Waste Detection using Machine Learning

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***Abstract*— This paper introduces TACO, an open image dataset tailored for litter detection and segmentation, progressively enriched through crowd contributions. The dataset is accompanied by bespoke tools developed to bolster its utility. Furthermore, we present the outcomes of employing Mask R-CNN for instance segmentation on the latest iteration of TACO. Despite its modest scale—comprising 1500 images and 4784 annotations—our results exhibit promising efficacy in tackling this intricate problem. Nonetheless, for effective deployment in real-world scenarios, substantial augmentation of manual annotations within the TACO dataset is imperative.**

***Keywords:* TACO, litter detection, segmentation, instance segmentation, Mask R-CNN, open image dataset, crowdsourcing, real-world scenarios, manual annotations.**

I. Introduction

The pervasive accumulation of litter presents a formidable environmental challenge, with profound repercussions for biodiversity and marine ecosystems, exacerbated by the inadequacies of local governance and international oversight. Despite widespread acknowledgment of littering as unlawful, effective strategies for its mitigation remain elusive, necessitating urgent interventions both technologically and legislatively.

In response to this imperative, a plethora of initiatives have emerged to implement litter monitoring systems, ranging from advanced remote sensing technologies to on-the-ground observations. However, to enable these systems to operate autonomously, there is a growing recognition of the imperative to harness the power of deep learning techniques. This entails the availability of annotated photographs depicting litter in authentic settings, as opposed to sanitized images against a neutral background, which currently dominate the available datasets.

The detection of litter in natural environments presents a myriad of challenges far surpassing those encountered in controlled settings such as recycling facilities or conveyor belts. In addition to the complexities of deformable, transparent, aged, fragmented, occluded, and camouflaged litter, models must also grapple with the rich diversity of features inherent to the natural world.

To address these multifaceted challenges, this paper introduces TACO, an initiative aimed at curating a comprehensive dataset of photographs captured across diverse global environments, including beaches and urban areas. Within this dataset, litter objects are meticulously segmented and annotated using a hierarchical taxonomy. This introduction provides a synopsis of TACO's salient features, current statistics, and accompanying supplementary tools. Subsequently, Section III presents the outcomes of litter detection experiments conducted using this dataset, accompanied by a thorough discussion of the results obtained for two distinct tasks.

II. Literature Review

Wahid et al. [1] explore the use of a CNN with 34 layers to classify image datasets into Digestible and Indigestible Waste, achieving a high classification accuracy of 95.3125%. The advantage is the high classification accuracy using a deep learning model, demonstrating its effectiveness in waste segregation. However, the disadvantage is that the specificity of classes (Digestible vs. Indigestible) might not cover other important categories of waste that could be included in recycling processes.

Susanth et al. [2] evaluated four different models—ResNet50, DenseNet169, VGG16, and AlexNet—for classifying various types of solid and recyclable waste, with the highest accuracy achieved by DenseNet169 at 94%. The advantage is the use of multiple advanced models, providing a comprehensive assessment of the best tools for image-based waste classification. The disadvantage is the lack of discussion on the computational costs or the scalability of deploying these models in real-world scenarios.

Srinilta et al. [3] used four distinct CNN architectures to classify municipal solid waste images into categories like General, Hazardous, Recyclable, and Compostable, achieving a top accuracy of 94.86% with ResNet-50. The advantage is the application of various pre-trained models, providing a robust evaluation across different waste types. The disadvantage is the lack of addressing the potential biases or inaccuracies in the dataset, which could affect model performance.

Adedeji et al. [4] utilized a 50-layer pre-trained ResNet-50 CNN model combined with SVM to classify solid waste images into glass, metal, plastic, and paper, achieving a maximum classification frequency of 87%. The advantage is integrating CNN with SVM to leverage the strengths of both deep learning and machine learning approaches. The disadvantage is the lower classification accuracy compared to other models, suggesting possible improvements in model training or parameter optimization.

Mindy Yang and Gary Thung [5] created a dataset of hand-clicked images classified into six categories using SVM and CNN, where SVM outperformed CNN with a maximum accuracy of 63%. The advantage is the study highlighting the effectiveness of SVM over CNN for specific datasets. The disadvantage is the relatively low accuracy rates of both models, indicating room for significant improvements in the methodologies.

The literature in [6] focuses on analyzing practical e-waste management solutions and the necessity for effective reverse supply chains and increased public awareness. The advantage is the provision of valuable insights for governments to develop sustainable e-waste practices. The disadvantage is the discussion of poor infrastructure issues without addressing how to implement proposed solutions effectively.

