AI-Powered Waste Detection and Localization Using Region Proposal Network and CNN

J.Monicaa[1], S.VenkataLakshmi[2] ,N.Nagapriya[3]

[1,3]Final Year Students, Department of Computer Science and Engineering, K.L.N. College of Engineering, Sivagangai, Tamilnadu, India.

[2]Associate Professor Department of Computer Science and Engineering, K.L.N. College of Engineering, Sivagangai, Tamilnadu, India.

---***---

Abstract - To reduce environmental pollution caused by improper waste disposal, efficient waste management solutions are essential. Traditional methods rely on manual monitoring, which is time-consuming and ineffective. Advancements in artificial intelligence and deep learning enable automated waste detection and localization, improving efficiency in waste management. Faster R-CNN, an advanced object detection model, enhances precision in recognizing and localizing waste in visual data. By utilizing deep learning techniques, waste detection achieves high accuracy, reducing dependence on manual inspections.The integration of Faster R-CNN with image processing techniques allows for real-time identification of waste objects in complex environments. Localization is achieved by drawing bounding boxes around detected waste, providing precise positional information. The Region Proposal Network (RPN) plays a key role in this process by generating candidate object regions through anchor boxes and refining them based on object scores. Tensor Flow's Object Detection API facilitates model training and optimization, ensuring accurate recognition of waste materials. High-performance convolutional neural networks enhance feature extraction, distinguishing waste from non-waste objects effectively. The use of deep learning in image-based waste detection supports scalable waste management solutions.Automated waste detection and localization contribute to sustainable urban development by enabling proactive waste management strategies. The ability to accurately identify and mark waste locations enhances the efficiency of cleaning processes and reduces environmental hazards. By analyzing waste distribution patterns, authorities can optimize resource allocation and improve waste disposal planning. The adoption of AI-driven approaches in waste detection minimizes human effort while promoting a cleaner and healthier environment.

***Key Words*:** AI-Driven waste detection, Faster R-CNN, Region Proposal Network, TensorFlow object detection API, Image processing and Localization.

1.INTRODUCTION

Waste management is a critical challenge in modern urban and industrial environments, where improper disposal and accumulation of waste contribute to environmental pollution and health hazards. Traditional methods of waste detection rely heavily on manual monitoring, which is time-consuming, inefficient, and prone to errors. The emergence of artificial intelligence (AI) has opened new possibilities for automating waste detection and localization, offering a more efficient and accurate approach to addressing this issue. By leveraging deep learning techniques such as Region Proposal Networks (RPN) and Convolutional Neural Networks (CNN), AI-powered waste detection systems can efficiently identify, classify, and locate different types of waste in real time.Region Proposal Networks play a crucial role in object detection by generating candidate regions where waste objects might be present in an image. This method enhances the accuracy of detection by reducing the number of unnecessary computations and focusing only on the most relevant areas. CNNs further refine the process by extracting high-level features from these proposed regions, classifying the waste types, and determining their exact locations. The combination of these two techniques allows for precise and scalable waste detection, even in complex environments such as streets, parks, or industrial sites, where waste materials may appear in various shapes, colors, and textures.The implementation of AI-driven waste detection systems has numerous benefits, including improved waste management efficiency, cost reduction in cleanup operations, and enhanced environmental sustainability. By integrating such technology into smart city infrastructure, authorities can proactively monitor waste accumulation, optimize collection routes, and ensure timely intervention to prevent pollution. Furthermore, AI-based waste detection can contribute to recycling efforts by automatically identifying recyclable materials, leading to more effective resource utilization. As AI continues to evolve, the adoption of intelligent waste management solutions will play a significant role in promoting cleaner and more sustainable urban environments.

2.Education technology in waste detection and localization using RCNN

RCNN is a deep learning framework designed for object detection and localization. It helps in identifying different types of waste in images and videos, making it valuable for waste management applications. This technology can be integrated into educational settings to teach students about AI-driven waste classification and its impact on environmental.

AI-Powered Learning Modules

Interactive courses provide insights into how machine learning models detect and classify waste. These courses incorporate visual demonstrations, coding exercises, and real-world examples to enhance comprehension. By engaging with AI-powered tools, learners gain practical experience in training models, refining data sets, and improving waste classification accuracy.

