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RESEARCH ARTICLE

Optimizing Solid Waste Management: A Holistic Approach by Informed Carbon Emission Reduction

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ABSTRACT Reducing carbon monoxide (CO) emissions is imperative for safeguarding human health and environment. CO adversely affects respiratory health, contributing to respiratory problems and, in severe cases, fatalities. Its reduction aligns with the broader efforts to combat climate change, as CO is often emitted alongside other greenhouse gases. Environmental consequences include air pollution and its detrimental impact on ecosystems. Compliance with emission standards is essential, and reducing Carbon emissions can lead to social and economic benefits, such as increased productivity and reduced healthcare costs. Moreover, the focus on emission reduction drives technological innovation, fostering the development of cleaner and sustainable technologies. In essence, addressing CO emissions is vital for creating a healthier, more sustainable future. However, in most of the cases, there has been no much importance given in scientific management of solid wastes. This has therefore resulted in large magnitude of carbon emission causing serious implications. This paper presents a novel approach to solid waste management, combining carbon emission assessment with advanced object detection technology. We develop an integrated waste management model that employs machine learning techniques for the identification and categorization of metals, non-metals, and plastics within the solid waste stream. To optimize waste sorting and recycling processes, we implement an efficient object detection system that leverages computer vision algorithms. This system enhances the precision of material identification within solid waste, thereby improving sorting accuracy. Additionally, we establish a database to quantify carbon emissions associated with distinct waste management methods, encompassing incineration, composting, recycling, bioremediation, and landfills is used for this work. The novelty of the work lies in the integration of CO2 emissions data and object detection resulting into a decision-making model, providing a holistic evaluation of the environmental impact of varied waste management scenarios. The formulation of recommendations for sustainable waste management practices based on the integrated assessment of carbon footprints and material identification is easy to implement in real world.The technical framework proposed here, aims to inform decision-makers on adopting environmentally conscious strategies for waste management.

INDEX TERMS CNN models, carbon estimation, waste management, solid waste, carbon footprint.

I. INTRODUCTION

Properly managing the disposal of solid waste is crucial for a multitude of reasons, spanning environmental, social, and economic dimensions. Efficient waste management practices, including recycling and responsible disposal, offer various benefits. Proper waste management helps prevent the release of harmful pollutants and contaminants into the air, soil, and water, mitigating environmental degradation and maintaining ecological balance. It contributes to reduced pollution and

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conserves valuable resources by promoting recycling and reuse. Promoting sustainable practices in waste management creates opportunities to enhance health equity. The UHI model discussed in [1] integrates health considerations into urban waste management practices. It emphasizes on leveraging technology to achieve this goal. In an interesting article [2] Shunichi Honda talks about how human activities contribute to excess greenhouse gases. The article emphasizes the importance of effective waste management in preserving both human health and environmental sustainability. Nearly half of the world's waste is improperly managed, leading to harmful consequences such as air pollution from open dumps and burning piles. It suggests practical actions that individuals, companies, and governments can take to mitigate these issues. Individuals are encouraged to reduce, reuse, and recycle, as well as properly separate waste and avoid littering. Meanwhile, companies can minimize packaging, design products for recyclability, and support, waste management regulations.

In terms of public health, effective waste management plays a significant role in preventing the spread of diseases. Inadequate disposal methods can lead to the contamination of water sources and the proliferation of disease vectors such as rodents and insects. Aesthetically, proper waste management reduces littering and enhances the visual appeal of the surroundings. This positively impacts the quality of life for communities, creating cleaner and more pleasant living environments [3].

From an economic standpoint, resource efficiency is a key advantage of proper waste management. Recycling involves converting waste materials to new products, thereby conserving resources that would otherwise be used to produce new products. Additionally, waste management initiatives create employment opportunities across various sectors. Addressing environmental concerns, proper disposal methods, especially in landfills, can help capture and utilize methane, a potent greenhouse gas produced during the decomposition of organic waste. This contributes to efforts aimed at mitigating climate change. In the regulatory sphere, adherence to environmental guidelines and standards is facilitated by proper waste management practices. Governments and regulatory bodies establish frameworks to control waste disposal, safeguard public health, and protect the environment.

At the community level, proper waste management fosters community pride and contributes to a healthier living environment. Clean and well-managed surroundings positively impact the quality of life for residents. In the context of sustainable development, effective waste management is a cornerstone. It ensures that current needs are met without compromising the ability of future generations to meet their own needs, promoting the responsible use of resources and minimizing environmental impact.

Invariably, the solid waste management (SWM) needs in high-density, low-income settlements are consistently underserved or entirely overlooked. Despite these areas having the most pressing demand for waste management services, the densely packed housing leaves no space for waste burial or composting. Additionally, residents in these settlements are often less capable of making alternative arrangements for waste disposal, exacerbating the challenge [4].

This paper introduces an innovative approach to solid waste management by amalgamating CO2 emission assessment with advanced object detection technology. Our work involves the creation of an integrated waste management model, incorporating machine learning techniques to identify and categorize metals, non-metals, and plastics within the solid waste stream. A detailed database quantifying CO2 emissions for various waste management methods, including incineration, composting, recycling, bioremediation, and landfills, is developed for this study. Additionally, we employ an efficient object detection system using computer vision algorithms to enhance the accuracy of material identification within solid waste, optimizing waste sorting and recycling processes.

Our work presents a forward-looking framework for solid waste management that embraces a comprehensive perspective. By amalgamating insights derived from an understanding of the carbon footprints and employing advanced deep learning techniques, the proposed approach seeks to offer nuanced recommendations for waste handling and disposal practices. The integration of the carbon footprints ensures a heightened awareness of the environmental impact associated with various waste management strategies. Simultaneously, the utilization of deep learning technologies allows for the intricate analysis of complex data sets, enabling the identification of patterns and relationships crucial for making informed decisions. This dual-pronged approach is designed to address the intricacies of modern waste management challenges and contribute to the development of sustainable practices. The paper aims to foster a more informed and environmentally conscious paradigm for solid waste management, aligning with the broader goals of minimizing ecological footprints and promoting sustainable resource utilization.

II. BACKGROUND

Effectively managing waste is a multifaceted undertaking that necessitates appropriate technical solutions, robust organizational capacity, and collaboration among diverse stakeholders. Seadon [5] emphasizes the interdisciplinary and multi-sectoral considerations essential for sound solid waste management, particularly in manufacturing contexts. The classification of solid waste is intricate, involving numerous primary and secondary categories, and waste streams from distinct sectors, such as residential and commercial, are frequently treated independently. Consequently, techniques often concentrate on addressing one type of waste at a time, emphasizing individual technologies rather than comprehensive waste management systems. This approach leads to the resolution of specific waste issues while unintentionally generating new problems in other areas, as each compartmentalized solution may create additional challenges.

