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YOU ONLY LIVE ONCE V7 SALVAGING AND GARBAGE CATALOGUING CENTERED ASSISTANT

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ABSTRACT

The ever-growing global population has heightened resource consumption and waste generation, emphasizing the urgent 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. Since wastes are generated at an unmanageable rate, automation of the waste segregation requires a highly efficient classification model. Many methodologies are proposed in various literature involving ML techniques and sensors to address this issue. These are unreliable and inefficient in real-time scenarios [7-8].

Figure 1: (A) Waste Dumps (B) Manual Segregation

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]. 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. But an AI based solution can reduce the machinery cost and size and also make the segregation process easier. 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].

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. A real-time classifier which performs detection and classification in an image, video and a live stream video via web camera is implemented. In this method, reducing the issues of overfitting and increasing the classification speed. 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. 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, the ecological balance may deteriorate over time. The wastes that are discarded can be separated into two categories: organic and recyclable. In

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their investigation, the authors recreated the dataset for trash classification using the Auto Encoder network. CNN architectures were then used to extract the feature sets from two datasets, which were then concatenated. The Ridge Regression (RR) technique, when applied to the merged feature set, reduced the number of features and displayed them more effectively. 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. The fact that their model required less time for the network to learn was still another advantage. Because of its superior generalizing qualities, the 15-layer network had been found to be the superior structure. 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. Using a comparison of YOLOv3 and YOLOv3-tiny algorithm findings, they established the efficacy and effectiveness of YOLOv3 in trash segregation. 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. 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.

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). The efficiency with which the mixed garbage was sorted into metal (94.67 percent), organic waste (28 percent), paper (12 percent), and plastics (41.3 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. They evaluated popular deep learning network designs for waste classification using a pooled dataset from their own efforts and Trash Net. 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 employed a dataset called MIO vision traffic, which is divided into 11 categories and includes a wide range of cars. 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.

3.1 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. Notably, the images are meticulously annotated and segmented, employing a hierarchical taxonomy, which enhances the dataset's utility for training and evaluating object detection algorithms. This

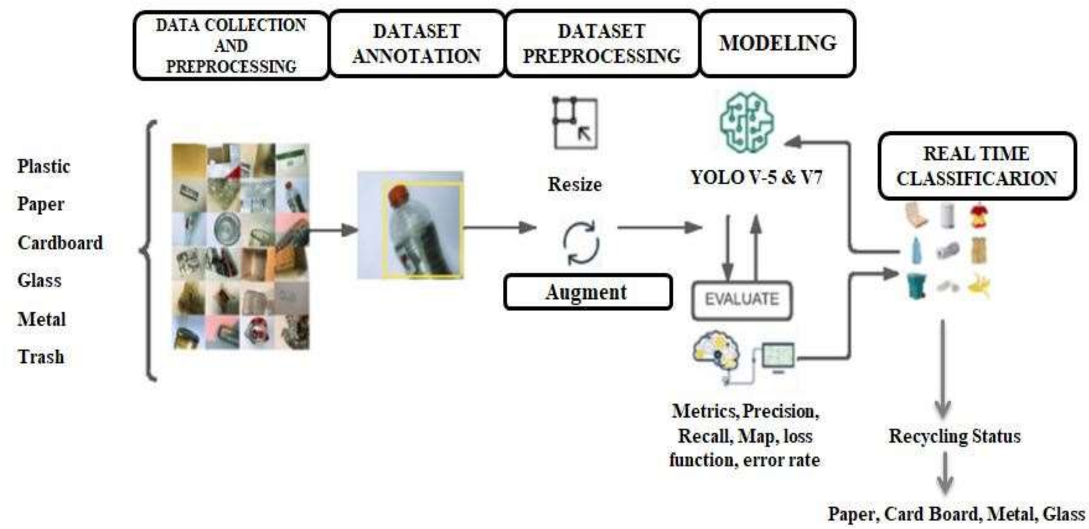

Figure 2: The Architecture Of The Proposed System

hierarchical approach allows for detailed categorization of waste, contributing to the dataset's richness. TACO's commitment to manual labelling ensures high-quality annotations, and with images hosted on Flickr, it provides a readily accessible resource for researchers and developers. The dataset's ongoing growth is facilitated by a dedicated server collecting additional images and annotations, reinforcing its relevance and applicability in advancing the capabilities of object detection algorithms for real-world waste management scenarios.
performed. The waste classification model is developed for the three YOLO versions of algorithm of YOLOV5, YOLOV7 and trained with the custom training dataset.

