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Non-Biodegradable Plastic Waste Detection and Classification Using Deep Learning: Bangladeshi Environmental Scenario

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***Abstract*— Non-biodegradable plastic waste is a major problem in Bangladesh. In particular, YOLOv8 is the most popular deep-learning technique for object recognition which is utilized for waste detection. Detecting and classifying some of the most common waste products on streets, yards, marketplaces, parks, educational institutions, etc. can be aided by VGG16, AlexNet, and ResNet50 which are used for higher validation accuracy. The Non-Biodegradable Plastic Waste Detection and Classification (NPWDC) method begins with an input picture that is fed into the YOLOv8m. It then outputs a cropped piece of the detected region along with a bounding box surrounding the waste area that has been discovered. The resulting picture will now be fed into many classification methods, such as ResNet50, VGG16, and AlexNet, which produce categorized output labeled with the image class name. Since this is an extremely difficult task, the original NPWDC dataset which was created by taking pictures of the wastes under various situations and from various angles is used to train the NPWDC model. This dataset is based on the actual environmental scenario in Bangladesh. The total size of the dataset after augmentation is 10024. According to test data, the NPWDC model has an impressive accuracy rate of 93%. With a focus on deep learning's ability to solve non-biodegradable plastic trash, the NPWDC highlights how deep learning may help Bangladesh and similar regions have a cleaner, more sustainable future.**

Keywords—NPWDC, Plastic waste, YOLOv8m, Object detection, VGG16, AlexNet, ResNet50, Object Classification

I. INTRODUCTION

The growing issue of non-biodegradable plastic waste in Bangladesh demands innovative ideas to mitigate its negative effects on the environment and public health. The quick build-up of plastic waste is overwhelming conventional waste management systems, contaminating yards, streets, hospitals, and even schools[1]. The Non-Biodegradable Plastic Waste Detection and Classification (NPWDC) method—a deep learning-driven strategy created especially to address this problem in the Bangladeshi context—is presented in this study.

NPWDC effectively detects four common plastic waste classes: polyethene, packets, plastic bottles, and hard plastics by utilizing YOLOv8m's advanced object recognition capabilities[2]. After this detection phase, a reliable classification procedure uses three well-known deep learning models that are well-known for their efficiency in image classification tasks: ResNet50, AlexNet, and VGG16.

One of NPWDC's key differentiators is its meticulously chosen Bangladeshi dataset, which focuses on the four waste classes mentioned above. The NPWDC dataset captures the distinct realities encountered in Bangladesh, in contrast to other datasets that frequently lack the context and diversity of waste landscapes. This covers differences in the kinds of waste, the surroundings, and the qualities of the image. This customized strategy guarantees the model's applicability and efficacy in tackling Bangladesh's unique plastic waste issues. The potential of NPWDC goes beyond waste classification and detection. It is a big step toward creating a more sustainable and clean future for Bangladesh. Similar regions that are struggling with plastic waste issues can be empowered by NPWDC by offering a framework that is both scalable and flexible. Additionally, this study advances the field of deep learning applications.

II. RELATED WORKS

Tamin et al. proposed a method using YOLOv5 and RGB-Near-Infrared fusion that can detect the unique properties of plastic waste[3]. Using existing datasets Sylwia Majchrowska et al. did automatic waste detection through a critical analysis with a two-stage detector using EfficientDet-D2 for localization and EfficientNet-B2 for classification[4]. An analysis of waste detection and classification techniques with precise and organized representation and compiling over twenty benchmarked trash datasets was done by Haruna Abdu et al. and they also backed up the study with the challenges of existing methods[5]. Wei Zhou Lei Zhao et al. proposed a framework of waste detection with a state-of-the-art few-shot detector named AFDNet which has a labor-intensive and time-consuming nature [6].