Researchers and technical experts have delved into the integration of Machine Learning (ML) in Municipal Solid Waste Management (MSWM), aiming to discern patterns in MSW generation and composition. Their goal is to enhance the efficiency of processes, laying the groundwork for circularity and Industry 4.0 principles in various stages of MSWM [6]. Notably, Kontokosta et. al [7] employed the Gradient Boosting Regression Tree model to estimate MSW generation in New York City, offering insights for optimizing collection routes. In a different context, Anh Khoa et. al [8], devised a cost-effective Internet of Things (IoT)-based mechanism connecting devices to monitor waste bin levels and utilize geolocated data for optimized collection routes in Vietnam.

The application of these methods is anticipated to elevate waste sorting efficiency through image classification, facilitating improved recovery of components. ANN models play a crucial role in identifying waste classes during sorting, with common categories encompassing metal or glass [9], paper, cardboard, metal, or glass [10], plastic, metal, paper, and non-recyclable [11], and metal or non-metal, which may include food, plastic, general, or paper waste [12]. Moreover, some approaches integrate IoT systems with robotics for waste allocation based on identified categories [11], [13]. Various Convolutional Neural Network (CNN) structures, such as ResNet50, InceptionV3, Xception, VGG16, AlexNet, Faster R-CNN Inception V2, and MobileNet, have demonstrated successful performance in waste management applications [14].

Tree-Based Models, extensively utilized, prove effective for various MSW prediction categories, including plastic and organic waste fraction generation and energy recovery [15], [16], [17]. Yang et.al [15] utilized Random Forest (RF) to estimate MSW generation in Chinese provinces, achieving an R2 of 0.91, outperforming Support Vector Regression (SVR) and ANN models. Other studies, such as [7], [14], selected the Gradient Boosting Regression Tree (GBRT) method, a combination of Decision Trees (DT) and Boosting methods, demonstrating success in predicting total weekly waste generation and organic and garden waste generation, respectively. The GBRT models achieved R2 values of 0.951 and 0.994, showcasing their effectiveness in waste prediction tasks.

Sultana et. al [18] reviews popular object detection models based on Convolution Neural Networks (CNN) and categorizes them into two approaches: two-stage and one-stage.The two-stage approach involves generating region or object proposals in the first stage and classifying and detecting those proposals using bounding boxes in the second stage. The one-stage approach performs classification and regression in a single shot using regular and dense sampling. The You Only Look Once (YOLO) model is an example of a single-stage network model used in this paper. The paper also discusses the Single-Shot Multibox Detection (SSD) model, which takes an entire image as input and predicts bounding boxes using convolutional feature maps of different levels. The authors of the paper have used VGG-16 and ResNet 101 as base networks for their experiments and have made modifications to these networks to capture high-level information and detect objects in multiple scales.

Shf and Zhao [19] provides a review of deep-based object detection algorithms, categorizing them into two types: two-stage detection algorithms and one-stage detection algorithms. Two-stage detection algorithms mentioned in the paper include R-CNN, Fast R-CNN, and Faster R-CNN. One-stage detection algorithms mentioned in the paper include YOLO and SSD. The paper also mentions the use of the R-CNN algorithm based on region proposal as a representative of two-stage algorithms. Additionally, the paper mentions the Faster R-CNN algorithm, which introduces a novel region proposal algorithm called Region Proposal Network (RPN)

Youzi et. al [20] discusses backbone networks, loss functions and training strategies, classical object detection architectures,to improve the DLL model performance. Further, they propose ShuffleNet algorithm which utilizes depthwise separable convolution, pointwise group convolution, and channel shuffle for object detection.

Saddique et. al [21] highlights the trade-off between accuracy and speed in object detection frameworks and emphasizes the importance of choosing the right framework based on implementation requirements. The paper introduces the Fast R-CNN architecture as a solution to the drawbacks of the SPP-Net architecture. The paper discusses unified architectures that predict class probabilities and bounding box values using a single CNN network, without the need for region proposals.The paper mentions the YOLO framework as an example of a unified architecture

Cao et. al [22] proposes a multi-scaled deformable convolutional object detection network that combines deep convolutional networks and deformable convolutional structures to improve object detection accuracy for small, dense objects with geometric transformations. The overall structure of the network is based on YOLO v3, and it includes deformable convolutional networks and multi-scaled feature fusion by up-sampling. Deep convolutional networks are used to obtain multi-scaled features, while deformable convolutional structures are added to handle geometric transformations. The multi-scaled features are fused by up-sampling to implement the final object recognition and region regression.

Zhang et. al [23] proposes a new algorithm called accurate R-FCN, which introduces a relation module to improve the detection and recognition accuracy of the R-FCN model. The algorithm also applies PSRoI Align (Position-Sensitive Region of Interest Align) with the RPN (Region Proposal Network) to address the problem of position deviation in the region of interest quantization. This helps generate accurate region proposals. Experiments were conducted on the MS COCO dataset to evaluate the performance of the accurate R-FCN algorithm. It achieved state-of-the-art accuracy compared to seven other classical algorithms

Shehab et. al [24] proposes a simplified CNN structure with a simple hardware system based on the Raspberry Pi with a compatible camera for real-time object detection. The model is implemented with less memory and less processing power while handling large amounts of data with Pascal VOC and Microsoft COCO datasets.The detection algorithm can quickly distinguish the object in 0.82 seconds and higher with an accuracy of 98 percent.

Adarsh et. al [25] provides a fundamental overview of object detection methods, including two classes of object detectors: two-stage detectors and one-stage detectors. Two-stage detectors covered in the paper include R-CNN, Fast R-CNN, and Faster R-CNN, which use selective search to detect regions and employ CNN for feature extraction.One-stage detectors covered in the paper include YOLO v1, v2, v3, and SSD, which distribute the input image into grids and predict targets within boundary boxes. The paper specifically focuses on an improved version of YOLO called YOLO v3-Tiny, which is a one-stage detector. The algorithm of YOLO v3-Tiny involves distributing the input image to a grid of cells, predicting parameters for each boundary box, and using the Darknet framework and ImageNet-1000 dataset for training. The paper also includes a graphical comparison of YOLO v3-Tiny with previous methods for object detection and recognition.

Bae [26] proposes a region decomposition and assembly detector (R-DAD) for more accurate object detection. The R-DAD approach involves decomposing an object region into multiple small regions and extracting CNN features within the whole object region and decomposed regions. The semantic relations between the object and its parts are learned by combining the multi-region features stage by stage with region assembly blocks. The proposed method also includes a multi-scale proposal layer that generates object proposals of various scales to improve region proposal accuracy The effectiveness of the proposed methods is evaluated through ablation studies, comparing the mAP (mean Average Precision) of the baseline detector (Faster R-CNN) with and without the proposed methods. The results show improved detection rates when applying the proposed methods, including the region decomposition and assembly method.