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 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.

3.2 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 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 5.6 illustrates the various augmentation techniques performed over a sample image. Over fitting is an issue that arises when the algorithm performs well on the training

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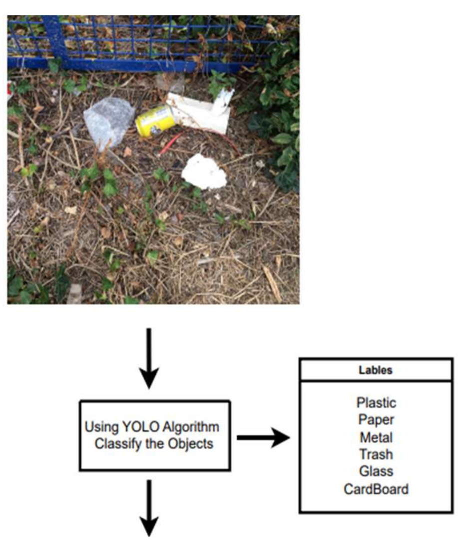
images with a good accuracy rate but fails to perform well and almost generalizes badly with less accuracy for unseen and the test images.

3.3 Experimental Setup

For the purpose of waste classification, to detect the location of an object detection algorithm is to be used. The best performing object detection models is the YOLO family. Deep Learning, in general, requires a diverse and large training dataset in order to ensure that the network understands the image features better. With the aim of addressing the problem of insufficient training data, the concept of transfer learning has been applied. In transfer learning, the model parameters are transferred from a similar network which was pre trained with another large dataset rather training the model parameters from scratch. In the proposed system, YOLOv7 is used. The proposed system with the transferred parameters is refined with the custom dataset that has been prepared. The transfer learning reduces the training time and the amount of training data required to train the model efficiently. It also helps in increasing the accuracy of the network model. The implementation of the proposed is done in Tensor-flow using GPU. The NumPy library is used for the numerical computations carried out. Python pillow is built upon the PIL (Python Image Library) and is used to add, manipulate, new formats of images in the library by creating new file decoders. 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.



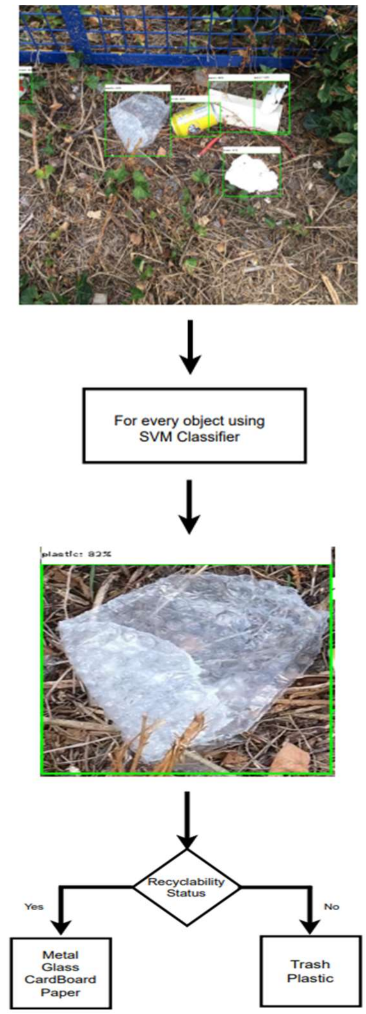


Figure 3: Flow diagram for Trash Classification

4. RESULTS AND DISCUSSIONS

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.

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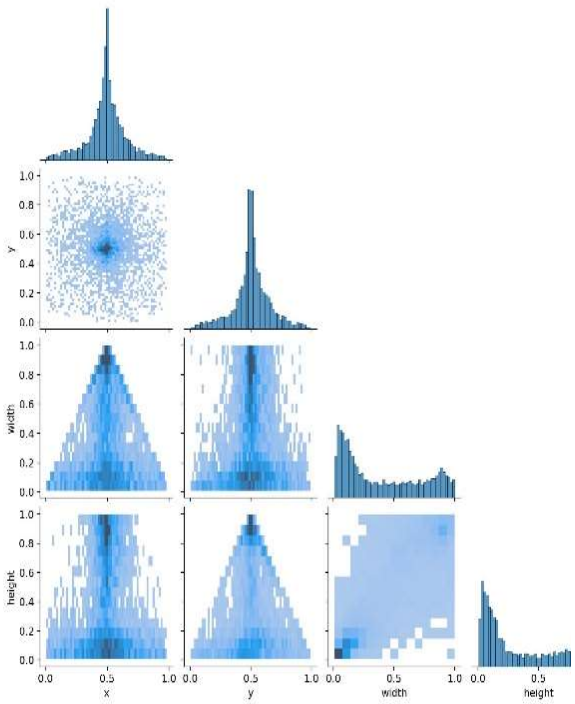