The study in [7] describes using prediction algorithms to create unique waste profiles for home grids, optimizing resource use for maintaining hygiene standards. The advantage is the offer of a cost-effective resource allocation method, promoting a clean environment. The disadvantage is the lack of discussion on learning optimal policies without the extensive need for predictive analysis.

The research in [8] reviews the hazardous materials in e-waste, their environmental and health impacts, and current management practices in some countries. The advantage is the provision of a comprehensive overview of the dangers associated with e-waste. The disadvantage is the highlighting of infrastructure challenges without suggesting practical implementation strategies.

The application in [9] proposes an app for civic bodies to upload images of garbage cans for content analysis, aiding in waste classification. The advantage is the innovation in waste management practices, potentially improving disposal methods. The disadvantage is the lack of addressing the classification and management of e-waste, which is increasingly important.

The project in [10] uses CNNs and ResNet 50 to automate and expedite the garbage classification process. The advantage is the cost-effective solution for speeding up waste segregation. The disadvantage is the requirement for labeled data for training, which could be a significant hurdle in environments where such data is scarce.

III. METHODOLOGY USED

A. Data Collection:

The first phase involved collecting a diverse dataset of images containing various waste items. Images were sourced from multiple sources to ensure representation of different waste categories and environmental conditions.

B. Data Annotation:

Each image in the dataset was annotated with bounding boxes delineating the boundaries of waste items. Annotations were performed manually, and each bounding box was assigned a corresponding waste item category label.

C. Preparation of TensorFlow Object Detection API:

The TensorFlow Object Detection API was prepared by installing TensorFlow and configuring the necessary dependencies. The API provides a framework for implementing object detection models efficiently.

D. Model Selection:

A pre-trained SSD model suitable for waste detection was selected based on criteria such as model accuracy, speed, and compatibility with the waste dataset. The chosen model served as the foundation for subsequent development.

E. Preprocessing:

The dataset underwent preprocessing, which involved resizing images to the input dimensions expected by the selected SSD model. Additionally, pixel values were normalized to facilitate model training and inference.

F. Training:

The pre-trained SSD model underwent further training using the annotated waste dataset. Fine-tuning of model weights was performed to enhance its performance on waste detection tasks.

G. Label Mapping:

A label map was created to establish a mapping between waste item categories and integer IDs. This label map facilitated model training and inference by enabling the identification of detected objects.

H. Integration with TensorFlow Object Detection API:

The visualization script of the TensorFlow Object Detection API was customized as needed to accommodate the visualization of detected waste items. Modifications were made to enhance the interpretability of detection results.

I. Implementation:

The methodology was implemented through the execution of code snippets in a suitable development environment. Paths to the dataset, annotations, and pre-trained model were configured within the code to facilitate seamless execution.

J. Testing:

Extensive testing of the waste detection system was conducted using a separate set of test images. Detection results were evaluated to assess the system's performance, identifying areas for improvement.

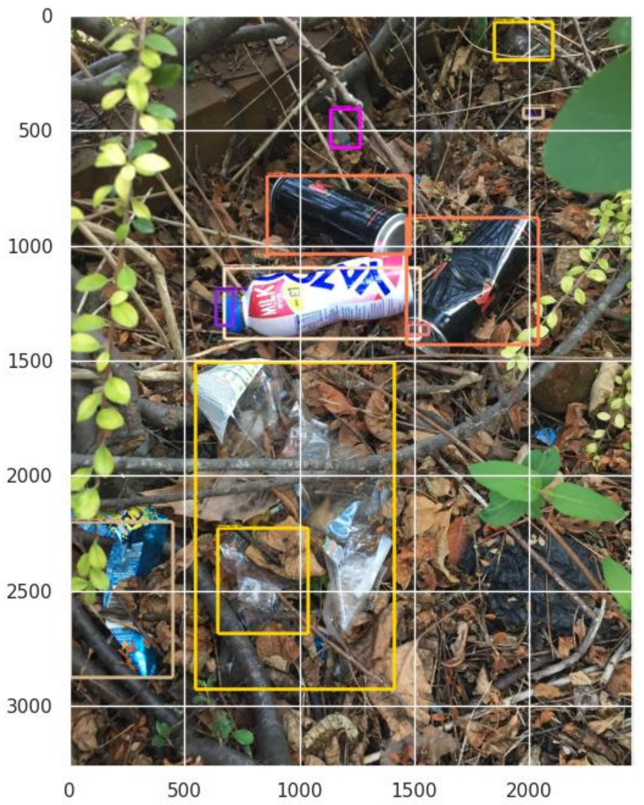

Fig. 1 Detection of waste

IV. PROPOSED WORK

Our proposed system is designed to leverage artificial intelligence (AI), machine learning, and computer vision to automate the traditionally manual process of garbage categorization. The aim is to develop a sophisticated model capable of accurately distinguishing between different types of waste, thereby addressing significant environmental challenges such as waste accumulation, global warming, and pollution.

