Advanced YOLO-Based Trash Classification and Recycling Assistant for Enhanced Waste Management and Sustainability

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1 author:

Madde Kumar
Guru Nanak Institutions Technical Campus,hyderabad

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Advanced YOLO-Based Trash Classification and Recycling Assistant for Enhanced Waste Management and Sustainability

[1]Dr. M.Guru Vimal Kumar, Associate Professor, Department of Computer Science and Engineering, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Chennai. Email: guruvimal09@gmail.com

[2]Madde Kumar, Assistant Professor, Department of Computer Science and Engineering (IoT), Guru Nanak Institutions Technical Campus, Hyderabad, India. Email: maddekumar@gmail.com

[3]Dr. K Narayana Rao, Associate Professor, Department of Computer Science and Engineering, RISE Krishna Sai Prakasam Group of Institutions, Ongole. AP, India. Email: narayanarao2@gmail.com

[4]Dr. P Syamala Rao, Assistant Professor, Department of IT, SRKR Engineering College, Bhimavaram. AP, India. Email: peketi.shyam@gmail.com

[5]Arepalli Tirumala, Department of Electronics and communication engineering, SRM University AP, Mangalagiri, Andhra Pradesh India, Email: tirumalaarepalli@gmail.com

[6]Eswar Patnala, Assistant Professor, Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, AP, India, Email: eswar.patnala@gmail.com

Abstract: The ever-growing global population has heightened resource consumption and waste generation, emphasizing the quick need for effective waste management to safeguard the environment. Unfortunately, the recycling industry grapples with persistent challenges, primarily in the realm of accurate trash classification, a critical factor for successful recycling. Manual sorting, often prone to errors due to subjective human judgment, hampers the recycling process, contributing to inefficiencies. Furthermore, the inherent risks associated with direct contact during the sorting of hazardous materials pose serious health concerns for the workers involved. In response to these challenges, we propose a revolutionary solution: the Trash Classification and Recycling Assistant utilizing YOLO variants V5-V7. This system, rooted in image classification techniques, seeks to elevate the precision of trash sorting. Notably, YOLO variant V7 emerges as the frontrunner, showcasing remarkable accuracy improvements. By harnessing the capabilities of advanced technology, this innovative approach not only streamlines waste sorting processes but also mitigates health risks linked to manual handling of toxic materials. The integration of YOLO variants V5-V7 represents a pivotal step towards ushering in a new era of efficiency and accuracy in recycling practices, thus significantly contributing to the overarching goal of environmental sustainability.

Keywords: *Trash Classification and Recycling, YOLO variants, trash sorting, waste sorting processes, toxic materials*

1. Introduction

Waste management is a critical component of transition of every country to a sustainable economy. A lot of waste is being generated in today's world of unmindful urbanization, and hence an efficient Solid Waste Management (SWM) mechanism is becoming increasingly important. Particularly, a fast- developing country like India, due to rapid industrialization and urbanization, huge amount of solid waste gets generated and warrants better management techniques. Waste is any substance that is discarded, quite often after its principal use or otherwise if any substance or object is not worthwhile, defective and is of little use. Usually, four types of wastes are encountered by the people who deal with waste [1]. They are trash, garbage, refuse, and rubbish. Trash is any waste substance that is dry, garbage is any waste substance that is wet, whereas refuse can be in both dry as well as wet forms, and rubbish is refuse plus construction and waste debris obtained from destruction of buildings, roads, bridges, or other man-made structures. Trash includes solid wastes such as papers, card boards, and others. Waste recycling is one of the key aspects of a proper waste management system [2-3]. The overall waste management techniques that are being currently adopted in India are inadequate. In a country like India – where more than seventy per cent of the citizens are residing in small towns and villages - efficient waste management has to be performed by automating the classification of wastes generated. Automation is essential since it not only improves public health but also reduces the cost of collecting and separating the trash [4-5].

Segregating the wet wastes is done first and then metal and iron particles are separated with the use of magnets. There are also methods that utilize water jets for classifications. But some wastes are still segregated by workers manually. Even though there are safety precautions adopted, it is still highly risky and dangerous for the manual labour. If this process is completely automated, then the segregation process can continue without human intervention. There are some robotic processes for this purpose, but installing them is tedious and expensive [6]. But an AI based solution can reduce the machinery cost and size and also make the segregation process easier. The goal here is to process the image and categorize it into their specific classes. Many CNN algorithms are available for the classification. Here, a deep learning approach is proposed for solid waste segregation. Wastes are generated at an uncontrollably high pace, hence automating trash segregation calls for an extremely effective categorization model. Numerous approaches using sensors and machine learning techniques are put out in the literature to deal with this problem. These are unreliable and inefficient in real-time scenarios [7-8].

