Yeeun Sohn, Jeongmin Yoo, Yooha Bae

Professor Byungkon Kang

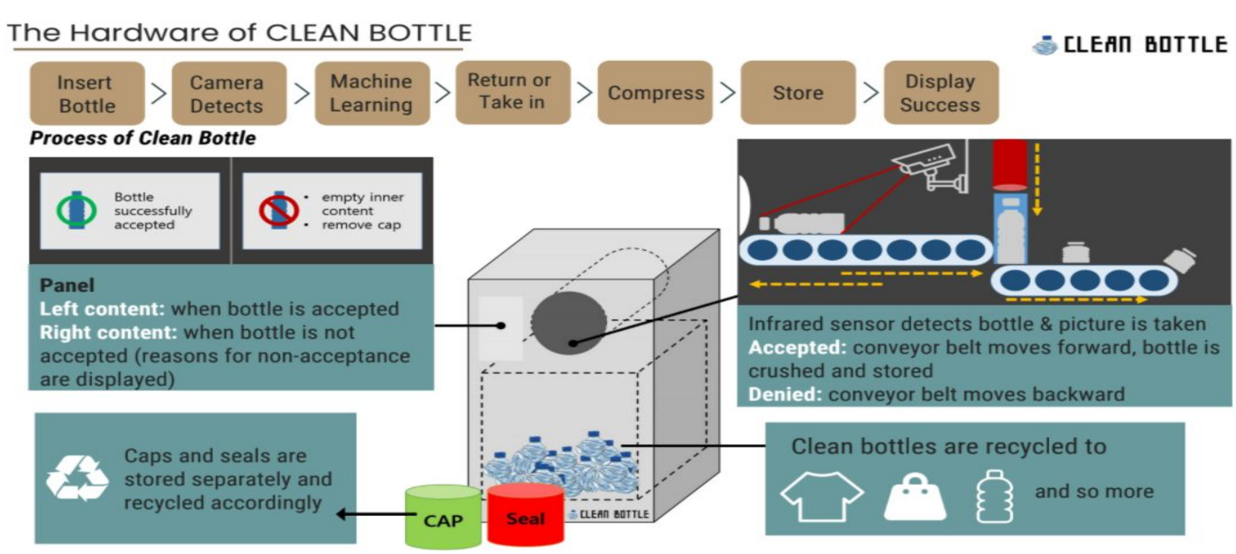
CSE 353

15 October 2020

Literature Review: Clean Bottle

Do you know how to recycle PET bottles correctly? Transparent PET bottles have the highest added value among plastics, making clothes, bags, and cosmetics containers by being recycled. However, only 10% of PET bottles discarded in Korea are recycled with high quality. This is because transparent PET bottles and colored PET bottles are mixed, and impurities are mixed during the process of discharge and collection (Yoo, par. 2). Then, how could we recycle PET bottles with high quality? First, separate colored PET bottles and transparent PET bottles. Then wash inside of the PET bottle, and remove the seal and cap. Finally, compress the PET bottle (Yoo). In Korea, it becomes mandatory to remove the seals and caps from the PET bottles and separate colored PET bottles and transparent PET bottles when recycling from December 2020 (Yoo, par. 1). Our team project, Clean Bottle, will help ease this process.

Clean Bottle is a RVM (reverse vending machine) with a guide screen, a bottle slot, conveyor belt, camera, infrared sensor.



When the user inserts a bottle, the camera detects it and determines to return the bottle or take in, then the compressor compresses the bottle. There will be four classification criteria; with a cap or not, with a seal or not, with the content or not, colored or not. The bottle will be taken in if the bottle is with no cap, no seal, and no content and transparent. Clean Bottle will decide this by using machine learning. Our team reviews some research papers to get helpful information for realizing Clean Bottle.

Mwangi and Mokoena proposed a RVM that awards incentives to users depending on the status of bottles and for each status, the amount of incentives varies. The bottle status classification criteria are based on the following features; With seal or without seal, with a cap or without a cap, with cap and seal, or if it has no cap, content and seal. Like the below picture (29).

