

# **A Comparative Study of DCNN Models and Transfer Learning Effect for Sustainability Assessment: The Case of Garbage Classification**

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**Abstract:** Recently, with the large development of AI, ML and DL with a wide range of different fields includes sustainability and environmental applications. Sustainability has three major pillars which are environment, economy and society in order to keep all systems balanced on earth for a larger number of generations. In this research, two modified DCNN models were implemented and tested for predicting and classifying garbage images into six types of garbage according to trashNet dataset. These models are CNN and VGG-16 and are implemented according to transfer learning aspect. Both models used in this research achieved high training accuracy on the train dataset for target classification of MSW garbage images. VGG-16 achieved higher training accuracy than CNN, 99.55% as an average, while CNN achieved 96.29% which is still high accuracy. Both models also achieved low training loss values for the same dataset details; VGG-16 got 1.20% loss compared to 12.57% for CNN.

**Keywords:** Deep convolutional neural network, sustainability, transfer learning, CNN, VGG-16.

## **I. Introduction**

Sustainability is the ultimate goal of today's global society and researchers in order to be able to meet human needs without compromising the ability of human generations to meet their own needs. In the broad terms, sustainability has three major pillars which are environment, economy and society in order to keep all systems balanced on earth for a larger number of generations. One of the main methods to go on sustainable environment is by improving a sustainable waste management by following the waste hierarchy that is goes through the stages of prevention, preparing for reuse, recycling, recovery and disposal [1], [2].

Municipal Solid Waste (MSW) shows the solid and semi-solid trash produced in daily urban life, including municipal, construction and demolition, industrial, institutional, and residential garbage. Rapid urbanization, economic expansion, and population growth have all led to a large increase in MSW [3], [4], and by 2025, there will be 2.2 billion tons of MSW produced year globally. The abundance of MSW poses a severe danger to the city and the surrounding ecosystem, which results in a number of problems such pollution and unlawful dumping [4]–[7]. MSW is seen as a significant global environmental issue, particularly in poorer nations [8], [9]. Because of this, creating effective MSW management (MSWM) is essential for safeguarding resources, the environment, and public health[10]. However, due to the diversity and heterogeneity of MSW, environmental problems are sometimes challenging to resolve [5], [11].

Recycling means breaking down items into base materials and converting them into future products while reusing is finding ways to repurposing items which otherwise are designed to be discarded. Recycling garbage is an extremely useful process since it helps conserving resources and raw materials, saving energy, protecting the environment (vulnerable ecosystems and wildlife from harm or eradication and allowing them to exist for subsequent generations). Recycling also helps reducing gas emissions, slowing the spread of landfills, supporting Sustainable Development Goals (SDGs).

There is now a lot of focus on Artificial Intelligence (AI), Machine Learning (ML) and Deep Learning (DL) methods in environmental fields that is related to the goals of sustainable

development [12]–[14]. An important factor is the MSWM (Municipal Solid Waste Management) [15] that is playing an important in achieving the objectives of sustainable development. Manual selection is the primary method used in traditional garbage sorting, although it has certain drawbacks, including low efficiency and a possible infection risk, particularly after the COVID-19 catastrophic event. An efficient method of supporting garbage and automatically classifying and detecting garbage type through DL and specifically in Deep Convolutional Neural Networks (DCNN) is a promising method nowadays. The most popular remedy is intelligent garbage cans that can sort themselves by categorizing one thing at a time that is on a transparent backdrop. The camera is often placed at the top of the upper container when only one compartment is employed. The rubbish is relocated to the suitable bottom container when the deep learning (DL) algorithm classifies the picture appropriately. [16], [17].

On of the methods to support garbage classification is ML and DL, simply placing the camera on top of the higher container when only one item is utilized. A smart self-sorting trash can is another option, as is placing a camera or sensor above a few different trash cans to lead those who are handling trash to the correct classification type [18], [19].

The stated achievements demonstrate that litter sorting and detection using deep learning technologies may be sped up. However, the question of how those strategies might be compared can come up. Even for humans, it might be challenging to determine whether something is garbage without any more information. Additionally, garbage may be abnormal, malformed, or discovered in a variety of uncontrolled natural circumstances. It is required to compare thoroughly annotated data, whose distribution should be suitable for the desired use case given the diversity of objects. Several waste databases have been made available, however they all contain different types of rubbish and have different waste classifications and annotations. Additionally, the majority of them frequently either offer a small adequate selection of annotated photographs or represent a specific sort of garbage. (e.g., cardboard or plastic) [17], [20].