Figure 1, segregating the wet wastes is done first and then metal and iron particles are separated with the use of magnets. There are also methods that utilize water jets for classifications. But some wastes are still segregated by workers manually. Even though there are safety precautions adopted, it is still highly risky and dangerous for the manual labour [9].

Figure 1: (a) Waste dumps (b) Manual segregation

Biodegradable wastes release toxic gasses, and non-degradable wastes like arsenic, batteries etc. could have adverse reactions. Some metals are even carcinogenic. Separating the municipal wastes manually would be dangerous. Nowadays, with the Internet of Things on stage, smart bins are making the segregation process easier, and Deep Learning may be adopted for this purpose [10]. Deep learning and image processing techniques are used for waste material detection and classification. The general population would not need to be concerned about dumping of their garbage in the appropriate container because the intelligent bin would be able to make that determination for them. This would also make the bins more user-friendly [11-13].

2. Literature Survey

Togacar et al. (2020), [14], have emphasised that if waste litter is not adequately addressed, with time, the ecological equilibrium could get worse. There are two types of waste that are disposed of the following: recyclables and organics. The feature sets from the two datasets were then extracted using CNN architectures and concatenated. In every experiment, SVM was utilized as classifier. The highest classification accuracy observed in the studies was 99.95 percent, indicating that the classification of waste categories was highly successful.

Bobulski et al. (2021), [15], have carried out experiments for the purpose of developing an autonomous waste management system. They improved the recycling process by applying image processing and artificial intelligence, particularly deep learning. Methods and processes for waste segregation were implemented for the most important categories of materials, including paper, plastic, and glass. This would result in the utilization of a lower number of features for the purpose of recognition. They came to the conclusion that since it was possible to employ smaller image sizes, the resulting images would have fewer distracting artefacts and more valuable details.

Saurav Kumar et al. (2020), [16], Detection and separation of trash into two distinct groups, namely biodegradable and non-biodegradable, had been proved to be effective and near real-time by the suggested study. On the basis of a comparison between YOLOv3-tiny and YOLOv3, it was determined that there was an increase in speed but a decrease in accuracy, primarily due to the Modified Model architecture of YOLOv3-tiny, resulting in a compromise between accuracy and speed.

According to Gary White et al. (2020), [17] smart bins, when combined with a compaction system that would improve the capacity of the bins, would automatically send real-time collection notifications to the appropriate parties. The scientists have presented Waste Net. They establish that an automatic trash classification system at the edge would make it possible for smart bins to make quick choices without requiring connection to the cloud. On the dataset used for testing, their model demonstrated an accuracy of prediction that was 97%. This level of categorization accuracy would reduce some of the more typical issues that arise with smart bins, such as recycling contamination.

According to Altikat et al. (2022), [18] the rate of consumption was rising all over the world as population growth was accelerating. The work of sorting wastes according to their composition should ideally require as little involvement from humans as possible. In this direction, the authors have utilized machine learning approach for garbage classification into 3 categories. They had implemented the Deep CNN algorithms with four and five layers respectively. It was found that the five-layer architecture was successful in differentiating the wastes.

Farzana Shaikh et al. (2020), [19] have presented a system that can classify waste items as dry waste or wet trash merely based on a photograph of the waste. It is a straightforward programme that requires municipal organisations to upload photographs of rubbish bins to the system in order to determine if the garbage is wet, dry, or mixed. The detection of the garbage's contents, which is the most important component, will be performed via machine learning. They feel that this concept can contribute in the near future to the analysis of people's garbage disposal patterns in different geographic areas. They have determined that this analysis can be used to raise awareness in the necessary areas and enhance trash disposal practices.

Angin et al. (2018), [20] have proposed a way for the creation of a trash-splitter using three separate sensors, including infrared, metal, and light sensors. This was done so that the trash could be divided more efficiently. The findings were more successful in demonstrating that the devices had the same accuracy in categorizing garbage as a metal (98 percent), organic waste (26.67 percent), paper (32 percent), and plastics (58 percent).

Dipesh Gyawali et al. (2020), [21] analysed the possibilities for automatic garbage sorting and collection in a way that would be beneficial to the recycling process. Image classification was performed using a CNN. The hardware designed in the shape of a garbage can was utilised to separate these wastes into distinct sections. As a result of

ResNet18 Network tuning, the best validation accuracy was determined to be 87.8 percent.

