Chapter 6
AI in Waste Management: The Savage of Environment

Sharda Bharti, Shourat Fatma, and Vinay Kumar

Abstract Disposal of waste has become a major challenge throughout the world due to uncontrolled disposal of domestic as well as industrial wastes in open spaces. Exposure to a variety of wastes may eventually lead to the spread of various diseases and, thus, may pose serious health hazards to the public and adversely affect the environment. To minimize such issues, integrated waste management system could be a sustainable solution. It is well known that sorting of the waste at the source can be the first and the most important step to start with for efficient management of waste. This can simply be done by putting a number of labeled bins specified for each kind of wastes at the point of generation itself. However, this is the most tedious step among all the steps involved in effective waste management. To fasten the process and efficiently manage the waste collection, artificial intelligence (AI) may play a critical role in waste management which starts with the use of smart garbage bins. These bins are often combined with an app that helps the users know the availability of nearest location of the waste bins, thus preventing the bins from overflowing. AI can also play an incredible role in sorting of the wastes, as sorting is another major issue for most of the waste management facilities. AI-based sensors can discriminate items composed of different materials and distinguish the items of the same material whether an item has been chemically contaminated, ensuring purity of the waste stream. A number of waste management companies have been using such techniques and are taking the advantage of Internet of Things (IoT) sensors to monitor the fullness of trash receptacles throughout the city. The advantage of using such smart bins have effectively optimized the routes, timing and frequencies of waste collection, and reducing the load of municipalities. Such automated process would provide the best use of technology for effective waste management to prevent the human health risks as well as to protect the environment. This review article includes

S. Bharti (✉)
Department of Biotechnology, NIT Raipur, Raipur 492010, India
e-mail: sbharti.bt@nitrr.ac.in

S. Fatma
Department of Life Sciences, NIT Rourkela, Rourkela 769008, India

V. Kumar
Department of Computer Science and Engineering, NIT Jamshedpur, Jamshedpur 831014, India

P. K. Paul et al. (eds.), *Environmental Informatics*,
https://doi.org/10.1007/978-981-19-2083-7_6

details on various techniques based on machine learning and the use of artificial intelligence for efficient waste management than could significantly minimize the risks associated with human health and environment.

Keywords Artificial intelligence · Internet of Things · Sensors · Smart waste management

6.1 Introduction

Solid waste generation is one of emerging issues nowadays. Population growth, industrialization, rapid urbanization, and lack of financial resources have enormously increased the generation of solid waste worldwide. The expanding population across the globe are becoming a main reason for accumulation of solid wastes and should be answerable for a clean, healthy, and safe climate [1–3]. The globe generates around 2.01 billion tons of municipal waste annually, with about 33% of the waste produced being dumped into unmonitored landfills and unchecked waste dumps (The World Bank) [4]. The more the amount of waste produced, the more resources they will invest in finding solutions. Global waste is expected to increase by 3.4 billion tons by 2050 (World Bank Group, 2022) [5]. As everyone is getting vaccinated for the COVID-19 virus, there has been a spike in the clinical waste exposure to various wastes that may eventually lead to the spread of various diseases, such as, tuberculosis, pneumonia, and diarrhea. Moreover, it also adversely affects the environment leading to soil contamination, land pollution, thereby causing the loss of aquatic, and terrestrial lives. The lack in handling waste materials and keeping the lanes clean leads to breeding mosquitoes, which is the sole reason for diseases such as dengue and malaria [3, 6]. Hence, there is an urgent need for the implementation of proper solid waste management. Insufficient operation and inadequate planning are the reasons behind poor solid waste management. Everything must be appropriately managed starting from the initial steps, i.e., waste disposal, collection, and preventing overflow of bins to proper disposal of the waste following the waste hierarchy [7]. In evolved countries, several smart waste management strategies are being invented, implemented, and adopted and enormous benefits are achieved. However, the waste management appears to be a challenge for developed and developing countries.

The waste hierarchy indicates that prevention (reduction) of waste material, reusing them, recycling, recovery, and adequate disposal can decrease the amount of solid waste generated. The overall waste management system comprises various parameters and are connected by complex processes affected by multiple socioeconomic factors. Sorting the waste at the source can be the first and the most crucial step to start with for the efficient management of waste management. Exposure of open municipal solid waste causes several diseases and adversely affects the environment [6, 7]. Hence, the industrial waste, biomedical waste, the radioactive waste, and non-radioactive waste should be segregated properly and handled carefully as the radioactive wastes may emit radiation leading to lethal skin diseases and increase the risk of skin diseases, abnormalities in birth and child maturity, and cancer [10]. In addition, direct disposal and poor waste management practices may also contaminate the soil and water, thereby causing land/soil pollution and thus deteriorating the land and water quality.

Therefore, classifying the solid wastes into domestic, industrial, and biomedical/hazardous waste is the primary step toward waste management. Moreover, the solid waste can be reused and recycled efficiently. For instance, urban solid waste (USW) can be converted into a different form of energy via biochemical, thermochemical, and mechanical ways.

6.2 Waste Management

Each step of waste management is crucial; however, reuse and recycle of waste have provided an additional advantage of economic gain to solid waste management [11]. Among these, waste-to-energy technology is identified as an excellent opportunity for sustainable and economical solid waste management. In this approach, the waste is converted into energy primarily via biochemical, mechanical, and thermochemical ways (as demonstrated in the Fig. 6.1). Incineration, pyrolysis, and gasification for conversion of organic matter contain less biodegradable substances, converted via

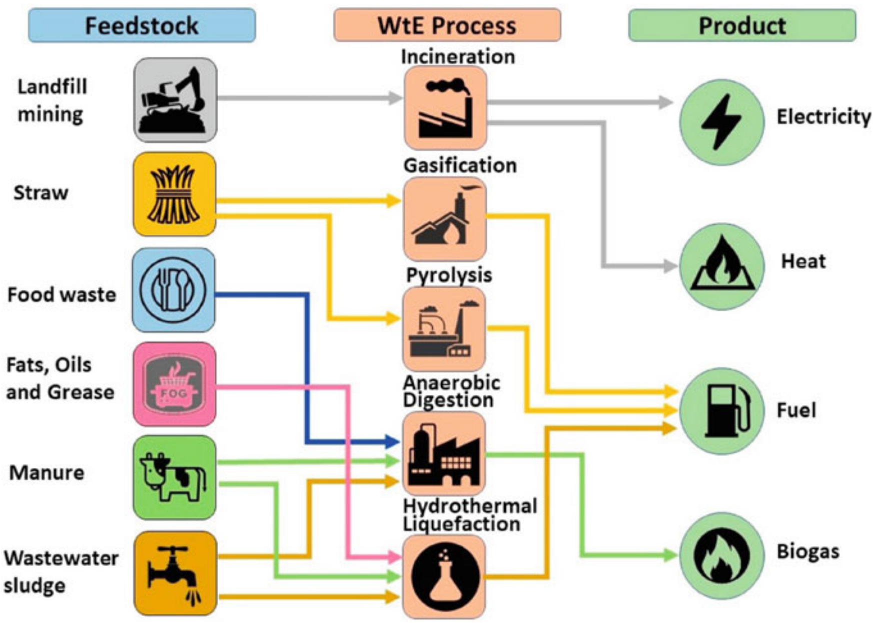

Fig. 6.1 Waste to energy conversion [12]

thermal conversion; the anaerobic digestion is done for waste with more extensive moisture content and biodegradable substance for methane gas production [2, 6, 9].