Real-Time Waste Identification

Mobile applications integrate RCNN models to facilitate instant waste recognition and classification. Users can capture images of waste items, and the system processes the data to determine appropriate disposal methods. This approach enhances community engagement by promoting responsible waste management while also serving as an educational tool for understanding AI-driven waste detection.

Improved Waste Management

AI-driven solutions improve waste disposal and recycling processes by enhancing detection accuracy and efficiency. Advanced machine learning models, such as RCNN, analyze waste characteristics and classify materials with high precision. Automated systems reduce contamination in recycling streams by accurately differentiating between recyclable and non-recyclable waste.

3. Existing system

Semi-supervised learning relies on both labeled and unlabeled data, which often introduces noise and inconsistencies due to incorrect feature extraction from ambiguous samples. Unlike fully supervised models guided by high-quality annotations, semi-supervised models face challenges in achieving high classification precision, particularly in dynamic environments. In waste detection, factors like varying lighting, angles, and occlusions further reduce model reliability, leading to fluctuating detection and classification results.

Object detection and localization in semi-supervised models often require separate training pipelines. Detection identifies the presence of an object, while localization determines its position within an image. Training these tasks independently increases computational complexity, requiring more labeled data, fine-tuning, and preprocessing. This limits efficiency, particularly in real-time or resource-constrained applications such as smart bins and IoT-integrated waste monitoring systems.

The heavy reliance on unlabeled or weakly labeled data reduces overall accuracy. Most semi-supervised waste classification models focus on common recyclables—plastic, paper, metal, and glass—while underrepresenting complex waste types like hazardous chemicals, electronic waste (e-waste), and biodegradable materials. This lack of diversity hinders the model's ability to detect and classify specialized waste accurately, which is critical for safe disposal and environmental compliance.

4. Proposed system

Fully supervised learning relies on high-quality annotated datasets, enabling the model to learn robust patterns for precise classification and localization. Unlike semi-supervised methods that introduce noise due to weak or unlabeled data, fully supervised models deliver consistent and accurate performance, making them ideal for real-time applications like smart waste bins, robotic sorters, and automated recycling systems.

The proposed system integrates Faster R-CNN, an end-to-end object detection framework that handles classification and localization simultaneously. This approach eliminates the need for separate training stages, reducing computational complexity and simplifying deployment. By utilizing Region Proposal Networks (RPNs), the model efficiently generates bounding boxes, improving localization accuracy and reducing false positives and negatives.

One of the key advantages of this approach is its ability to generalize across diverse environments. The use of high-quality labels ensures the model performs reliably despite variations in lighting, background clutter, or object orientation. This robustness is crucial for effective deployment in urban settings and industrial facilities.

Unlike traditional models focused mainly on common recyclables like plastic, paper, and glass, the proposed system can also detect electronic waste (e-waste), hazardous materials, and biodegradable waste. This broader detection capability enhances environmental safety by enabling proper disposal of harmful materials. Faster R-CNN's advanced feature extraction and multi-scale analysis also allow the model to handle occlusions and overlapping objects, ensuring accurate classification in cluttered scenes such as landfills and waste bins.

5. Architecture

ImageInput

The process begins with an image input, which could be captured from cameras installed in urban areas, industrial sites, or waste disposal facilities. This image contains various objects, including waste materials, which need to be identified and localized.

Convolutional Neural Network (CNN)

The input image is passed through a CNN, which extracts important features such as shapes, textures, and colors. The CNN acts as a feature extractor, converting the raw image into a set of feature maps that highlight potential waste objects in the image.

Region Proposal Network (RPN)

The RPN is responsible for identifying candidate regions in the feature maps where waste objects might be present. It generates region proposals, which are areas in the image that have a high probability of containing waste. This step helps narrow down the focus to relevant parts of the image rather than scanning the entire frame.

Classification and Regression

Classification: The proposed regions are classified to determine whether they contain waste or not. If waste is detected, the type of waste (plastic, metal, organic, etc.) can also be identified.

Regression: This step refines the bounding box coordinates around detected waste objects, ensuring precise localization.