While such products were doing very well in affluent countries, the same could not be said of poor countries, as observed by Abdul Azeem Sikander & Hamza Alihave (2021), [22] The authors made it their mission to develop a CNN model capable of identifying traffic signs in Pakistan, and they addressed the problem of picture classification by employing the CNN. A data collection of German traffic signs was chosen for preliminary training, and then the model was fine-tuned using a dataset from Pakistan. More dataset was collected to increase the size of photos in every class in the data set, which resulted in the best results possible in terms of accuracy.

Jung et al. (2017), [23] have introduced ResNet-based algorithms for the categorization and localisation of vehicles by making use of recordings taken from real traffic surveillance systems. They used a method known as Joint Fine-tuning (JF) to increase the classification performance, and they proposed a dropping CNN (Drop CNN) method to generate a synergy effect with the JF. Both of these were done in order to improve performance. For the purpose of localization, they implemented the fundamental ideas behind the most cutting-edge region-based detector in combination with a backbone convolutional feature extractor by employing 50 and 101 layers of residual networks and then combining the results of both of these into a single model.

3. Proposed Model

The detection and classification of waste materials are done by deep learning and image processing techniques. The classification is performed by the YOLOR method, which includes pre-processing of the input images using image processing techniques to improve the accuracy of classification. The proposed algorithms are designed to predict the class labels in a multi object image and also to detect the waste object's location with bounding boxes. It can, thus, detect several waste materials within a single image and label them accordingly. Multiple versions of YOLO object detection algorithms are used for classification.

A. Dataset

TACO (Trash Annotations in Context) stands as an expanding and valuable image dataset specifically curated for waste detection in real-world settings. The dataset comprises images capturing litter in diverse environments such as woods, roads, and beaches, reflecting the challenges of waste detection in varied and uncontrolled scenarios.. This hierarchical approach allows for detailed categorization of waste, contributing to the dataset's richness. TACO's commitment to manual labeling ensures high-quality annotations, and with images hosted on Flickr, it provides a readily accessible resource for researchers and developers.

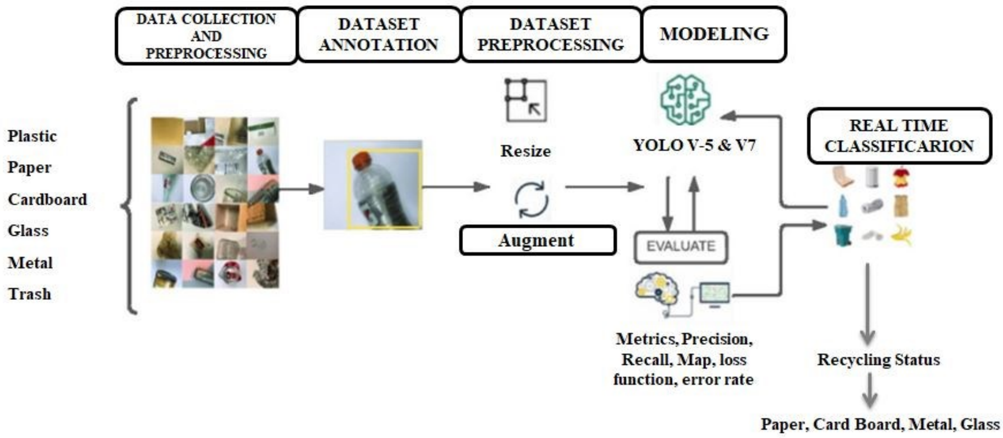

Figure 2: The architecture of the proposed system

The proposed method mainly consists of two phases namely (i) Training the YOLO-v7 model with the custom dataset and (ii) Developing the trained model into a real time classifier of waste in both images and videos. In the first phase, the new YOLO-7 object detection algorithm is trained with the custom dataset with 10 different classes. In the second phase, real time classification is performed using the trained YOLO-7 object detection algorithm in images, videos and live video via web camera. Data augmentation and other pre-processing steps are performed. The waste classification model is developed for the two YOLO versions of algorithm of YOLOV5, YOLOV7 and trained with the custom training dataset. Then, in testing phase the custom test dataset is used on the model to classify the waste objects. The models are evaluated based on the metrics such as mAP, accuracy, and loss. The best classification algorithm is identified by comparing the deep learning algorithms of the YOLO family.

B. Data Preparation:

The images in the dataset are captured using mobile phones. All images in the custom dataset are of different pixel sizes. Hence to ensure same aspect ratio and size, all the images are resized to 512 X 512 pixels. In addition, this also reduces the training time and aids in eliminating unnecessary parameters or features to be learnt. The mean values for every pixel for all the images in the training set are visualized. To ensure uniform data distribution of each input parameter, data normalization is used. This aids faster convergence while training the network. To normalize the data, the mean value is subtracted from each pixel and the resultant is divided by the standard deviation. This data distribution resembles a zero-cantered

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Gaussian curve. To increase the number of images to train the neural network, various image augmentation techniques are performed. Horizontal flip, random crop, and zoom are performed to produce variants of the images, so that the system classifies the unseen data precisely.