Chandan et. al [27] combines the Region-based Convolutional Neural Networks (R-CNN), Faster-R-CNN, Single Shot Detector (SSD), and You Only Look Once (YOLO) algorithms for object detection and tracking. The algorithm utilizes the combination of SSD and MobileNets for efficient implementation of object detection and tracking. The paper describes the use of deep learning and Convolutional Neural Networks (CNN) for feature extraction and classification. The Single Shot Detector (SSD) algorithm, based on the VGG-16 architecture, is used for object detection. The paper also mentions the use of background subtraction (BS) method for localizing objects in motion from video captured by a stationary camera.

Cao et. al [28] proposes an improved algorithm for small object detection based on the Faster R-CNN framework. It utilizes a two-stage detection approach, with a focus on addressing challenges such as complex background, occlusion, and low resolution in small object detection. In the positioning stage, the paper introduces an improved loss function based on intersection over Union (IoU) for bounding box regression. This helps to improve the accuracy of object localization. To address the problem of positioning deviation, the paper incorporates bilinear interpolation to enhance the regions of interest (RoI) pooling operation. In the recognition stage, the paper employs multi-scale convolution feature fusion to ensure that the feature map contains more information, enhancing the detection performanceThe paper also introduces an improved non-maximum suppression (NMS) algorithm to avoid the loss of overlapping objects during the detection process.

Zhang et. al [29] proposes a novel object detection model that combines a shallow CNN and an improved deep CNN using skip-layers connection method to improve the detection ability for small objects. The model incorporates the region proposal mechanism in Faster R-CNN and uses 12 kinds of anchors to generate object candidates, further improving the detection accuracy. A dimensional reducer is designed by connecting ROI-Pool layer and 1×1 convolutional layer, which accelerates the detection of the overall network.

Hassan et. al [30] explores two different methods of detection for small objects within large images: a two-part procedure with image processing and R-CNN based detection using Edge Boxes algorithm, and Faster R-CNN Object Detection with Instance Segmentation (Mask R-CNN).The first method involves a two-step process, starting with image processing and followed by R-CNN based detection using the Edge Boxes algorithm for region proposal extraction.The second method is solely based on Faster R-CNN Object Detection with Instance Segmentation, also known as Mask R-CNN. Both methods are evaluated based on training time, detection time, accuracy, and suitability for deployment in edge computing devices.The preferred method based on the results is the HSV + R-CNN approach, which achieves an accuracy of 95.5 percent and can be deployed in edge devices.

Archana et. al [31] discusses the use of Convolutional Neural Networks (CNN) and RetinaNet for object detection, specifically in the context of deep learning techniques. The Viola-Jones algorithm is mentioned as a machine-learning object identification framework for detecting faces, which involves identifying Haar-like features, creating an integral picture, running AdaBoost training, and creating cascades. The HOG (Histogram of Oriented Gradients) feature descriptor is discussed, which involves splitting the image into cells, computing edge orientations for all pixels in each cell, and summing histograms to create the descriptor. The SIFT (Scale-Invariant Feature Transform) model is mentioned, which involves constructing a vector representing image gradients to identify key points.

Pulipalupula et. al [32] utilizes the You Only Look Once (YOLO) V3 technique for object detection, which provides instant identification of different objects in images or videos. The object identification process in YOLO is conducted as a regression problem, where class probabilities of the discovered photos are provided.The implementation of the work is done using Python and OpenCV The results of the work show improved accuracy in object detection using the YOLO algorithm.

Kandagatla et. al [33] utilizes a Convolutional Neural Network (CNN) for object detection and tracking in digital images and videos. The CNN model is used to generate feature maps for detecting and locating objects.The research work focuses on implementing object detection using a web camera and deep learning methods.

Dong et. al [34] proposes an improved network structure of YOLOv2 for object detection, which includes the following methods:Addition of a 1×1 convolutional layer to improve detection accuracy. Changing the output sizes of several layers from 13×13 to 26×26 to extract more features from multi-pixel images They also include optimization of the loss function to adapt to the size of objects in the image

Wang et. al [35] proposes an object detection and depth estimation approach based on deep convolutional neural networks (CNNs). Transfer connection blocks (TCBs) are incorporated to improve object detection, particularly for small objects in real time.Binocular vision is introduced to the monocular-based disparity estimation network for depth estimation. The epipolar constraint is used to improve the prediction accuracy of depth estimation. The two-dimensional (2D) location of the detected object is integrated with the depth information to achieve real-time detection and depth estimation. The proposed approach is compared to conventional methods and demonstrates better results.

The work presented in [36] introduces a visual tracking system that integrates a high-speed camera and a pan-tilt galvanometer system, enabling the creation of large-scale high-definition images in the monitored area. Employing a CNN-based hybrid tracking algorithm, the system exhibits robust tracking capabilities for multiple high-speed moving objects concurrently. Experimental findings showcase the system's effectiveness, successfully tracking up to three moving objects simultaneously within an 8-meter range. Performance evaluations were conducted through experiments involving the simultaneous zoom shooting of multiple moving objects in a natural outdoor setting.

Shen et. al [37] introduces a novel object detection framework named OS-Net, which enhances accuracy, particularly for small objects, by combining feature representations learned from both object-centric and scene-centric datasets. This two-stage detection framework integrates information from these datasets and utilizes pre-training on large image datasets, ImageNet and Places, using a deep convolutional neural network (CNN). The proposed OS-Net framework is further elucidated through the visualization of activation maps, providing insights into the learned features and regions of interest for CNNs.

In a related context, Song et. al [38] proposes a Multi-Scale Attention Deep Neural Network (MSA-DNN) for object detection. The MSA-DNN method incorporates a multi-scale feature fusion module (MSFFM) to construct high-level semantic features. Additionally, it introduces a multi-scale attention module (MSAM) based on the fused layers of the MSFFM to capture global semantic information and guide detection. The MSA maps generated by MSAM play a key role in locating objects at different scales. To further enhance performance, the paper employs an attention-based hard negative mining strategy, effectively filtering out negative samples and reducing the search space during the detection process. A snapshot of all these works is given in TABLE 1.

The body of prior research works, collectively supports a multifaceted approach to object detection using machine learning and it also optimizes waste management processes, in distinct contexts. Keeping this as a foundation, we now introduce a pioneering methodology that capitalizes on the capabilities of deep learning-based object detection in conjunction with carbon reduction techniques. This innovative approach aims to provide a practical and viable solution tailored to address real-world waste management challenges.

III. PROPOSED WORK

With large carbon dioxide (CO2) emissions, solid waste management is a crucial environmental concern. Existing waste disposal options has various carbon footprints, including incineration, composting, recycling, bioremediation, and landfills. The current difficulty, however, is the lack of a structured method that includes item detection technology for the identification and separation of metals, nonmetals, and plastics in the waste stream. This technique has the potential to greatly enhance waste sorting and recycling efficiency while lowering environmental impact.

The fundamental issue is the lack of an integrated methodology that integrates Carbon emission assessment with item detection capabilities for metals, nonmetals, and plastics. This study tries to address this issue by creating a model that identifies the objects in the waste lot and recommends a waste management method informed by the carbon emission data. Thus this model serves as a holistic approach for waste management.