Proposal Generation and Detection Localization

The refined proposals are used to generate final detections. The system localizes waste objects by marking their positions with bounding boxes. This enables authorities or robotic waste collection systems to take appropriate action based on the detected waste distribution.

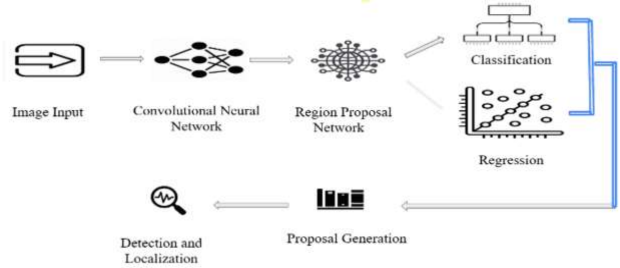


Figure 1: Architecture Diagram

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 04 | April - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

6. LIST OF MODULES

- High-Performance Feature Map Generator
- Candidate Object Locator
- Foreground-Background Classification Score
- Regression-Based Proposal Selector (RBPS)
- Object Localization & Neural Network-Based Live Detection

HIGH-PERFORMANCE FEATURE MAP GENERATOR

Waste detection and localization have become critical challenges in modern urban management. With the increasing accumulation of waste in public areas, efficient and accurate detection techniques are needed to facilitate timely clean-up and proper waste disposal. One of the key components in waste detection using artificial intelligence (AI) and deep learning is the feature map generator—a system that extracts and processes image features for accurate classification and localization.

Feature Map GeneratorA feature map generator is an essential component of convolutional neural networks (CNNs) that extracts spatial and semantic features from images. These feature maps help in detecting and classifying objects in a given frame. When applied to waste detection, a high-performance feature map generator enhances accuracy by efficiently recognizing different types of waste, such as plastic, paper, organic waste, and metals, from street images.

Core Components of a High-Performance Feature Map Generator

Convolutional Layers: Convolutional layers apply filters to an image, capturing essential features such as edges, textures, and shapes. These layers extract hierarchical feature representations that aid in detecting and classifying different types of waste.

Activation Functions: Activation functions such as ReLU (Rectified Linear Unit) ensure non-linearity in the model, allowing it to learn complex patterns from waste images.

Pooling Layers: Pooling layers, such as max pooling and average pooling, reduce the spatial dimensions of the feature maps, improving computational efficiency while preserving key information.

Normalization and Optimization Techniques: Techniques such as batch normalization and dropout prevent overfitting and enhance model stability, making the waste detection system more robust.

Application of Feature Map Generators in Waste Detection

Feature map generators play a crucial role in waste detection and localization by providing meaningful visual representations for AI-based models. The process involves the following steps:

Image Preprocessing: Collected images from urban streets undergo preprocessing, including resizing, normalization, and data augmentation to enhance the model's robustness.

Feature Extraction: Convolutional layers extract essential features from the images, transforming them into structured feature maps that represent waste objects with high precision.

Object Detection Models: Models such as Faster R-CNN, YOLO (You Only Look Once), and SSD (Single Shot MultiBox Detector) use feature maps to identify and classify waste objects.

Localization and Bounding Box Prediction: The extracted feature maps help in placing bounding boxes around detected waste items, allowing for precise localization within an image.

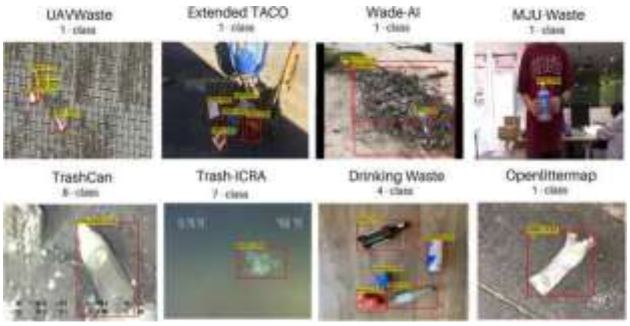


Figure 2: Feature Map Generator

CANDIDATE OBJECT LOCATOR

Waste detection and localization play a critical role in smart waste management systems, environmental monitoring, and automated cleaning processes. To achieve accurate detection, deep learning models utilize Region Proposal Networks (RPNs) to locate potential waste objects in an image. The Candidate Object Locator is responsible for identifying promising regions that might contain waste by scanning a feature map generated from a Convolutional Neural Network (CNN).

