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Deep Learning Approach for Garbage Classification

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***Abstract*— This research introduces a pioneering framework designed to address the critical challenges of real-time garbage detection and classification, anchored by a comprehensive garbage dataset meticulously categorizing waste items into Biodegradable, Non-Biodegradable, Clothes Waste and Hazardous Waste, this study contrasts the performance of YOLOv5, YOLOv7, and YOLOv8 models. The project unfolds with a rigorous sequence encompassing data preprocessing, model training, meticulous evaluation and exhaustive testing. Significantly, the study demonstrates the unparalleled effectiveness of the model in real-time garbage classification, offering a scalable and efficient solution to bolster waste management, recycling endeavors and broader environmental conservation initiatives. By showcasing the model's efficacy in discerning diverse waste items, this research paves the was for the integration of technology into waste management practices, potentially revolutionizing resource allocation, and fostering sustainable environmental practices.**

I. INTRODUCTION

The management of municipal waste has become a crucial global concern in a time of growing urbanization and risi ng consumerism. Unchecked garbage buildup puts a strain on resources and energy needed for waste removal while also posing risks to the environment. Traditional waste sorting techniques rely significantly on manual labor, which is not onlt time consuming but also error-prone. It gets harder and harder to manage waste streams properly as the amount of waste produced worldwide keeps increasing. Innovative solutions are urgently needed to meet the challenges of trash management and advance sustainable practices due to the ever-increasing and rising garbage output.

A crucial first step towards effective waste management and resource recovery is garbage categorization, Which entails the methodical grouping of waste items into separate categories biodegradable, non-biodegradable, hazardous waste and clothes waste including paper, plastic, glass, metal and organic waste as sub-categories. Trash should be properly categorized to limit contamination in recycling streams, reduce landfill trash, save precious resources, and simplify recycling procedures. However, due to labor-intensive requirements, the possibility of human mistakes, and scalability has turned out to be a difficult obstacle when carried out manually.

Previous studies on garbage categorization mainly used conventional computer vision techniques or early deep learning models, which frequently had accuracy and scalability issues. Even though some had a modest amount of success, their use in practical situations was still limited. These models found it difficult to account for the complexity of waste classification, which includes differences in lighting, object occlusions, and waste type diversity. As a result, their usefulness in automating waste management processes remained restricted.

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In order to address the challenges of garbage categorization, this research makes use of the advantages of yolov7, a cutting-edge object detection model. The exceptional ability of yolov7 to maintain real-time processing capabilities while maintaining high accuracy makes it aa leading candidate and refining a special lyolov7 model on a varied garbage dataset, we want to go beyond the limitations of previous research and develop a system that not only excels in accuracy but also works well in practical situations. And evaluating how well the yolov7 performs in contrast to its previous, newer versions. Bases on these tests and comparisons, we may determine which was more appropriate for garbage classification to use in practical applications.
The remaining part of the paper is organized a follow: Section II explains the proposed methodology, Section III explains the results and results comparison between the models and conclusion in Section IV.

II. PROPOSED METHODOLOGY

The proposed work consists of two phases: preparing the dataset and training the models

A. Workflow Of The Model

The workflow of the proposed model is shown in Fig.1. Initially, a custom dataset is formulated and data preprocessing ensures through partitioning into train, validation, and test folders. Subsequent to dataset preparation, training is conducted employing diverse versions of yolo v5, v7, v8. For each iteration, weights are acquired, output is obtained, and performance is meticulously evaluated. Following this, transfer learning is applied and performance evaluation is reiterated. Ultimately real-time object detection is executed, wherein the identification of garbage triggers the creation of a bounding box, accom-panied by the assignment of a confidence score to the respective input image.

B. Phase-1: Preparing The Dataset

A collection of 5000 images in jpeg format was amassed for this study. The dataset was meticulously curated r encompass eight distinct categories of garbage. Subsequently, the dataset was partitioned into three subsets, 3000 images for training purpose, 1200 images for validation and 800 images for testing. Annotations for each image were generated and saved in json format. The labeling process involved manual annotations using the polygon method for all 5000 images. Specifically, the garbage present in each image was identified and labeled with its corresponding class names.