To improve waste detection accuracy and speed Jing MengPing Jiang et al. introduced a MobileNet-SSD model with FPN which works on annotated datasets and the model incorporates Focal Loss to reduce foreground-background sample imbalance[7]. The importance of region-specific databases for accurate waste sorting automation was shown by Wei Lung Mao et al. with the TRWD-trained Yolo-v3 model[8]. An improved oriented waste detection method based on YOLOv5 was proposed by Weizhi Yang et al. It can generate an oriented detection box for a waste object that is placed at any angle which increases the angular prediction ability of the model[9]. For performing fast and efficient detection of waste targets in the sorting process Jinhao Fan proposed a data augmentation and YOLO_EC waste detection system with the optimization of DCGAN by improving the loss function. Though they used Yolo-v4 as the basic model, EfficientNet was used as the backbone feature extraction network with the HPU_WASTE dataset[10].

III. Non-Biodegradable Plastic Waste Detection and Classification (NPWDC)

Outstanding performance in precisely detecting and classifying waste is ensured by the seamless integration of YOLOv8 with VGG16, AlexNet, and ResNet50. Currently, an RGB image is used as the input for the YOLOv8 model, which outputs a set of bounding boxes denoting waste zones that have been identified. The cropped photos of the detected waste areas are then used as inputs for classification using the VGG16, AlexNet, and ResNet50 approaches in additional processing of this output. The several kinds of garbage that are included in the cropped photographs are being actively detected and classified by these classification algorithms. Figure 1 depicts the entire procedure of the NPWDC Model.

The proposed approach is divided into two sections. Section A discusses about waste detection phase. The recognition phase is discussed in section B.

A. Detection

As the dataset has diversity, detection is applied before classification which significantly increases the accuracy of the model. Among various CNN architectures, Yolo-v8 is used for detection as it is one of the fastest object detection models and is specifically designed to focus on constrained edge device deployment at high-inference speed. That's why the YOLOv8 model is selected to detect a wide or small object[11], that's mainly focused on reducing the classification time and increasing accuracy. Figure 2 depicts the workflow of waste detection model.

The CNN architecture is responsible for processing the input image in the YOLO model to extract features, which will help to detect objects. The latest release of YOLO version 8 (YOLO-v8)[12] is one of the fastest object detection models and is specifically designed to focus on constrained edge device deployment at high-inference speed. That's why the YOLOv8 model is selected to detect an object, that's mainly focused on reducing the classification time and increasing accuracy. The working flow of the Waste detection model using the YOLOv8 model is illustrated in Figure 2.

The YOLOv8 Model takes an image as an input and preprocesses it for further use. Initially, the preprocessed image is divided into several $S \times S$ grid and extracts features from every individual grid. Each grid cell with an object in the center, predicts a bounding box (BB) and confidence score (CS). The BB consists of five predictions denoted by (x, y, w, h) and the CS. The (x, y) coordinates represent the center of the grid cell's BB, while $(\ \ , h)$ provides the width and height of the complete image.

The CS indicates how certain objects are to exist in each BB that can be expressed by Equation 1.

$$CS = Pr\,(Object) \times IoU_{pred\ truth} \tag{1}$$

The CS is derived by multiplying the object probability ($Pr\,(Object)$) by the intersection over union (IoU) [13]. Here, equation 2 is used to determine the $Pr\,(Object)$, where x is the raw output value corresponding to the object.

$$Pr\,(Object) = \frac{1}{1+e^{-x}};\ \begin{cases} 0, if\ no\ object \\ 1, otherwise \end{cases} \tag{2}$$

The Pr (Object) validate the presence of objects, if no object exists, $Pr\,(Object)$) will be zero. The IoU of two BB is a measure of how strongly they overlap. It is determined by dividing the area of the two boxes' intersection by the area of the two boxes' union, shown in Equation 3.

$$IoU = \frac{Intersection\ Area\ of\ bounding\ \ boxes}{Union\ Area\ of\ bounding\ \ boxes} \tag{3}$$

The IoU score can vary between zero to one, with Zero indicating no overlap and one pointing that the boxes exactly match each other. By using those images the model will predict parallelly whether the object is waste or not waste.