IV. METHODOLOGY

There are several methods of disposing of solid waste, each with its own advantages and disadvantages. The choice of the disposal method often depends on factors such as the type of waste, environmental considerations, and available infrastructure.

TABLE 1. Summary of the related works.

Authors	Model	Contributions
Kontokosta et al. [7]	Gradient Boosting Regression Tree (GBRT)	Estimated MSW generation in New York City, optimizing waste collection routes.
Anh et al. [8]	IoT-based mechanism	Developed a cost-effective system to monitor waste bin levels and optimize collection routes in Vietnam using geolocated data.
Yang et al. [15]	Random Forest (RF)	Estimated MSW generation in Chinese provinces.
Adeeji et al [14],	Gradient Boosting Regression Tree (GBRT)	Predicted total weekly waste generation and organic waste generation with high accuracy.
Sultana et al. [18]	VGG-16 and ResNet 101	object detection tasks.
Youzi et al. [20]	ShuffleNet	ShuffleNet algorithm for object detection, utilizing depthwise separable convolution, pointwise group convolution, and channel shuffle.
Saddique et al. [21]	Fast R-CNN	predict class probabilities and bounding box values using a single CNN network, without the need for region proposals.
Cao et al. [22]	Multi-scaled Deformable Convolutional Network	Proposed a network combining deep convolutional networks and deformable convolutional structures to improve accuracy for detecting small, dense objects with geometric transformations.
Shehab et al. [24]	Simplified CNN	simplified CNN structure implemented on Raspberry Pi for real-time object detection.
Adarsh et al. [25]	YOLO v3-Tiny	The algorithm of YOLO v3-Tiny involves distributing the input image to a grid of cells, predicting parameters for each boundary box.
Bae et al. [26]	R-DAD (Region Decomposition and Assembly Detector)	Proposed a detector that decomposes object regions into smaller regions for improved detection accuracy. Enhanced detection rates by combining multi-region features and using multi-scale proposal layers.
Chandan et al. [27]	SSD, MobileNet, R-CNN	Combined SSD and MobileNet for efficient object detection and tracking, along with background subtraction for localizing objects in motion from stationary video.
Cao et al. [28]	Improved Faster R-CNN	Proposed an algorithm for small object detection, incorporating IoU-based loss function, bilinear interpolation for RoI pooling, and an improved NMS algorithm to enhance detection accuracy and performance.
Zhang et al. [29]	CNN with Skip-Layers	combines shallow and deep CNNs with skip-layer connections to improve small object detection, using Faster R-CNN and 12 anchor types for candidate generation.

TABLE 2. *(Continued.)* Summary of the related works.

Authors	Model	Contributions
Hassan et al. [30]	HSV + R-CNN, Mask R-CNN	Explored methods for small object detection, comparing a two-part procedure with R-CNN based detection and Mask R-CNN for instance segmentation, with a focus on edge device deployment.
Archana et al. [31]	CNN, RetinaNet, SIFT	Discussed object detection methods including CNN, RetinaNet, and SIFT, with specific mention of the Viola-Jones algorithm for face detection and HOG feature descriptor for image analysis.
Pulipalupula et al. [32]	YOLO V3	Utilized YOLO V3 for object detection, providing instant identification of different objects in images or videos.
Kandagatla et al. [33]	CNN	Used CNN for object detection and tracking in digital images and videos, focusing on higher accuracy and performance.
Dong et al. [34]	Improved YOLOv2	Proposed an improved YOLOv2 structure for object detection, including a 1×1 convolutional layer and adjusted output sizes for better accuracy. Optimized the loss function for object size adaptation.
Wang et al. [35]	CNN with Transfer Connection Blocks (TCBs)	Proposed an object detection and depth estimation approach using CNNs with TCBs for better small object detection. Integrated 2D location and depth information for real-time applications.
Li et a.l[36]	CNN-based Hybrid Tracking Algorithm	Introduced a visual tracking system with a high-speed camera and pan-tilt galvanometer for tracking multiple high-speed moving objects within an 8-meter range.
Shen et al. [37]	OS-Net	a novel object detection framework enhancing accuracy for small objects by combining object-centric and scene-centric datasets.
Song et al. [38]	Multi-Scale Attention Deep Neural Network (MSA-DNN)	Proposed MSA-DNN for object detection, incorporating multi-scale feature fusion and attention modules. Introduced hard negative mining to improve detection performance.

A. SWM APPROACHES

Following are some the solid waste disposal approaches

1) Landfilling: It involves burying waste in designated areas. Modern landfills are designed with liners and monitoring systems to prevent environmental contamination. Landfilling is a widely used and cost-effective method for disposal, suitable for a variety of waste types.
2) Incineration: It is the controlled burning of waste at high temperatures. It reduces the volume of waste and can generate energy in the form of heat or electricity. Incineration reduces the volume of waste, minimizes the need for land, and can produce energy.
3) Recycling: Recycling involves the collection and processing of waste materials to manufacture new products. Common recyclables include paper, glass,

plastics, and metals. Recycling conserves resources, reduces energy consumption, and minimizes the environmental impact of extracting raw materials.

4) Composting: It is the natural decomposition of organic waste into nutrient-rich compost. It is suitable for food scraps, yard waste, and other biodegradable materials. Composting reduces the volume of organic waste, enriches soil, and mitigates the production of greenhouse gases in landfills.
5) Bioremediation: It uses microorganisms to break down or neutralize hazardous substances in waste. It is often employed for contaminated soils. Bioremediation is an environmentally friendly method that can be effective for certain types of waste.

The choice of the solid waste disposal method depends on the specific characteristics of the waste stream, environmental regulations, and the available infrastructure in a given region. Sustainable waste management often involves a combination of these methods, emphasizing waste reduction, recycling, and environmentally responsible disposal.

B. CARBON EMISSION IN WASTE MANAGEMENT TECHNIQUES

The specific carbon emission values associated with waste management methods can vary widely based on numerous factors, including the type of waste, technology used, operational efficiency, and local conditions. Simplified formula for calculating Carbon emissions from a single source category:

$$E = AF \times Q \tag{1}$$

where: - E is the CO emissions (in units such as kilograms or tons).

- AF is the emission factor (in units of CO emitted per unit activity).

- Q is the activity level (e.g., vehicle miles traveled, fuel consumed).