The main methodological contributions in this research includes the following:

1. An improved garbage classification model depending on the modified DCNN models (CNN and VGG-16) and transfer learning principle was investigated for multi-class classification and detection of six types of garbage and has a significant improvement in the accuracy of garbage classification.
2. The suggested models' network structures, computation effectiveness, and computation complexity were extensively examined and contrasted.
3. The prediction accuracy and loss of these models was compared and discussed on the MSW TrashNet dataset to account for the varying levels of effect.

An overview of the related works and existing garbage dataset is presented in section II. The main methodology and framework of this research for DCNN including CNN and VGG-16 classification and detection will be addressed in section III. Section IV discusses the training results and discussions. Finally, section V outlines conclusion and future work.

## **II. Related Work**

DCNN techniques empower many aspects of modern societies. This section discusses some of the most related researches to the field of sustainability and especially garbage classification.

P. Nowakowski, et al, in 2020 presented a novel R-CNN (Region-based CNN) identification procedure for e-waste classification from photos with recognition and classification accuracy ranged from 90% to 97%. It is worth mentioning that this model is server/ mobile app supported [21].

K. Kylili, et al, in 2019 proposed with the aid of DL a fast, cost-effective and scalable model for automatic identification of floating marine plastics. The authors used an augmented dataset of 4000 marine image with 20% of them was reserved for testing and 80% for training. The validation accuracy of this model was approximately 86% with approximately 4% [22].

J. Huang, et al, in 2021 proposed an MLDPAF model for energy and waste management preparing. The NN was used for the prediction of the waste amount while ML algorithm was used for the improvement of centered on sustainable energy marketplaces for garbage collecting. According to the simulation study, the suggested strategy reduces waste amount by 90%, landfill analysis by 40%, and transportation by 15% [23].

Q. Zhang, et al, in 2021 relied on DL to propose a classification model of recyclable waste images. They used the self-monitoring module with RNN for integrating the relevant features of all channel graphs, having a global receptive field and compressing the spatial dimension features. They used TrashNet dataset to classify recyclable waste and get a classification accuracy of 95.87% [24].

L. A. Akanbi, et al, in 2020 developed a DL model for estimating the volume of salvage and trash materials that the UK demolition industry would get from 2280 buildings before they were demolished. The three deep learning models' mean R-squared value is 0.97, while their mean absolute error ranges from 17.93 to 19.04 [25].

### **III. Methodology**

This section is about the statistics and the theoretical details of garbage detection and classification method. The methodology and training procedure of this model has been also described in this section.

#### **1. Proposed garbage benchmarks**

Recently, many attempts were made to develop various MSW datasets with different annotations and ambiguous garbage categories. The main problem, yet, is the lack of images provided for each single type of garbage (i.e., metal cans or bottles). Moreover, there isn't a single, widely accepted experimental methodology; thus, the result is a fair and valid comparison of methodologies, incoherent metrics and data splits, and reported research uses different datasets [26].

Considering those limitations, the TrashNet dataset for MSW classification was proposed. This dataset considers increase the amount of data instances to overcome the aforementioned restrictions and evenly distributing garbage types. It is open accessed on Kaggle company website and is well established [27]–[29].

All individual data annotations were combined into a single standard style throughout the data preparation step. All subsets' rubbish labels were changed to correspond to the article's suggested categories. The distribution of each subset was carefully considered before splitting each dataset. The resulting training, validation, and test subsets were then combined into datasets for trash detection and waste classification.

Garbage classification for the newly merged dataset has eight classes with corresponding examples are as follows:

- Cardboard: different types of cardboard packaging, catalogues, and books.

- Glass: glass objects such as glass bottles, jars, cosmetics packaging.
- Plastic: scrap metal and non-ferrous metal, beverage cans, plastic beverage bottles, plastic shards, plastic food packaging, or plastic straws.
- Metal: metal cans, aluminum cans, etc.
- Paper: different types of papers, receipts and newspapers.
- Trash: construction and demolition, bulky garbage (such tires), outdated home and electrical gadgets, batteries, paint and varnish cans, or unused medications are some examples.