Figure 4: Labels Correlogram

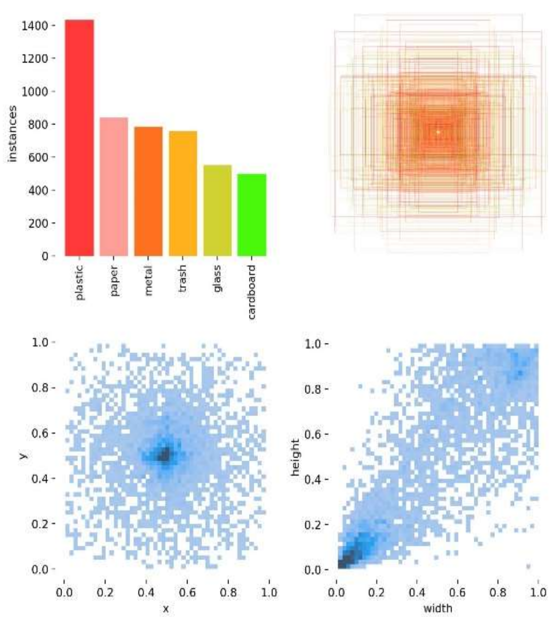

Figure 5: Labels

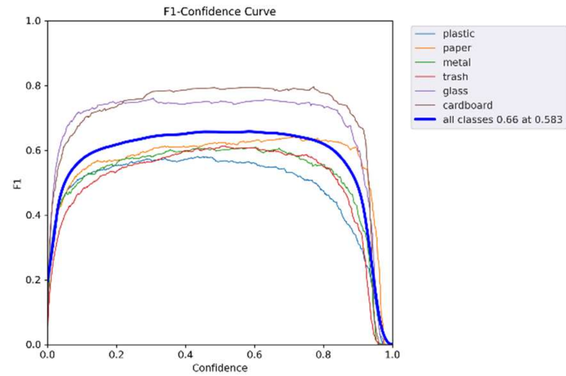

Figure 6: F1 Vs. Confident Curve

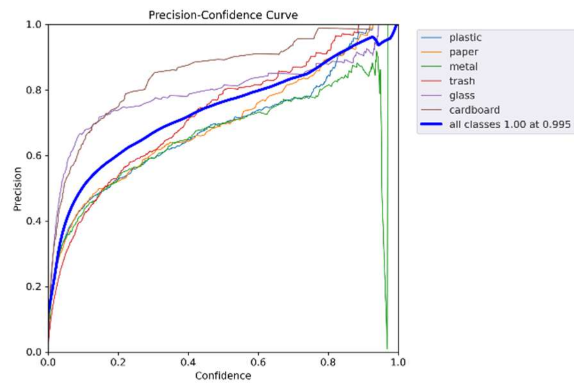

Figure 7: Precision Vs. Confident Curve

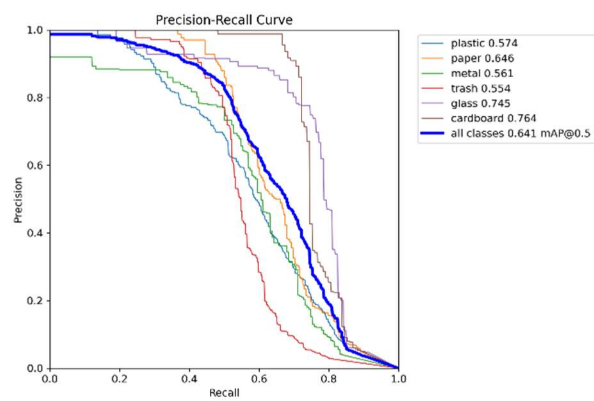

Figure 8: Precision Vs. Recall Curve

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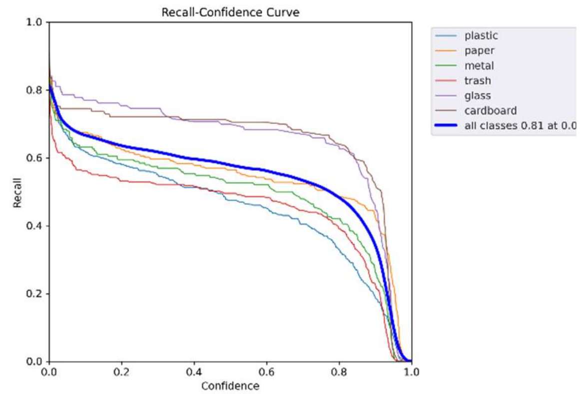

Figure 9: Recall Vs. Confident Curve

The figures depicting F1 vs. Confidence Curve, Precision vs. Confidence Curve, Precision vs. Recall Curve, and Recall vs. Confidence Curve provide a comprehensive visual analysis of the YOLO_V5 model's performance. The F1 vs. Confidence Curve illustrates the harmonic mean between precision and recall across varying confidence thresholds, offering insights into the model's balance between precision and recall. The Precision vs. Confidence Curve showcases how the precision of the model changes concerning the confidence scores assigned to predictions, aiding in understanding the trade-off between accuracy and confidence. Meanwhile, the Precision vs. Recall Curve provides a holistic view of the model's ability to balance precision and recall, with potential insights into 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.