Region Proposal Network (RPN) for Waste Localization

The RPN is a key component in object detection models like Faster R-CNN. It is responsible for proposing regions in an image that are likely to contain objects, in this case, different types of waste materials.

The process involves several steps:

Sliding Window Approach: The RPN moves across the feature map using a sliding window technique. This method involves Scanning different regions of the feature map, Placing small windows over different sections of the image, Checking each section to determine if it contains potential objects and this helps in identifying areas where waste objects are likely to be present.

Anchor Boxes for Object Guessing: The RPN uses anchor boxes of various sizes and aspect ratios to make predictions about object locations.These anchor boxes act as predefined bounding boxes placed at different locations in the image.Each box guesses whether an object is present or not. Assigning Object Scores: Once anchor boxes are placed, the RPN assigns a score to each box, indicating:How likely the box contains an object, Higher scores mean greater confidence in an object's presence

Refining Object Location: If an anchor box is identified as likely containing an object, the RPN refines the position and dimensions of the bounding box by:Adjusting the coordinates to more accurately fit the object, Resizing the box if necessary, Ensuring that waste objects are precisely localized within the image.

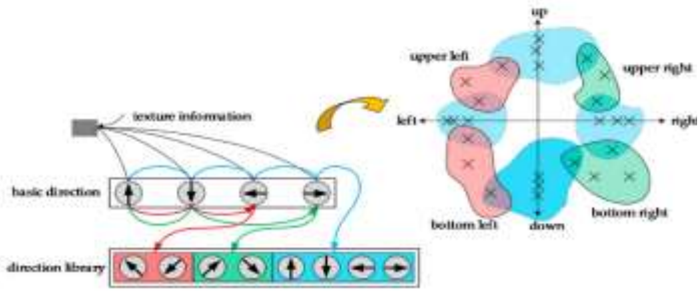


Figure 3: Candidate Object Locator

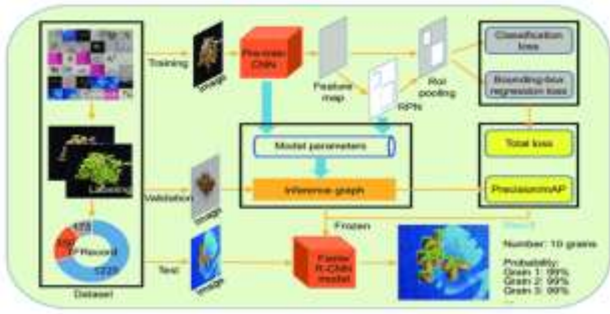


Figure 4: Foreground-Background Classification score

FOREGROUND-BACKGROUND CLASSIFICATION SCORE

Object detection and localization are essential in computer vision applications like waste detection. Deep learning models must distinguish waste items from background noise. A crucial step in this process is the Foreground-Background Classification Score, which filters out irrelevant regions, enhancing both efficiency and accuracy. The Region Proposal Network (RPN) plays a key role by assigning object scores to different image regions, determining whether they contain objects (foreground) or background. These scores guide further refinement through regression-based adjustments, improving the precise localization of waste items and ensuring that only relevant regions are processed during detection.

Role of the Foreground-Background Classification Score

The Foreground-Background Classification Score helps in distinguishing between potential objects (waste) and non-relevant areas in an image. The Region Proposal Network (RPN), which is part of many object detection frameworks such as Faster R-CNN, computes this score.

Assigning Object Scores: Each region (bounding box or anchor box) in the image is evaluated. The model assigns a score that estimates the likelihood of the region containing an object. A high score indicates a strong possibility of an object being present (foreground).A low score suggests that the region is part of the background and can be ignored.

Filtering Out Irrelevant Regions: Many bounding boxes are generated, but not all contain meaningful objects. The classification score helps filter out irrelevant regions, reducing unnecessary computations. This ensures that only the most promising candidate regions are passed for further processing.