Mwangi and Mokoena's research paper's classification criteria of bottle status are very similar to ours although we will not provide incentives because we will use our project to government policy. Mwangi and Mokoena save the images in a network server (Samba) directory created on a Linux computer during the taking photo process of training images. Also, they use a deep learning model (SqueezeNet) deployed on the raspberry pi for the prediction process (29). SqueezeNet is a network structure that achieves similar accuracy to AlexNet, but reduces parameters by 50 times and has a model size of only 0.5MB (Iandola et al., 1). So, Mwangi and Mokoena selected SqueezeNet for the neural network because it is small enough to be executed on Raspberry pi (30). Our team might use SqueezeNet because we will also use Raspberry pi to realize our project. In addition, Mwangi and Mokoena used LEDs to show that the classification criteria are satisfied or not (30). This way would be useful for us. When we realize our project, we cannot make the RVM, so we can use LEDs to show the classification.

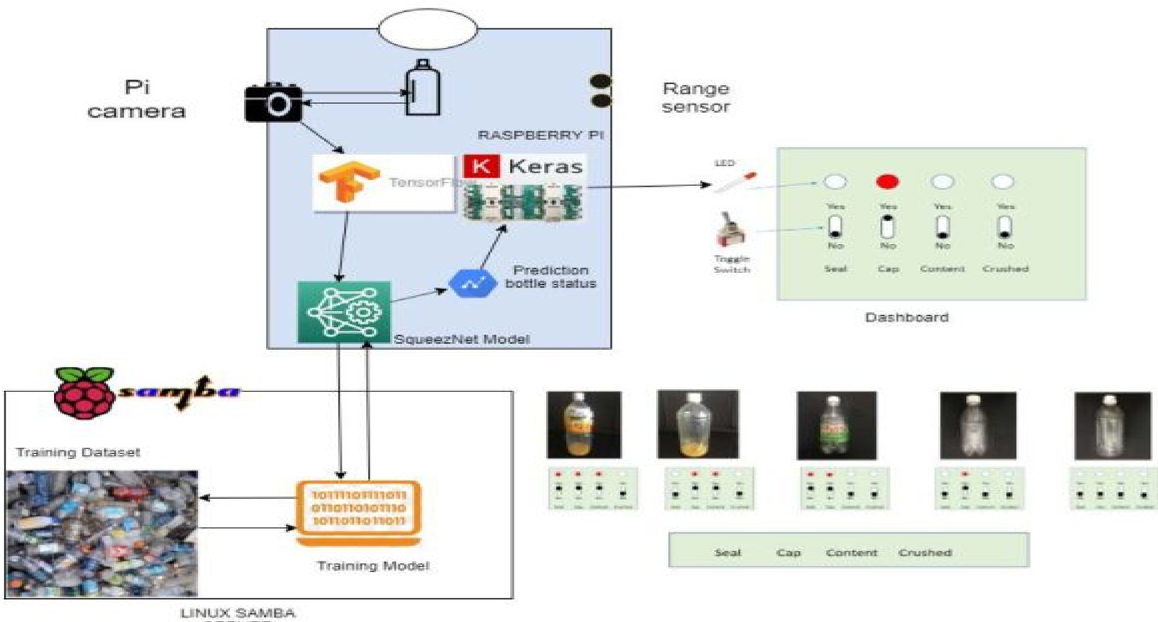
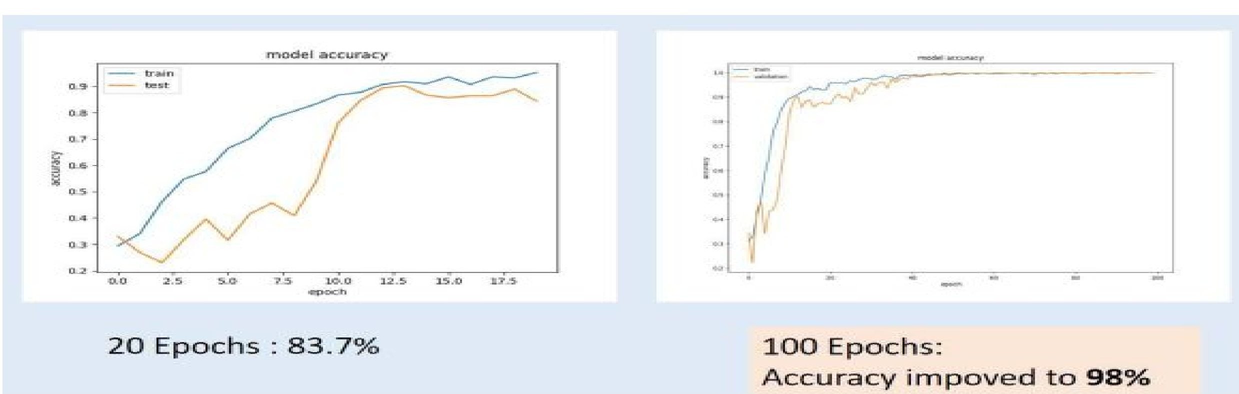


