WASTE AND WASTE MANAGEMENT

# Waste Management

## Strategies, Challenges and Future Directions

Nanda Gopal Sahoo, PhD

Editor

NOVA

## 1. Introduction

The escalating global waste crisis, projected to surge by 70% by 2050 without intervention [1], demands innovative solutions. Diverse waste management techniques, from source reduction to education initiatives, strive to combat this issue [2]. Yet, the absence of a standardized waste classification system results in regional disparities [3], emphasizing the need for efficient waste identification, crucial for integrated solid waste management [4]. Recent advancements leverage deep learning (DL) models to streamline waste sorting and management [5]. These models, like RWNet and ConvoWaste, exhibit high accuracy, emphasizing the role of accurate waste disposal in mitigating climate change and reducing greenhouse gas emissions.

Some studies incorporate IoT and waste grid segmentation to classify and segregate waste items in real time [6]. Integration of machine learning (ML) models with mobile devices presents a promising avenue for precise waste management [7, 8]. As the advancements are happening, the computing related climate impact of ML models are not explored much. The Information and Communications Technology (ICT) industry contributes to about 1.4% of total global greenhouse gas (GHG) emissions. Out of this percentage, roughly one-third of the emissions are due to the production and management of physical materials [9]. Using transfer learning (TL) [10] various waste classification techniques have been purposed [11, 12] that shows promising results. However, the number of classes used here are quite limited and does not talks about the operational carbon emissions. Besides this, models like EfficientNetV2 that have faster training speed and better parameter efficiency has not been tested [13]. The aim of

## 2. Related Works

The growing challenge of waste management has spurred research into automated classification methods using deep learning. This section explores existing works related to our study, focusing on transfer learning applications, deep learning architecture comparisons, and dataset and model choices. Several studies have demonstrated the effectiveness of transfer learning for waste classification. Lilhore et al. achieved a 95.45% accuracy for two waste categories using a hybrid CNN-LSTM model with transfer learning, highlighting its potential for efficient classification [15]. Similarly, Wulansari et al. employed transfer learning for medical waste classification with an impressive 99.40% accuracy [16], showcasing its adaptability to diverse waste types.

While these studies offer valuable insights, our work specifically focuses on organic and residual waste classification, exploring the impact of transfer learning on both accuracy and training time for VGGNet-16 and ResNet-50 architectures. Comparing the performance of different deep learning architectures is crucial for identifying optimal solutions. Mehedi et al. compared VGG16, MobileNetV2, and a baseline Convolutional Neural Network (CNN) for waste classification, with VGG16 achieving a 96.00% accuracy [17]. Huang et al. proposed a combination model utilizing VGG19, DenseNet169, and NASNetLarge with transfer learning, achieving 96.5% and 94% accuracy on two datasets [18].

These investigations demonstrate the effectiveness of pre-trained models and model fusion, while our work delves deeper into the performance variations between VGGNet-16 and ResNet-50 for organic and residual waste, analyzing their representation capabilities through dimensionality reduction techniques. The choice of dataset and model architecture plays a critical role in determining the success of waste classification systems. Srivatsan et al. used pre-trained models on the CompostNet dataset for 7-class waste classification, achieving 96.42% accuracy with DenseNet121 [19]. Das et al. created a new 17,628-image dataset for 11 trash categories and compared ResNet152, DenseNet169, and MobileNetV2, with DenseNet169 achieving 93.10% accuracy [20]. These examples highlight the importance of dataset size and diversity, and the impact of model selection on specific tasks.


The Future Of
Waste Management
Metal
Plastic
Glass
Paper


The Evolution of Waste Management Practices
1 Early Practices
2 Recycling Revolution
3 Technological Advancements
4 Composting and Biogas
5 Zero Waste Philosophy
6 Policy and Regulation
7 Public Participation and Education
8 Innovative Business Models
9 Global Collaboration
FasterCapital

*3.1. Dataset.*

The waste dataset consists of 23672 images, decomposed into ten classes: metal, glass, biological, paper, battery, trash, cardboard, shoes, clothes, and plastic. The number of image files contain in Metal class is 1869, Glass class is 4097, Biological class is 985, Paper class is 2727, Battery class is 945, Trash class is 834, Cardboard class is 2341, Shoes class is 1977, Clothes class is 5325 and Plastic class is 2542. These images are collected from various internet sources and also from the MWaste misclassified images. The dataset contains various sizes of images and has a class imbalance as shown in Figure 1. Some of the sample images are shown in Figure 2. The class imbalance can negatively affect the training results of the model and cause it to be biased towards the largest class.