Refining Object Localization Using Regression

Adjusting Position and Size: If an anchor box is classified as containing an object, the model adjusts its position and size using regression. The adjustments aim to align the bounding box more accurately with the actual object.

Learning Offset Values: Instead of relying on predefined anchor boxes, the model learns how to fine-tune the bounding boxes. It calculates offset values:

- Δx and Δy: Adjust the center of the bounding box.
- Δw and Δh: Adjust the width and height of the boundingbox.

REGRESSION-BASED PROPOSAL SELECTOR (RBPS)

Object detection and localization involve identifying meaningful objects in an image and accurately determining their locations. In applications such as waste detection, it is crucial to filter out irrelevant areas while ensuring precise object localization. This is where the Regression-Based Proposal Selector (RBPS) comes into play.RBPS refines and selects the most relevant candidate regions (bounding boxes) based on object scores. The adjusted bounding boxes, improved through regression, undergo a ranking and filtering process, ensuring that only the most confident and non-overlapping proposals are forwarded for further processing. This approach significantly improves localization accuracy, computational efficiency, and overall detection performance.

Understanding the Role of RBPS

RBPS is a key step in object detection pipelines like Faster R-CNN, where a Region Proposal Network (RPN) generates candidate object regions. These proposals are refined through regression and selection to ensure only the most accurate ones are used for final detection.

Bounding Box Refinement Using Regression: RPN initially generates multiple bounding boxes that may not perfectly align with objects. A regression model adjusts their positions and dimensions, learning transformations that better fit each object. The refined set of bounding boxes becomes the region proposals.

Ranking Proposals Based on Object Scores: Each refined box receives an object score, reflecting the likelihood of containing an object (e.g., waste). Higher scores indicate more reliable detections, while lower scores suggest background or false positives.

Filtering Using Non-Maximum Suppression(NMS): To handle overlapping proposals, Non-Maximum Suppression eliminates redundant or low-confidence boxes, retaining only the highest-scoring, non-overlapping proposals for final processing.

Impact of RBPS on Waste Detection

Improving Localization Accuracy: By refining bounding boxes, RBPS ensures that waste objects are detected with higher precision. Reduces cases where detected objects are partially cropped or misaligned.

Reducing False Detections: NMS eliminates redundant detections, ensuring that a single object is not detected multiple times. Low-confidence proposals are filtered, minimizing false positives.

Enhancing Computational Efficiency: By filtering out unnecessary proposals, RBPS ensures that only the most relevant bounding boxes are forwarded. Reduces the computational load in later detection stages.

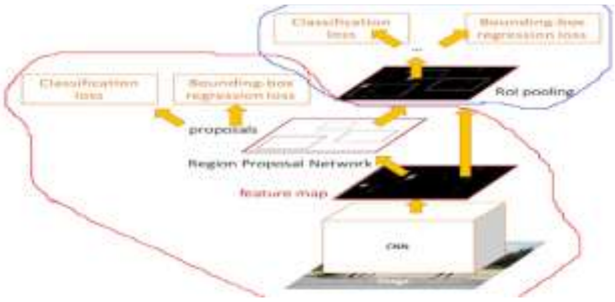


Figure 5: Regression-Based Proposal Selector (RBPS)

OBJECT LOCALIZATION & NEURAL NETWORK-BASED LIVE DETECTION

Object localization and neural network-based live detection are critical components of modern computer vision applications, enabling machines to identify, classify, and track objects in real-time. These techniques have become fundamental in various industries, such as autonomous vehicles, surveillance, medical imaging, and robotics. This elaboration will provide an in-depth explanation of object localization, the role of neural networks in live detection, and how Faster R-CNN refines the detection process for accurate results.

Understanding Object Localization

Object localization refers to the process of identifying and marking objects within an image or video. Unlike mere classification, which determines the presence of an object, localization involves detecting its exact position by drawing bounding boxes around it. This enables applications like object tracking and autonomous navigation.

The process consists of:

Feature Extraction: Convolutional Neural Networks (CNNs) extract relevant features from an image.

Region Proposal Generation: Proposals (potential object locations) are generated to pinpoint where an object might be.

Bounding Box Refinement: The model adjusts the bounding boxes to better fit the detected objects.

Classification and Final Output: The system assigns labels to objects and outputs accurate bounding boxes.