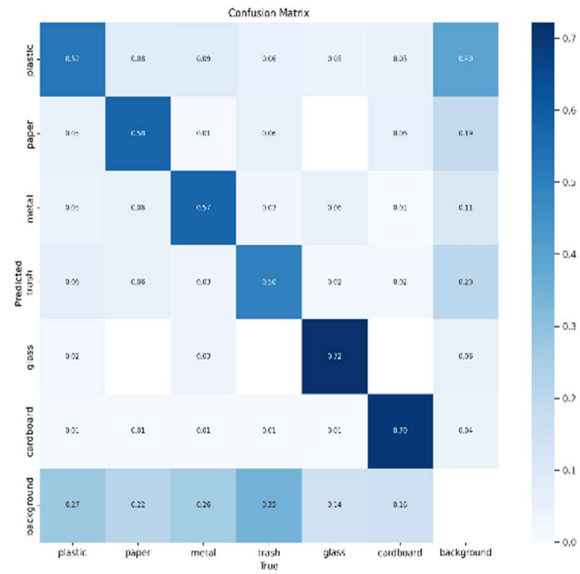

Figure 10: Confusion Matrix With Actual Vs Predicted Label For YOLO V5

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, suggests that the YOLO_V5 (You Only Look Once) model is being utilized to analyze and detect patterns within datasets. Scatter plots, commonly employed in data visualization, are likely generated to visually represent relationships between different data points. In the context of YOLO_V5, which is a popular object detection algorithm, these scatter plots may illustrate how well the model is performing in terms of detecting and localizing objects within the dataset. 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. By examining the distribution and clustering of points on the scatter plots, one can gain insights into the model's ability to recognize patterns, identify correlations, or potentially uncover areas where the model may require improvement. Overall, this figure serves as a visual tool for exploring the relationships and performance of the YOLO_V5 model on the given datasets.