Figure 5: System Configuration Diagram

Mwangi and Mokoena successfully trained the dataset by using the SqueezeNet. Total parameters are 541,332 which have 540,812 training parameters and 540 non-trainable parameters (30). Moreover, the accuracy (number of correct predictions / total number of predictions) in the training of PET bottles is 83.7% for 20 epochs and then becomes 98% for 100



epochs (31). We cannot be sure that our prediction's accuracy is high such as this because the number of parameters of our project would be much fewer than Mwangi and Mokoena's. We expect 4,000 parameters, so our accuracy might be lower than 98% but we will try to get the highest accuracy possible.

Kveim's research focused on PET bottle cap detection. In this research, the RVM has six cameras that capture digital images as the plastic bottles inserted into the RVM. These six cameras make a sequence of images from each delivery of plastic bottles with 6 different angles

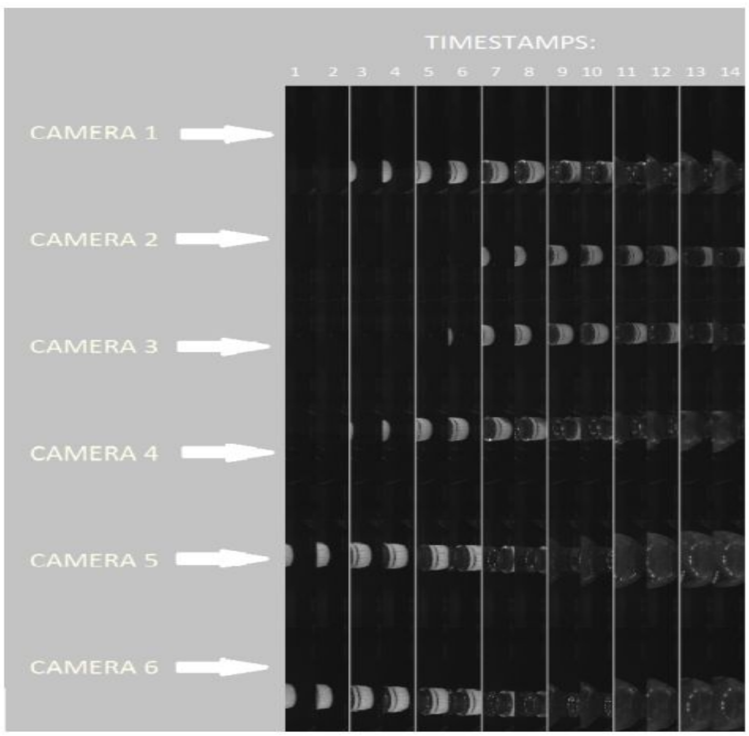


Figure 26: High resolution overview image of all single images of one bottle going through the reverse vending machine.

(36). Like the below image, six cameras placement is also used by Tur et al.'s research about a RVM that classifies plastic bottles and cans (4). If our team develops the RVM, it might be helpful to refer to this way of the camera placement.

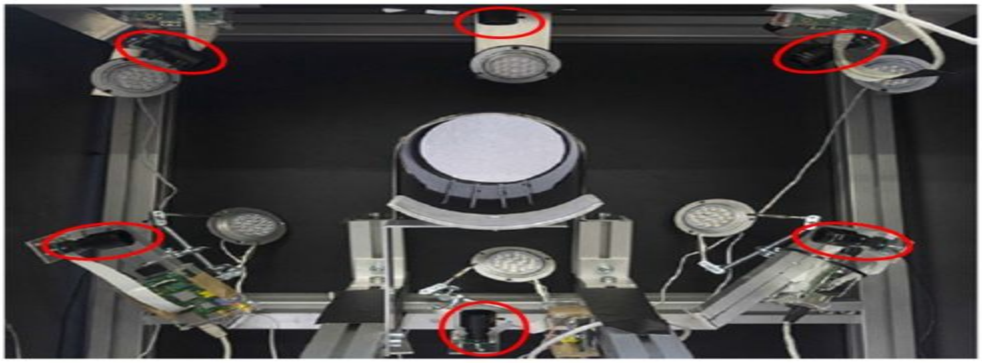


Figure 1. Cameras location in the identification block of RVM [5]