C. Phase-2: Training The Different Models And Applying Transfer Learning

Google Colab is employed as the taring platform for our model, and Algorithm 1 and Algorithm 2 outline the training and testing procedures. The initial step involves activating the Nvidia tesla T4 GPU and allocating high RAM resources within the colab notebook. Subsequently, we install necessary prerequisites including OpenCV, pillow, tensor board, torch vision, pandas, etc., and integrate the yolov7 source code from the yolov7.git repository. Data importation follows comprising data.yaml as well as images designated for testing, training and validation. The training process commences on the yolov5, v7, v8 datasets, utilizing a batch size of 16 and weights specified by the yolov_training.pt file, contingent on the yolo versions. The culmination of training yields the best weight, stored as best.pt in the weights directory, representing the highest achieved accuracy.
Subsequently, to initiate transfer learning, we further train the model using the best.pt file. This entails the model retraining with the optimal values derived from the initial neural network training. The application of transfer learning leads to an aug-mented model accuracy compared to conventional training methods. Utilizing the optimal weights obtained from the best.pt file a comprehensive evaluation of the models wo=within its operational framework is conducted to assess its functionality and determine the accuracy and efficiency resulting from the employed transfer learning.
To ascertain the model's capability to predict attributes based on its assigned class or classes, the subsequent step involves testing. This is executed either by uploading an image or through real-time detection.

Algorithm-1: Training of the model

Input: Custom dataset containing images of garbage
Output: Trained data
1: START
2: Enable GPU in google colab
3: Clone YOLOv7
4: Load the custom garbage dataset

5: Set the hyperparameters
6: Start training
7: Get the best.pt file
8: And again, train the model using the best.pt (transfer learning)
9: END

Algorithm-2: Testing of the model

Input: Image/Video
Output: Bounding box around the detected garbage
1: START
2: Provide test data or any real-time image
3: For every object detected in the image
4: Compare trained data with input
5: If threshold > 0.3
6: Create color bounding boxes
7: Assign confidence scores and label
8: Display image
9: else
10: No bounding box will be created
11: END

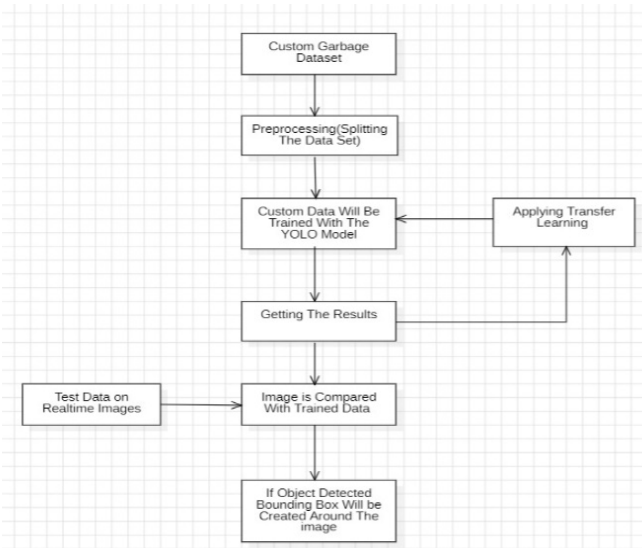

Fig.1. Workflow of the proposed model

III. RESULTS AND COMPARISON

A. Training Without Transfer Learning

TABLE I. RESULTS FOR TRAINING WITHOUT TRANSFER LEARNING

Model	Precision	Recall	mAP
YOLOv7	86.6%	71.9%	91.2%
YOLOv8	83.6%	88.3%	9.3%
YOLOv5	76.8%	64.9%	72.2%

Table I shows that mAP or accuracy of the model is greater in yolov8 compared to yolov5 and yolov7. But the precision is high in yolov7 than yolov5 and yolov8.

B. Training With Transfer Learning

TABLE II. RESULTS FOR TRAINING WITHOUT TRANSFER LEARNING

Model	Precision	Recall	mAP
YOLOv7	82.1%	86.5%	93.2%
YOLOv8	89.7%	73%	92.3%
YOLOv5	85.7%	69.6%	79%

Table II shows that yolov7 has mAP was increased compared to yolov5 and yolov7 after applying transfer learning.