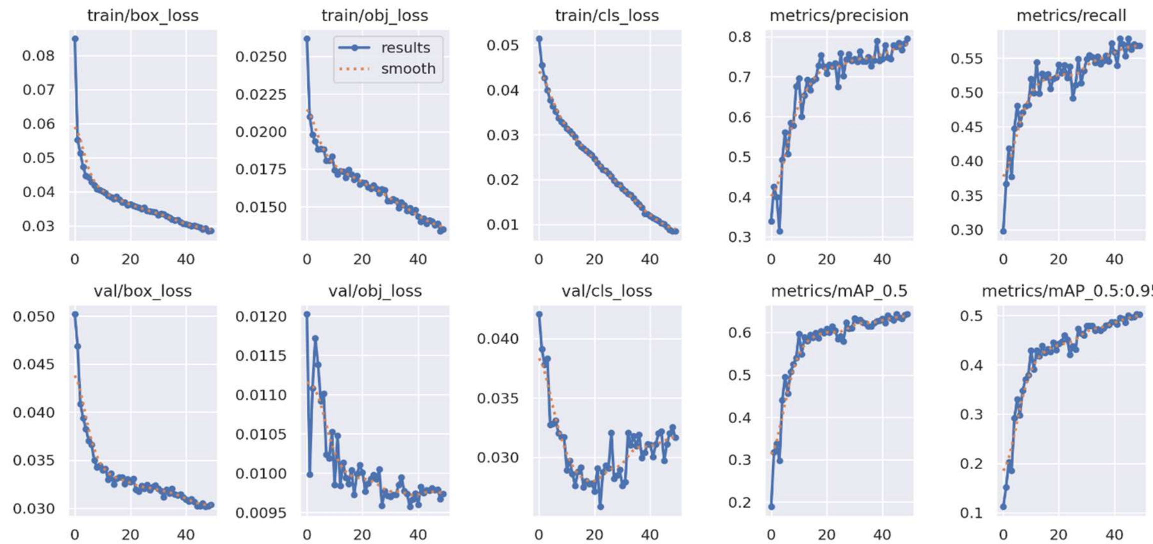

Figure 11: Scatter plots for visually exploring relationships between data sets by using YOLO_V5 Model

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

Class	Images	Instances	P	R	mAP50	mAP50-95
All	915	1364	0.783	0.568	0.641	0.503
Plastic	915	400	0.718	0.463	0.574	0.406
Paper	915	218	0.731	0.546	0.646	0.511
Metal	915	190	0.714	0.526	0.561	0.412
Trash	915	301	0.808	0.485	0.554	0.423
Glass	915	126	0.822	0.683	0.745	0.62
Cardboard	915	129	0.905	0.705	0.764	0.647

The table 1 presents an evaluation of object detection performance for different classes of waste materials in terms

of 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). The overall results indicate that the model achieved a mAP50 of 64.1%, with a precision of 78.3% and recall of 56.8%, across all classes. Individually, the performance varies across waste categories. Notably, the 'Glass' and 'Cardboard' classes exhibit higher precision and recall, with mAP50 values of 74.5% and 76.4%, respectively. On the other hand, the 'Trash' class shows lower precision and recall, indicating challenges in accurately detecting and classifying this type of waste. These metrics provide a comprehensive overview of the model's effectiveness in identifying specific waste materials, with considerations for precision, recall, and mAP at different intersection over union thresholds.