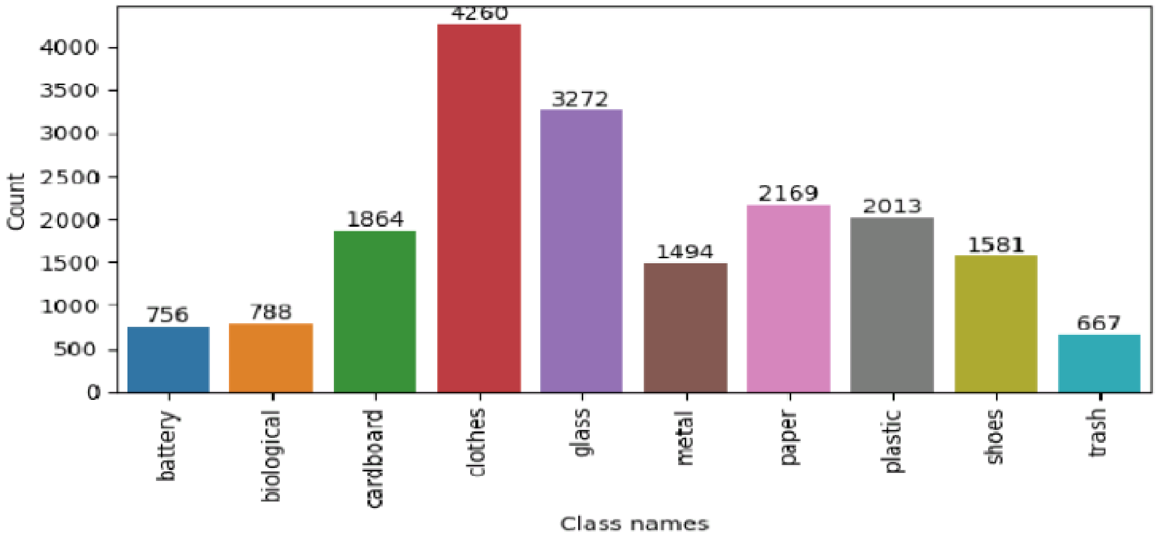
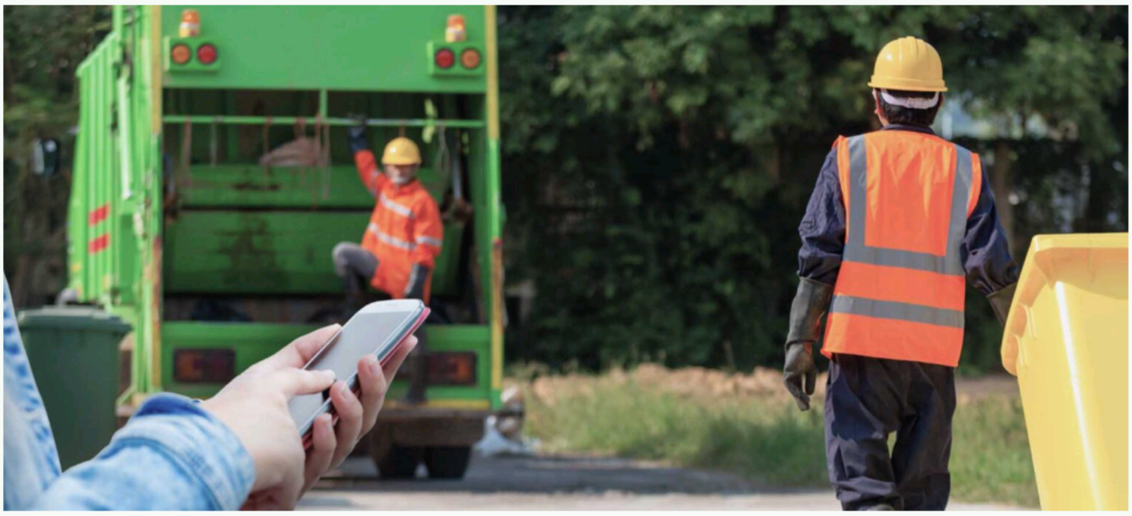



**Figure 1.** Image count on each class of Garbage Dataset.


**Figure 2.** Sample images from each class of the Garbage Dataset.

There are different approaches to solving this problem, the applicability of which depends on the problem being solved [21]. We will use the method of insufficient sampling (random undersampling) [22], which consists of randomly excluding some examples from large classes. We limit the number of images in large classes to 1000 images. The updated class distribution is shown in Figure 3. Some classes are still sparse, to solve this data augmentation techniques are applied. The average height and width are calculated from dataset and is applied to the images. The dataset is then divided into three sets: train, test and val. The train data contains 80% of total images that will be used to train the model, the val set contains 10% and