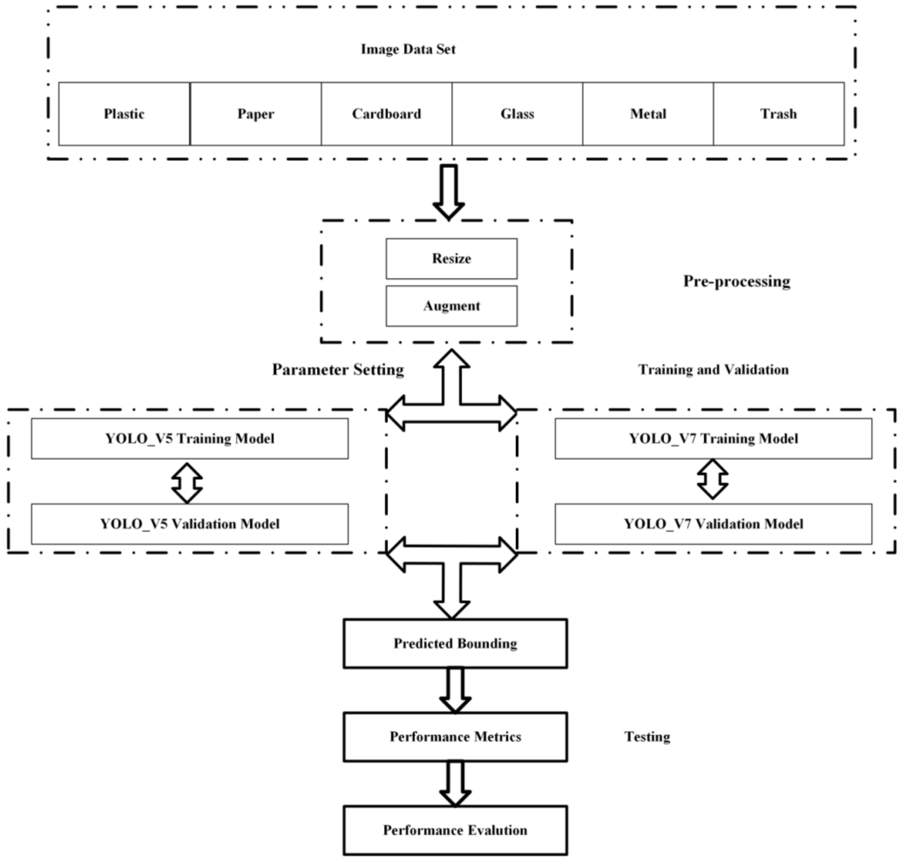

Figure 3: Flow diagram for Trash Clasification

C. Experimental Setup

For the purpose of waste classification, to detect the location of an object detection algorithm is to be used. The YOLO family represents some of the most effective object detection models. Deep learning generally necessitates a large and varied training dataset to enhance the network's ability to understand image features. To tackle the issue of limited training data, transfer learning has been utilized. This approach involves transferring model parameters from a similar pre-trained network, which was trained on a large dataset, rather than training the model from scratch. In the proposed system, YOLOv7 is employed, and its parameters are fine-tuned using a custom-prepared dataset. Transfer learning not only reduces the training time and the volume of data required but also enhances the model's accuracy. This proposed system is implemented in Tensor Flow using a GPU. The NumPy library is used for the numerical computations carried out. Python pillow is built upon the PIL (Python Image Library). This library has functions to open, display, resize, flip, rotate, get information and size, enhance the image, adjust the brightness and sharpness, save, blur, merge, and other functions on the images.

4. Results and Discussion

The input images to the model (both training and testing) are annotated with their respective classes using the Robo flow tool individually. The dataset is loaded and all the classes present in the dataset are listed. It may be noted that proposed model produces a very good Precision, Recall and mean Average Precision in successive epochs. Here the testing is done by providing the images that are unseen by the model during training. Any algorithm must be evaluated based on some metrics like time complexity and space complexity. But a machine learning algorithm or a deep learning algorithm should be evaluated on various other parameters as well. For the verification of performance improvement of the proposed system, evaluation metrics used are Precision, Recall, f1 score.

