An Object Detection and Scaling Model for Plastic Waste Sorting

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Abhishek Sunil Padalkar
Student ID: x19221576

School of Computing
National College of Ireland

Supervisor: Dr. Paul Stynes

National College of Ireland
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School of Computing

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An Object Detection and Scaling Model for Plastic Waste Sorting

Abhishek Sunil Padalkar
x19221576

Abstract

Plastic waste sorting involves mechanical and chemical separation of plastic into PET, HDPE, and PP. Currently, PS and Other types of plastic are not sorted for recycling. Research has shown that higher recycling output is possible if most plastic types of waste are segregated at first. This research proposes an Object Detection framework solution to sort plastic waste. The framework combines an Object Detection and Scaling model and an ANN model incorporating implicit features to detect five different types of plastics: PET, HDPE, PP, PS, and Other. The "WaDaBa" Plastic waste dataset is used for training purposes which consists of four thousand plastic waste images. This image classification dataset is pre-processed to object detection dataset, and pre-trained Scaled-Yolov4 and EfficientDet scaling models are applied on the plastic dataset. The results of eight trained models are presented in terms of accuracy, mean average precision(mAP), f1-measure for each plastic type, train time, inference time, and model size. This research demonstrates the potential of using the Scaled-Yolov4-CSP object detection model on higher resolution images to sort plastic waste.

1 Introduction

Plastic recycling has been a challenge from the start of its production. As compared to 2019, plastic production increased to approximately 30% in 2020. Moreover, plastic waste and pollution are grown due to mismanagement of plastic items[1]. An estimated 10-14% of plastic is recycled out of the total globally produced plastic. Where the other calculated 24% is burned for fuel and energy production and, the rest 58-62% is discharged into landfills, water, or scattered around.[1] This problem of less than 15% of the global recycling rate lies in the process of recycling, where the primary focus goes on plastic waste collection and sorting. There are many plastic polymer types, out of which seven types of plastics are out in the market with recyclable ability. These are Polyethylene Terephthalate (PET) (1), High-Density Polyethylene (HDPE) (2), Polyvinyl Chloride (PVC) (3), Low-Density Polyethylene (LDPE) (4), Polypropylene (PP) (5), Polystyrene (PS) (6), Other (7). Due to their durable and flexible properties, PS, LDPE, HDPE, PP, and PET are majorly used in the packaging industry. [2]. The difficulty in plastic sorting leads to a lower recycling rate and poor quality recycled products.

[1]OECD 2018, Improving Plastics Management: `https://www.oecd-ilibrary.org/content/paper/c5f7c448-en`

For many years, mechanical sorting, mainly Near-infrared(NIR) technology, is used to sort the plastic in the recycling centers. Today, an increasing number of studies are published in image-based smart waste recycling using neural networks(NN). Similar to waste segregation for recycling, plastic waste also needs to be sorted into its individual types to be recycled. One study by Bobulski & Piatkowski in 2018 performed image classification to classify PET and Non-PET plastic using canny edge filter and histogram approach on the "WaDaBa" dataset, which resulted in a 75.68% recognition rate[3]. The challenge in the above study is to improve the poor feature extraction technique with one of the best techniques in computer vision. This research pioneers in performing object detection on the plastic waste only dataset to detect different types of plastic to aid in plastic waste sorting.

The aim of the research is to investigate to what extent an Object Detection and Scaling Model(ODSM) can precisely and accurately sort plastic waste. The second objective is to examine if the accuracy of ODSM can be improved using additional implicit plastic object features. To address the research question, the researchers derived the following specific sets of research objectives:

1. Transform the "WaDaBa" plastic dataset to "WaDaBa" object detection dataset,
2. Investigate the state-of-the-art ODSMs on our plastic waste dataset,
3. Evaluate and compare ODSMs based on mAP, accuracy, f1-score, train time, inference time and model size,
4. Introduce an ANN model trained on implicit features of plastic objects as the second stage and evaluate its effectiveness on the classification accuracy of ODSMs.

The major contribution of this research is introducing the ODSM approach to sort plastic waste and a novel strategy to include implicit features after object detection to improve the sorting of plastic waste. This research is helpful for plastic recycling centers to start using computer vision-based object detection to sort plastic waste with ease and less complex systems.

This paper will cover the following structure in order. First, we discuss related work in Section 2. The research methodology adopted in this work is discussed in Section 3. Section 4 discusses the design specification. Section 5 discusses the implementation of the project. Section 6 discusses the evaluation, experiments performed and discussion in this research. Section 7 concludes the research and discusses the future work.