Fig. 1: Overall process of the NPWDC Model

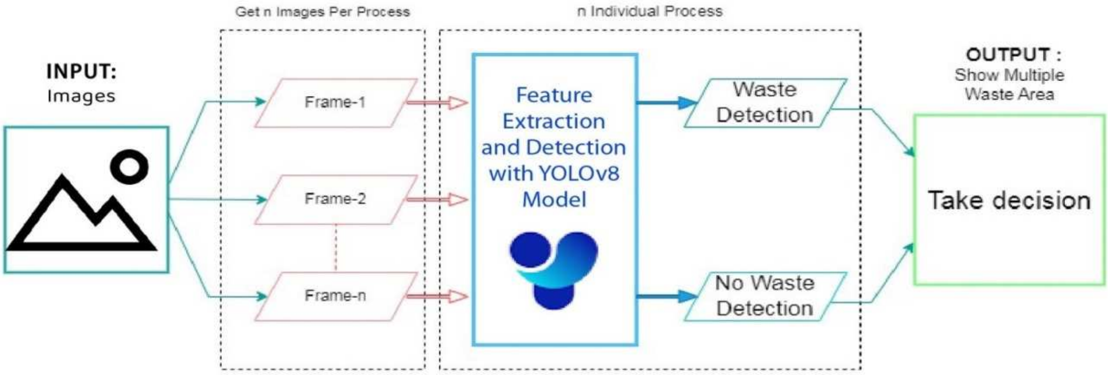


Fig. 2: The workflow of waste detection model

B. Classification

To classify waste, various techniques, including VGG16, AlexNet, and ResNet50, are applied to processed output images generated from the detection model. ResNet50 proves to be exceptionally accurate, leading the waste detection model to continue with it, shown in figure 3. The output of the detection model undergoes processing before feeding into the ResNet50 model[14]. This involves cropping the detected area and organizing it according to the input structure of classification models. Due to the diverse types of waste in varying sizes and shapes, a detailed classification technique is essential. The model is trained with a higher layer density and lower batch size, achieving a precise balance. This combination of batch size and layer density contributes to a very high accuracy in classification.

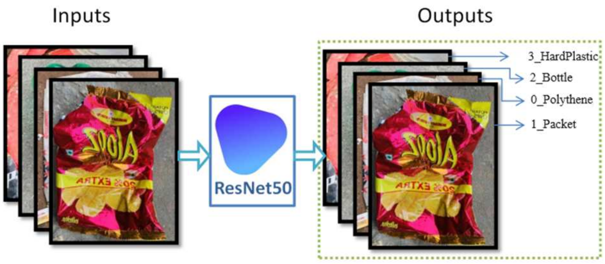


Fig. 3: Classification with ResNet50

Focusing on waste categorization, the section systematically breaks down various waste types The workflow of the waste detection model, simplifies the understanding of the diverse waste landscape. ResNet50 is highlighted as a crucial actor, with an examination of its capabilities and why it excels at decoding visual complexities. Recognizing the spectrum of waste variations, the nuances of parameter adjustments in ResNet50 are handled, ensuring a deep grasp of each waste category. The part closes with a visual tutorial that unfolds a step-by-step journey of waste classification with ResNet50, providing an insider's insight into the classification approach.

IV. Experimental Result and Analysis

Section A and Section B explain the whole data collection and preprocessing steps that include augmented data into 7 different models[15]. In the following section C, and D provides in brief overview of the training process of the NPWDC model, result analysis, and detection and classification results comparison respectively.

A. Data Collection

A rich dataset is required to train this model. we made our dataset by capturing photos with the phone camera from different angles and different conditions.