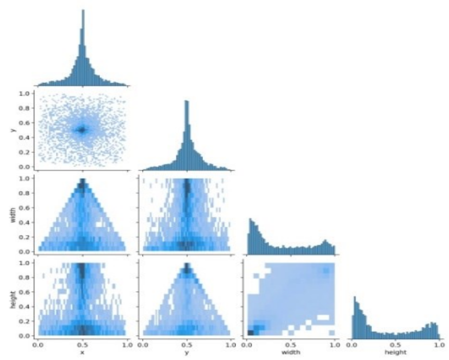

Figure 4: Histogram representation of YOLO based trash classification

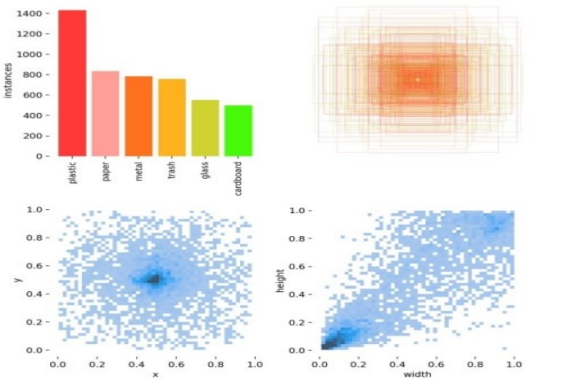

Figure 5: Visual Analysis of Recycling Categories and Spatial Relationships

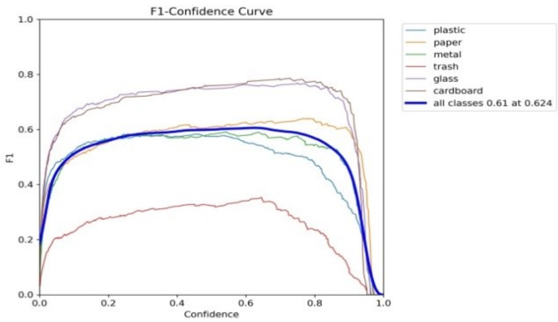

Figure 6: F1 vs, Confident Curve

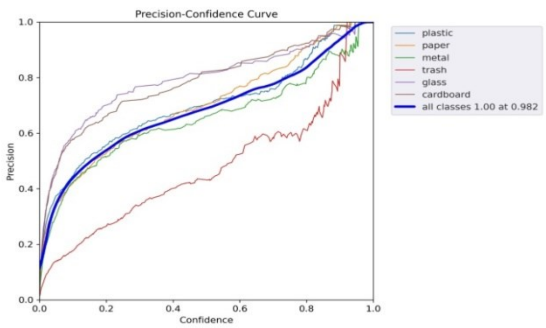

Figure 7: Precision vs. Confident Curve

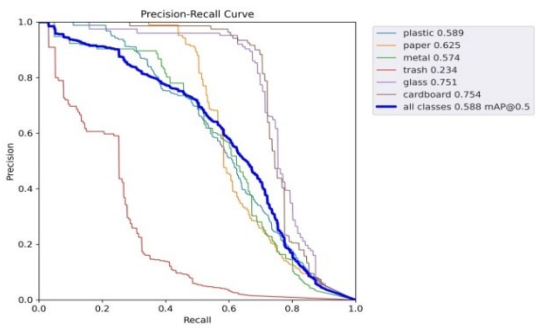

Figure 8: Precision vs. Recall Curve

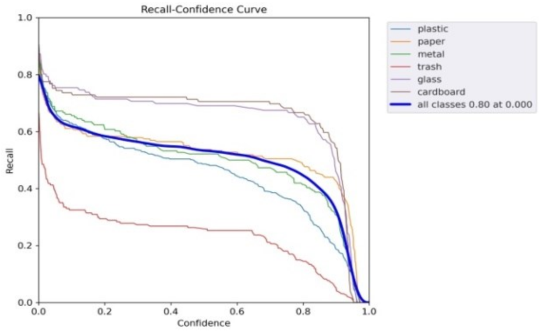

Figure 9: Recall vs. Confident Curve

The graphs illustrating the F1 vs. Confidence Curve, Precision vs. Confidence Curve, Precision vs. Recall Curve, and Recall vs. Confidence Curve offer a thorough visual evaluation of the YOLO_V5 model's performance. The F1 vs. Confidence Curve demonstrates the harmonic mean of precision and recall at various confidence thresholds, providing insights into the model's precision-recall balance. The Precision vs. Confidence Curve shows how the model's precision varies with the confidence scores assigned to predictions, helping to understand the trade-off between accuracy and confidence. Additionally, the Precision vs. Recall Curve gives a comprehensive view of how the model balances precision and recall, potentially revealing optimal operating points. The Recall vs. Confidence Curve sheds light on the model's recall rates at different confidence levels, aiding in understanding the model's sensitivity to varying confidence thresholds. These figures collectively offer a nuanced evaluation of the YOLO_V5 model's performance, enabling a deeper understanding of its strengths and limitations across different confidence thresholds and precision-recall trade-offs.