The distribution and number of images of these types are as shown in Fig. 1, where we can see that most of garbage types are recyclable and thus, we can maintain sustainability by making less errors in the classification process. The efficient role of artificial intelligence algorithms can be seen at this point of view.

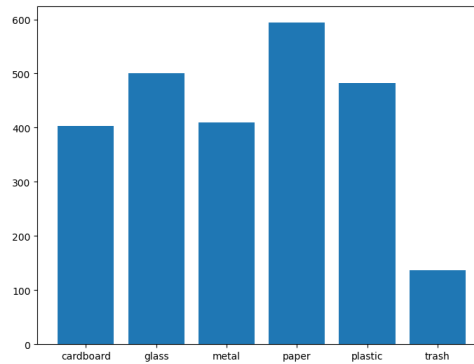


Fig. 1: TrashNet garbage distribution

## 2. Proposed detection framework

To better emphasize the topic of the trash and minimize inaccuracy, it is recommended to center crop the image using the center of the image. The trash pictures were then uniformly shrunk to 128x128 pixels after cropping in order to fulfill the input size specifications of the modified DCNN networks utilized in this article. To avoid poor training outcomes brought on by considerable data disparities, normalization can arrange the data in the three channels of the picture into a [1, 1] interval. After that, data labeling was performed on the images in order to compare classification results with real results to get accurate estimation for the proposed models. Training, testing, and validation datasets were created from the data in the following order: 8: 1: 1. DL framework was used in Python programming environment to create deep learning models. The first stage of the model is the preprocessing stage where the dataset was divided into 20% for both validation and testing equally, while the other 80% is for training with 123 seed and 64 patch size for each division.

The sequential CNN model was built with four Conv2D Keras [30] layers each with different filter size (i.e., 128, 64, 64, 123 filters sequentially) and three dense (128, 64 and 6 for the final SoftMax output layer) Keras layers for the output phase with class labels. ReLU activation function was used in this model.

The base VGG-16 model has been used according to the transfer learning principle with extracting the top layer and the dropout ratio is set to 0.25. Then, another proposed Dense layer has been added at the top with activation functions ReLU and SoftMax. The dense layer is composed four NN layers of 1024, 512, 128 and 6 neurons in each layer with Adam optimizer and sparse\_categorical\_crossentropy loss. Finally, the model was set into 20

epochs, 100 steps per epoch and 100 validation steps. The number of the trainable parameters was 8,980,870.

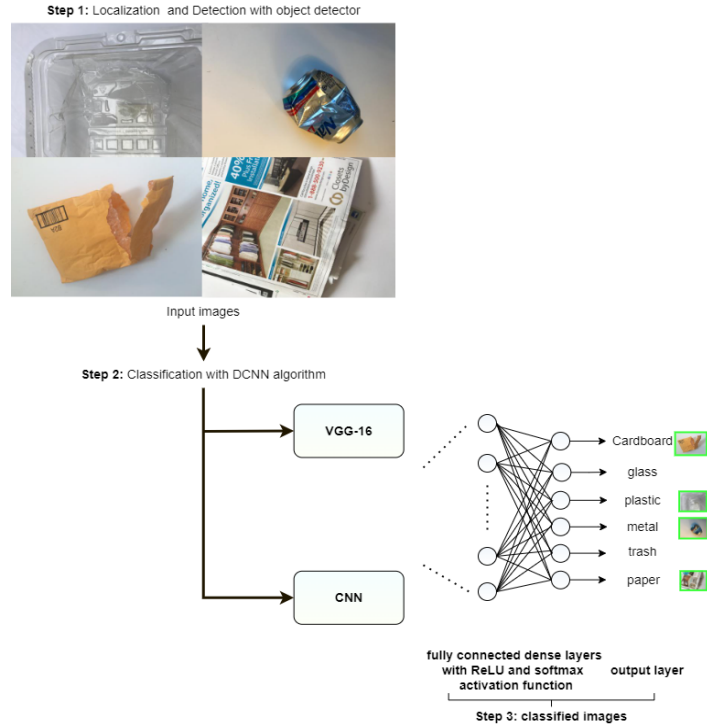


Fig. 2: Two-stage pipeline framework with dataset samples

#### IV. Experiments and Results

This section is about the conducted experiments and results presentation for the proposed methodology with a comparison to other related researches to make sure the remedy is effective. The performance of DCNN model performance was tested using Python 3.9 environment and results were collected according to the already implemented CNN and VGG-16 models. Object detectors, usually, require large amounts of data with proper annotations especially when the dataset doesn't meet the requirements of having rich-enough classification labels; thus, there was a detection and classification for the dataset to fully utilize the available data. As illustrated in Fig.3 below, Data pre-processing, dataset partitioning, DCNN model creation, and accuracy evaluation comprise the majority of the experimental stages. The following sections provide detailed explanations of each stage.