## Solution Summary

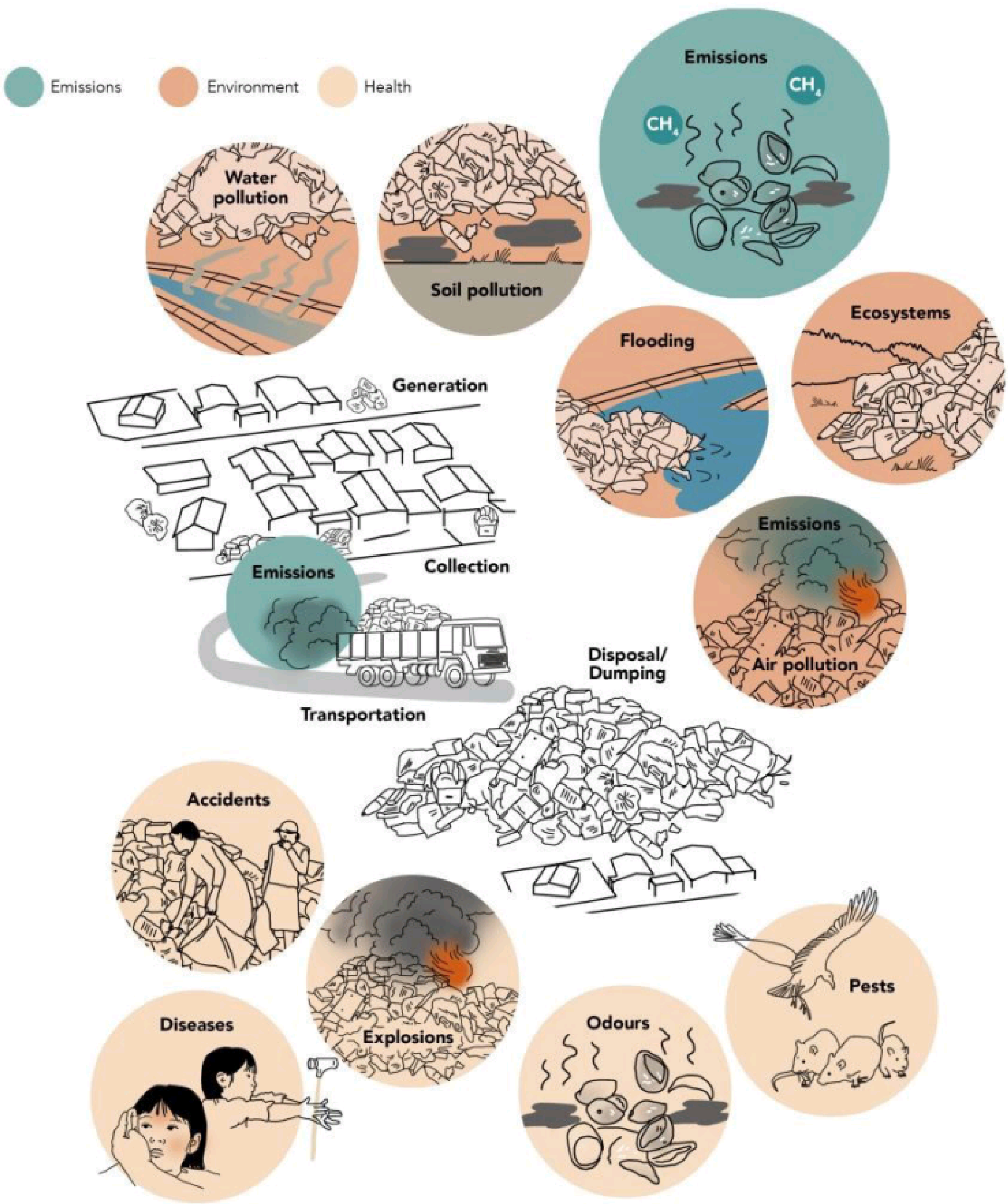
The Integrated Web and Mobile Platform for Waste Management is a comprehensive solution designed to streamline and optimize waste management processes. It combines a user-friendly web interface and mobile applications to provide a seamless experience for waste management authorities, service providers, and the general public.

The Solution covers Waste Collection Management, Bin Monitoring and Tracking, Smart Bins and Sensors, Data Analytics and Reporting, Waste Segregation and Recycling, Billing and Invoicing, Mobile Applications, Customer Service and Engagement etc.

## 1.3 Waste Management in context of climate change, health and environment

Increasing waste generation and unscientific management of solid waste leads to higher Greenhouse Gas (GHG) emmisions, negative impacts on public health and environmental degradation. The Intergovernmental Panel on Climate Change (IPCC) estimates that solid waste management accounted for around 3% of GHG emissions in 2010, with most of this associated with methane emissions from landfill sites. These emmisions are due to unscientific disposal of waste by burning, open composting, direct disposal in dumpyards, etc. This pollutes the air, water and soil ecosystems. The collection and transportation vehicles also consume fossil fuels adding to the air pollution. Leachate from landfill contaminate ground water and surface water. Open dumping of waste can contaminate soils and block drainage network in cities. This unscientific management of waste leads to public health issues like diarrhoea, respiratory infections and gastrointestinal parasites.