Utilizing images from the TACO dataset, our approach involves a robust feature extraction algorithm where pythonCOCO tools and BBox have been identified as optimal for classifying the data accurately. By adjusting the parameters within these tools, we are able to detect waste materials, predict their positions, annotate, and classify them into specific categories. This method ensures that all initially unclassified data is systematically categorized, enhancing the overall efficiency of the process.

Incorporating automation into waste collection, as discussed in reference [22], residents use standardized containers for their waste, which are then handled by an automated collection system. On collection days, containers are placed at the curb, where a specially designed vehicle equipped with mechanical arms, operated by the driver from within the vehicle, picks up and empties the container. This system not only streamlines waste collection by reducing the need for manual labor but also contributes to cutting labor costs and improving worker safety and productivity.

By integrating these advanced technologies into waste management, our project aims to redefine the industry standards and provide a more sustainable, efficient solution to waste management challenges.

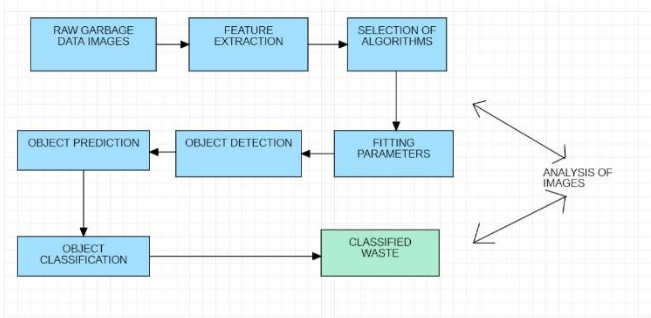

Fig. 2 Block semantic diagram for autonomous garbage sorting device in step-by-step fashion.

V. DATASET DESCRIPTION

The TACO dataset consists of high-resolution images predominantly captured using mobile phones, which are sourced and managed by Flickr. The images are stored on Flickr, while the server manages the annotations. Periodically, a crawler is deployed to gather additional potential images of litter. These images are available under free copyright licenses and are annotated and segmented using the online annotation tool at http://tacodataset.org/annotate.

Each image is described using scene tags that denote their background contexts, with tags being non-exclusive. Litter instances within the images are meticulously segmented and labelled through a hierarchical taxonomy, which includes 60 litter categories grouped into 28 super categories. This taxonomy features a specific category- “Unlabelled litter”, designated for objects that are ambiguous or do not fit neatly into other categories. This is in stark contrast to other datasets like COCO, where clear distinctions between classes are crucial. In the TACO dataset, all objects are broadly classified under the single category of litter. Due to the potential visual indistinguishability between certain classes, such as plastic and glass bottles, the categories can be restructured to better serve specific research needs.

In this research paper, the focus was placed on 9 super categories based on the number of instances, while the remaining categories were grouped under the label "Other Litter," thus forming the TACO 10 taxonomy.