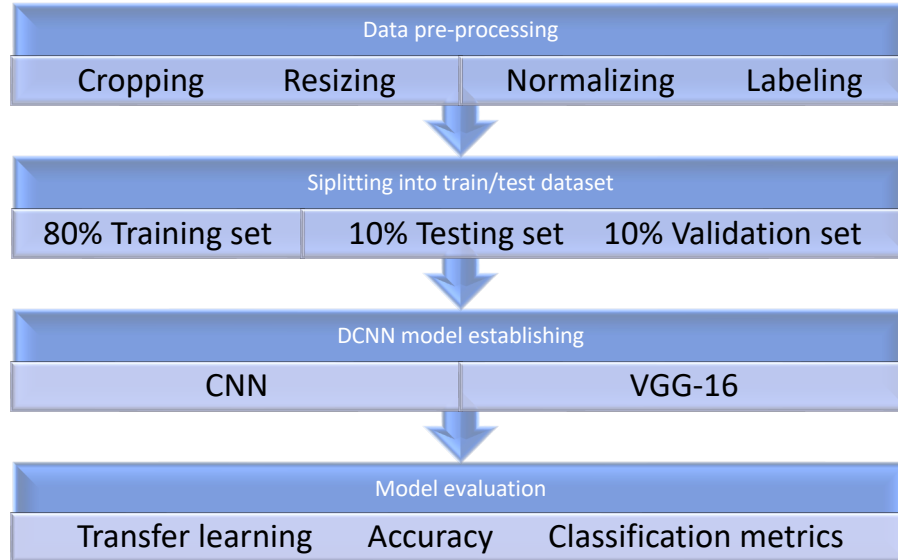


Fig.3: Data processing, modeling and analysis flowchart.

1. Data

The trashNet dataset was used for the detection and classification benchmark of the proposed detect-classify waste operator. 80% of the original images were randomly selected as the training set, 10% as validation, and 10% as the test set. each instance in the dataset must first be passed to the detector to detect objects and then passed to the classifier for labeling process. Each group in the detection and classification processes was split separately in order to avoid data leakage as described in the methodology section.

2. Performance metrics

This paper focuses on three aspects of model evaluation: the impact of transfer learning on model accuracy, the accuracy of different DCNN models, and model calculation efficiency. In this paper, we will explore the effects of transfer learning on accuracy in the garbage image target-recognition problem by training and predicting each CNN model used directly and using transfer learning followed by prediction.

To compare the accuracy of different models, an evaluation indicator must be employed to analyze the accuracy of the calculated results. We chose accuracy to evaluate the performance of this study’s eight classical CNN models. The garbage items identified from the images in this study are valid objects, so the ratio of correct predictions to the total number of samples is used to evaluate the model. As shown in Table 1, the accuracy can be defined as [31]:

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \dots\dots\dots(1)$$

In this equation, false positive (FP) represents the number of plastic items that were mistakenly classified as metal, true positive (TP) is the number of cardboard items that were correctly identified as cardboard, true negative (TN) is the number of glass items that were wrongly classed as trash, and so on. F1-score was mostly utilized for categorization since it strikes a balance between Precision and Recall measures as follows:

$$F_1\_score = 2 \times \frac{precision \times recall}{precision + recall} \dots\dots\dots(2)$$

Precision shows how accurate predictions are, while Recall shows how many samples from this class were correctly predicted. The  $F_1$  score is a widely used measure for uneven class distribution, which is the case in most waste datasets [19].

3. Garbage localization and classification using DCNN and modified-VGG16

The findings attained have demonstrated the significance of data quality in the DL-based system learning process. In addition to varying image quality and environmental conditions, the quantity and kind of waste classifications varied according to the dataset under analysis. The annotated garbage items also varied in size and form. In order to find garbage in both urban and rural settings, an experiment using six different waste classifications was also conducted.