C. Results Of Models Without Transfer Learning

The Fig.2 shows that the hazardous waste class resulted only 1.4% of mAP or accuracy without transfer learning, and over-all, all classes resulted in 72% for mAP@50 which is greater than the threshold and satisfactory.

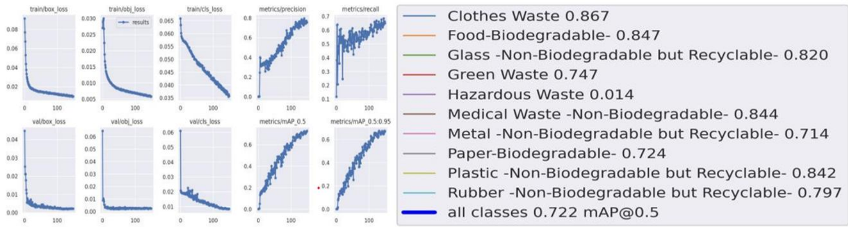

Fig.2. YOLOv5 Result without Transfer Learning

The Fig.3 shows that the hazardous waste class obtained very low accuracy of 16.6% apart from the hazardous waste class all other classes performed very well and got exceptional accuracy without transfer learning. All classes including hazardous waste got 80.9% of mAP@50 which is above threshold value and great accuracy.

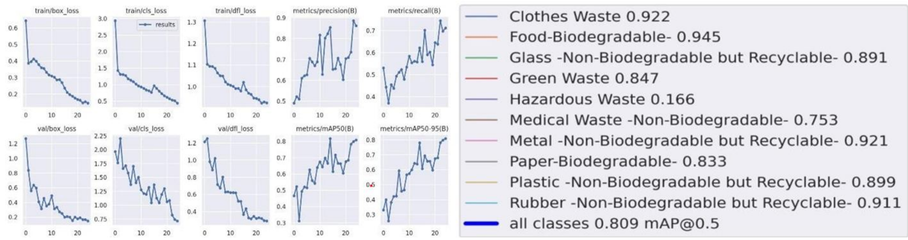

Fig.3. YOLOv8 Result without Transfer Learning

The Fig.4 shows that the hazardous waste class obtained very low accuracy of 33.2% apart from the hazardous waste class all other classes performed very well and got exceptional accuracy without transfer learning. All classes including hazardous waste got 82.3% of mAP@50 which is above threshold value and great accuracy which is above the yolv8.

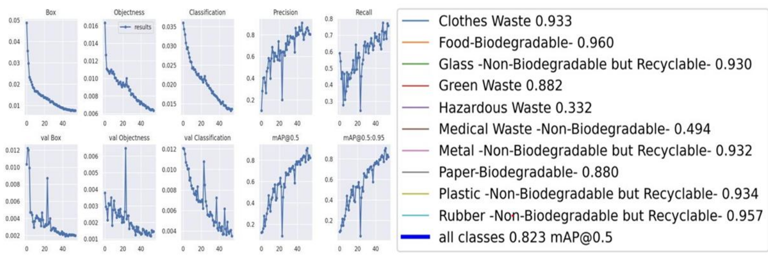

Fig.4. YOLOv7 Result without Transfer Learning

D. Results Of Models With Transfer Learning

The Fig.5 shows that good accuracy was attained after applying transfer learning in comparison to the without transfer learning. The hazardous class increased the accuracy from 1.4% to 2.9% which is not a good sign for the model to use. Although the remining classes performed well, this model was not appropriate for hazardous waste due to its extremely poor accuracy. Nevertheless, the total mAP, which includes the hazardous waste class, produced an acceptable mAP@50 result of 79%, over the threshold value.