Neural Networks in Live Detection

Neural networks, particularly deep learning models like Faster R-CNN, YOLO (You Only Look Once), and SSD (Single Shot MultiBox Detector), are used for live detection. These models process incoming frames in real-time to:

Detect multiple objects simultaneously.

Identify their locations with high precision.

The Role of Faster R-CNN in Object Detection

Faster R-CNN is a widely used object detection framework that improves upon previous methods by efficiently generating high-quality region proposals. It consists of:

Region Proposal Network (RPN): Suggests potential object locations.

ROI Pooling: Converts proposals into a fixed-size feature map.

Fast R-CNN Classification: Classifies objects and refines bounding boxes. The detection process starts with RPN generating proposals, followed by ROI pooling, which standardizes these proposals. Finally, the Fast R-CNN module assigns object categories and fine-tunes the bounding boxes.

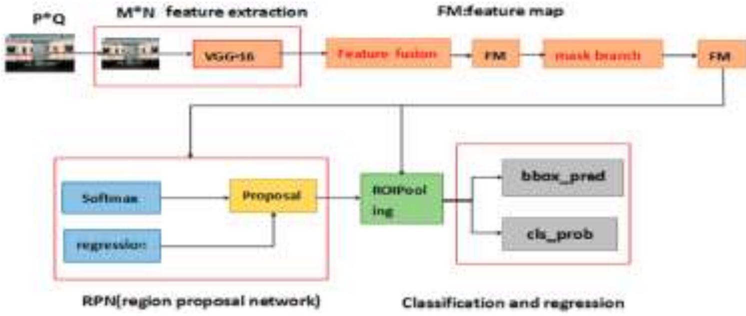


Figure 6: Object Localization & Neural Network-Based Live Detection

7. RESULT

The implementation of a Region Proposal Network (RPN) for waste detection and localization greatly improves accuracy, efficiency, and real-time performance. By leveraging deep learning, the system effectively identifies various waste types, distinguishing between recyclable and non-recyclable materials. The classification module ensures accurate categorization, enabling automated segregation and enhancing overall waste management. A major advantage of RPN is its ability to generate precise bounding boxes around detected waste. The regression module refines these boxes, improving localization and minimizing false detections. This is particularly beneficial in complex environments like streets, landfills, or industrial areas, where waste may be partially hidden or overlapping with other objects. When combined with Convolutional Neural Networks (CNNs), RPNs help separate waste from background elements, significantly reducing false positives and false negatives for higher reliability. RPN also boosts processing efficiency by focusing only on relevant image regions rather than scanning the entire frame. This reduces computational load and enables real-time waste detection across applications such as smart waste monitoring, autonomous garbage collection, and environmental surveillance. Accurate detection and localization lead to cleaner urban environments, optimized waste collection routes, and better sustainability practices—making AI-powered waste detection a valuable innovation in modern waste management.

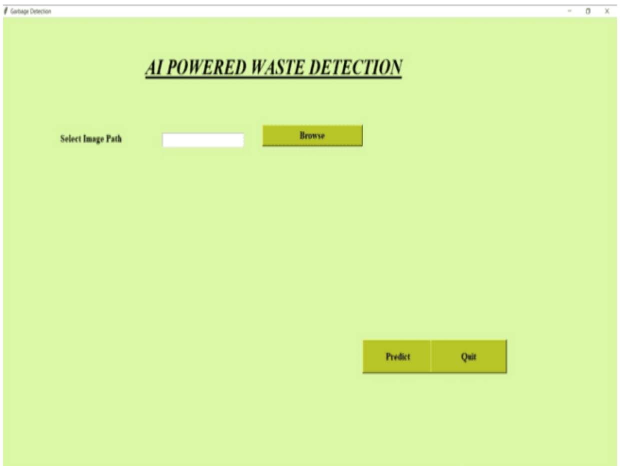


Figure 7a: Home Page

This is the home page of the system where it provides with the option to choose the image path and then the image that their vehicle have captured to predict the waste in and around it.