2 Related Work

Today, plastic waste is sort into its polymer types using only mechanical methods. These methods have become old, and not much research has been performed to improve these processes. On the other hand, research in smart waste recycling using technology is increasing. This section discusses related work in plastic waste sorting and smart methods in the following sub-sections. Section 2.1 discusses current SOTA techniques used for plastic segregation in recycling centers. The studies and research performed in smart waste segregation are discussed in Section 2.2. Section 2.3 discusses the researches done so far in smart plastic waste sorting and reviews object detection models and feature extraction methods.

2.1 Current Plastic Waste Sorting technologies

Plastic Waste Sorting technologies are applied in recycling centers. Mechanical and chemical recycling is the current widely used process to recycle plastic. This subsection discusses a brief review of current technologies for plastic waste sorting using mechanical, chemical approaches and a new system proposed in MaRek research.

Mechanical plastic sorting technologies include Near-Infrared radiation (NIR), Hyperspectral Imaging (HSI), X-ray transmission, Fourier transformed Infrared Technique (FT-IR), etc. [4, 5]. X-ray transmission cannot detect plastics other than PVC, whereas plastics can be inaccurately recognized in LIPS. NIR technology is highly used in sorting plastic, but black colored plastics, plastic films, and some colored plastic remain undetected.

Chemical methods proved in plastic waste sorting are triboelectric separation, and froth floatation [6]. Froth floatation can only separate high-density polymers, whereas the triboelectric separation technique can separate plastic with sizes only 2-4mm.

An entire new plastic producing method is proposed by the MaReK research, where plastics produced will have a fluorescent color to distinctively separate plastic waste with their unique tracer technology [7]. This major shift in the whole new plastic production and recycling process is difficult to achieve.

The mechanical technologies used in plastic waste sorting are complicated, rigid, and non-flexible in terms of future upgradation, including using the technology. Furthermore, these technologies generate negative value in plastic recycling due to the high expense and low recycling output.

2.2 Towards the future of Smart Waste Segregation

Smart waste segregation is a modern approach in waste management and recycling where waste is segregated or classified using computer vision(CV) and neural network(NN) based models. In waste management, it is necessary to segregate recyclable waste from the other non-recyclable waste. In this subsection, recent studies on smart waste segregation are discussed briefly.

Smart waste segregation using CV involves different NN architectures where it is essential to know which neural network architecture performs better in sorting waste [8]. With the best performing NN architecture, an object detection model is built to detect and sort waste into different classes [9]. Further, a cloud-based smart waste segregation architecture can be built using an object detection model to sort recyclable waste [10]. After waste segregation and plastic recycling, further segregation of differentiating pure and impure recycled plastic granulates using machine learning can be performed to obtain high-quality recycled plastic by removing the impure plastic [11].

The ability of Convolution Neural Networks (CNNs) to provide reliable accuracy, learn new unique and abstract features shows promise in the domain of computer vision [12, 13, 14].

2.3 Smart Plastic Waste Segregation Today

Smart plastic waste segregation, similar to smart waste segregation, is to sort plastic waste further into different plastic types using CV and NN-based models. The plastic sorting problem is at an early research stage in the CV domain and needs further study. Many types of research have been performed to classify different waste materials. However, for plastics, further segregation into their individual plastic category is necessary for recycling.

A study proposed by Kokoulin et al. where CV-based sorting technique was carried as a second stage after mechanical sorting to improve the classification rate based on color, shape [15]. Using MobileNet, the authors achieved 98% accuracy on their test set; however, when tested in real-time with different camera settings dropped the accuracy significantly to 61%.

Bobulski & Piatkowski, in their research, directly addressed the plastic waste sorting problem where they proposed a plastic waste "WaDaBa" dataset and performed a simple classification to classify PET plastic types from rest types [3]. The approach used was using color-histogram and Canny-edge-gaussian filter, which resulted in only 75.68% accuracy. The image histogram method fails to incorporate features like shape, texture which can improve classification results. The proposed dedicated plastic waste dataset is necessary to expand on this problem domain.

2.3.1 Object Detection for Plastic Waste Sorting

The object detection model in plastic sorting is to detect multiple plastic waste types in a single image frame. No research, to knowledge, is published in using object detection in plastic-waste sorting. Thus, a relevant CV-based approach applicable to the plastic dataset needs to be studied. In this section, different object detection models and their relevance in this study are discussed.