Kveim set three important criteria for the plastic bottle cap classification problem; Accuracy, classification time, and size of the classification algorithm. “Accuracy is important to have a reliable classification. Classification time is important because the RVMs demand real-time classification. Size of the classification algorithm is important because RVMs have limited memory” (1). With these criteria, Kveim compares the different approaches, pattern recognition, machine learning, and deep learning. Then, Kveim concluded that the best performance is with deep learning, more precisely CNNs (Convolutional Neural Networks). Kveim said, “CNNs find relevant features in digital images on its own, unlike the other approaches where these features must be found manually. The features found in the CNNs proved to be good features and the networks managed to separate cap images from no-cap images with high accuracy” (1).

Moreover, there are two ways for CNNs; CNNs from scratch and CNNs with transfer learning. CNNs worked well both when training from scratch and with transfer learning, but CNNs from scratch gave the best results on classification time and size of the network, and the transfer learning approaches gave the best results on the accuracy (Kveim, 72). We might use the approach with CNNs with transfer learning because Keveim mentioned that creating CNNs from scratch is rarely recommended for image classification with a small amount of data (51). This is because the accuracy of the networks is highest for the networks with the highest number of learnable parameters. When the number of learnable parameters decreases the accuracy gets worse (Kveim, 52). We might not be able to get such that huge data, so we determine to use CNNs with transfer learning, not from scratch. In Kveim's research, there are three models for transfer learning; AlexNet, SqueezeNet, GoogLeNet (63).

Transfer learning					
Name	Model and approach	Validation accuracy	Size	Learnable parameters	Classification time*
Transfer_1	AlexNet freeze weights	0.9971 99.71%	207 242 kB	61 million	0.0158 s
Transfer_2	SqueezeNet freeze weights	0.9899 98.99%	3 134 kB	1.2 million	0.0289 s
Transfer_3	SqueezeNet fine tuning	0.9993 99.93%	3 134 kB	1.2 million	0.0286 s
Transfer_4	GoogLeNet fine tuning	0.9902 99.02%	22 230 kB	7 million	0.0535 s

Table 3: Table of the results of CNNs trained with transfer learning. *Average time per data sample.

With the observation, Kveim stated that SqueezeNet is the best model that is suitable for plastic bottle cap classification. Although the training dataset is quite small, SqueezeNet achieves the best result by fine-tuning weights (71). "The SqueezeNet networks do not seem overfitted, the training- and test-set are uncorrelated and consists of a variety of plastic bottles. With this in mind, the minimal gaps between the training and validation accuracy shows credible networks which are able to generalize and classify new samples with high accuracy" (Kveim, 71). Therefore, Kveim argued that SqueezeNet performs best for three important criteria because SqueezeNet has the best accuracy and size and second-best in classification time among three models (71). By reviewing research papers, we can find that two research papers recommend using SqueezeNet. So, we can get sure of determining to utilize SqueezeNet.

To successfully approach color classification, based on the theoretical background, Yahia Tachwali designed imaging hardware (70). Since plastic bottle manufacturers are using a spectrum of colors to take advantage of the marketing edge, the need for color classification in automatic plastic bottle sorting is increasing. To classify the color of plastic bottles, Yahia mentioned that it is required to convert the usual RGB signals that are generated by traditional CCD cameras into HSI (hue, saturation, intensity). (71) Still, it is sensitive to lighting variation,

$$S = 1 - \frac{3\min(R,G,B)}{R+G+B}$$

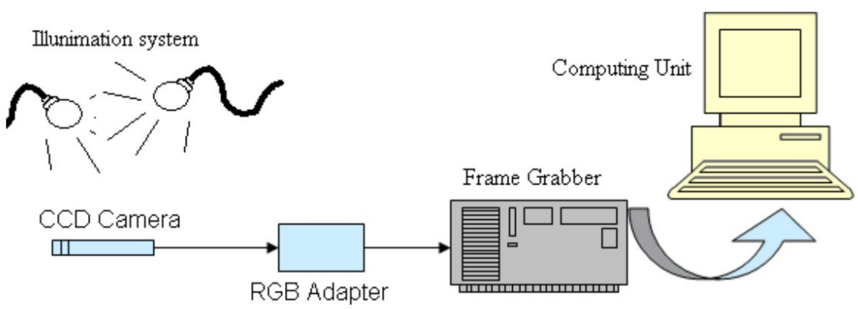
$$I = \frac{R+G+B}{3}$$

$$H = \cos^{-1}\left(\frac{\frac{1}{2}[(R-G)+(R-B)]}{\left[(R-G)^2 + (R-B)(G-B)\right]^{1/2}} \right)$$

so the writer considers it when working on hardware.