The waste-to-energy conversion system includes several key steps such as collection of waste input, bio-conversion approaches, conversion of waste to energy, and the energy carriers [13]. The waste input includes the carbonaceous wastes which are collected from sources such as municipal solid waste, agricultural residues, sewage sludge, forest residues, and wastes from food industries [2, 6]. Subsequently, the waste materials based on their characteristics are segregated into three groups for the conversion process. These processes involve the biochemical processes, thermochemical processes, and mechanical processes. The energy carriers are produced based on abovementioned process. Ultimately, a controlled disposal of waste in sanitary landfills and preventing overflow should be done.

With the advancement in research toward revolutionizing urban waste management, artificial intelligence (AI) and machine learning (ML) are being widely explored for a sustainable waste management [14–17]. Different methods based on the Internet of Things (IoT) and AI are being developed to increase waste management efficiency [17]. All the smart bins are connected digitally through the Internet to display the level of waste in the bins and their respective locations [18]. The IoT-integrated smart bins send the volume of the bins to the Internet over the servers. With efficient optimization techniques and associated algorithms, different methods are being proposed.

Recent machine learning techniques including neural networks is being explored in temporal models to predict the generation of solid waste. The Artificial Neural Network (ANN), Genetic Algorithm, fuzzy logic (FL), and other AI models can solve human traits such as problem-solving, reasoning, and understanding [12, 16, 17]. As reported by Zade and Noori [21], a feed-forward artificial neural network (ANN) was employed for prediction of waste generation pattern on weekly basis in Mashhad city, Iran [21]. Expert systems, such as, FL can solve complex mapping systems and provide results wherever systems like Genetic Algorithms (GA) use the Darwin theory of natural selection to select the set of data that best fits the procedure for handling certain conditions [22]. The sensors are connected to detect different types of waste materials. Computer vision annotation and intelligent algorithms allow the sensors to sense the different garbage to be placed in the smart bin. Artificial intelligence has been employed to solve several issues on large scale such as air pollution, soil erosion, wastewater management, and several environment-related problems. Adaptive Neuro-Fuzzy Inference System (ANFIS) models are helpful to forecast and optimize wastewater plant treatment processes [19]. Multi-layer perception (MLP) algorithm is used for weather forecasting, measuring the levels of atmospheric carbon dioxide and nitrous oxides [23]. Adaptive Neuro-Fuzzy Inference System (ANFIS) models help predict particulate matters and check different waste management processes. There are still several techniques reported in literature, and many are in their way of being prepared. ANFIS is widely used to remove turbidity in chemical industries and check methane gas production and other solids during anaerobic digestion for biochemical conversions of waste to energy [12, 20]. Thus, AI-based models offer an effective alternative approach with stand-alone and hybrid models to optimize urban waste management (UWM) models [11, 21]. This article has discussed waste segregation, waste hierarchy, and recent trends in artificial intelligence and machine learning for USW (Urban Solid Waste) management, recycling waste, and fewer case studies. To explore the prospective application of AI models in solid waste management, the emerging application of AI and machine learning techniques is crucial to employ for an efficient solid waste management. Various models based on artificial intelligence and machine learning algorithms have been explored to improve existing SWM schemes for each of the stages, starting from waste collection to final disposal. Hybrid AI-based models and various comparative studies employing AI/non-AI models have been included in this article for better understanding of the waste management.

6.3 Waste Management

6.3.1 Classification of Waste Management

If we go by the definition of waste, there would be several definitions for waste. According to the waste framework directive of the European Union, "Waste" means any substance or object which the holder discards or intends or is required to discard (European Union, 2011). Defining waste can be a case-to-case decision as well. Removal of waste improves the quality of life. Efforts are being made globally at their best to reorient the face of solid waste management (SWM) toward sustainability. There are different ways of managing the solid waste produced in the developed countries, such as USA, South Korea, and Japan, and in the developing countries like India and China. In most cases, a significant amount of waste generated is taken care by the respective municipal bodies, as per the Government norms. The facility for the recyclable materials (papers, drink cans, and plastics) is better in the developed economies, whereas compostable organic matter is minor in countries with lower GDP (INTOSAI, 2020). In developed countries, recycling occurs almost at every stage of product usage, whereas this system is lacking in developed countries, leading us to understand a more solid waste approach. The classification of solid waste can be done on different criteria such as source of waste generation, composition of wastes, hazardous properties of the waste, and who manages the waste. Broadly, the solid waste is categorized into Hazardous and Non-Hazardous waste (Depicted in Figure 6.2). Further classifications occur under these two divisions. Hazardous waste constitutes radioactive waste, e-waste, and biomedical waste. The radioactive waste emits radiation that can either degrade the DNA of the cells or mutate them. Exposure to such radiation may cause acute respiratory syndrome (ARS) or even cancer (CDC, 2021). Hence, the separate bins have been used to collect these wastes separately. Finally, they should be disposed of properly. Incineration, high temperature, and chemical treatments are a few ways to treat them.

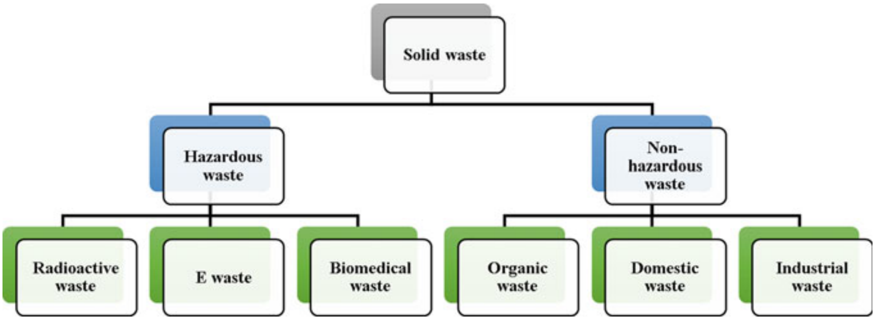

Fig. 6.2 Classification of waste

6.3.1.1 Types of Hazardous Waste

E-waste: These waste materials are produced from unused or broken electrical and electronic appliances after the end of their useful life. It contains toxic elements like radium, barium, mercury, lead, cadmium, arsenic, and certain carcinogens leaching into the environment and may cause cancer in humans and animals, and particularly, lead can trigger neurological damage [5, 8, 23]. When these electronic parts are mishandled during disposal, they mix with soil, water, and air and adversely affect the human, animal health, and environment.