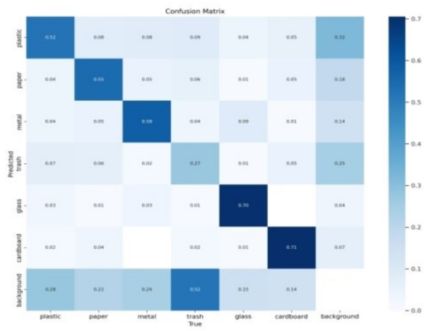

Figure 10: Confusion matrix with actual vs predicted label for YOLO V5

A confusion matrix for YOLO_V5 would typically be organized into rows and columns, representing the actual and predicted labels, respectively. The matrix would be populated with counts of instances falling into different categories. This model is primarily used for object detection rather than classification. In object detection, each object is treated as a separate entity, and the primary evaluation metrics involve precision, recall, and average precision.

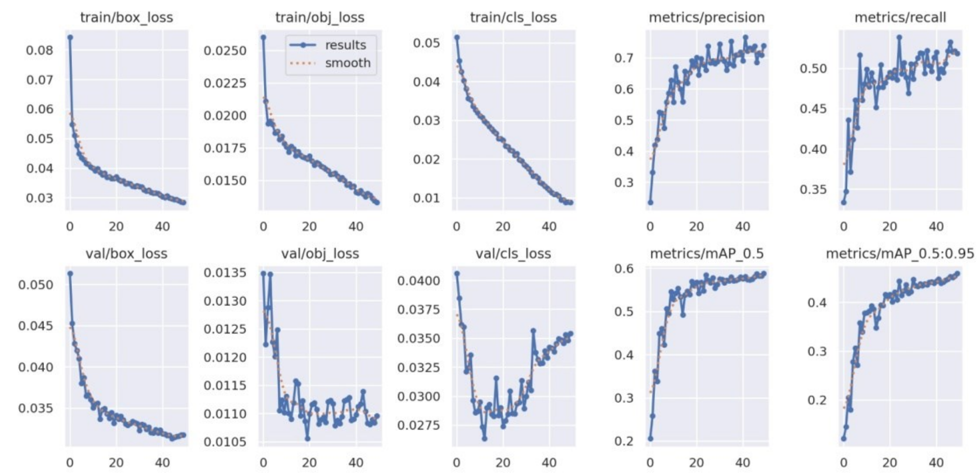

Figure 11: Scatter plots for visually exploring relationships between data sets by using YOLO_V5 Model

Based on Figure 11, it appears that datasets are being analysed and patterns are being found using the YOLO_V5 model. Scatter plots are frequently used in data visualisation and are probably created to show the correlations between several data elements visually. These scatter plots may show how well the model is doing in terms of finding and localising objects within the dataset in the context of YOLO_V5, a well-known object identification technique. Each point on the scatter plot could represent an instance of an object, with the x and y coordinates corresponding to certain characteristics or features of the detected objects. Overall, this figure serves as a visual tool for exploring the relationships and performance of the YOLO_V5 model on the given datasets.

Table 1: Object Detection Performance Evaluation for Waste Material Classes using YOLO_V5 Model

Classs	Images	Instances	P	R	mAP50	mAP50-95
All	808	1254	0.652	0.589	0.62	0.487
Plastic	808	399	0.615	0.549	0.599	0.429
Paper	808	219	0.662	0.584	0.66	0.537
Metal	808	187	0.601	0.674	0.658	0.5
Trash	808	194	0.436	0.247	0.223	0.142
Glass	808	126	0.799	0.77	0.825	0.671
Card board	808	129	0.798	0.713	0.756	0.645

The evaluation of object detection performance for various waste material classes is shown in Table 1 in terms of mean average precision at 50% intersection over union (mAP50), mean average precision from 50% to 95% intersection over union (mAP50-95), recall (R), and precision (P). The overall results indicate that the model achieved a mAP50 of 62%, with a precision of 65.2% and recall of 58.9%, across all classes. Individually, the performance varies across waste categories. The 'Glass' and 'Cardboard' classes, with mAP50 scores of 79.9% and 79.8%, respectively, show notable improvements in precision and recall. However, the 'Trash' class exhibits worse recall and precision, suggesting difficulties in correctly identifying and categorising this kind of rubbish. These metrics offer a thorough summary of how well the algorithm works to identify particular waste types, with considerations for precision, recall, and mAP at different intersection over union thresholds.