Plastics have different visual properties, but differentiating between similar-looking plastics can be challenging. To extract such visual features, out of five feature extraction methods, CNNs performs best consistently [16]. It is seen that images having shape, texture, and color present together help DCNNs to achieve the best accuracy, and DCNNs can detect transparent object features better [17, 18, 19]. Furthermore, DCNNs show the ability to distinguish between transparent overlapping objects and non-transparent ones with the same shape.

However, it is also crucial to select the best performing neural network architecture (NNA) to extract more features in object detection. While the DenseNet and InceptionNet perform well in the waste classification, the current state-of-the-art CSPDarkNet53 and EfficientNet perform better than them on the COCO dataset [8, 20, 21]. Also, including a feature fusion(FF) module to enhance feature extraction shows improvement in overall mAP [22]. Evidently, performing controlled scaling on classification and regression modules and FF modules also increase mAP in object detection [23].

In object detection, objects that fall in the 32x32 pixel or lower category are categorized as small objects [22]. Plastic waste can be of varied sizes, and it cannot be assumed that plastic waste is of large or medium size. With a realistic notion in mind, our hypothesis is that a plastic waste sorting model must be able to detect and predict small and large-sized plastic waste for a higher recycling rate commercially.

The main challenge in small object detection is to extract features, and since they are in low resolution, comparatively, very less feature information is present. As discussed above, a good NNA combined with an FF module improves the detection accuracy. Furthermore, an NNA learns small object features better if contextual features are captured [24, 25].

Traditional object detection models show poor performance on small objects [22, 24]. Whereas, current state-of-the-art object detection models, Scaled-Yolov4 and Efficient-

Det, confirm an increase in the performance of small as well as large objects with their backbone NNA and FF modules [23, 26]. Scaled-Yolov4-P7 and EfficientDet-d7 achieved 55.5 and 53.7 mAP, respectively, on the COCO dataset. Thus, scaling on the backbone network and feature fusion module increases the mAP for small and large objects.

In conclusion, mechanical spectroscopy-based plastic waste sorting techniques are costly, complex, non-flexible, whereas it is seen that object detection-based smart waste segregation results in better value. However, CV-based plastic waste sorting in plastic recycling has been largely understudied. While Bobulski et al. investigated the potential of plastic waste classification using the image histogram-based feature extraction method, their work was limited to this basic method [3]. It is seen that current state-of-the-art object detection models are efficient and have higher feature extraction capability for small and large objects. Aiming to address this gap, this work investigates a novel object detection and scaling model approach with better feature extraction capability to solve plastic waste sorting.

3 Methodology

In this section, the steps followed in the research methodology are discussed. This research follows mainly five steps: data collection, pre-processing, transformation, data modelling and training, and evaluation, as shown in fig.1.

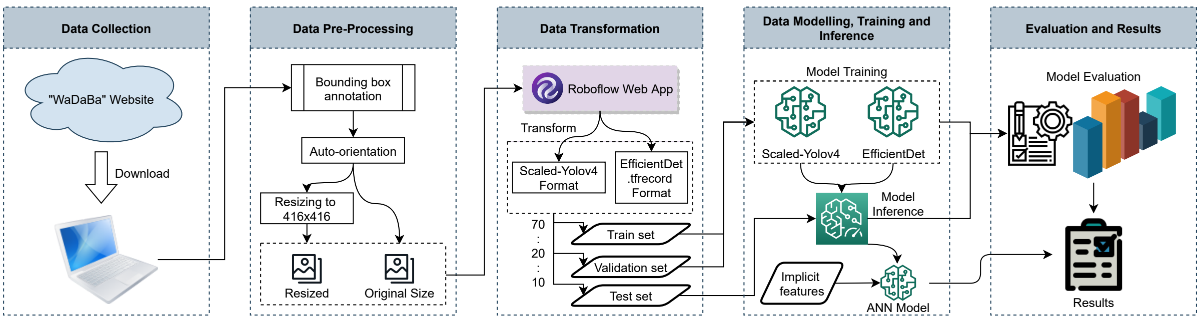


Figure 1: Research Methodology

In the first step, Data Collection, the “WaDaBa” plastic dataset published by Bobulski and Piatkowski (2018) was collected from the official website [3].[2] The dataset consists of four thousand plastic waste images of 5 plastic types: 1) PET, 2) HDPE, 3) PP, 4) PS, 5) Other. An ethical license agreement was signed to use this dataset for this research.