This formula can be applied to each source category, and the results can be aggregated to estimate the total CO emission rate. Further we note that each of the previously mentioned waste disposal method has a certain carbon emission associated during the process. Briefly put as follows:

1) Landfilling: - The main greenhouse gas emitted from landfills is methane (CH4), which has a much higher global warming potential than CO2. The amount of CO2 emitted from landfills can depend on factors such as waste composition, landfill design, and gas capture systems. Wood, ash and some industrial waste can be suitable for landfilling.
2) Incineration: - Modern incineration facilities are equipped with emission control technologies that help minimize air pollutants, including CO2. The exact CO2 emissions depend on the efficiency of the incineration process and the type of waste being burned. Non recyclable materials and industrial waste go for incineration.
3) Recycling: - Recycling generally results in lower CO2 emissions compared to traditional disposal methods. The specific emissions depend on the materials being recycled and the energy required for the recycling process. Paper, glass, plastics can be recycled.
4) Composting: - The CO2 emissions from composting are generally lower than those from landfilling. The composting process itself releases some CO2, but it is considered part of the natural carbon cycle. All organic materials can be given for composting.
5) Bioremediation: - Bioremediation processes may involve the breakdown of organic waste, which can release CO2. The emissions are influenced by the specific waste type and the efficiency of the bioremediation process. Materials made up of petroleum-based substances are good candidates.

C. SOLUTION FRAMEWORK

In their study, Rakib et al. [39] delve into the impact of improper waste management practices, shedding light on how they foster the proliferation of disease vectors like insects and rodents. Agamuthu and Fauziah [40] underscore the implications of the absence of waste segregation methods during waste management and its effects on the environment and community health. Hence, there arises a critical need to establish a system capable of discerning various types of waste and processing them accordingly. The proposed system is an integrated waste management model that combines Carbon emission assessment with object detection technology for identifying metals, non-metals, and plastics, clothes, paper within the solid waste stream. We maintain a database of Carbon emissions associated with various waste management methods, including incineration, composting, recycling, bioremediation, and landfills. Next step is to implement a reliable object detection system capable of accurately identifying metals, non-metals, and plastics within solid waste, improving waste sorting and recycling efficiency. Finally, we use this assessment to recommend the most sustainable waste management approach for mixed waste streams, considering both carbon emissions and the efficient recovery of materials through object detection.

The flowchart in Figure 1. delineates a structured approach to solid waste management, integrating data analysis, technology implementation, and ongoing monitoring to achieve environmentally sound and sustainable waste handling practices. The process navigates through key stages, from input data collection to waste sorting, method implementation, and continuous evaluation, aiming for optimal efficiency and environmental responsibility.

1) Input Data Collection: The process begins with the collection of input data related to waste management. This includes information about the composition of the waste stream, existing waste management methods, and other relevant data.

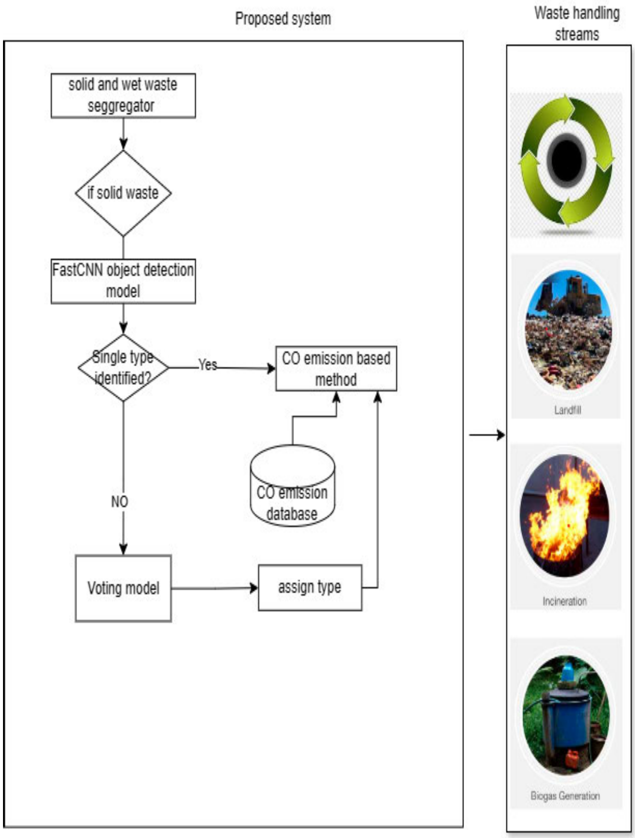

FIGURE 1. Framework for the proposed solution.

2) Waste Stream Analysis Complete: In this step only solid waste is considered for further analysis. A conveyor belt runs the SWM on it and this is captured by the overhead camera to capture the composition of the lot.
3) Object Detection: If the waste stream analysis is complete, various types of materials have to be detected from the captured lot. This involves the use of technology to identify and categorize objects within the waste stream, such as metals, non-metals, and plastics.
4) Waste Sorting & Separation: After object detection, where the waste is sorted based on the identified materials. Here, there can exist 2 scenarios. One where the entire lot is the same type of object of multiple items and the other case where multiple items are of various types. In the first case, the model processes the identified objects directly. In the second case, a voting classifier is used to label the lot. Once this is done, a management method can be selected.
5) Waste Management Method Selection: If the waste stream analysis is not complete, the flow moves to Waste Management Method Selection. This step involves choosing an initial waste management method based on available data or default procedures until a more detailed analysis is conducted. Here the carbon emission is learnt based on the label provided by the previous step.
6) Implementation of Waste Management Method: Following the selection of a waste management method, the process moves to implementation. This step signifies the practical application of the chosen waste management approach, whether it's incineration, composting, recycling, or another method.

D. OBJECT DETECTION MODEL

CNNs have demonstrated remarkable success in various computer vision applications due to their ability to automatically learn hierarchical features from raw pixel data as discussed in [18]- [38]. In the context of waste management, where images of waste items need to be classified accurately for sorting and recycling purposes, CNNs offer a robust solution [9]- [17]. Furthermore, CNNs have shown superior performance compared to traditional image classification methods in handling complex and diverse visual data. Mathematically, the operations in a CNN can be represented as follows:

1. Convolutional Layer: - Let I be the input image with dimensions $W_{in} \times H_{in} \times D_{in}$ (width, height, depth). - Let F be the set of filters with dimensions $F_w \times F_h \times D_{in} \times D_{out}$ (filter width, filter height, input depth, output depth). - Convolution operation (with padding P and stride S) at position (i, j) in the output feature map:

$$O(i,j) = \sum_{m=0}^{F_h-1} \sum_{n=0}^{F_w-1} \sum_{k=0}^{D_{in}-1} I(i \times S + m, j \times S + n, k) \times [t] F(m, n, k, :) + b \tag{2}$$

where b is the bias term.

2. Activation Function: - Typically ReLU: $A(i, j) = \max(0, O(i, j))$ (element-wise operation)

3. Pooling Layer: - Max pooling: Reduce the spatial dimensions by taking the maximum value in each pooling window. - Average pooling: Similar to max pooling but taking the average instead of the maximum.

4. Fully Connected Layer: - Flatten the output from the previous layers into a vector. - Let X be the flattened feature vector. - Each neuron in the fully connected layer computes:

$$Z = X \cdot W + b \tag{3}$$

where W is the weight matrix and b is the bias vector.