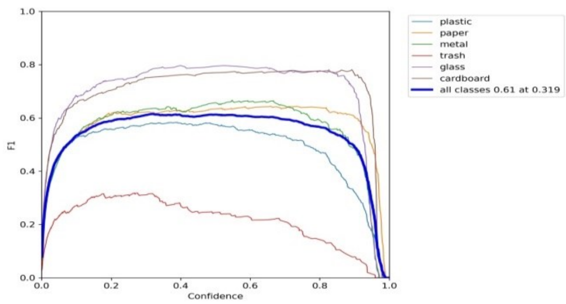

Figure 12: F1 vs, Confident Curve

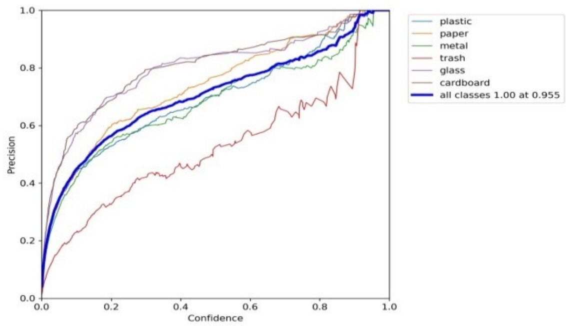

Figure 13: Precision vs. Confident Curve

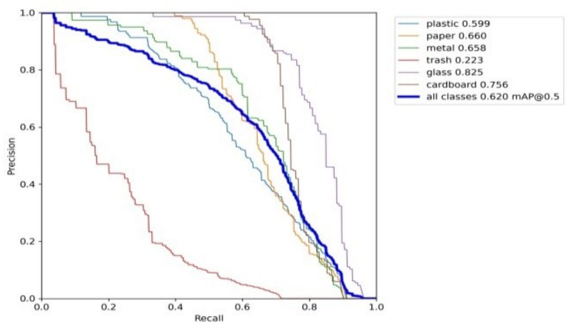

Figure 14: Precision vs. Recall Curve

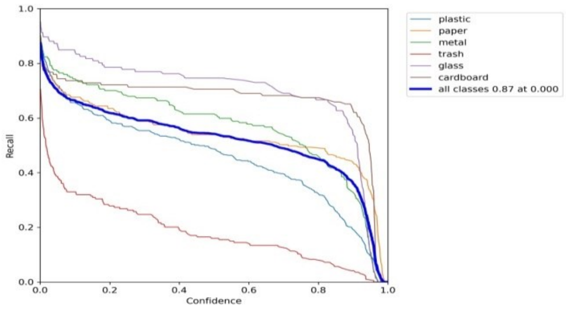

Figure 15: Recall vs. Confident Curve

The performance of the YOLO_V7 model is comprehensively visualised in the figures F1 vs. Confidence Curve, Precision vs. Confidence Curve, Precision vs. Recall Curve, and Recall vs. Confidence Curve. The F1 vs. Confidence Curve provides information about how the model balances accuracy and memory by displaying the harmonic mean of precision and recall across different confidence thresholds. Understanding the trade-off between accuracy and confidence is made easier by looking at the Precision vs. Confidence Curve, which illustrates how the model's precision varies depending on the confidence ratings given to predictions. In the meantime, the Precision vs. Recall Curve offers a comprehensive perspective on the model's capacity to strike a balance between precision and recall, along with possible clues regarding ideal operating settings. The Recall vs. Confidence Curve sheds light on the model's recall rates at different confidence levels, aiding in understanding the model's sensitivity to varying confidence thresholds. These figures collectively offer a nuanced evaluation of the YOLO_V7 model's performance, enabling a deeper understanding of its strengths and limitations across different confidence thresholds and precision-recall trade-offs.

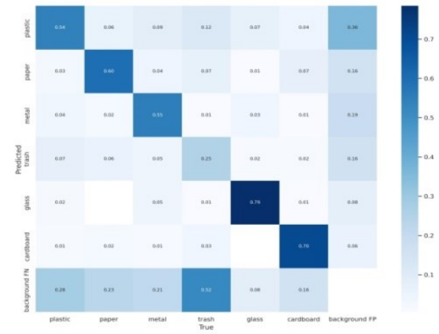

Figure 16: Confusion matrix with actual vs predicted label for YOLO V7

A confusion matrix for YOLO_V7 would typically be organized into rows and columns, representing the actual and predicted labels, respectively. The matrix would be populated with counts of instances falling into different categories. This model is primarily used for object detection rather than classification. In object detection, each object is treated as a separate entity, and the primary evaluation metrics involve precision, recall, and average precision.