In the second step, Data Pre-processing, the image dataset was first converted to an object detection dataset by manually creating bounding boxes(BB) for 4000 plastic waste images. Auto-orientation was also applied as the final pre-processing to the dataset. These images then were resized to 416x416 size for faster training of the object detection models. Another set of the original-sized images was also saved.

In the third step, Data Transformation, the image dataset was transformed in the object detection model format of Yolo and EfficientDet. Using Roboflow web app, the image dataset along with BB file was converted into Yolo format with BB format as (class, BB centre x, BB centre y, BB width, BB height), and into EfficientDet format as .tfrecord file with BB as xmax, xmin, ymax, ymin with a class label. Finally, the dataset was split into 70:20:10 ratio as train, validation, and test, respectively.

[2] “WaDaBa” Dataset: `http://wadaba.pcz.pl/index.html`

In the fourth step, Data Modelling and Training, state of the art object detection models, Scaled-Yolov4 and EfficientDet with their individual baseline and highest scaled models were trained on the transformed plastic dataset [23, 26]. These models were pre-trained on the COCO dataset and using transfer-learning finetuned on our plastic dataset. For Scaled-Yolov4, first, the baseline scaled-yolov4-csp model was trained with batch size 16, followed by the scaled-yolov4-p7 model with batch size 8. For the EfficientDet, first, efficientdet-d0 was trained with batch size 32 for faster training, and efficientdet-d7x was trained with batch size 8. The batch size was reduced for both of the scaled models due to excessive memory usage while training. All these four models were trained for 100 epochs, and the learning rate for both efficientdet models was made to 0.05 to obtain convergence. The trained models were then used for inference on the test set. The final classification result was passed to an artificial neural network(ANN) model trained on the additional textual implicit features of each plastic object. The model was created using Keras library with one input layer of 128 nodes, 3 hidden layers of 64, 32, 16 nodes using 'tanh' activation function, and final output layer using 'softmax' activation function. The model was compiled using categorical cross-entropy function, optimized using Adam optimizer and trained for 100 epochs.

In the fifth step, evaluation, the inference output of each model is evaluated based on mean average precision and accuracy. The model performance is compared based on training time, model size, and inference time. For each plastic-type, the model f1-score is also evaluated. The final results of each model are compared and visualized using the matplotlib python library.

4 Design Specification

The framework architecture of the implemented plastic sorting object detection and scaling model contains two modules, object detection and scaling model, followed by an artificial neural network(ANN) model as shown in fig. 2. The inner components of the object detection and scaling model are discussed in section 4.1. The components of ANN model is discussed in section 4.2.

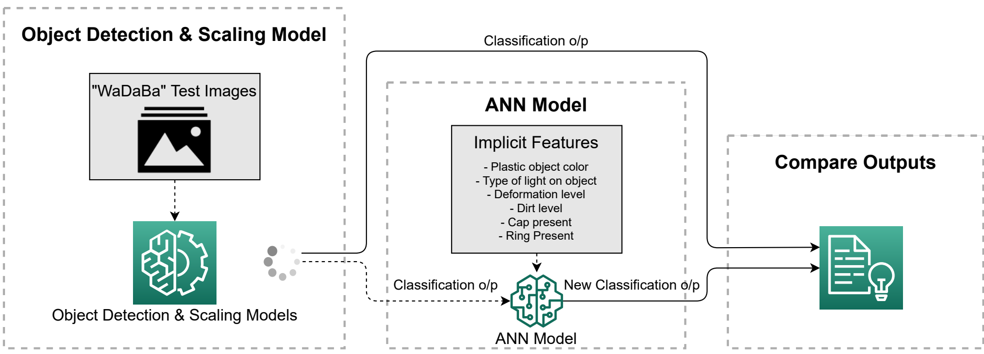


Figure 2: Framework architecture of Research Project

4.1 Object Detection and Scaling Model

Plastic sorting starts with getting an image or set of images with plastic object waste. This image/s is then passed on to object detection and scaling models to make an inference. These models are based on Scaled-Yolov4 and EfficientDet. An output inference detection for plastic object image/s is generated, with a classified plastic object type along with the bounding box and prediction score. This classification result is passed on to the next ANN model for further improvement on classification.

4.2 ANN Model

The ANN module contains an implicit knowledge input and the classification output from the object detection model as the input. The ANN model is trained based on the implicit knowledge about the plastic object present in the dataset. The model is trained on implicit features of plastic object images. The model takes the input features to generate the final classification of the object.