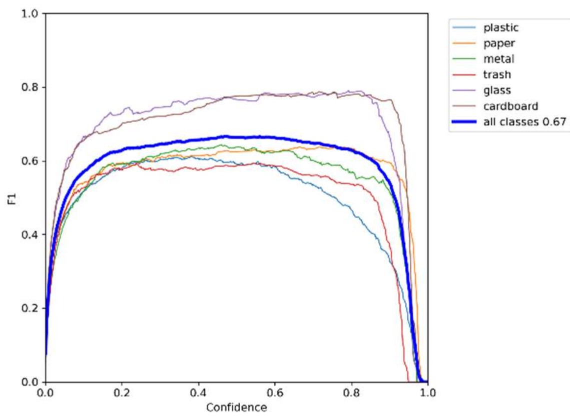

Figure 12: F1 vs. Confident Curve

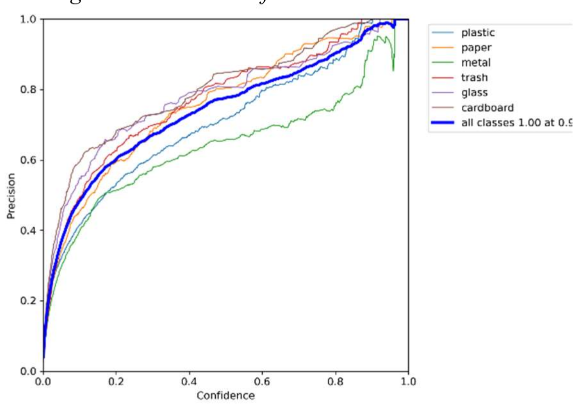

Figure 13: Precision vs. Confident Curve

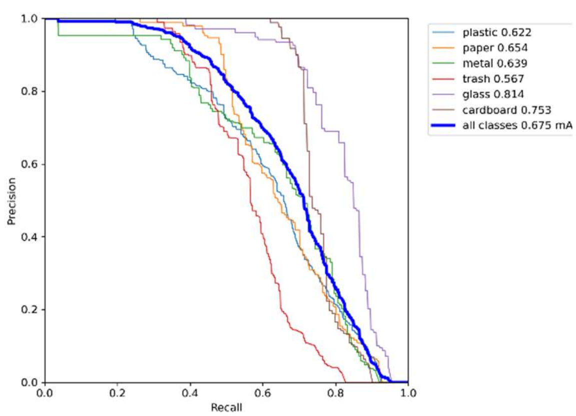

Figure 14: Precision vs. Recall Curve

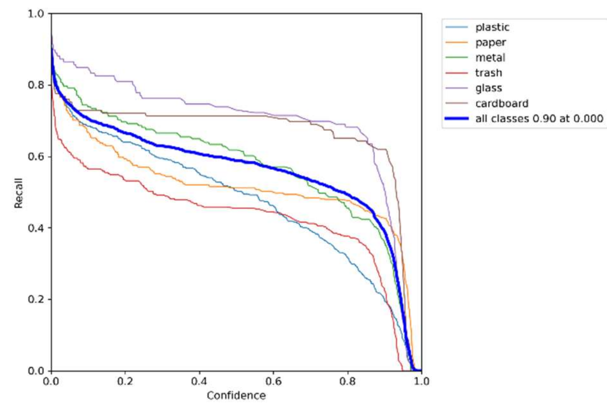

Figure 15: Recall vs. Confident Curve

The figures depicting F1 vs. Confidence Curve, Precision vs. Confidence Curve, Precision vs. Recall Curve, and Recall vs. Confidence Curve provide a comprehensive visual analysis of the YOLO_V7 model's performance. The F1 vs. Confidence Curve illustrates the harmonic mean between precision and recall across varying confidence thresholds, offering insights into the model's balance between precision and recall. The Precision vs. Confidence Curve showcases how the precision of the model changes concerning the confidence scores assigned to predictions, aiding in understanding the trade-off between accuracy and confidence. Meanwhile, the Precision vs. Recall Curve provides a holistic view of the model's ability to balance precision and recall, with potential insights into 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_V7 model's performance, enabling a deeper understanding of its strengths and limitations across different confidence thresholds and precision-recall trade-offs.

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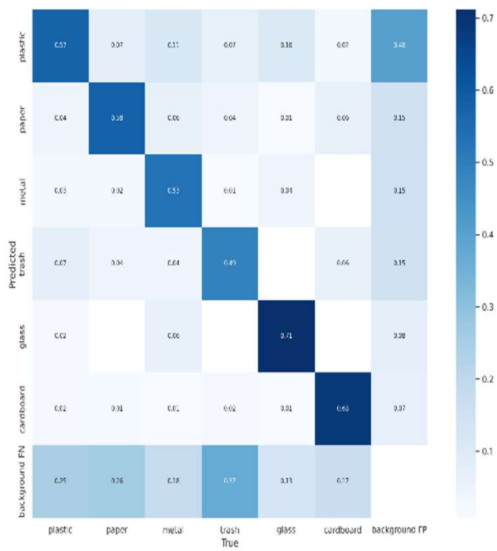

Figure 16: Confusion Matrix With Actual Vs Predicted Label For YOLO V7

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.
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.

The 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. The scatter plots could provide insights into the performance of the model, showcasing how well it localizes and identifies objects within the given data sets. Visualizing the relationships between the predicted and actual positions of objects can offer valuable information about the model's accuracy, precision, and potential areas for improvement.

Table 2: Object Detection Performance Evaluation For Waste Material Classes Using YOLO V7 Model

Class	Images	Instances	P	R	mAP50	mAP50-95
All	918	1370	0.772	0.594	0.675	0.531
Plastic	918	402	0.704	0.517	0.622	0.443
Paper	918	221	0.803	0.516	0.654	0.521
Metal	918	191	0.654	0.624	0.639	0.488
Trash	918	301	0.816	0.458	0.567	0.425
Glass	918	126	0.807	0.738	0.814	0.666
Cardboard	918	129	0.845	0.713	0.753	0.644

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 67.5%, with a precision of 77.2% and recall of 59.4% across all classes. Notably, the 'Glass' and 'Cardboard' classes exhibit high precision (80.7% and 84.5%, 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. These metrics collectively
provide insights into the model's strengths and weaknesses across various waste material classes.