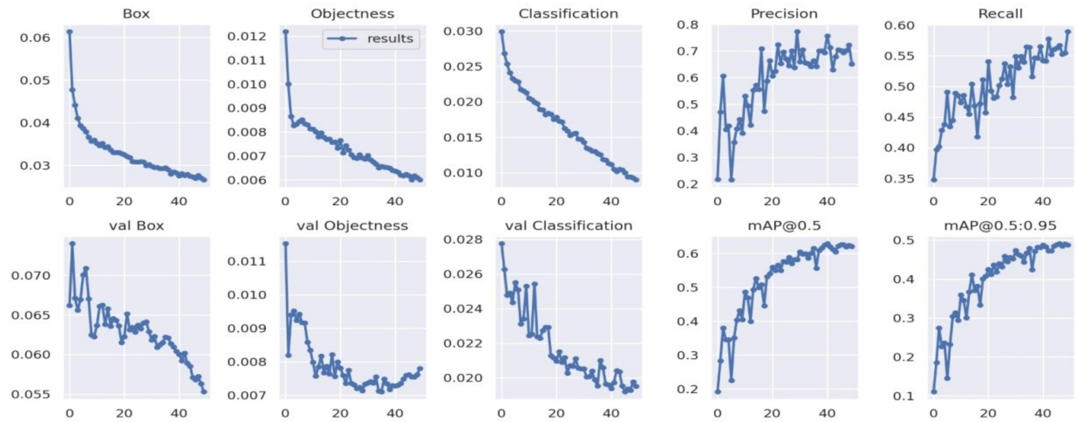

Figure 17: Scatter plots for visually exploring relationships between data sets by using YOLO_V7 Model

Figure 17, suggests the presentation of scatter plots generated with the YOLO_V7 (You Only Look Once version 7) model for the purpose of visually examining relationships between different data sets. Scatter plots are graphical representations that use points to display values from two different variables, with one variable on the x-axis and another on the y-axis. In this context, the YOLO_V7 model, which is a popular object detection algorithm, is likely employed to generate predictions or detections within the data sets.

Table 2: Object Detection Performance Evaluation for Waste Material Classes using YOLO_V7 Model

Classs	Images	Instances	P	R	mAP50	mAP50-95
All	808	1248	0.735	0.52	0.588	0.459
Plastic	808	397	0.733	0.443	0.589	0.41
Paper	808	216	0.77	0.528	0.625	0.506
Metal	808	186	0.688	0.5	0.574	0.436
Trash	808	194	0.525	0.253	0.234	0.148
Glass	808	126	0.853	0.689	0.751	0.619
Card board	808	129	0.842	0.705	0.754	0.637

The table represents a comprehensive evaluation of an object detection model's performance across different waste material classes, including Plastic, Paper, Metal, Trash, Glass, and Cardboard. The evaluation metrics include precision (P), recall (R), mean average precision at 50% intersection over union (mAP50), and mean average precision from 50% to 95% intersection over union (mAP50-95). Overall, the model achieved a mAP50 of 58.8%, with a precision of 73.5% and recall of 52.0% across all classes. Notably, the 'Glass' and 'Cardboard' classes exhibit high precision (85.3% and 84.2%, respectively) and relatively good recall, showcasing the model's effectiveness in accurately identifying and localizing instances of these materials. On the other hand, the 'Trash' class presents challenges with lower precision and recall, indicating potential difficulties in the model's ability to accurately detect and classify this waste type.

5. Conclusion

In conclusion, the Trash Classification and Recycling Assistant, employing YOLO variants V5-V7, has proven to be a ground breaking solution in addressing the persistent challenges within the recycling industry. The ever-expanding global population had necessitated urgent action in waste management to protect the environment, and our proposed system played a pivotal role in enhancing the accuracy of trash classification. YOLO variant V7, in particular, emerged as a frontrunner, showcasing substantial accuracy improvements and setting a new standard for precision in waste sorting. The utilization of advanced image classification techniques not only streamlined the recycling process but also significantly reduced health risks associated with manual handling of hazardous materials. The successful integration of YOLO variants V5-V7 represents a historical milestone, marking a transformative shift towards efficiency and accuracy in recycling practices. Furthermore, this article envisions the incorporation of robotics and automation to minimize the direct contact of workers with hazardous materials, significantly mitigating health risks. The integration of sensor technologies and data analytics will provide real-time insights into waste composition, aiding in better decision-making for recycling processes.

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