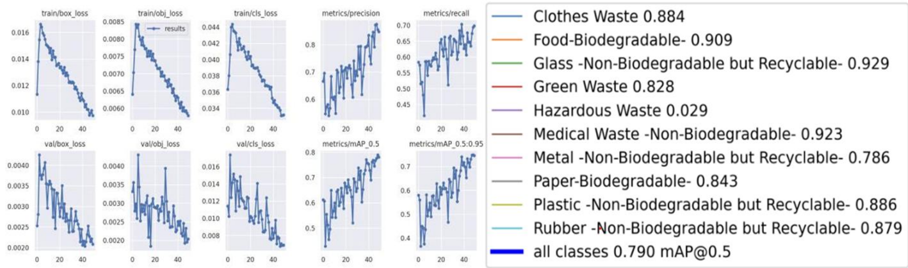

Fig.5. YOLOv5 Result with Transfer Learning

The Fig.6 shows that the accuracy increased from 80% to 89.9% for mAP@50 after transfer learning, however the green waste class only received a respectable 76%. All of the classes received extremely good values, which is outstanding [per-formance for the domain.

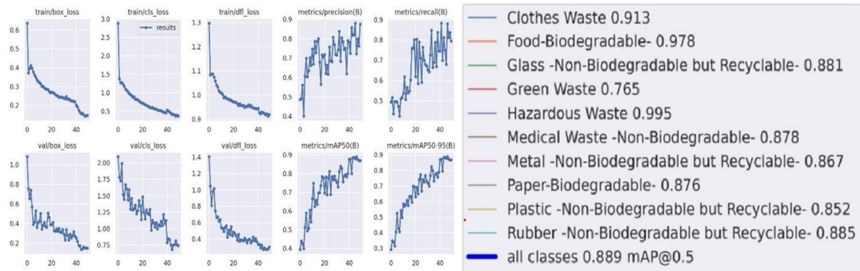

Fig.6. YOLOv8 Result with Transfer Learning

The Fig.7 shows that this is the greatest accuracy that has been obtained thus far across all architectures with remarkable values for every class in transfer learning rising from 82.3% to 93.2%. This represents a significant improvement for the model and the top performance in comparison to other models.

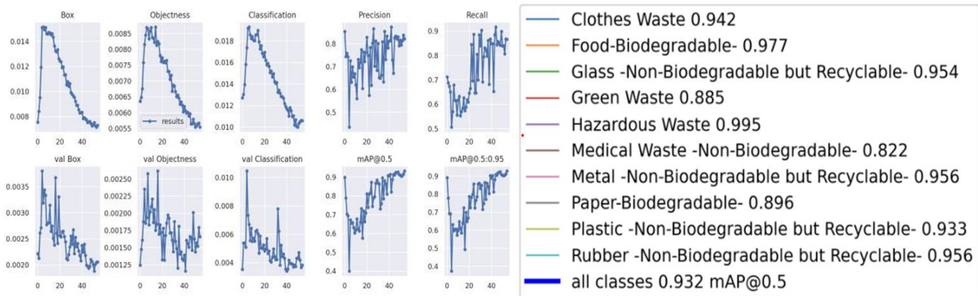

Fig.7. YOLOv7 Result with Transfer Learning

IV. CONCLUSION

This research explored the potential of yolo models (v5, v7 and v8) for automated waste classification. By leveraging trans-fer learning, we significantly enhanced their accuracy and enabled real-time object recognition. Our results demonstrate the efficacy of yolov7 in tackling critical waste management challenges. Notably, yolov7 achieved 93.2% mAP with improve-ment of 6.7% mAP in transfer learning in waste classification tasks, out performing other models tested. This paves the way for innovative and impactful solutions in the waste management industry. Specifically, our findings suggest the feasibility of developing yolov7 based systems for:

• Automated waste sorting at recycling facilities, improving efficiency and accuracy.

• Real-time waste monitoring in public spaces, promoting responsible waste disposal and enhancing environmental man-agement practices.

• Developing mobile applications for waste identification and education, empowering individuals to contribute to sustainable waste management practices.

Further research could explore the integration of yolov7 with advanced technologies like robotics and sensors for automated waste collection and sorting. Additionally, investigating the effectives of yolov7 in diverse waste streams and environmental conditions will be crucial for broader real-world implementation. By advancing the field of automated waste conditions, yolov7 holds significant promise for revolutionizing waste management and promoting a more sustainable figure.

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