Biomedical waste: It arises from medicals, hospitals, pharmaceuticals, bandages, and body fluids. They can be infectious and may contain toxic and radioactive microorganisms [27]. Exposure to these chemical compounds can interfere with the immune system and cause diseases [25, 26]. Around 16 billion injections are dispensed globally every year, however, most of these needles and syringes are not discarded properly after their use. Sometimes, these are burnt directly through open burning or incineration of such biomedical wastes which may result in the emission of dioxins, furans, and particulate matter in some cases (WHO, 2018).

Radioactive waste: These wastes are produced from nuclear activities including earth mining, nuclear research, fuel processing plants, and nuclear power generation. They need special treatment for handling and disposal processes. Storage of used fuel is usually done underwater for five years and then in dry storage. Deep geological is the widely used method for their disposal [30].

6.3.1.2 Non-Hazardous Waste

Non-hazardous wastes include waste that can be recycled and reused but may lead to profound environmental and health impacts when left untreated and uncontrolled. They are broadly classified into municipal waste and industrial waste. Municipal waste can be classified into organic, packaging, and industrial wastes. They are disposed of in different ways, like taking them to a disposable site, recycling the waste, and working with a disposable company [31].

6.3.2 *The Waste Hierarchy*

With increasing population and urbanization, the solid waste generation rate has been increasing tremendously. Currently, as several countries have chosen to follow social distancing and declare a lockdown as a protection measure from COVID-19, waste production has increased again. The pandemic effect is forcing retailers to use low-grade plastic materials for packaging. The recycling of waste products has slowed down due to COVID virus transmission and disturbance in the supply chain. The International Finance Corporation (IFC, 2021) report also notes an uptick in single-use plastic production, mainly prompted by the increased use of plastic-based personal protective equipment (PPE) and packaging materials (ISM Waste and Recycling, 2021). The waste hierarchy is a ranking system used for different environmental waste management options at the individual and organizational levels. Prevention is the most preferred, followed by reuse, recycling, recovery, and disposal. All these five priorities are often illustrated as the five-tier pyramid, as depicted in Figure 6.3 (ISM Waste and Recycling, 2021). Thus, the maximum benefits can be extracted from the products we use while minimizing the waste output produced when waste management hierarchy is being followed. These includes:

1. Reduce: We can prevent extra packaging materials, reuse materials, less disposable, and less filled landfill sites. Avoiding waste is the essential and most preferred option in the waste industry. Wherever possible, reducing the usage

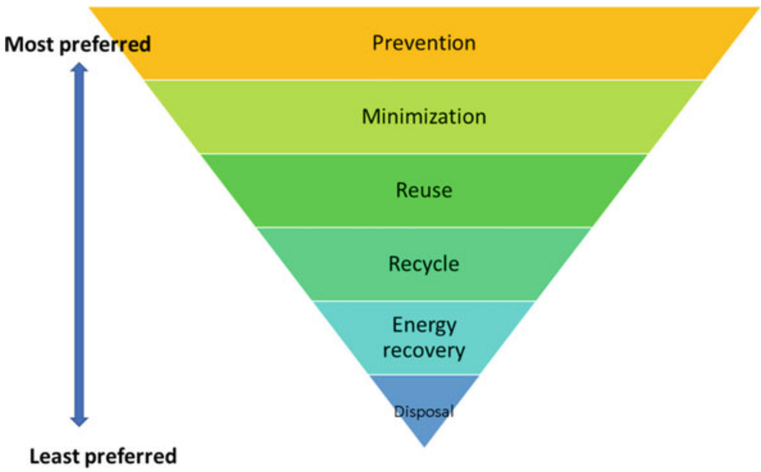

Fig. 6.3 Waste management hierarchy

of materials before it becomes waste is preferred. Cleaning, repairing, and refurbishing items can increase reusability.

2. Reuse: Reusing materials is the second-best waste management approach. It also allows us to avoid spending money on new goods and materials.
3. Recycling: Recycling turns into new items that can be used for different purposes, thus reducing the industrial raw materials used. Plastics, paper, cardboard, and metal products can be recycled.
4. Recover: Wherever we cannot use the 3R's (reduce, reuse, and recycle), we should recover the waste material in the form of waste to energy. Waste to energy helps reduce fossil fuel emissions and carbon footprints. Domestic wastes from the kitchen can be converted to compost and manures by composting.
5. Disposal: The least sustainable option in the waste hierarchy is disposal which is the most expensive method. This is the most unsustainable method done by incineration and filling landfills. For example, one ton of landfilled food waste can produce 450 kg of carbon emissions.

6.3.3 Conventional Waste Management Scenario

The waste management and its handling rules in India are governed by the Ministry of Environment and Forests (MOEF). Waste is a potential resource; the primary goal is to extract waste and effective waste management. In small towns, per capita MSW generation in India is approximately 0.17 kg per person per day whereas, in cities, it is about 0.62 kg per person per day (CJES, 2009). Solid waste management (SWM) is a major challenge for urban places in India due to the rising population, industrialization, and economic growth. Currently, the solid waste produced in India is approximately 42 million tons on annual basis, which fluctuates from 200 to 600 kg/capita/day, with a collection efficiency varying from 50 to 90% (CJES, 2009). Achieving sustainable waste management is difficult for India, with a high population density. The informal sector, which accounts for almost 90% of the waste produced, dumps it randomly rather than properly landfilling it (CJES, 2009).

6.3.4 Current Waste Management Practices in India

Municipal authorities are accountable for enforcing the laws issued by management and handling the rules of MOEF. The municipal authorities formulate the rules for executing the regulations and develop the methods and techniques for waste management including the collection, transportation, segregation, storage, processing, and final disposal. However, rag pickers are usually seen collecting the domestic and industrial waste manually and sell the collected waste to earn money and thus are dependent on waste for their social and economic benefits despite the health risks associated with it. Some of them collect from home, some work in recycling industries and waste management associations. Sometimes, it is the only source of livelihood for a significant population.