5. Softmax Layer: - Apply the softmax function to the output of the fully connected layer to obtain class probabilities.

E. FASTER-RCNN WITH INCEPTION AND RESNET

Faster R-CNN with InceptionNet or ResNet as backbone networks leverages their respective strengths in computational efficiency (InceptionNet) and ability to handle deep architectures (ResNet). These backbone networks play a critical role in extracting informative features from input images, which are subsequently used for generating region proposals and performing object detection tasks efficiently and accurately.

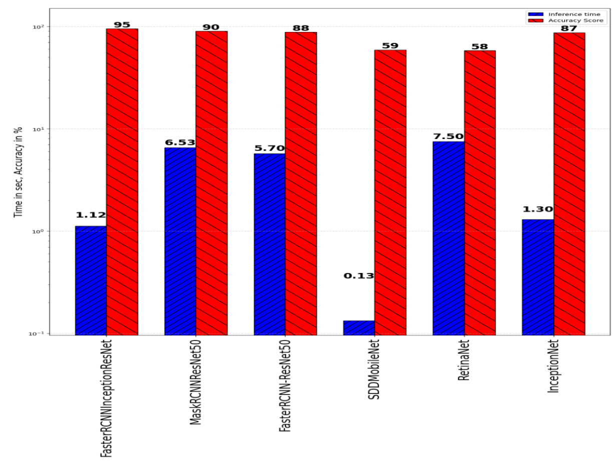

FIGURE 2. Comparison in terms of accuracy score and inference time across various models.

The Background section deliberates on the efficacy of Faster R-CNN with InceptionNet and ResNet along with it, positioning it as a promising contender for our project. We have run experiments on SDD-MobileNet [27], [41], [42], InceptionNetV3 [43], Faster RCNN-ResNet50 [44], MaskCNN-ResNet50 [30] and Retina-ResNet50 [31] models to support our claim. For this purpose, we selected a few samples representing all six categories of items. Additionally, we chose samples that lacked clear features and dimensions and were distorted, posing a significant challenge for image detection. Our approach was to use these images, which represented the worst-case scenario for item identification, to test our system. The results on their maximum accuracy score and inference time is presented in Figure 2. The results supports our claim that Faster R-CNN-Inception-ResNet50 architecture is a better choice for identifying objects in terms of accuracy and inference time taken together.

Thus, we employed Faster R-CNN [44] where the Inception-ResNet model serves as a backbone architecture for the classification of items. The Inception-ResNet model is a deep convolutional neural network architecture that combines the principles of both the Inception and ResNet architectures, aiming to achieve high performance in image classification tasks while maintaining computational efficiency. The implementation starts with building Inception-ResNet, which integrates the strengths of both architectures by incorporating residual connections within the Inception modules. This combination enables deeper networks while maintaining computational efficiency and improving gradient flow during training. Similar to the original Inception Network, Inception-ResNet incorporates inception modules. These modules allow for the efficient extraction of features using multiple convolutions of different sizes within the same layer. Inception-ResNet introduces residual connections within the inception modules. These connections help alleviate the vanishing gradient problem and facilitate training of very deep networks by allowing gradients to flow more easily during backpropagation. As a result, Inception-ResNet achieves state-of-the-art performance on various image classification benchmarks with relatively lower computational costs compared to other deep architectures. Inception ResNet's feature maps are fed into the Faster RCNN's RPN, which predicts regions likely to contain objects based on anchor boxes and scores them for subsequent processing. Through the architecture's use of a Region Proposal Network (RPN), Faster R-CNN increases object detection speed. Our previously trained Inception-ResNet model serves as a backbone architecture for this learning. This network locates and classifies items inside an image by effectively producing region proposals. The final stages of Faster R-CNN with Inception ResNet involve two parallel heads. A classification head having a softmax layer predicts the probability of each proposal belonging to various object classes. The regression head predicts adjustments (offsets) to the bounding box coordinates proposed by the RPN to better fit the object. Faster R-CNN offers excellent performance at high speed by sharing convolutional features between the RPN and the succeeding object detection network.

In this work Faster RCNN Inception ResNet model trained on Open Images V4 with ImageNet pre-trained Inception Resnet V2 as image feature extractor is employed. The InceptionResNetV2 feature extractor was trained on ImageNet and fine-tuned with FasterRCNN head on OpenImages V4 dataset, containing 600 classes.

V. EXPERIMENT AND RESULTS

For our study, we used the TrashNet dataset [45], which is a publicly available dataset designed for the task of trash classification. Trashnet had six classes, namely trash, plastic, paper, metal, glass and cardboard. We collected images from different datasets available publicly and added six more classes to the dataset which increased the number of images in the dataset to 14205 as seen in Figure 3. The dataset was intended to facilitate the development and evaluation of machine learning models for automated trash recognition. The dataset typically includes images of trash items belonging to different categories, such as paper, cardboard, glass, metal and plastic. Images in the TrashNet dataset are often annotated with labels indicating the category of the trash item. These annotations are essential for training and evaluating machine learning models. The waste disposal methods can have subcategories within broader classes, and specific features can be extracted by our model to identify these cases effectively. In the context of glass waste disposal, subcategories may include different recycling processes or sorting methods based on color and composition and the model can be trained to identify such features.

A. SINGLE TYPE OF WASTE

The object detection system was tested on images containing individual waste items to evaluate its performance in identifying single object classes. Sample results for the detection of common waste categories like paper, plastic bottles, metal cans, etc. are presented.

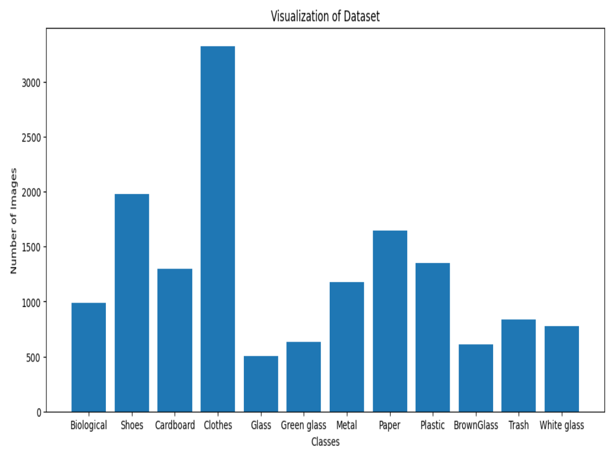

FIGURE 3. Visualization of Dataset.

The experiment delved into the meticulous evaluation of an object detection system's proficiency in identifying singular waste items, aiming to shed light on its effectiveness in discerning specific waste categories. Presented herein are results showcasing the system's adeptness in detecting common waste types, including paper box, plastic bottles, metal cans, and cloth, as elegantly portrayed in Figure 4 through Figure 8.