- Local Focus: Images were meticulously sourced from diverse locations within Bangladesh to capture the unique characteristics and variations inherent to the regional landscape.
- Real-world Representation: A substantial repository exceeding 3500 real-time images was amassed, ensuring a comprehensive representation of the data space.
- Environmental Diversity: The collection process encompassed a wide range of lighting conditions and backgrounds, capturing the dynamic essence of waste types amidst their natural surroundings.
- Curation Refinement: After the initial compilation, a careful curation process was carried out to eliminate duplicate instances, resulting in a refined and simplified dataset.

B. Data Augmentation

A comprehensive augmentation process was implemented. Introducing those transformative steps to enrich the dataset and enhance model robustness.

Rotation: Rotations of 18 degrees were applied both clockwise and counterclockwise, preparing the model to recognize objects in different orientations.

Flip: Vertical and horizontal flips were incorporated, simulating alterations in object perspectives and orientations, further diversifying the dataset.

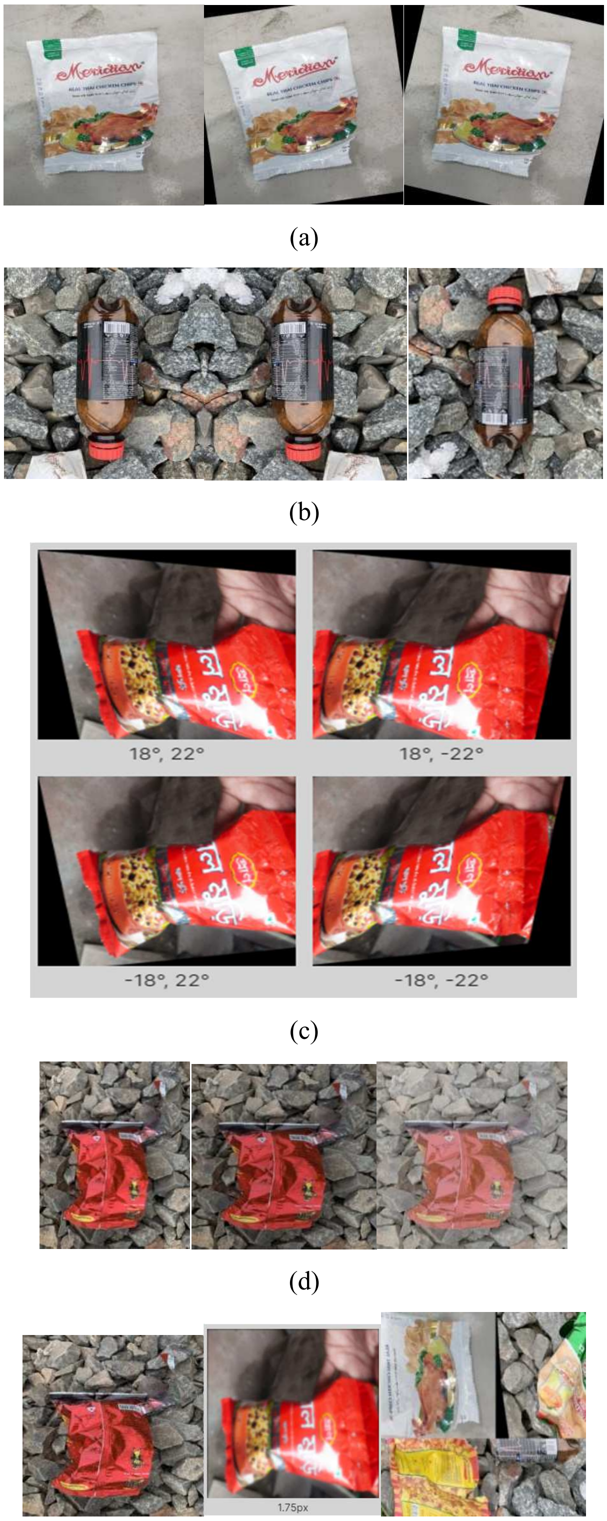
Shear: Horizontal and vertical shear transformations were employed, introducing variations in object shapes and perspectives, contributing significantly to the dataset's robustness.