Biodegradable waste and inert waste are often dumped openly at several places. Municipality and other local bodies are involved in their management who put an expenses of around Rs. 500–1000 per tons on SWM, and out of which, 70% of the total amount is spent on collection and 20% on transport [2]. Nowadays, engineered landfills provide an alternative way of solid waste disposal that minimizes the exposure of the waste with the environment. Properly managed landfills in India will allow the safe removal and protect groundwater from contamination, avoid odors, fire hazards, and air emissions, and reduce the emission of greenhouse gases [2]. Properly managed landfills will slowly replace waste dumping areas in India.

6.3.5 Barrier and Challenges for Waste Management in India

India is facing challenges in waste management due to lack of awareness among people, lack of proper knowledge, and training for the workers which is required for an efficient waste management. Ever-increasing urbanization is driving additional force on landfill sites situated in urban areas. Waste management becomes difficult when the waste segregation is not accomplished and different kinds of wastes including the recyclables, biodegradable waste, and industrial and toxic wastes all are dumped together [32]. In general, people directly throw the household/domestic solid waste in a common bin which is not a good option. It is because domestic waste also contains several hazardous/toxic materials which should not be discarded directly with other non-toxic/non-hazardous household wastes. Dumping them together makes all the wastes hazardous in nature. This reduces the possibility of recycling of the wastes or conversion of wastes into other usable forms. Hence, household wastes must be segregated at the household level itself and should be collected separately into wet, dry and domestic/household hazardous waste categories. As per the Solid Waste Management Rules, 2016, domestic hazardous waste includes the discarded paint drums, pesticide cans, compact fluorescent lightbulbs, tube lights, expired medicines, broken mercury thermometers, used batteries, used needles and syringes and so on generated in houses. Hence, the most crucial barriers in rural part of India are recognized as household hazardous waste, inadequate assets for research on SWM, lack of local architecture, a shortage of staff capability, and a lack of a standard operating process for data collection and analysis. There is insufficient budget allocated for managing the urban waste produced. Limited qualified waste management professionals, lack of environmental awareness, and less motivation among people have hindered the adoption of new technologies to solve waste management in India. In such cases, AI, along with machine learning techniques, could give a unique shape to waste management in India. When coupled with proper management skills from the people and waste management association, an effective and sustainable waste management may be achieved in India.

6.4 Waste-to-Energy Technologies: Transformation Through Biochemical, Thermochemical, and Mechanical Pathways

At a time, it was being predicted that the developing countries like India and other such countries in the world may also increase the waste generation rate and may reach to value comparable to the MSW generation rate of developed countries [8, 9]. The rate of solid waste generation is projected to achieve 2.2 billion tons per year by 2025 and 4.2 billion tons per year by 2050 [33]. In other words, the solid waste produced is directly proportional to the country's Gross Domestic Product (GDP). Hence, this might have become a huge problem for developing countries like India. Subsequently, people around the globe realize the power of waste to energy (WTE) as the energy supply in the current situation is less as compared to the real energy expected for consumption. This paves the way for WTE from Urban Solid waste (USW). WTE is sustainable, ecofriendly, and economically attainable for developing countries like India. They can be applied to different kinds of waste: from solid (thickened sludge from treatment plants) to liquid (sewage discharge) and gaseous (refinery gases) waste. Various methods including thermochemical, biochemical, and mechanical conversion approaches can be employed toward energy generation from the waste (as summarized in Table 6.1), which are discussed in the following sub-section.

6.4.1 Thermochemical Conversion

Thermochemical conversion involves thermal organic matter treatment into heat energy, fuel, and gases. They are mainly used for dry waste with a high concentration of non-biodegradable waste. It involves three treatment processes that differ among

Table 6.1 Methods for waste-to-energy conversion

Methods for waste-to-energy conversion	Thermal conversion	Biochemical conversion	Mechanical conversion
Temperature	Incineration:850–1200 °C Pyrolysis: 400–800 °C Gasification: 800–1600 °C	150–450 °C	900–1200 °C
Type of waste	Dry waste	Organic waste	Organic and dry waste
Methodologies used	Incineration Pyrolysis Gasification	Decomposition Anaerobic sludge digestion	Aerobic degradation Fermentation Acetogenesis Methanogenesis Oxidation

the temperature and oxygen content used. Incineration is the complete oxidative combustion at 850–1200 °C of any kinds of solid combustible wastes (i.e., solid, liquid, or gaseous) predominantly to carbon dioxide, water vapor, other gases, and a relatively small, non-combustible residue known as ashes. The ashes are disposed further in the landfills in an ecofriendly manner. The incineration process includes two key processes: primary and secondary processes. Primary processes include a number of stages, which comprises drying, volatilization, combustion of fixed carbon, and burnout of char of the solids, whereas a secondary process includes the complete combustion of the products generated during the primary process, i.e., vapor, gases, and particulates driven off.

Pyrolysis is the degradation of organic matter without oxygen at 400–800 °C, which can be used for any kinds of solid waste and are easy to be adapted to any changes in their composition. Gasification is the partial oxidation at 800–1600 °C. Gasification can be described as the thermo chemical conversion of a solid or liquid carbon-based waste material (feedstock) into a combustible gaseous product (combustible gas) in the presence of suitable gasification agent. It converts solid wastes into combustible gases, integrated into other technology sources (Paul and Helmet, 2015).

In thermochemical conversion, all types of waste materials, i.e., of the organic matter, biodegradable as well as non-biodegradable, produces the energy output. However, the amount of energy recovered is dependent on the efficiency of the selected process in SW management schemes; In other words, the efficiency of energy recovery is dependent on the rate of conversion of heat energy contained in fuel into usable energy. The two key factors influencing process efficiency are as follows: (a) electrical efficiency of the power generation technology and (b) amount of heat recovery [28]. The choice of technology such as incineration vs. gasification is an important determining factor for determining the process efficacy, and the degree of productive utilization of generated heat and electricity.

6.4.2 Biochemical Conversion

This is the decomposition of the organic waste of USW by microbial decomposition, mainly used when the waste is filled with biodegradable organic materials and moisture content. Anaerobic digestion degrades organic biowaste without oxygen that produces biogas and stabilizes the sludge. The sludge can be used as manure in agricultural fields. As reported in literature, the anaerobic digestion is more efficient as it can generate 2–4 times of the methane per tons of solid waste in just 3 weeks as compared to that produced through landfill approach in 6–7 years [35].

6.4.3 Mechanical Conversion

Sanitary landfilling is the regulated disposal of the waste on landfills for decreasing environmental impacts through the leachate method and biogas recovery. The degradation of organic matter in landfills produces landfill gas (LFG) by five different methods: aerobic degradation, fermentation, acetogenesis, methanogenesis, and oxidation [1, 6].