5 Implementation

The project was implemented with steps from dataset annotation, data transformation to final output classification on different platforms. The dataset was first downloaded from the WaDaBa website. The acquired dataset was uploaded to Labelbox, a platform to create a personal custom object detection dataset. The final object detection dataset was created by annotating bounding boxes for each plastic object image and was exported as a .json file. This dataset is in a generic Labelbox object detection format that differs from the format needed for Scaled-Yolov4 and EfficientDet models. The new labelled dataset is uploaded on Roboflow, a web application that can pre-process and transform the dataset into a desired object detection model format. Using Roboflow, two versions of the dataset were created. One with an original image size of 1920x1277 and the other resized to 416x416 smaller size. On both versions, a pre-processing step, auto-orientation, is performed and is exported to Scaled-Yolov4 format and TFrecords EfficientDet format.

The generated dataset is uploaded on google drive and then imported to Google Colab Pro for model training. Scaled-Yolov4 model implemented in Pytorch and EfficientDet model implemented on Tensorflow are used. These pre-trained models were cloned from Github from the actual authors of the models to Google Colab Pro [23, 26]. [3,4] All experiments performed on Google Colab with machines having Tesla P100 or V100 16GB graphics card with 32GB memory. A total of 8 models were finetuned on our plastic dataset, Scaled-Yolov4 baseline model, Scaled-Yolov4 P7 scaled model, EfficientDet-d0 baseline model, and EfficientDet-d7x scaled model on the resized dataset and original-sized plastic dataset.

A training dataset for implicit features is created using the pandas library. This dataset contains features of a plastic object such as color, type of light on the object, deformation level, level of dirt on the object, if the object has a cap on it, and if the object has a ring on it. These features available in the original dataset in the file name are used to investigate if utilizing them can improve the accuracy of class identification. Another input variable is created called a predicted class which is the output from the ODSMs. All combinations of classes are paired with the implicit features to ensure no bias and reliable results based on the implicit features. These input features are then mapped to the output class variable. Fig.3 displays the creation of the ANN training

[3]Scaled-Yolov4 Github link: `https://github.com/WongKinYiu/ScaledYOLOv4/tree/676800364a3446900b9e8407bc880ea2127b3415`

[4]EfficientDet Github link: `https://github.com/google/automl/tree/9c58b0b487995d5e6b95ba366cb56cff8f17cd26/efficientdet`

dataset. This dataset is used to train the ANN model. Then the inference on the test set from each model is passed to the ANN model, and results are noted.

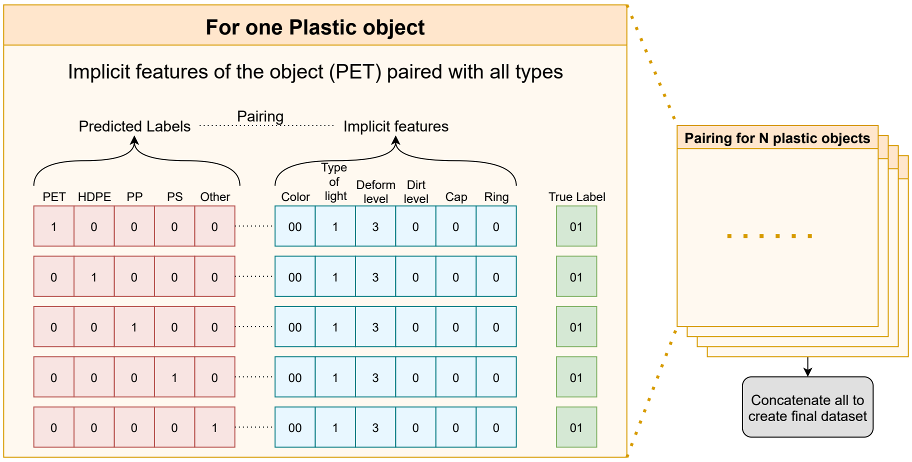


Figure 3: Implicit features data creation

6 Evaluation

In this research, four experiments were performed which are described in subsections 6.1, 6.2, 6.3, and 6.4. Experiment 1, 6.1, is performed to replicate the PET vs. Non-PET study by Bobulski et al. (2018). Experiment 2, 6.2, Object detection and Scaling models are trained and tested on the final resized plastic dataset. In experiment 3, 6.3, Object detection and Scaling models are trained and tested on the final original sized plastic dataset. In experiment 4, 6.4, an ANN model further incorporating implicit features of plastic objects is implemented. All the experiments were performed on the Google Colab Pro setup discussed in the previous section, 5. Finally, the results of all the models are compared.