Exposure: Exposure adjustments within the range of ±26% were implemented, simulating variations in lighting conditions, and ensuring adaptability to diverse environments.

Noise: Deliberate introduction of 6% noise-emulated imperfections commonly encountered in real-world environments.

Blur: the application of a 1.75-pixel blur effect further enriched the dataset's complexity, mimicking subtle distortions inherent in the image capture process.

Mosaic patterns: Another layer of complexity has been added to the dataset through a strategic integration of 2x2 mosaic patterns, enabling a more detailed and complex dataset.



(a) (b) (c) (d) (e) (f) (g)

Fig. 4: Augmented data into 5 different methods: (a) Rotation; (b)Flip; (c)Shear; (d)Exposure; (e)Noise; (f)Blur; (g)Mosaic Pattern;

C. *Dataset Splitting*

1) *For Detection:*

- Train set (80%): This set is used to train the detection model, allowing it to learn the patterns and features of waste objects.
- Validation set (10%): This set is used to fine-tune and evaluate the performance of the model during training, ensuring optimal generalization and avoiding overfitting.
- Test set (10%): This set is used to assess the final performance of the trained model on unseen data, providing an objective measure of its effectiveness.

The process is shown in figure 6.

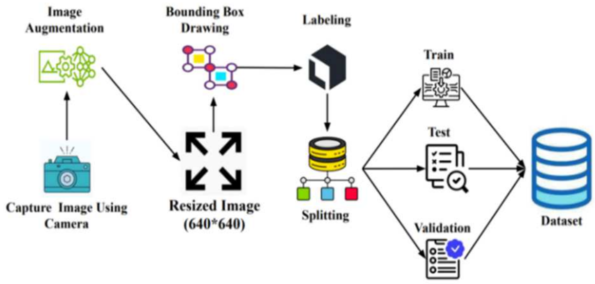


Fig. 5: Dataset-making process for detection

2) *For Classification:*

- Train set (80%): This set is used to train the classification model, allowing it to learn the features of different waste types.
- Validation set (20%): This set is used to evaluate the performance of the model and identify potential areas for improvement.

The process is shown in figure 7.

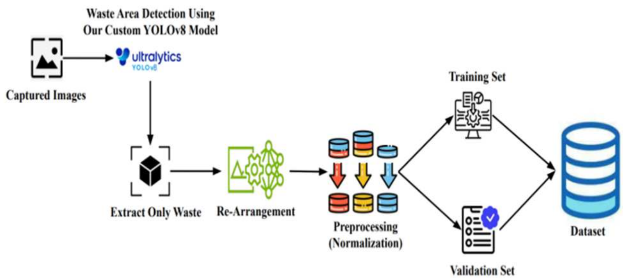


Fig. 6: Dataset-making process for classification

This comprehensive data acquisition, augmentation, and pre-processing pipeline ensure a high-quality dataset that is well-suited for both waste detection and classification tasks within the context of Bangladesh. The specific split ratios for each task guarantee sufficient data for training, validation, and testing, leading to robust and accurate models. Ultimately, this approach contributes to effective waste management solutions. The total number of data collected from the environment is 3681 and after processing and augmentation, there are 10024 data in the database, depicted in figure 8. There are 4 main class in the dataset- polyethene, packets, plastic bottles, and hard plastics. ‘Packets’ is a combination of 3 sub classes- large, medium and small.

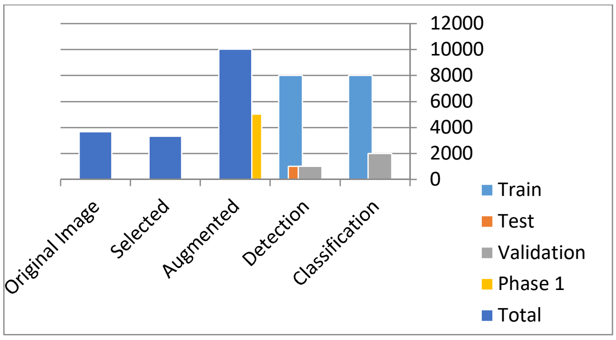


Fig. 7: Dataset Overview

This report details the methodical approach taken to gather and prepare a robust dataset for waste detection within the specific context of Bangladesh.