Figure 4 provides a demonstration of the system's precision, accurately delineating a paper box and appropriately labeling it as "Box" and Figure 5, where the system seamlessly identifies a plastic bottle. Figure 6 shows the model classifies the object accurately as metallic objects, and Figure 7, shows the efficacy of our model in detecting cans. Figure 8 shows the model's ability to discern cloth amidst intricate backgrounds, demonstrating its adaptability to varying waste material compositions. These results underscore the system's resilience in navigating complex visual landscapes, thereby bolstering its utility in real-world waste recognition scenarios.

Complementing these qualitative assessments, quantitative analyses on dedicated test sets reveal a commendable classification accuracy upto 98% for individual waste categories.

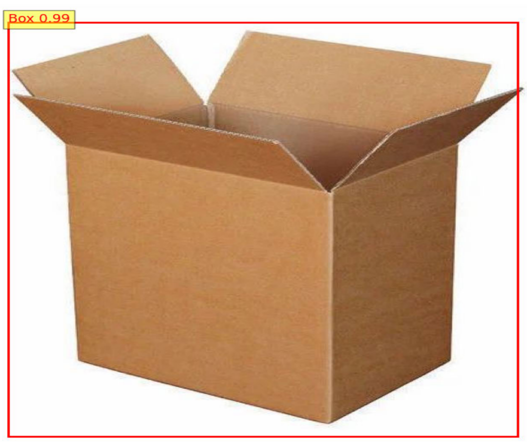

FIGURE 4. Paper box identified.

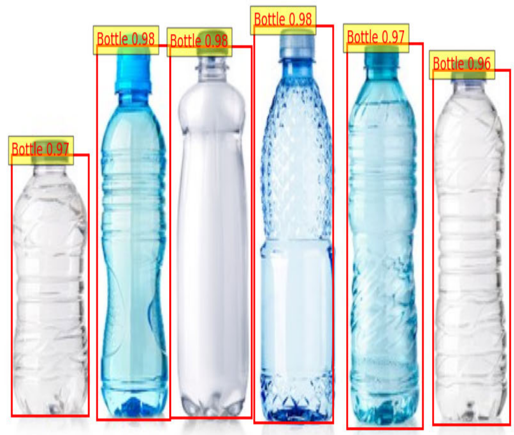

FIGURE 5. Bottle identified.

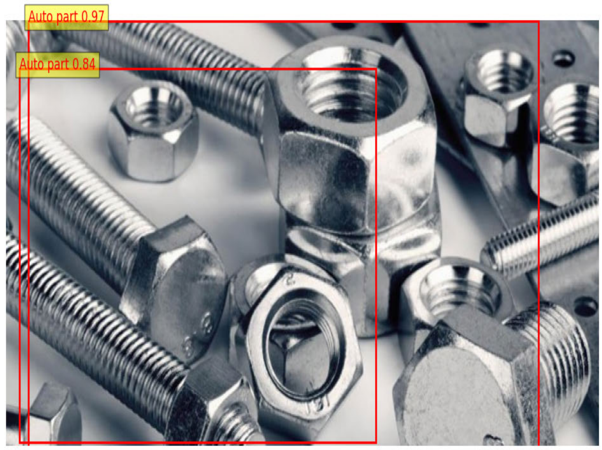

FIGURE 6. Metal identified.

FIGURE 7. Can identified.

B. MULTIPLE WASTE TYPES DETECTED

The nature of the garbage classification job is such that, often, we will face situations where different waste objects are present in a single image.

FIGURE 8. Cloth identified.

To cover such cases, we also tested the object detection system on images containing different waste materials to see the model's capabilities in correctly identifying different materials simultaneously. Sample results for materials like plastic bottles, glass bottles, plastic bags, tin cans, and kitchenware are presented in Figure 9 through Figure 12.

Figure 9 and Figure 10 show the object detection system's ability to efficiently identify different materials when they are kept side by side without any overlap. We further extended our experiments to detect objects that were overlapped. This is a common scenario on a conveyor belt. Objects are likely to be cluttered and obscured. Our model was suitably optimized with adding more images to the existing dataset, to identify such cases. The results show the efficacy of our model in correctly identifying objects as seen in Figure 11 and Figure 12. These images show the difficulty of garbage classification and present an accurate world picture before us. It demonstrates the applicability of the proposed model in real scenario. The object detection system correctly identifies the materials even when they overlap, and the boundaries of materials are unclear. These results show the remarkable capability of the object detection system and its usage to navigate the complex problem of garbage classification.

These findings lay a robust foundation for advancing waste detection technologies, poised to revolutionize waste management practices and bolster environmental conservation efforts.

FIGURE 9. Multiple objects separated with distance identified 1.

FIGURE 10. Multiple objects identified with distance.

C. VOTING MODEL FOR MULTIPLE TYPE

When the object detection model identifies multiple objects in a single frame, a voting mechanism is employed to determine the label assigned to the majority of the detected objects. This voting process involves each detected object 'voting' for its corresponding label. Each label receives a vote for every object associated with it within the frame.

For example, if there are three detected objects within the frame, with labels "cardboard", "can", and "can", the voting process would assign two votes to label "can" and one vote to label "cardboard". After all objects have voted, the label with the highest number of votes is considered the majority label for that frame.

This majority-assigned label is then selected as the representative label for the group of objects within the frame. It's important to note that this approach helps in handling cases where multiple objects of different types are present in the frame and aids in determining the dominant category.

Subsequently, this representative label is used as a crucial factor in determining an appropriate CO-based disposal strategy through mapping. By associating the majority label with a specific disposal strategy, the system can efficiently

FIGURE 11. Multiple overlapping objects separated with distance identified 2.

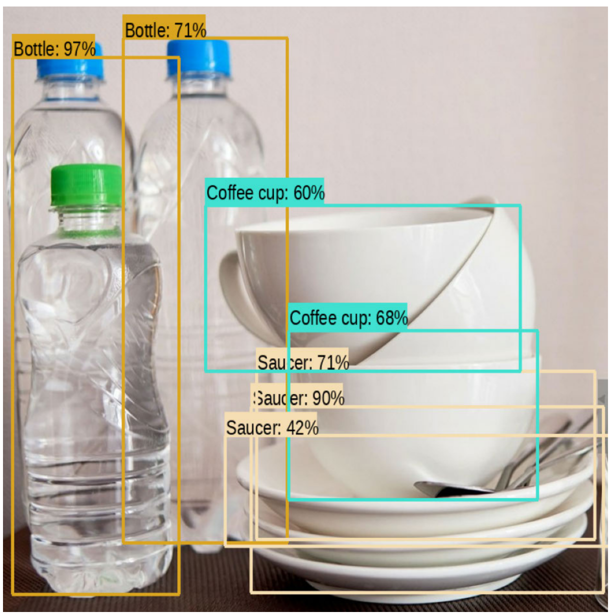

FIGURE 12. Overlapping Multiple objects identified.

manage waste disposal processes based on the types of objects identified in the frame.

The process described involves a simple form of a voting mechanism, commonly known as a voting classifier [46] in machine learning. In the context of object detection, this method is often used when there are multiple predictions made by the object detection model for objects within a single frame, and a decision needs to be made about the most likely label for the group of objects.