6.1 Experiment 1: PET vs Non-PET

The aim of this experiment was to replicate the histogram-based using canny edge filter PET plastic classification of Bobulski et al. (2018). In this experiment, the same steps were followed as given in the paper. We used the Canny Edge filter using Gaussian filter, locate the object using thresholding, and finally used a histogram to detect PET plastics vs. Non-PET plastics. Table 1 demonstrates the comparison of our achieved results as compared to Bobulski's original study results. Our results came around the same as the original study.

Table 1: Comparison between Original Study and our Replicated study results

	Accuracy	False Acceptance Rate	False Rejection Rate
Bobulski Result	75.68%	21.45%	2.86%
Our Result	73.77%	24.22%	2%

6.2 Experiment 2: ODSMs on resized plastic dataset

The aim of this experiment was to train and evaluate four ODSMs on the resized plastic dataset. This was split into two sub-experiments, where EfficientDet(ED) was trained first and then Scaled-Yolov4(SV4). Both models utilized were pre-trained on the COCO dataset to achieve better detection and accuracy.

Sub-Experiment 2.1: ED-d0 and ED-d7x finetune on "WaDaBa"

In this sub-experiment, the ED-d0 baseline model and ED-d7x scaled model was trained on the transformed resized dataset. The classification accuracy for ED-d0 and ED-d7x was 75% and 71% respectively and mAP was 67% and 55% respectively. The accuracy achieved was slightly lower than that of the Bobulski study.

Sub-Experiment 2.2: SV4-CSP and SV4-P7 fine-tune on "WaDaBa"

The SV4-CSP baseline model and SV4-P7 scaled model were trained on the transformed resized dataset in this sub-experiment. The classification accuracy for SV4-CSP and SV4-P7 was 97% and 90%, respectively, and mAP was 79% and 63%, respectively. This sub-experiment demonstrated significantly better results than the previous one.

6.3 Experiment 3: ODSMs on original image size plastic dataset

The aim of this experiment was to train and evaluate four object detection and scaling models on the original size plastic dataset. This was split into two sub-experiments with the same settings as the previous experiment. Here, we check if changing the resolution size can improve the results for plastic sorting.

Sub-Experiment 3.1: ED-d0 and ED-d7x finetune on "WaDaBa"

In this sub-experiment, the ED-d0 baseline model and ED-d7x scaled model was trained on the transformed original sized dataset. The classification accuracy for ED-d0 and ED-d7x was 69% and 71% respectively and mAP was 65% and 56% respectively. This showed lower results than the previous two sub-experiments.

Sub-Experiment 3.2: SV4-CSP and SV4-P7 fine-tune on "WaDaBa"

The SV4-CSP baseline model and SV4-P7 scaled model were trained on the transformed original sized dataset in this sub-experiment. The classification accuracy for SV4-CSP and SV4-P7 was 97% and 95% respectively, and mAP was 97% and 72% respectively. This sub-experiment demonstrated the highest results than all the previous sub-experiments.

6.4 Experiment 4: Artificial Neural Network incorporating implicit knowledge

The aim of this experiment is to build and train an artificial neural network model which takes the final class output of the trained ODSMs along with six implicit knowledge of each plastic object image as input and gives a final class output. The aim was to find out if utilizing additional implicit knowledge of plastic objects can improve the class prediction accuracy of the trained ODSMs further. The table 2 shows the before and after the accuracy of the class prediction of all the models using the final ANN module.

Table 2: Class Accuracy comparison before and after using implicit features

Model	Class Prediction Accuracy	
	Before ANN	After ANN
Scaled-Yolov4-Baseline (Original size image)	97%	81%
Scaled-Yolov4-p7 (Original size image)	95%	81%
Scaled-Yolov4-Baseline (Resized image)	97%	83%
Scaled-Yolov4-p7 (Resized image)	90%	83%
EfficientDet-d0 (Original size image)	69%	79%
EfficientDet-d7x (Original size image)	71%	79%
EfficientDet-d0 (Resized image)	74%	83%
EfficientDet-d7x (Resized image)	71%	83%

6.5 Discussion

In this research study, a total of four pre-trained object detection models were fine-tuned on two variations of the "WaDaBa" plastic dataset. This section critically compares the results of the experiments mentioned above to understand ODSMs performance in given settings and the value of additional implicit plastic object features for classification.