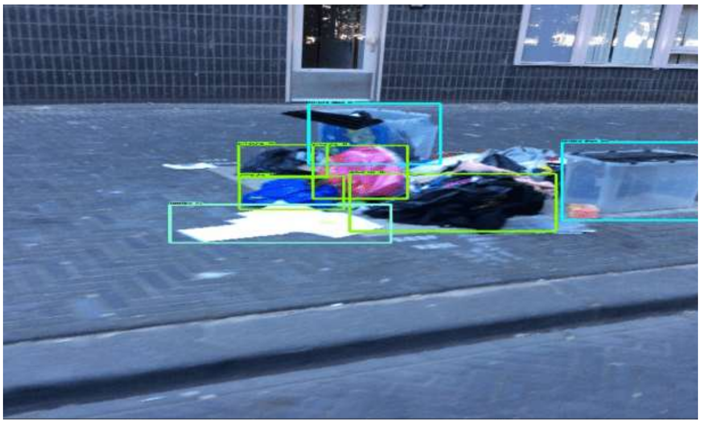


Figure 7b: Detection and Localization of Waste

From the uploaded image the system detects the waste and marks the location of the waste identified. Thus it helps to maintain a clean and safe environment .

8. Conclusion

Automated waste detection using Faster R-CNN and deep learning significantly improves waste management efficiency by reducing manual monitoring efforts. By accurately identifying and localizing waste, this technology supports sustainable urban development and promotes environmental cleanliness. Real-time waste identification enables quicker response times, preventing environmental hazards, reducing contamination risks, and promoting better public health and hygiene in urban and rural areas. Ultimately, it contributes to cleaner cities, sustainability, and a more efficient waste management ecosystem by reducing pollution, conserving natural resources, and encouraging responsible waste disposal practices.

9. Reference

Awe, Oluwasanya, Robel Mengistu, and Vikram Sreedhar. 2017. Smart Trash Net: Waste Localization and Classification. CS229 Project Report. Stanford University: Stanford.

Bircanoğlu, Cenk, Nafiz Arıca, 2018. A Comparison of Activation Functions in Artificial Neural Networks. In: 2018 26th Signal Processing and Communications Applications Conference(SIU),doi:10.1109/SIU.2018.

Bochkovskiy, Alexey, Chien-Yao Wang, Hong-Yuan Mark Liao, 2020. YOLOv4: Optimal Speed and Accuracy of Object Detection. arXiv Preprint arXiv:2004.10934.

Brunner, P.H., Rechberger, H., 2015. Waste to energy – key element for sustainable waste management. Waste Management 37, 3–12.

Carion, Nicolas, Francisco Massa, Gabriel Synnaeve, Nicolas Usunier, Alexander Kirillov, and Sergey Zagoruyko, 2020a. End-to-End Object Detection with Transformers. In: European Conference on Computer Vision, 213–29. Springer.

Dalal, Navneet, Triggs, Bill, 2005. Histograms of Oriented Gradients for Human Detection. In: 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05), 1:886–93. IEEE.

Díaz-Romero, Dillam, Wouter Sterkens, Simon Van den Eynde, Toon Goedemé, Wim Dewulf, Jef Peeters, 2021. Deep learning computer vision for the separation of Cast- and Wrought-Aluminum scrap. Resources, Conservation and Recycling, Volume 172, 105685, ISSN 0921-3449. https://doi.org/10.1016/j.resconrec.2021.105685.

European household waste collection (Eurostat). 2018. Waste statistics [Data file]. Retrieved from https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Waste_statistics.

Foundation, Let's Do It. 2016. "Wade-Ai." GitHub Repository. https://github.com/letsdoitworld/wade-ai; GitHub.

Fulton, M., Hong, J., Islam, M.J., Sattar, J., 2019. Robotic Detection of Marine Litter Using Deep Visual Detection Models. In: 2019 International Conference on Robotics and Automation (ICRA), 5752–8. doi:10.1109/ICRA.2019.8793975.

Girshick, Ross, 2015. Fast R-CNN. In: Proceedings of the IEEE International Conference on Computer Vision, 1440–8.

Gu, Chunhui, Lim, Joseph J., Arbeláez, Pablo, Malik, Jitendra. 2009. Recognition using regions. In: 2009 IEEE Conference on Computer Vision and Pattern Recognition, 1030–7. IEEE.