D. Result Analysis

1) Accuracy: A classification model's accuracy is determined by how many of its overall predictions are accurate. [12].

$$Accuracy = \frac{Correct\ Predictions}{All\ Predictions} \quad (3)$$

2) Recall: Recall is the fraction of true positives that are correctly identified by the model. To measure how well the model identifies all of the positives, the recall:

$$Recall = \frac{True\ positive_{class}}{True\ positive_{class} + False\ Negative_{class}} \quad (4)$$

3) Precision: Precision is the fraction of predicted positives that are actually true positives. In the same way, the precision is:

$$Precision = \frac{True\ positive_{class}}{True\ positive_{class} + False\ positive_{class}} \quad (5)$$

YOLOv8 model is chosen over various models [12] for waste detection. In the classification process, it performed very poorly. While in detection it has an accuracy of 81.75%, in classification it has an accuracy of 75.5%. That's why two different model is used for waste detection and classification. For detection, YOLOv8m is used and for classification, ResNet50 is used. After using ResNet50, the classification result is 93%, which is 17.5% better than the classification accuracy of YOLOv8m.

TABLE I. PERFORMANCE COMPARISON WITH RELETED WORKS

Paper Ref.	Models used	Accuracy
NPWDC	YOLOv8, ResNet50	93%
[3]	YOLOv5	92.96%
[4]	EfficientDet-D2 EfficientNet-B2	75%
[7]	MobileNet-SSD	93.63%
[8]	YOLOv3	92.12%

Table 1 shows a comparison of the proposed NPWDC performance with recent relevant works.

Firstly, YOLOv8s is trained which performed not so well. It detects waste with an accuracy of 65% and classifies waste with an accuracy of 55.5%, which is very low to go on. Figure 9 shows the confussion matrix of YOLOv8s Model.

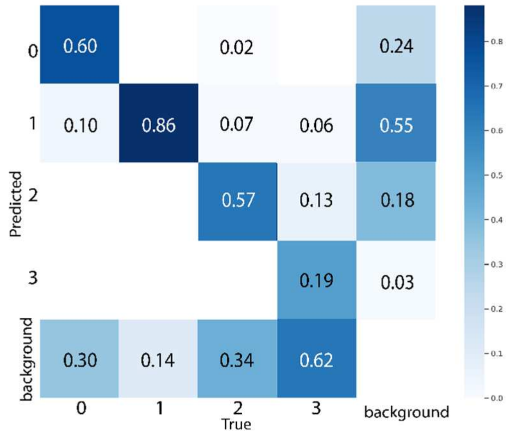


Fig. 8: YOLOv8s Confusion Matrix

As this accuracy is not sufficient for the NPWDC model, then YOLOv8m is trained[16]. This time a better result is found. With YOLOv8m 81.75% accuracy was found in waste detection and 75.5% accuracy was found in waste classification. Figure 10 shows the confusion matrix of YOLOv8m Model.