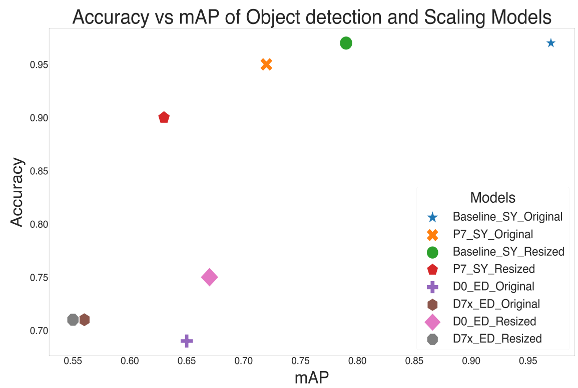
A comparison of the four models on two variations of the dataset by accuracy and mAP is shown in the fig.4a. The accuracy scores are on the test set, while the mAPs are on the training set. The accuracy confirms how accurately the model classifies plastic waste, whereas the mAP proves how precisely the model detects the object considering the bounding box edges around the objects for each class. Models trained on original-sized images show better accuracy and mAP score than those on resized images. Also, the baseline scaled-yolov4-csp model on the original sized image shows promising results with 97% accuracy and 97% of mAP on the "WaDaBa" dataset.

A comparison of the four models on two variations of the dataset by f1-scores for each plastic-type is shown in fig.4b. The f1-score is calculated on the test data. All ODSMs achieved a high f1-score for PET plastic objects, whereas none for Other plastic types. Moreover, PP and PS plastic objects are less precisely detected than PET and HDPE plastic types. This result demonstrates the limitation of this study directly relating to our imbalanced dataset. The class proportion in the dataset is 55% for PET, 15% for HDPE, 16% for PP, 13% for PS, and 1% for Other. It is also seen that the Scaled-Yolov4 models outperform the EfficientDet models in all plastic types impressively.

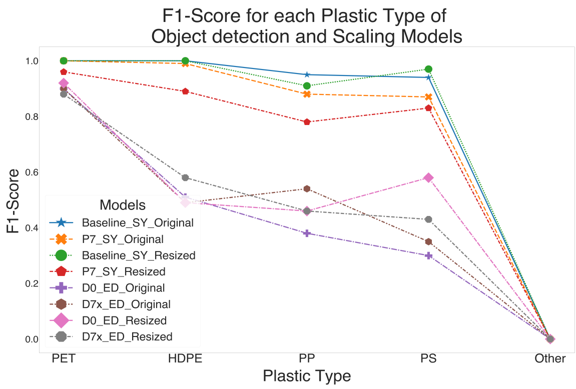
A comparison of the four models on two variations of the dataset by training time and inference time is displayed in fig.5a. Training time is the total time consumed by the model to train over 100 epochs. Inference time is the time taken for the model to detect and classify the plastic object. For both, less time indicates better model performance. It is also seen that Baseline Scaled-Yolov4-CSP models consumed significantly less time to train and make an inference with 1.48 hrs and 0.02s, respectively, on original-sized images with higher accuracy, mAP, and F1-score.

Model size comparison of the four models trained on two variations of the dataset is shown in fig.5b. It is seen that EfficientDet models require significantly less memory to store the model weights being more efficient in size than Scaled-Yolov4.

In this research, an additional experiment was performed to train an ANN model with