From Yahia's research, the plastic bottle's color classification system consists of two parts: the mechanical part and the vision system. Yahia was motivated by the machine used in practical situations, which carry away plastic bottles from domestic wastes by conveyor belt drives and operate on the plastic bottle images grabbed in motion by the inspection system. The conveyor system represents the mechanical design, which is a rubber belt-driven by an AC motor with a gearbox. A frequency inverter controls the motor speed; this system transmits the inspected bottle through the inspection chamber installed in the middle of the system. The box was built to isolate the inspected bottle from external lighting and provide fixed lighting for the testing area by lamps mounted at the box's top. The lamps surround the CCD camera, which is mounted in the middle of the box roof. The system prototype is designed to identify the bottle color on the fly without stopping the motor for inspection. Therefore the speed of the engine was determined to provide a range of linear acceleration. The picture shows a schematic diagram of the system.

Yahia worked on the vision system that has the task of grabbing the images of the plastic bottles, processing the acquired images, extract color features, and classifying the bottle's color. It consists of the CCD camera with an RGB adapter, the frame grabber, an illumination unit, computing, and display unit. The CCD camera provides analog signals that are the CCD pixels' responses to the three different wavelength ranges (Red, Green, and Blue). These signals are received by the RGB adapter and transformed into an analog NTSC TV signal. The frame grabber acquired the TV signal and made them as a digital colored image. The image is analyzed by the processing unit, which executes the algorithms for color classification. The following picture shows the necessary components of a machine vision system.



Our team wants to ease the process of recycling. It becomes mandatory in South Korea to remove the seals and the plastic lid from the clear plastic bottle when recycling starting from December 2020. The lifecycle of a plastic bottle largely contributes to climate change. So it is essential to know that plastic caps, seals, colored plastic bottles, inner content create low-quality regenerative material and try to recycle plastic bottles. For the hardware of our machine, we used a vending machine with a conveyor belt. When people insert bottles into the vending machine, a camera is equipped in the device to detect the bottle. Then the machine figures out whether it is acceptable or not. If the bottle is regenerative material without a plastic lid mill and seal, then accept it by compressing it but if it is not acceptable, then return it. For the CSE353 Machine

Learning project, our team will show you the classification of acceptable plastic or unacceptable one. There are 4 labels; with a cap, with a seal, with content, and colored or not. By using more than 4000 images, our project is based on using CNN, SqueezeNet.

Works Cited

Iandola, Forrest N., et al. "SqueezeNet: AlexNet-Level Accuracy with 50x Fewer Parameters and <0.5MB Model Size." *ArXiv.org*, 4 Nov. 2016, arxiv.org/abs/1602.07360.

Kveim, Kjetil. *Plastic Bottle Cap Detection - DUO*. 2019, www.duo.uio.no/bitstream/handle/10852/69809/master_cap_detection_final.pdf?sequence=1&isAllowed=y. Accessed 15 October 2020.

Mwangi, Hellen Wanini, and Mpai Mokoena. "Using Deep Learning to Detect Polyethylene Terephthalate (PET) Bottle Status for Recycling." *Global Journal of Computer Science and Technology*, 2019, pp. 27–31., doi:10.34257/gjcstgvol19is4pg27.

Tur, A I, et al. "Beverage Container Collecting Machine Project." *IOP Conference Series: Earth and Environmental Science*, vol. 317, 2019, p. 012006., doi:10.1088/1755-1315/317/1/012006.

Yahia, Tachwali. "AUTOMATIC PLASTIC BOTTLE CLASSIFICATION SYSTEM FOR RECYCLING " ScienceDirect, Dec. 2007, https://doi.org/10.1016/j.resconrec.2007.03.008 . Accessed 15 October 2020.

Yoo, Jiyeon. "라벨은 떼고, 뚜껑은? 투명페트병 분리수거 이렇게 하세요 [Remove the seal, and then how about the cap? The way of recycling transparent PET bottles]." Joongang Daily, 19 Jul. 2020, https://n.news.naver.com/article/025/0003018686. Accessed 15 October 2020.