The suggested approach's second stage involved performing supervised, multi-class classification for seven different types of garbage after training the classification networks on the classify-waste benchmark.

Fig.4 abbreviates the classification report performance metrics (precision, recall and f1-score) of implemented models. Depending on these results, modified VGG-16 achieved the highest performance by recording 99.83% precision, 99.83% recall and 100% f1-score. The reason is that it is a special type of the regular CNN and it uses small 3x3 convolutional filters and deeper networks besides to being trained for two to three weeks on four high-end GPUs. The region of the input picture that a node in the network is looking at when using CNNs is referred to as the receptive field. The phrase is taken from neuroscience and the network of neurons in the visual field that analyzes inputs from the human eye.

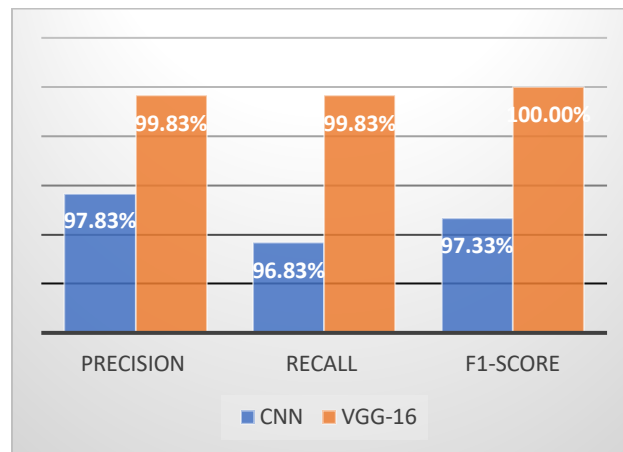


Fig. 4: Performance metrics’ results

CNN, Fig.5 a and c below, illustrates the performance variation curves in terms of training data accuracy and loss of the training data with epoch. From this figure, it is noticeable that the accuracy of validation accuracy is cumulative where the precision is 97.83%, recall is 96.83% and f1-score is 97.33%. while the training loss is 15.36% and the validation loss is 9.77%. The loss of training and validation in this figure decreases exponentially to low percentage rates while accuracy increases exponentially due to the transfer learning that is aimed to improve the training accuracy of DCNN models.

VGG-16, in Fig.5 b and d below, illustrates the performance variation curves in terms of training data accuracy and loss of the training data. From this figure, it is noticeable that the accuracy of validation accuracy is cumulative where the precision is 99.83%, recall is 99.83% and f1-score is 100%. while the training loss is 1.85% and the validation loss is 0.54%. This model differs from the previous one in that accuracy and loss curves’

variations are linear which is considered an advantage in lower values of epochs. Because of their unique designs, different DCNN models react to transfer learning in different ways and their responds to various types of images. However, model's structure influences how much progress there is, and accuracy varies from simple DCNN models to the more complicated ones where it becomes higher in these models (i.e., VGG-16). Finally, VGG-16 achieved higher training accuracy than CNN, 99.55% as an average, while CCN achieved 96.29% which is still high accuracy. It is worth mentioning that the proposed model was tested on external selected images on specific types of garbage and results were correctly classified.