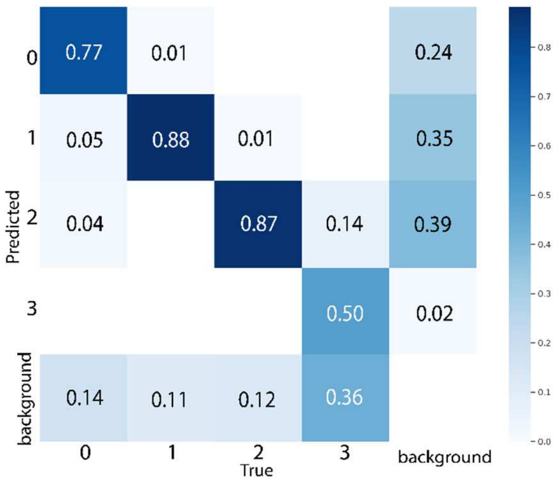


Fig. 9: YOLOv8m Confusion Matrix

As the classification result of YOLO-v8m is not satisfactory, some more techniques named AlexNet, VGG16, and ResNet50 are applied to the output of YOLOv8m[17]. Among them, ResNet50 has the highest classification accuracy. While AlexNet has an accuracy of 60.01%, VGG16 has an accuracy of 60.24%, and ResNet50 has an accuracy of 93% in waste classification which is depicted in figure 11. Table-2 shows the classification report of the classes and Table-3 shows the overall classification report of ResNet50:

TABLE II. CLASS BY CLASS CLASSIFICATION REPORT

class	precision	recall	f1-score	support
0_Polythene	0.92	0.94	0.93	333
1_Packets	0.96	0.95	0.95	968
2_Bottles	0.84	0.87	0.86	281
3_HardPlastics	0.89	0.64	0.74	25

TABLE III. OVERALL CLASSIFICATION REPORT OF RESNET50

	precision	recall	f1-score	support
accuracy			0.93	1607
macro avg	0.90	0.85	0.87	1607
weighted avg	0.93	0.93	0.93	1607

ResNet50 is trained multiple times to get a good result. In that phase parameters were changed to fit with the dataset and also to improve the accuracy. It results in a Lower Learning Rate and higher Layers Density. Finally classification process is done with a high accuracy.

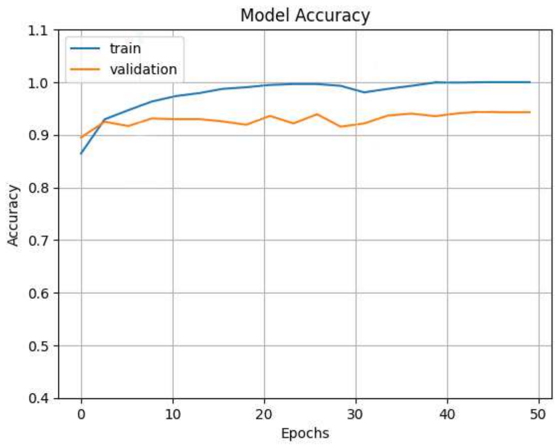


Fig. 10: Model Accuracy of Classification

V. CONCLUSION

The NPWDC model, which uses the YOLOv8m framework to detect waste anywhere and the ResNet50 framework for waste classification, is introduced in this study. The main goal of this model is to detect and classify waste to reduce environmental pollution from non-biodegradable plastic waste. This study thoroughly outlines the processes required to implement the NPWDC model and provides a detailed empirical analysis to determine its effectiveness. Experimental results show that the proposed NPWDC model performs very effectively. Notably, it has an accuracy rate of 81.75% in detection and 93% in classification. More data class could improve the effectiveness as we've worked with only 4 classes. As well as in the similar region, the dataset can be used as it has the diversity and a large number of high quality plastic waste images are used to make the NPWDC dataset.

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REFERENCES

[1] A. T. Williams and N. Rangel-Buitrago, "The past, present, and future of plastic pollution," *Mar. Pollut. Bull.*, vol. 176, p. 113429, Mar. 2022, doi: 10.1016/j.marpolbul.2022.113429.

[2] R. Bawankule, V. Gaikwad, I. Kulkarni, S. Kulkarni, A. Jadhav, and N. Ranjan, "Visual Detection of Waste using YOLOv8," in *2023 International Conference on Sustainable Computing and Smart Systems (ICSCSS)*, IEEE, Jun. 2023, pp. 869–873. doi: 10.1109/ICSCSS57650.2023.10169688.

[3] O. Tamin *et al.*, "On-Shore Plastic Waste Detection with YOLOv5 and RGB-Near-Infrared Fusion: A State-of-the-Art Solution for Accurate and Efficient Environmental Monitoring," *Big Data Cogn. Comput.*, vol. 7, no. 2, p. 103, May 2023, doi: 10.3390/bdcc7020103.