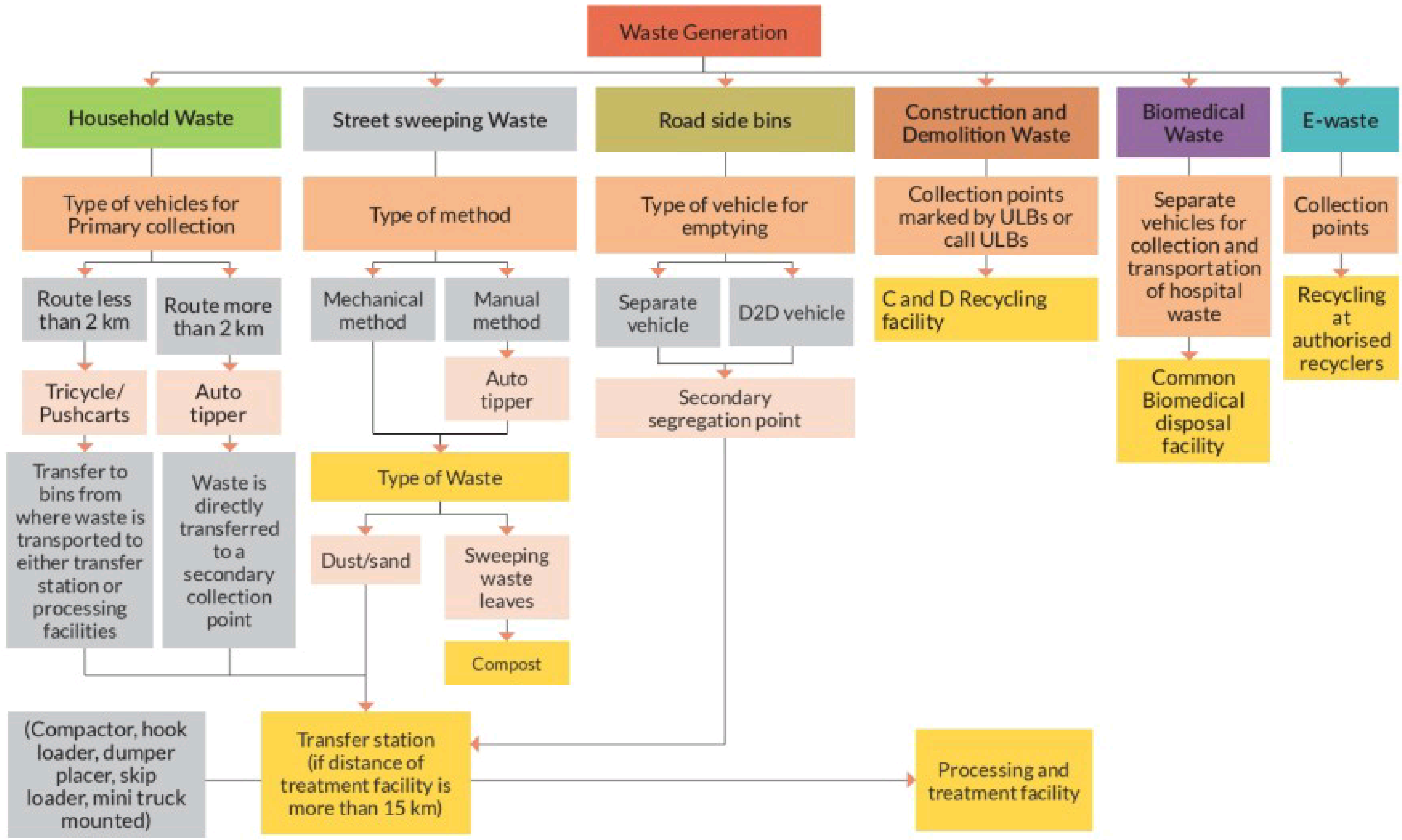
**Figure 1.6: Impact on climate, environment and human health**




*Source: CSD Engineers,adapted by Zoi*

Using a lifecycle approach, it has been estimated that a 10 to 15% reduction in GHG emissions can be achieved through landfill mitigation and diversion, energy from waste, recycling, and other types of improved solid waste management process. Reducing waste generation can potentially further increase this contribution to 15 to 20%. (Wilson, 2015)

**Figure 2.5: Waste Collection and Transportation - Decision points**




*Source: Author*