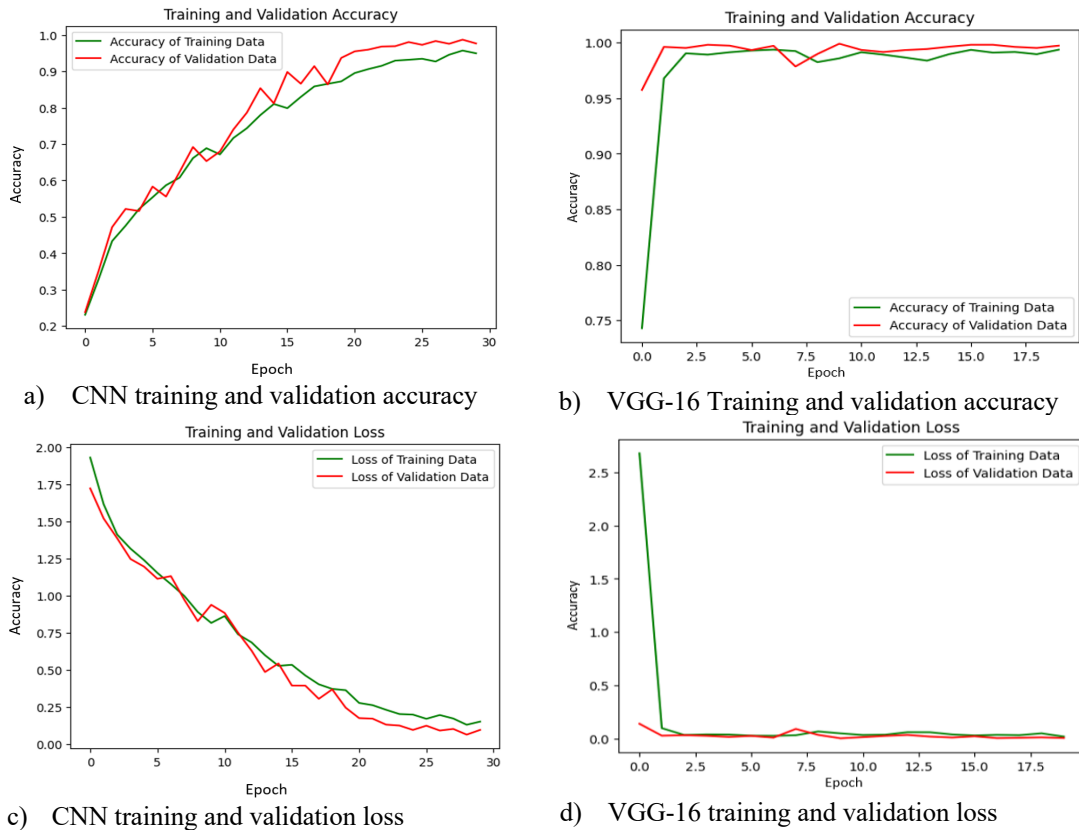


Fig. 5: Accuracy and loss of proposed models

Finally, for computing the difficulty and efficiency of the proposed framework, the largest barriers to the development of DL are the complexity of the computation and the amount of network parameters. If the model lifespan is excessively long or the hardware requirements are too rigorous, it is not advantageous for the broad use of DL approaches. This study also offers a quick comparison of the DCNN models' computational efficiency and amount of network parameters. As implemented in the experiments, CNN has 16 layers and execution time 36.431ms for training the model only with 1.280.586 trainable parameters while VGG-16 has 26 layers and execution time of 72.131 ms for training the model only with 8.980.870 trainable parameters. According to these recordings, the efficiency metric on selecting the best model is a trade-off between processing time and model's complexity as compared to results' accuracy.

## V. Conclusions

Sustainability is a very important factor in today's researches due to its importance in serving human needs and protecting the environment for the next generations. Recently, with the large development of AI, ML and DL with a wide range of different fields includes sustainability and environmental applications. Sustainability has three major pillars which are environment, economy and society in order to keep all systems balanced on earth for a larger number of generations.

In this article, two types of DCNN models have been applied after certain modifications which are CNN and VGG-16 with the concept of transfer learning. The final complete comparative findings of the suggested DCNN models' calculation efficiency, accuracy, calculation complexity, and network structure are as follows:

- 1) transfer learning aspect improves the accuracy of DCNN models depending on the architecture used. The structural design of the model's network has also an important effect on the accuracy and how much transfer learning enhances its precision.
- 2) Both models used in this research achieved high training accuracy on the train dataset for target classification of MSW garbage images. VGG-16 achieved higher training accuracy than CNN, 99.55% as an average, while CCN achieved 96.29% which is still high accuracy. Both models also achieved low training loss values for the same dataset details; VGG-16 got 1.20% loss compared to 12.57% for CNN.
- 3) A comprehensive analysis of the validation accuracy and computational difficulty for both DCNN models manifests that VGG-16 has the highest accuracy and lowest loss but has more computational complexity and execution time thus it is not recommended for wide-spread usage.
- 4) Although CNN has lower accuracy and higher loss but the structural design and execution time makes it more suitable for widespread usage and requires less hardware requirements.
- 5) The model was tested on captured image for garbage and imported into the model and results were satisfying where garbage was correctly classified.

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