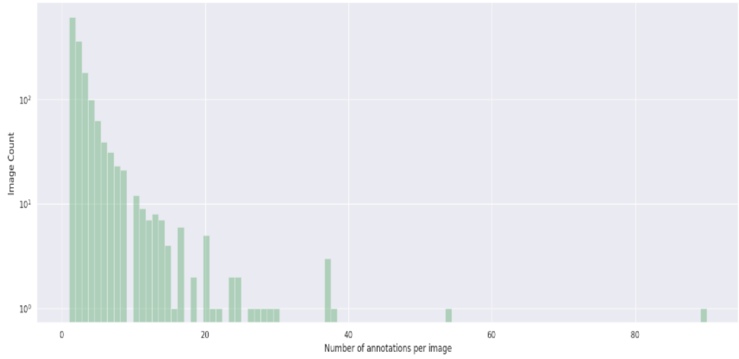

Fig. 3 Number of Annotations per image

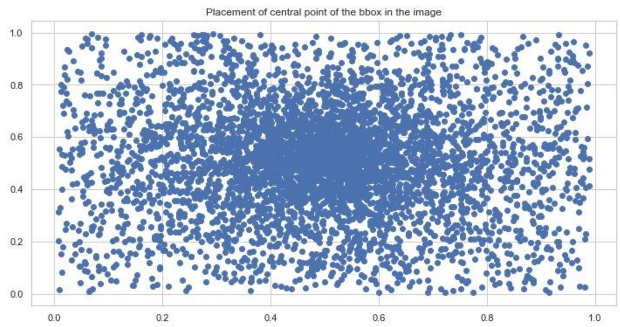

Fig. 4 Placement of central point of the bbox in the images

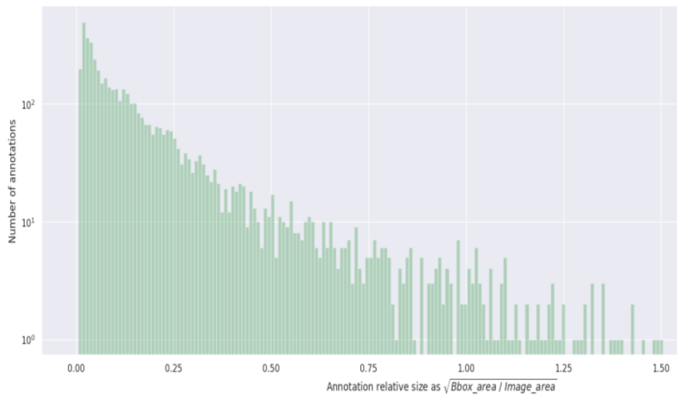

Fig. 5 Annotations relative size

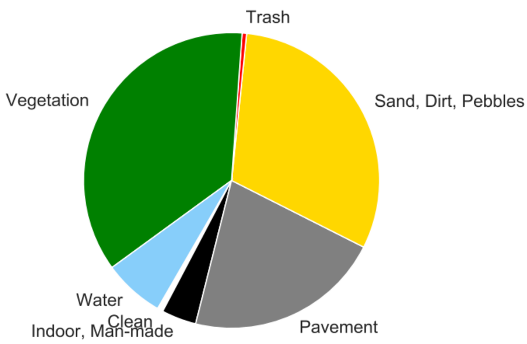

Fig. 6 Pie chart for Background_id

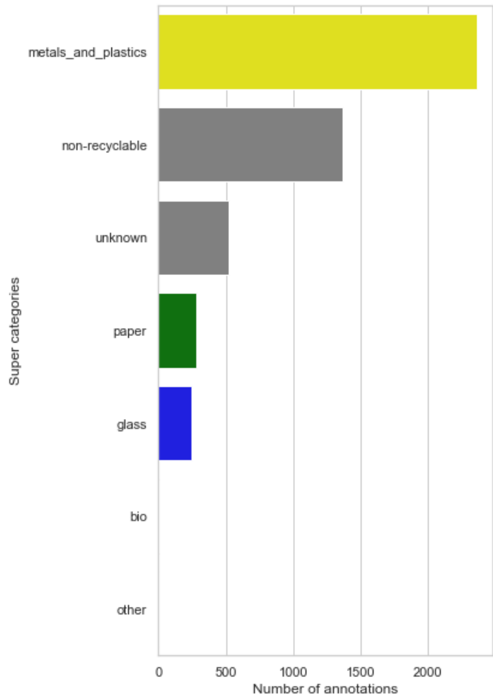

Fig. 7 Annotations per detectwaste category

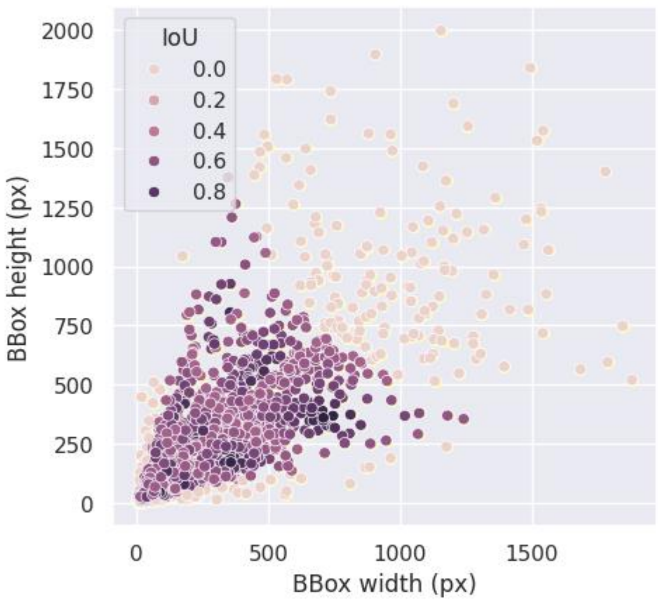

Fig. 8 BBox dimension plot

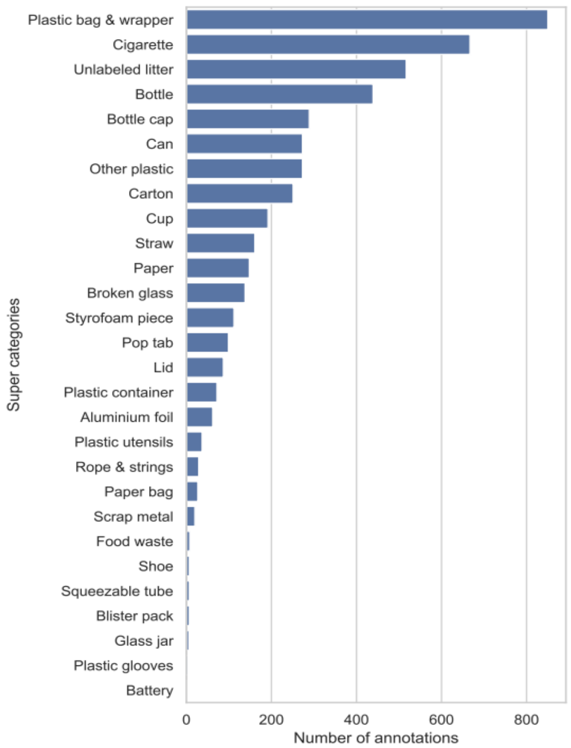

Fig. 9 Bar plot for annotations and categories

VI. Results And Discussion

Initially, the dataset was examined to gain an understanding of its composition. It consists of a considerable number of images, annotations, and categories, providing a rich source of information for waste detection and classification tasks.

Upon categorizing the annotations into super categories, it became evident that certain waste types were more prevalent than others. This categorization facilitated a clearer understanding of the waste distribution within the dataset, essential for model training and evaluation.

To align the dataset with DetectWaste categories based on recycling standards, a conversion process was undertaken. This involved mapping Taco dataset labels to corresponding waste types in DetectWaste categories. Some manual adjustments were necessary to ensure accuracy, particularly for categories not directly represented in the Taco dataset.

The presence of scene categories in the dataset further enriched the analysis. Understanding the context in which waste items appear can provide valuable contextual information for waste detection models.

An in-depth analysis of bounding box statistics shed light on the size and distribution of annotations. Insights into the mean and median dimensions of bounding boxes, as well as the number of bounding boxes per image, were crucial for understanding annotation characteristics.

Image analysis revealed the distribution of image resolutions and common image shapes present in the dataset. The visualization of bounding box placement within images provided insights into the spatial distribution of annotated objects.

Model inference using a reconstructed Tensorflow model yielded promising results. Sample detection outcomes on test images showcased the model's ability to identify waste objects accurately.

Further insights were gained through object area analysis and anchor box analysis. Understanding the relative size of annotated objects and assessing the quality of annotations through intersection over union (IoU) metrics are essential for model performance evaluation.