[4] S. Majchrowska *et al.*, "Deep learning-based waste detection in natural and urban environments," *Waste Manag.*, vol. 138, pp. 274–284, 2022, doi: 10.1016/j.wasman.2021.12.001.

[5] H. Abdu and M. H. Mohd Noor, "A Survey on Waste Detection and Classification Using Deep Learning," *IEEE Access*, vol. 10, pp. 128151–128165, 2022, doi: 10.1109/ACCESS.2022.3226682.

[6] W. Zhou, L. Zhao, H. Huang, Y. Chen, S. Xu, and C. Wang, "Automatic waste detection with few annotated samples: Improving waste management efficiency," *Eng. Appl. Artif. Intell.*, vol. 120, p. 105865, Apr. 2023, doi: 10.1016/j.engappai.2023.105865.

[7] J. Meng, P. Jiang, J. Wang, and K. Wang, "A MobileNet-SSD Model with FPN for Waste Detection," *J. Electr. Eng. Technol.*, vol. 17, no. 2, pp. 1425–1431, Mar. 2022, doi: 10.1007/s42835-021-00960-w.

[8] W. L. Mao, W. C. Chen, H. I. K. Fathurrahman, and Y. H. Lin, "Deep learning networks for real-time regional domestic waste detection," *J. Clean. Prod.*, vol. 344, 2022, doi: 10.1016/j.jclepro.2022.131096.

[9] W. Yang, Y. Xie, and P. Gao, "Improved Method for Oriented Waste Detection," *Axioms*, vol. 12, no. 1, p. 18, Dec. 2022, doi: 10.3390/axioms12010018.

[10] J. Fan, L. Cui, and S. Fei, "Waste Detection System Based on Data Augmentation and YOLO_EC," *Sensors*, vol. 23, no. 7, p. 3646, Mar. 2023, doi: 10.3390/s23073646.

[11] H. Lou *et al.*, "DC-YOLOv8: Small-Size Object Detection Algorithm Based on Camera Sensor," *Electronics*, vol. 12, no. 10, p. 2323, May 2023, doi: 10.3390/electronics12102323.

[12] M. Hussain, "YOLO-v1 to YOLO-v8, the Rise of YOLO and Its Complementary Nature toward Digital Manufacturing and Industrial Defect Detection," *Machines*, vol. 11, no. 7, p. 677, Jun. 2023, doi: 10.3390/machines11070677.

[13] R. Huang, J. Pedoeem, and C. Chen, "YOLO-LITE: A Real-Time Object Detection Algorithm Optimized for Non-GPU Computers," *Proc. - 2018 IEEE Int. Conf. Big Data, Big Data 2018*, pp. 2503–2510, 2019, doi: 10.1109/BigData.2018.8621865.

[14] M. S. Nixon and A. S. Aguado, *Feature Extraction and Image Processing for Computer Vision*. Elsevier, 2020. doi: 10.1016/C2017-0-02153-5.

[15] C. Shorten and T. M. Khoshgoftaar, "A survey on Image Data Augmentation for Deep Learning," *J. Big Data*, vol. 6, no. 1, p. 60, Dec. 2019, doi: 10.1186/s40537-019-0197-0.

[16] G. Singh, S. F. Stefenon, and K.-C. Yow, "Interpretable visual transmission lines inspections using pseudo-prototypical part network," *Mach. Vis. Appl.*, vol. 34, no. 3, p. 41, May 2023, doi: 10.1007/s00138-023-01390-6.

[17] D. Theckedath and R. R. Sedamkar, "Detecting Affect States Using VGG16, ResNet50 and SE-ResNet50 Networks," *SN Comput. Sci.*, vol. 1, no. 2, p. 79, Mar. 2020, doi: 10.1007/s42979-020-0114-9.