In a voting classifier, each individual prediction contributes to the final decision by ''voting'' for a particular class label. The class label with the most votes is then selected as the final prediction. This method can help improve the robustness and accuracy of predictions, especially when dealing with uncertain or ambiguous cases.

D. WASTE DISPOSAL STRATEGY

The proposed approach integrates an advanced object detection system with comprehensive waste management strategies to enable sustainable and environmentally conscious disposal practices. The object detection model, employing machine learning techniques, precisely identifies and categorizes various components within the solid waste stream, including metals, non-metals, plastics, paper, cardboard, textiles, and organic matter.

Upon receiving the unsorted waste, the integrated system initiates the object detection process, leveraging computer vision algorithms and deep learning models to analyze the waste stream. This step accurately distinguishes and classifies the diverse materials present, enabling precise segregation and streamlining subsequent processing steps.

Metallic components, both ferrous and non-ferrous, are directed to specialized metal recovery units. These facilities utilize techniques such as shredding, magnetic separation, and sorting to extract valuable metals for recycling, minimizing the need for virgin metal extraction.

Plastic waste, categorized into various types like PET, HDPE, and PVC, undergoes processing in plastic recycling streams. Machinery such as shredders, extruders, and pelletizers transform sorted plastics into recycled products or feedstock, reducing the demand for new plastic production and lessening the environmental impact.

Paper and cardboard materials are sent to paper recycling units where they undergo processes like pulping and pressing to produce recycled paper products. This reduces reliance on fresh wood pulp, lessening the environmental strain caused by deforestation and energy-intensive paper manufacturing.

Textile waste, including clothing and fabrics, is diverted to specialized recycling or repurposing facilities. Techniques such as sorting and shredding are employed to transform textile waste into new products or raw materials, reducing landfill waste and promoting sustainable textile practices.

Organic matter, such as food and yard waste, is segregated and transported to composting units. Through processes like windrow composting or anaerobic digestion, organic waste is converted into nutrient-rich compost for soil amendment, reducing landfill volumes and greenhouse gas emissions.

After diverting the recyclable, compostable, and hazardous fractions, the remaining non-recyclable and non-compostable waste is either directed to modern sanitary landfills or incineration facilities with energy recovery systems. Landfills incorporate robust environmental safeguards, such as liners, leachate collection systems, and gas monitoring mechanisms, to mitigate potential contamination. Incineration facilities employ advanced emission control technologies and heat recovery systems to minimize air pollutants while generating energy from the combustion process.

Hazardous waste components identified during the detection process are segregated and subjected to specialized bioremediation units. These units employ microorganisms capable of breaking down or neutralizing hazardous substances present in the waste materials, ensuring safe and environmentally responsible treatment of such waste streams.

E. DISCUSSIONS

Using advanced image recognition model such as Faster R-CNN Inception ResNet for garbage classification offers several advantages when compared to traditional garbage collection and management systems. Traditional methods often rely on manual sorting, which is labor-intensive, time-consuming, and prone to errors. In contrast, these advanced models provide high accuracy in detecting and classifying objects, significantly improving the efficiency of the waste management process.

The proposed model effectively extracts features from images, enabling better differentiation between various types of waste. Unlike traditional methods that may require separate processes for different categories, the model can handle the classification of multiple types of garbage in a single pass. This capability demonstrates the model's efficiency and effectiveness in dealing with diverse waste streams simultaneously.

Furthermore, these models can be trained to recognize new categories of waste as needed, providing flexibility and scalability to adapt to changing requirements. Automated systems can operate continuously without fatigue, ensuring a consistent and reliable performance that traditional methods cannot match.

Machine learning models offer consistent results, ensuring that classification standards are maintained uniformly across different batches of waste. This consistency leads to better recycling processes, reducing contamination and improving the quality of recycled materials. Consequently, efficient waste management helps optimize resource use and reduce carbon footprints, contributing to a more sustainable environment.

Utilizing advanced image recognition systems like Faster R-CNN Inception ResNet significantly enhances the efficiency of garbage classification providing up to 98% accuracy, compared to other models and is a obvious advantage over traditional methods. Experiments provide a proof that even in the scenario where items are deformed or overlapping, our system is able to accurately identify them. Further, these systems facilitate automation, consistency, and scalability, which are essential for effective waste management and environmental sustainability. Our contribution lies in developing a hybrid system that merges two technologies, demonstrating the substantial impact of advanced object detection on waste sorting machinery. By employing advanced deep learning models, we achieve precise identification and categorization of multiple items in a single frame, improving the accuracy and efficiency of waste segregation and processing. The study also introduces a voting classifier mechanism to improve the robustness and accuracy of object detection in waste management. This method tackles the challenge of multiple predictions within a single frame, enhancing decision-making in uncertain or ambiguous situations. By experimental results we can conclude that an integrated system that combines efficient object detection with specialized waste processing machinery presents itself as a solution for waste management. We highlight that these technologies perform well and can be integrated seamlessly into existing systems.

VI. CONCLUSION AND FUTURE WORK

In our study, we showcased the fusion of CO2 emissions data with object detection, culminating in a decision-making model that provides a comprehensive assessment of the environmental impact associated with diverse waste management scenarios. Our findings not only illustrate the generation of recommendations for sustainable waste management practices but also underscore the importance of an integrated evaluation involving both carbon footprints and material identification.

The incorporation of carbon footprints ensures heightened awareness of the environmental consequences linked to various waste management strategies. Simultaneously, the use of deep learning technologies enables the intricate analysis of complex datasets, facilitating the identification of patterns and relationships crucial for well-informed decision-making. This dual-pronged approach is tailored to address the complexities of contemporary waste management challenges, contributing to the establishment of sustainable practices.

The overarching goal of our paper is to promote a more informed and environmentally conscious paradigm for solid waste management. Aligned with broader objectives of minimizing ecological footprints and encouraging sustainable resource utilization, our work aims to play a role in fostering positive advancements in waste management practices.

As a future work we can develop predictive models to anticipate future waste generation and associated CO2 emissions, allowing for proactive planning and intervention. Adaptability of the proposed framework to other sectors beyond waste management, such as agriculture, construction, or manufacturing can be taken up, to assess its versatility and potential for broader application. Also, the model can include other environmental metrics, such as water usage, energy consumption, or biodiversity impacts, to create a more holistic environmental assessment tool.

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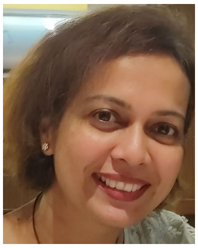

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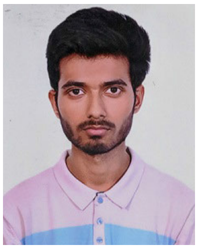

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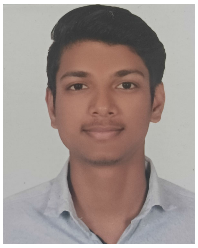

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