Although waste-to-energy technologies for solid waste management are developing nowadays, the inconsistent composition of solid waste, the complexities of the designing of the system, and specific social, economic, and environmental issues may limit the applicability of the waste-to-energy technologies [12]. To improve the efficacy of such technologies, there is a critical requirements of the analysis of composition of the solid wastes, and accordingly, a suitable preprocessing step should be included along with minimal impacts on environment. Overall, the overall process should be done in such as a way that the technologies should provide a solution to the solid waste management in a cost-effective and environmentally sustainable manner. Energy technologies may arise afterward. All these factors should be considered for the development of this technology.

6.5 Opportunities of Digitalization in Waste Sorting

Increasing population is increasing the human need in day-to-day life. Hence, there is advancement in science and technology to improve the lifestyle and fulfill the human need in a more efficient manner and in less time. As we all know that the twenty-first century is becoming a digital world, so many processes are being improved due to digitalization. This is not only improving human life in their daily life, but also has created revolution in industrial sector including the environmental sector. As a result of digitization, there is significant revolutionary changes in the waste management sector [35]. This is because the digitalization will empower any economy in recovering the economic gain and useful substances through efficient conversion of the waste materials. In addition, this will provide additional advantages that it minimized the amount of waste to be handled and raw materials, thereby reducing the adverse impacts on the environment and climate. The consequences have been felt in all developed economies.

Waste management processes are a complex managerial task that involves significant involvement of manpower which increases the expenses tremendously, thereby putting an economical pressure [36]. This created an urgent need of alternative technologies that may reduce the requirement of manpower. Digitalization may play a crucial role in minimizing such economic stress due to high manpower requirements. Moreover, it also increases the job opportunities in high-value sectors of the supply chain. One of such opportunities is waste sorting, which is associated with increased possibility of reuse and recycling of the waste [32, 33].

Several major manufacturers of commodities, such as electronics, are already using artificial intelligence-based image processing techniques aided by robotic sorters [35]. Alternative possibilities include using watermarks, quick-response codes, or other digitally readable identifiers on product labels. The advantage of using such technique assist the automated sorters by sending the required data on composition of waste material and the product setup, allowing high-value materials to be recovered more easily [2, 25]. Robotic sorters could also generate data about the materials they have sorted, allowing them to improve artificial intelligence or optimize following procedures. For example, these data streams may be used to identify trends in incoming garbage loads and to acquire the information about efficacy of the waste sorting in order to forecast how sorting lines should be set up. When these information are connected to other data, such as market prices of secondary raw material, the procedures to be employed may be modified as and when required. As illustrated in Fig. 6.4, various digital technologies which includes robotics, the IoTs, artificial intelligence, cloud computing, and data analytics can be employed to predict the influence on the efficiency of the industries in waste management in future (European Environmental Agency, 2021).

Recently, the digital technology has been widely explored in various stages of waste management including garbage collection [36]. An advancement in digital technologies has improved various stages of garbage collection, predominantly the logistics which involves the process of organizing, creating scheduled collection,

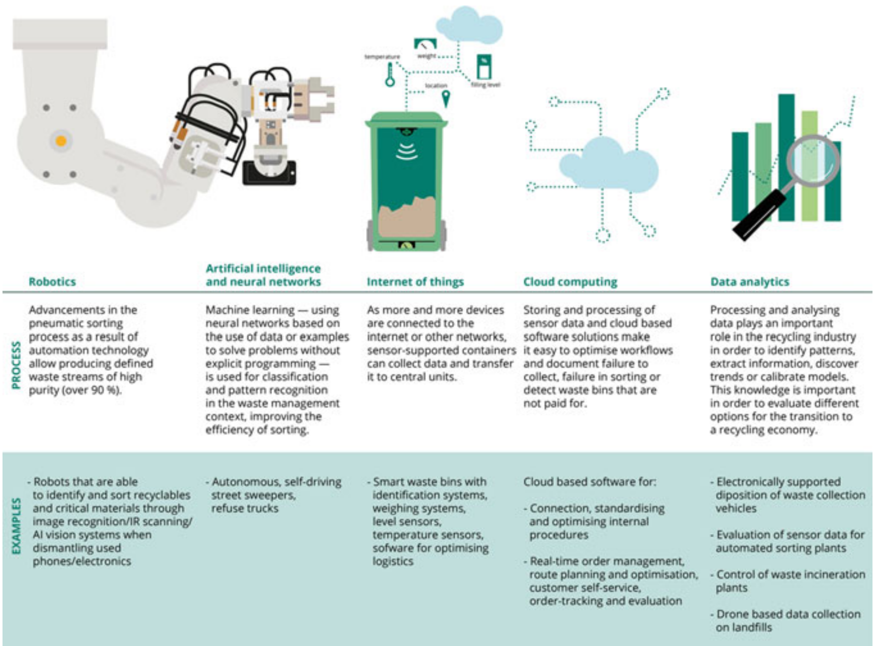

Fig. 6.4 Applications of digital technologies for waste sorting and management [38]

and demonstrating the tasks, persons, and vehicles for garbage collection. Using the digital technologies has enhanced the overall efficiency by storing the data, processing, analyzing, and optimizing the required information. The data can be monitored in real time for the garbage collection process, including the progress of the task or any incidents. The overall process starts becoming complicated in nature as more and more data is collected over time. The use of optimization algorithms may be helpful in defining and selecting the most suitable options for allocating various resources, such as manpower or vehicles in such cases. Hence, application of telematics plays a crucial role, which involves vehicle routing systems, navigation and use of vehicle tracking software, enterprise resource planning systems, and other associated digital technologies. The outcome of employing such technologies can be seen in terms of enhanced efficiency of the overall process.

The application of IoTs in improving the efficacy of waste management is another suitable example, which incorporates various applications, such as use of smart bins for waste collection at the site of waste generation and use of robotics for semi-autonomous trash collection vehicles [15, 35]. However, there is still a lot of scope of improvement to further enhance the efficiency of the garbage collection and linking them in the future, as per the demands of a circular economy. Hence, it must be flexible in adapting the new and emerging technologies rapidly to everchanging pattern of waste generation and waste management purposes, including the installation of required system and services to make the customized services better. The conventional garbage collection process involves paperwork, communication, and billing processes as their part. A transition from paper-based management systems toward digital systems on continuous basis will enhance the process efficiency and information flow. Use of digital identity tags for trash bins and waste containers, digital mode of order processing, invoicing, and payment can improve the efficacy. The digital user interfaces for communication with the customer and linking the garbage collection corporations to the appropriate governmental databases are also the part of digital technologies that can improve the overall efficacy. Such digital technologies can be exploited toward collection of the data related to waste generation/collection from the public working in documentation-related sectors. Subsequently, the collected data can be converted into valuable information by the data analytics. This might help in endorsing a circular economy by offering an “improved knowledge of the geographical and temporal patterns of trash creation” [39]. Moreover, the local governments may be provided with further information by collecting multiple single-data points than only providing cumulative values of the data.

