative information, we developed a classification program to generate exact volume and weight information for products requested for pick-up. We introduce CNN-based image recognition technology to automatically sort appropriate product types and identify the specific model numbers of candidate products.

As future research, the present method could be applied to several types of consumer electronics. Further investigation will also be needed to check the performance of this study by evaluating the increasing rate of pick-up vehicle's loading capacity between pre-defined representative information (AS-IS) and exact volume and weight information (TO-BE). Additional repetition and fine tuning are also necessary to increase the model's classification accuracy of 93.33% with 100 rounds of repeated supervised learning.

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