He, K., Zhang, X., Ren, S., Sun, J., 2016. Deep Residual Learning for Image Recognition. In: 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 770–778. https://doi.org/10.1109/CVPR.2016.90.

Kaza, Silpa, Lisa C. Yao, Perinaz Bhada-Tata, and Frank Van Woerden. 2018. What a Waste 2.0. World Bank Publications 30317. The World Bank. https://ideas.repec.org/b/wbk/wbpubs/30317.html.

Liu, Wei, Anguelov, Dragomir, Erhan, Dumitru, Szegedy, Christian, Reed, Scott, Fu, Cheng-Yang, Berg, Alexander C, 2016. SSD: Single Shot Multibox Detector. In: European Conference on Computer Vision, 21–37. Springer.

Redmon, Joseph, Farhadi, Ali, 2017. YOLO9000: In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 7263–71.

Tan, Mingxing, Le, Quoc, 2019. EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks. In:

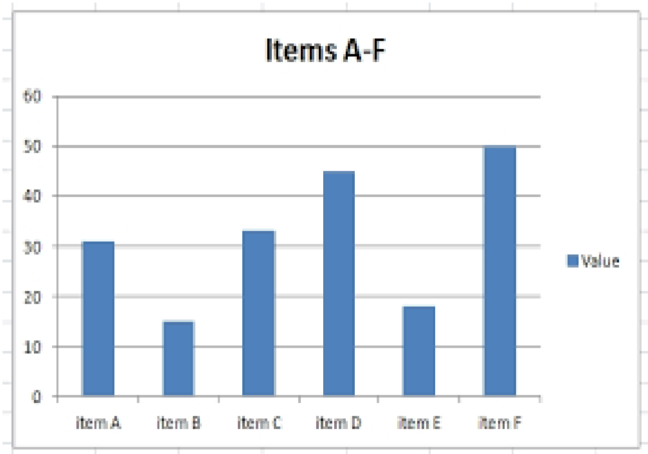
Proceedings of the 36th International Conference on Machine Learning, edited by Kamalika Chaudhuri and Ruslan Salakhutdinov, 97:6105–14.

Vaswani, Ashish, Shazeer, Noam, Parmar, Niki, Uszkoreit, Jakob, Jones, Llion, Gomez, Aidan N., Kaiser, Lukasz, Polosukhin, Illia, 2017. Attention Is All You Need. arXiv Preprint arXiv:1706.03762.

Wang, Chien-Yao, Bochkovskiy, Alexey, Liao, Hong-Yuan Mark, 2020. Scaled-YOLOv4: Scaling Cross Stage Partial Network. arXiv Preprint arXiv:2011.08036.

Fig -1: Figure

Charts



3. CONCLUSIONS

The online version of the volume will be available in LNCS Online. Members of institutes subscribing to the Lecture Notes in Computer Science series have access to all the pdfs of all the online publications. Non-subscribers can only read as far as the abstracts. If they try to go beyond this point, they are automatically asked, whether they would like to order the pdf, and are given instructions as to how to do so.

ACKNOWLEDGEMENT

The heading should be treated as a 3rd level heading and should not be assigned a number.

REFERENCES

1. Baldonado, M., Chang, C.-C.K., Gravano, L., Paepcke, A.: The Stanford Digital Library Metadata Architecture. Int. J. Digit. Libr. 1 (1997) 108–121
2. Bruce, K.B., Cardelli, L., Pierce, B.C.: Comparing Object Encodings. In: Abadi, M., Ito, T. (eds.): Theoretical Aspects of Computer Software. Lecture Notes in Computer Science, Vol. 1281. Springer-Verlag, Berlin Heidelberg New York (1997) 415–438
3. van Leeuwen, J. (ed.): Computer Science Today. Recent Trends and Developments. Lecture Notes in Computer Science, Vol. 1000. Springer-Verlag, Berlin Heidelberg New York (1995)
4. Michalewicz, Z.: Genetic Algorithms + Data Structures = Evolution Programs. 3rd edn. Springer-Verlag, Berlin Heidelberg New York (1996)

BIOGRAPHIES (Optional not mandatory)

1'st Author Photo	Description about the author1 (in 5-6 lines)