6.5.1 Recent Trends of Artificial Intelligence Usage in Municipal Solid Waste Management

Due to various interrelated processes at work and the highly variable demographic and socioeconomic aspects affecting the complete waste management systems, the waste management processes have complex processes and non-linear features. Moreover, it is a challenging task to achieve good performance in solid waste management systems without threatening other health and environmental issues. Therefore, artificial intelligence approaches are being explored to determine their suitability in the solid waste management system sector [11–13, 21]. AI is concerned with the use of computer systems and programs to imitate human characteristics to solve the problem, gain knowledge, perceive, understand, find reasons, and awareness of their environment. Therefore, application of various AI models, such as the artificial neural network, expert system, genetic algorithm, and fuzzy logic, can solve the complex issues, create complicated maps, and anticipate consequences [19].

Recent trends suggest that there are six main AI application sectors in municipal solid waste management. Detection of levels in the waste bin, prediction of the waste characteristics, forecasting the process parameters, process output, vehicle routing, and approaches used for solid waste management are the key sectors where AI can be applicable. Detection of levels in the waste bin is linked with the monitoring the filling of waste bins, whereas prediction of the waste characteristic involves categorization of the waste, waste compression ratio, waste creation, patterns, or trends. The heating value and co-melting temperature of the waste comes under the projected process parameters. Similarly, simulation and optimization of biogas generation in the landfill and leachate creation over time comes under the process output forecast. The garbage collection route and frequency optimization problem is part of the vehicle routing problem. Finally, waste management planning includes the placement of waste facilities, the build-up of garbage, and unlawful dumping locations, as well as the financial and environmental implications of collection, transportation, treatment, and disposal. Evidently, there has been a recent surge in enthusiasm for AI research in solid waste management [23].

6.5.2 Machine Learning for Forecasting the Generation of Municipal Solid Wastes

Most of the applications of artificial intelligence toward solid waste management have focused on forecasting the characteristics of municipal solid waste. Predicting municipal solid waste generation is an application that has received the greatest attention in these investigations. In such applications, artificial neural networks are commonly used, followed by support vector machines. Spectral analysis, correlation analysis, response surface modeling, generalized linear modeling, gene expression programming, partial least squares, hybridized wavelet de-noising, Gaussian mixture models, hidden Markov models, Viterbi algorithms, and principal component analysis are all used in conjunction with the AI models [36–38]. For waste generation, several short-term and long-term forecasting periods are used. The rarity of research mimicking everyday waste generation is almost certainly a result of the unavailability of such data.

Various research studies have examined a broad variety of input variables impacting waste creation. They have also examined the categorization of waste materials for automated sorting systems that reduce the need for manual waste segregation. The bulk of these investigations employed artificial neural networks to classify various waste components. One such study employed hyperspectral imaging and multi-layer artificial neural networks to identify different varieties of plastics in e-waste [41]. The suggested technique identified these materials with an accuracy of 99%. Another group of researchers used deep convoluted neural networks to attempt to automate the waste sorting procedure [16]. In comparison with human sorting, the automated procedure significantly reduced the time required for garbage sorting and categorization. Similar to the previous example, deep convoluted neural networks were utilized to differentiate multiple kinds of paper and cardboard [36]. The model's mean accuracy varied between 61.9 and 77.5%; these low results were linked to the training database's small size comprising of only 24 images. Chu et al. employed convoluted neural networks to extract features and MLP to classify garbage into recyclable and non-recyclable components [44]. The hybrid technique achieved a maximum accuracy of 98.2%, which was almost 10% greater than the accuracy achieved using simply convoluted neural networks. Additionally, a few researchers evaluated the usefulness of other machine learning algorithms for garbage categorization [25, 45]. Singh et al. demonstrated that RF, Nu-, and C-LibSVM were all capable of classifying with an accuracy of better than 90%. On the other side, Naïve Bayes and closest neighbor algorithms scored badly, with accuracy rates of 44.8 and 84.8%, respectively. Only a few studies have been conducted to determine the influence of various characteristics on waste creation. Márquez et al. used data mining algorithms like cluster analysis and decision tree classifier to associate sociodemographic and behavioral characteristics with garbage creation [46]. The tree classifier performed admirably, with an error rate of as low as 3.6%. Another research employed data mining techniques to ascertain garbage generation patterns by home type and seasonal fluctuations [47]. Furthermore, decision tree has been used in conjunction with Quinlan's M5 method to anticipate the MSW compression ratio, a valuable tool for assessing settlement of the waste during municipal landfill design [48]. The model has been trained and validated using a variety of solid waste elements and properties, including dry density, moisture content, and biodegradable proportion. The model performed satisfactorily throughout the testing phase, with a correlation value of 0.92.

6.5.3 Smart Waste Management Using Artificial Intelligence

Smart waste management is the practice of proposing solutions to the current waste management problem using Internet, Smart Sensors, and Mobile Applications [10, 35, 38, 44]. Waste management, in general, can be broken down into several problems, such as waste segregation where we have to separate solid waste from the wet one, a task which when left to every individual sees minimal success and when given to an organization seems very difficult to overcome due to the overwhelming amount of waste that is created on a daily basis which will only increase with the increase in population. Some other problems are the collection of waste, when to collect them, the amount of manpower required, and the next obvious problem after collection is disposing of waste. Smart waste management tries to solve some of these problems using sensors, Internet, and continuous monitoring but there is only so much that can be done by this because there comes a point where human intelligence needs to intervene like sending a truck when a Smart Bin notifies that is has been filled or deciding the route for the truck, the manpower required, etc.

Artificial intelligence can play a big role in Smart Waste Management [13, 45]. Deep learning models for Image Recognition and Object Identification can be used to help segregate the waste inside a Smart Bin, or Predictive models that can predict changes in environment to see how carbon dioxide emissions will change and schedule a pickup [46, 47]. Fuzzy Logic Algorithm that can markup the route for the pickup truck reducing manpower and fuel consumption can also decide the destination of the dumping ground using sensors information provided by the ones fixed there and calculating which would be the most optimum for waste dumping at that given point of time [19, 20].