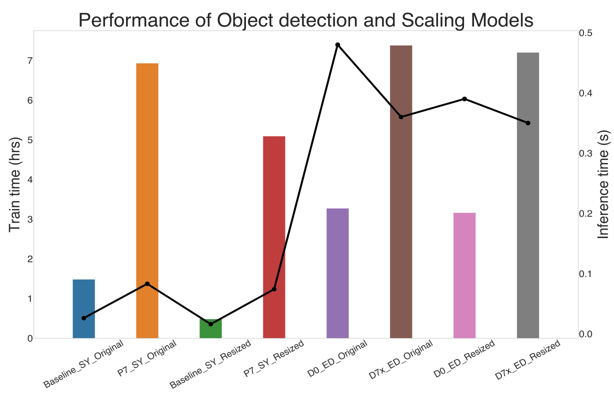


(a) Accuracy vs mAP

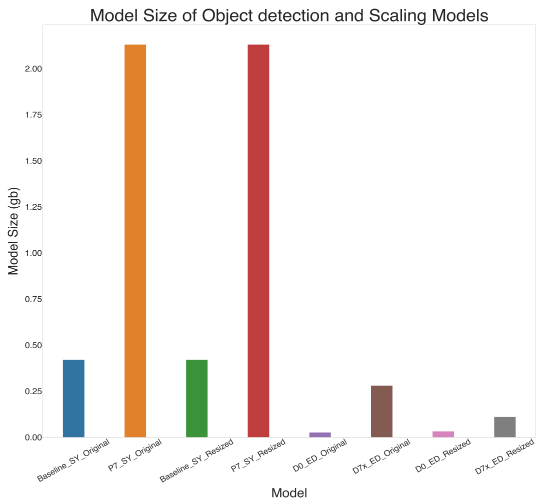


(b) F1-score for each Plastic object type

Figure 4: Model Metric Summaries



(a) Train vs Inference time



(b) Model Size

Figure 5: Model Performance Summaries

six implicit plastic object features to investigate if the final classification accuracy of the ODSMs can be improved further. It is seen that feeding the output of the class from the ODSM along with the implicit features does not guarantee improvement in the classification accuracy. This is because the ANN model is trained on the features independent of those from ODSMs, thus not fully incorporating the convolution-based output from the object detection model. Thus, Scaled-Yolov4 models classification accuracy output more than 90% were degraded to 81-83%. In contrast, the EfficientDet model's classification accuracy output was improved to 79-83%. This is the limitation of this study where the implicit features trained independently on the ANN model not incorporating image feature output from ODSM.

This research demonstrated the potential of ODSMs on plastic waste sorting as compared to the current mechanical or chemical-based sorting. The models trained were fine-tuned on our dataset showing the ability of continuous improvement using transfer learning. ODSMs can also upgrade for better results with more research in ease. This will also make the process cost and time-effective.

This research study aimed to explore the performance of Object detection and scaling models based on accuracy and precision to sort plastic waste. Additional model performance was evaluated in train time, inference time, and model size for practical industrial use. Lastly, an experiment was aimed to evaluate the effectiveness of implicit features using an ANN model on final classification accuracy for plastic objects. The key implications resulted from the research study is given as follows:

- Baseline Scaled-Yolov4-CSP trained on higher resolution images of "WaDaBa" dataset shows industry acceptable performance based on accuracy, mAP, and F1-scores, train, and inference time with considerable model size.
- Scaled-Yolov4 ODSM outperforms in plastic recognition than histogram Canny edge filter based study by roughly 23% accuracy on "WaDaBa" dataset.
- Incorporating implicit textual features of plastic objects trained independently on the ANN model does not guarantee the increase in plastic classification accuracy.
- Practical use of ODSMs in plastic waste sorting can reduce cost and time as these models are flexible to improve further, able to continuously train on new images on the cloud, and use transfer learning to transfer weights when necessary.
- The class imbalance in the dataset affected the true model training capacity for each plastic type object.
- The dataset size with only 4000 images is still less for object detection and scaling model to demonstrate the potential results.

7 Conclusion and Future Work

The aim of this research was to explore the extent of object detection and scaling models in smart plastic waste sorting. This research demonstrated that Scaled-Yolov4-CSP on the original sized "WaDaBa" dataset shows promising industry-standard results in accuracy, mAP, train, and inference time with considerable model size. Another objective was to check if implicit plastic object features can further improve accuracy using ANN as an additional model. The improvement in classification accuracy is not guaranteed when an independently trained ANN on implicit features is added. Object detection and scaling model with FPN shows better results in small objects like plastic waste than using a Canny edge gaussian filter. This research shows the potential of using the Object detection and Scaling model for plastic waste sorting in practice, but it still has a few limitations which can be addressed in future work.

The limitation of the "WaDaBa" dataset having only 4000 plastic waste images can be addressed by increasing the dataset size and more plastic object samples with a balanced ratio of classes. Another limitation was that independently trained ANN did not demonstrate a true value addition of the implicit features to the final classification accuracy. This can be explored as a future work by developing a new object detection model where the final classification NN layer also incorporates the implicit features inputs along with convolution output such that the model takes an image and implicit features as the input at once. In this study, the plastic waste small objects were detected using only FPN as a feature enhancement. In future work, an object detection model which utilizes contextual features to detect small objects can be studied.

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