Figure 17: Scatter Plots For Visually Exploring Relationships Between Data Sets By Using YOLO_V7 Model

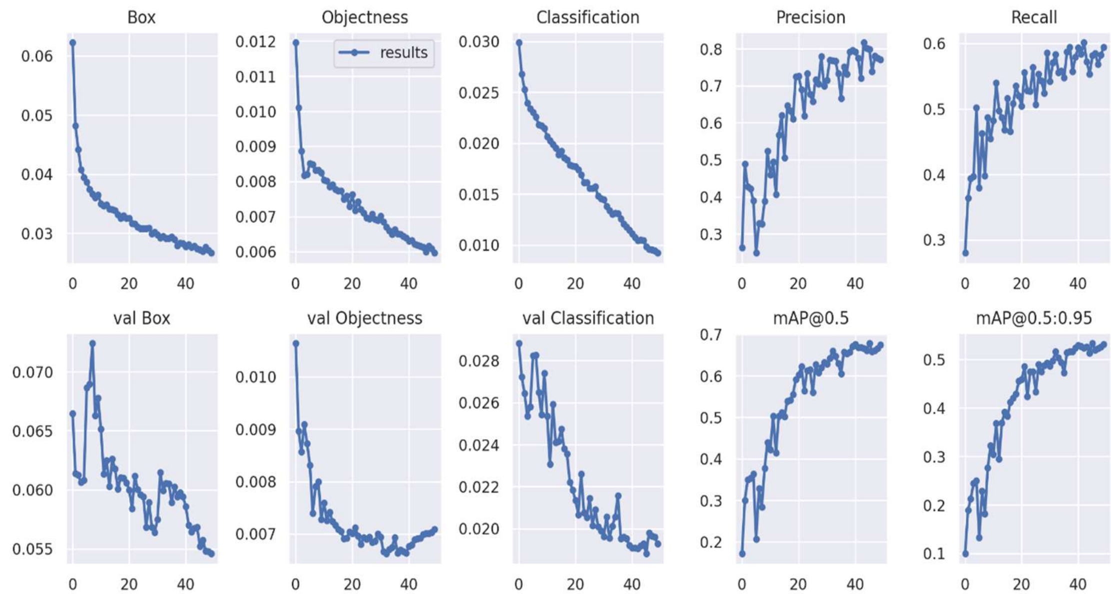

Table 3: Comparison Of Performance With Different Models Based On Trashnet Dataset.

Model	Accuracy (%)	Epochs
YOLO v5*(single class)	91.07	50
YOLO v6*(single class)	90.52	50
YOLO v7*(single class)	96.24	50
YOLO v5*(multi class)	70.82	50
YOLO v6*(multi class)	62.38	50
YOLO v7*(multi class)	75.53	50
Unoptimized DenseNet121(single class)	89.24	40
Optimized DenseNet121(single class)	94.02	40
Resnet50(single class)	95.35	40

*: Proposed models

Proposed model based on TrashNet + TACO dataset.

NOTE: By increasing Epochs size (up to 500-1000) for YOLO multi-class, Accuracy of more than 90% can be achieved.

5. CONCLUSIONS

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. This innovative approach has, indeed, contributed significantly to the overarching goal of environmental sustainability, leaving a lasting impact on the trajectory of recycling technology.

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. Collaboration with waste management facilities, municipalities, and technological innovators is vital to create a standardized system that can be seamlessly implemented across various recycling infrastructures.

REFERENCES

[1]. Abdallah, M, Talib, MA, Feroz, S, Nasir, Q, Abdalla, H & Mahfood, B 2020, 'Artificial intelligence applications in solid waste management: A systematic research review', Waste Management, vol. 109, pp. 231-246.

[2]. Ahmad, K, Khan, K & Al-Fuqaha, A 2020, 'Intelligent fusion of deep features for improved waste classification', IEEE Access, vol. 8, pp. 96495-96504.

[3]. Benbarrad, T, Eloutouate, L, Arioua, M, Elouaai, F & Laanaoui, MD 2021, 'Impact of image compression on the performance of steel surface defect classification with a CNN', Journal of Sensor and Actuator Networks, vol. 10, no. 4, P. 73.