6.5.3.1 Smart Bins

The most logical problem to conquer would be waste segregation. And the point where we can tackle is right at the start of the waste management cycle that would be the bin where people dump their garbage. Many researches have been done to create a smart bin let us talk about one that particularly picked my interest, where the researchers have developed smart bin using Internet-based smart system [52], where they have created a Smart Bin (Figs. 6.5 and 6.6). In the smart bin, the camera module is associated with Raspberry Pi to catch the waste picture with the end goal of item location and recognizable proof. After the waste is distinguished, servo engines constrained by the Raspberry Pi will activate the opening and shutting of the top of the waste compartment. The kickoff of the cover permits waste to tumble from the waste location compartment into its particular waste compartment.

A radio-frequency identification (RFID) module is associated with the Raspberry Pi to distinguish approved staff having access cards. When approved faculty are distinguished, RFID module will activate Arduino Uno to open the electronic compartment. Correspondence of the RFID module comprises two sections, a RFID module that has a receiving wire liable for sending and getting a transmission through radio waves, and a detached RFID label that contains a receiving wire and incorporated circuit that stores the ID code and other data. Since the motivation behind the RFID module is to just permit approved staff to get to the receptacle using RFID labels, a rundown of distinguishing proof codes that accompany the RFID labels are encoded into the framework so the framework will possibly react when it experiences enlisted RFID labels. The framework reacts by opening the electronic compartment. Since the RFID module depends on a backscattered framework, the power sent

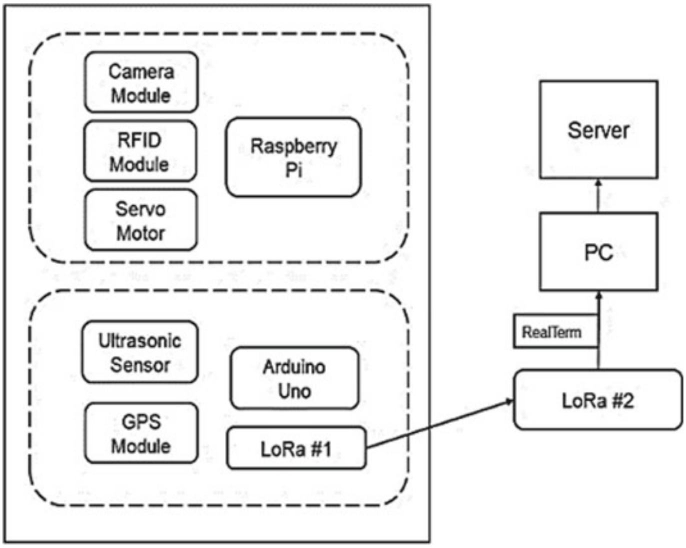

Fig. 6.5 Block diagram representing the overall system [52]

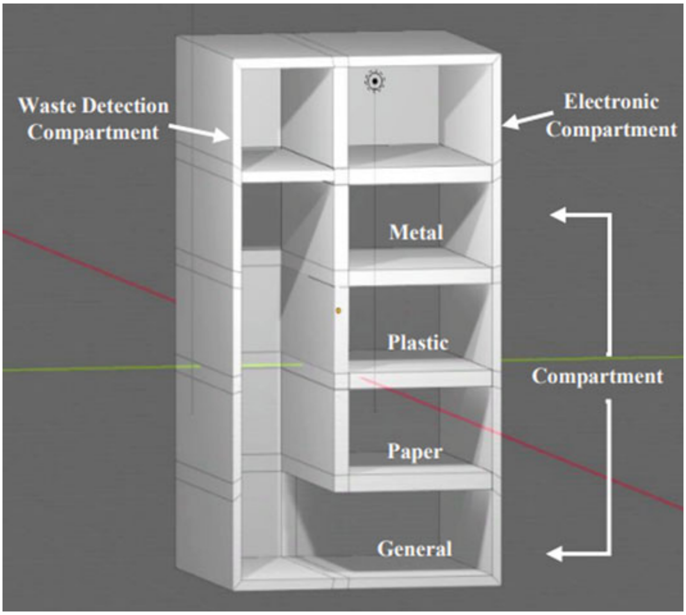

Fig. 6.6 3D model of smart bin [52]

between the RFID module and tag may fluctuate with its position, which eventually influences the exhibition of the RFID module. To settle this issue, we have arranged the RFID so it is effectively reachable and has no hindrances over the outer layer of the RFID module. The last option guarantees great transmission of force between both the RFID module and tag [15, 35, 47, 48].

The ultrasonic sensor is associated with Arduino Uno to screen the filling level of every one of the receptacle's waste compartments. It involves a plastic, metal, paper, and general waste compartment. The ultrasonic sensor utilizes sonar to quantify the time taken for the sign to go from the transmitter end to the recipient end, and the time contrast is utilized to compute the filling level of waste inside the container. A GPS module gives data on the area (scope, longitude) just as the constant of the canister from the satellite. The filling level, area, and constant container are gathered and moved through a LoRa module from the canister to the Waspmote passage, which is associated with the PC [15, 47].

Waste ID is performed utilizing the TensorFlow article discovery API running on the Raspberry Pi. This object identification API runs on a pre-prepared item location model, SSD MobileNetV2, which is lightweight and appropriate to run on low registering power gadgets like Raspberry Pi [54]. The engineering of MobileNetV2 depends on straight bottlenecks profundity distinguishable convolution with upset residuals, and it is an improvement over the past variant, MobileNetV1 [55]. Profundity distinct convolution requires less calculation by parting convolution into two separate layers, depth wise convolution and point wise convolution (Fig. 6.7).

Here, the ArticleNote button was provided to capture any note to the content that will be placed in the first page according to the author preference.

6.5.4 Vehicle Routing

The most logical problem to conquer would be waste segregation. And the point where we can tackle is right at the start of the waste management cycle that would be the bin where people dump their garbage. Vehicle Routing is another area that can be focused on using AI models and algorithms let us have a look at Assessment of waste characteristics and their impact on GIS vehicle collection route optimization using ANN waste forecasts [56].

Information of week-by-week gathered trash, fortnightly gathered single stream recyclables, waste structure, and number of families were gathered from Austin's Open Data Portal. Thickness of waste was determined in light of waste organization and explicit load of every material from a USEPA study (2016b). The following stage is an ANN time-series examination to figure out future recyclables and trash age paces of each sub-assortment region in the year 2023 (Fig. 6.8).