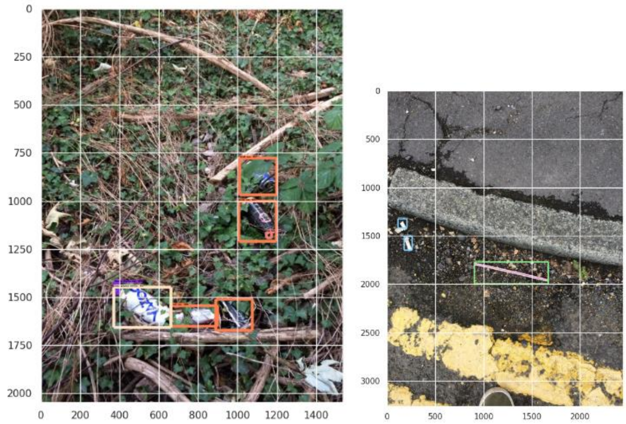

Fig. 10 Detected Waste Objects

Conclusion

The dataset characteristics reveal a diverse range of waste categories, with an uneven distribution of annotations across the different classes. This suggests the need for robust models that can handle class imbalance and ensure effective detection across the full spectrum of waste types. The wide variety of image resolutions, with a majority of the images within the 1024x1024 pixel range, highlights the importance of developing models that can accommodate varying input sizes and maintain high performance. The analysis of the bounding box properties provides valuable insights for model design and training. The mix of small, medium, and large objects, with a significant number of small items, indicates the necessity for models that can effectively detect objects at different scales. The diverse aspect ratio of the bounding boxes suggests the importance of using anchor boxes or other techniques to handle a wide range of object shapes and orientations. The intersection-over-union (IoU) analysis between the bounding boxes and the predefined anchor boxes reveals that a small number of annotations do not have a high IoU with any of the anchor boxes. This implies the need for either a larger set of anchor boxes or more adaptive anchor box generation strategies to better match the object characteristics in the dataset. The insights gained from the dataset analysis can inform the design and training of deep learning models for waste classification and management applications. Adjusting the anchor box configurations, handling varying object scales, and addressing the class imbalance in the dataset can contribute to the development of more robust and effective object detection models. The deployment of such models in real-world scenarios could lead to improved waste segregation and management, ultimately enhancing recycling rates and promoting environmental sustainability.

FUTURE WORK

Firstly, there is a need to expand the dataset by incorporating more diverse waste types, including those specific to different geographic regions and cultural contexts. This expansion would enhance the model's ability to generalize across various waste categories and improve its performance in real-world scenarios. Secondly, refining the annotation process to include more detailed labelling, such as instance segmentation, could provide richer information for model training and evaluation. Moreover, exploring advanced deep learning techniques, such as multi-scale object detection architectures or attention mechanisms, could further enhance the model's accuracy and efficiency in waste detection tasks. Additionally, conducting field trials and real-world deployment studies to evaluate the model's performance in practical settings would validate its effectiveness and identify any practical challenges or limitations. Finally, considering the environmental impact of waste detection systems and incorporating sustainability considerations into model development and deployment processes could contribute to more responsible and eco-friendly waste management solutions.

REFERENCES

[1] M. W. Rahman, R. Islam, A. Hasan, N. I. Bithi, M. M. Hasan, and M. M. Rahman, “Intelligent waste management system using deep learning with iot,” Journal of King Saud University-Computer and Information Sciences, vol. 34, pp. 2072–2087, 2020.

[2] G. S. Susanth, L. J. Livingston, and L. A. Livingston, “Garbage waste segregation using deep learning techniques,” in IOP Conference Series: Materials Science and Engineering, vol. 1012. IOP Publishing, 2021, p. 012040.

[3] C. Srinilta and S. Kanharattanachai, “Municipal solid waste segregation with cnn,” in proceedings of 5th International conference on engineering, applied sciences and technology (ICEAST). IEEE, 2019, pp. 1–4.

[4] O. Adedeji and Z. Wang, “Intelligent waste classification system using deep learning convolutional neural network,” Procedia Manufacturing, vol. 35, pp. 607–612, 2019.

[5] M. Yang and G. Thung, “Classification of trash for recyclability status,” CS229 project report, vol. 2016, no. 1, p. 3, 2016.

[6] Doan, L. T. T., Amer, Y., Lee, S. H., & Phuc, P. N. K. (2019). Strategies for E-waste management: a literature review. International Journal of Energy and Environmental Engineering, 13(3), 157-162.

[7] S. Ahmad, Imran, N. Iqbal, F. Jamil and D. Kim, "Optimal PolicyMaking for Municipal Waste Management Based on Predictive Model Optimization," in IEEE Access, vol. 8, pp. 218458-218469, 2020, doi: 10.1109/ACCESS.2020.3042598.

[8] Kiddee, P., Naidu, R., & Wong, M. H. (2013). Electronic waste management approaches: An overview. Waste management, 33(5), 1237- 1250.

[9] Shaikh, F., Kazi, N., Khan, F., & Thakur, Z. (2020, July). Waste profiling and analysis using machine learning. In 2020 Second International Conference on Inventive Research in Computing Applications (ICIRCA) (pp. 488-492). IEEE.

[10] A. Patil, A. Tatke, N. Vachhani, M. Patil and P. Gulhane, "Garbage Classifying Application Using Deep Learning Techniques," 2021 International Conference on Recent Trends on Electronics, Information, Communication & Technology (RTEICT), 2021, pp. 122-130, doi: 10.1109/RTEICT52294.2021.9573599.