[4]. Bernal, J, Kushibar, K, Asfaw, DS, Valverde, S, Oliver, A, Martí, R & Lladó, X 2019, 'Deep convolutional neural networks for brain image analysis on magnetic resonance imaging: A review', Artificial Intelligence in medicine, vol. 95, pp. 64-81.

[5]. Bi, H, Deng, J, Yang, T, Wang, J & Wang, L 2021, 'CNN-based target detection and classification when sparse SAR image dataset is available', IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 14, pp. 6815-6826.

[6]. Liu, Y, Ge, Z, Lv, G & Wang, S 2018, 'Research on automatic garbage detection system based on deep learning and narrowband internet of things', in Journal of Physics: Conference Series, IOP Publishing, vol. 1069, no. 1, P. 012032.

[7]. Mao, WL, Chen, WC, Wang, CT & Lin, YH 2021, 'Recycling waste classification using optimized convolutional neural network', Resources, Conservation and Recycling, vol. 164, P. 105132.

[8]. Medus, LD, Saban, M, Francés-Víllora, JV, Bataller-Mompeán, M & Rosado-Muñoz, A 2021, 'Hyperspectral image classification using CNN: Application to industrial food packaging', Food Control, vol. 125, P. 107962.

[9]. Melinte, DO, Travediu, AM & Dumitriu, DN 2020, 'Deep convolutional neural networks object detector for real-time waste identification', Applied Sciences, vol. 10, no. 20, P. 7301.

[10]. Pang, S, Du, A, Orgun, MA & Yu, Z 2019, 'A novel fused convolutional neural network for biomedical image classification', Medical & Biological Engineering & Computing, vol. 57, no. 1, pp. 107-121.

[11]. Rahman MW, Islam R, Hasan A, Bithi NI, Hasan MM & Rahman MM 2020, 'Intelligent waste management system using deep learning with IoT', Journal of King Saud University-Computer and Information Sciences.

[12]. Shabbir, A, Ali, N, Ahmed, J, Zafar, B, Rasheed, A, Sajid, M & Dar, SH 2021, 'Satellite and scene image classification based on transfer learning and fine tuning of ResNet50', Mathematical Problems in Engineering.

[13]. Srinilta, C & Kanharattanachai, S 2019, 'Municipal solid waste segregation with CNN', in 2019 5th International Conference on Engineering, Applied Sciences and Technology (ICEAST), IEEE, pp. 1-4.

[14]. Toğaçar, M, Ergen, B & Cömert, Z 2020, 'Waste classification using AutoEncoder network with integrated feature selection method in convolutional neural network models', Measurement, vol. 153, P. 107459.

[15]. Bobulski, J & Kubanek, M 2021, 'Deep learning for plastic waste classification system', Applied Computational Intelligence and Soft Computing.

[16]. Kumar, S, Yadav, D, Gupta, H, Verma, OP, Ansari, IA & Ahn, CW 2020, 'A novel yolov3 algorithm-based deep learning approach for waste segregation: Towards smart waste management', Electronics, vol. 10, no. 1, P. 14.

[17]. White, G, Cabrera, C, Palade, A, Li, F & Clarke, S 2020, WasteNet: Waste Classification at the Edge for Smart Bins, arXiv preprint arXiv:2006.05873.

[18]. Altikat, AAAGS, Gulbe, A & Altikat, S 2022, 'Intelligent solid waste classification using deep convolutional neural networks', International Journal of Environmental Science and Technology, vol. 19, no. 3, pp. 1285-1292.

[19]. Shaikh, F, Kazi, N, Khan, F & Thakur, Z 2020, 'Waste profiling and analysis using machine learning', in 2020 Second International Conference on Inventive

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Research in Computing Applications (ICIRCA), IEEE, pp. 488-492.

[20]. Angin, DP, Siagian, H, Suryanto, ED & Sashanti, R 2018, ‘Design and development of the trash spliter with three different sensors’, in Journal of Physics: Conference Series, IOP Publishing, vol. 1007, no. 1, P. 012057.

[21]. Gyawali, D, Regmi, A, Shakya, A, Gautam, A & Shrestha, S 2020, Comparative analysis of multiple deep CNN models for waste classification, arXiv preprint arXiv:2004.02168.

[22]. Sikander, AA & Ali, H 2021, Image Classification using CNN for Traffic Signs in Pakistan, arXiv preprint arXiv:2102.10130.