Various situations are considered with various recyclables and trash creations. The anticipated recyclables and trash age rates were utilized to process anticipated volume of waste in trucks. The anticipated waste volumes from the objective regions are inputs into the GIS–Network Analysis apparatus (ArcGIS—adaptation 10.5.1) to

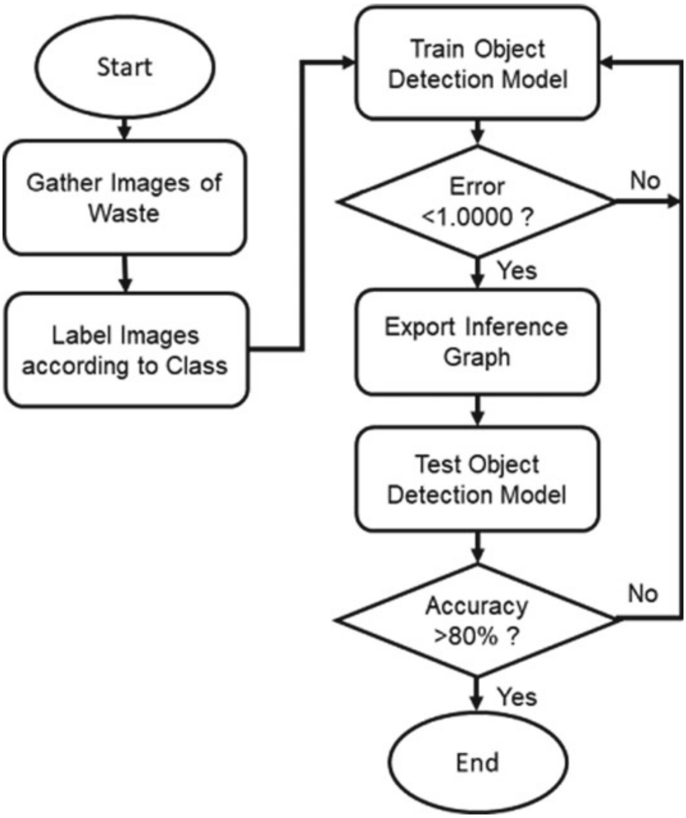

Fig. 6.7 Flowchart of obtaining Object Detection Model [52]

foster ideal truck courses. It is expected that during the 5-year gauging period there will be no significant changes in the road and street network setup and the number and area of assortment focuses (family) are comparative. A sum of 36 situations are created to analyze the impacts of changing waste attributes on ideal truck courses with negligible travel distance [20, 51].

ANN time series and GIS–Network Analysis–VRP models were joined to look at what waste creation and the mass of waste means for truck courses just as air outflows from the trucks. The ANN model showed better outcomes when waste info information had less outrageous qualities for both recyclables and trash. The coordination of ANN expectation model with GIS streamlining detailed in this study uncovers the interrelationships between waste organization and GIS enhanced courses and permits WMS chiefs to better reaction to the progressions in waste synthesis [20, 51].

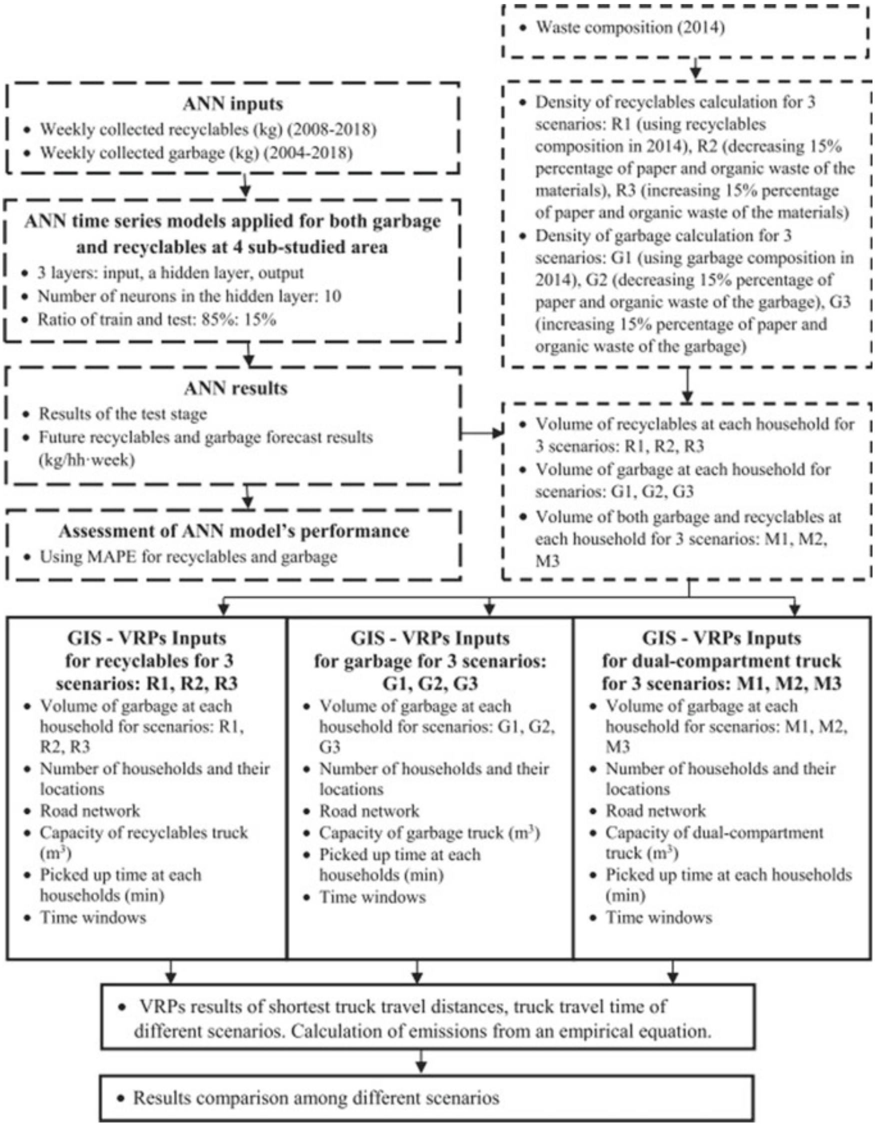

Fig. 6.8 Methodology flowchart for vehicle routing [56]

6.5.5 By-Product Utilization

Being able to predict useful by-products of garbage and the harmful ones and the quantity in which they are used is big part of waste management and AI can help us with this too. Combining fuzzy logic (FL) and artificial neural networks (ANN) in modeling landfill gas production is a great paper that has worked on this exact field

[23]. The work utilizes a cross breed ANN-FL model that utilizes information-based FL to depict the interaction subjectively and carries out the learning calculation of ANN to enhance model boundaries. The model was created to recreate and anticipate the landfill gas creation at a given time in view of functional boundaries. The exploratory information utilized were ordered from laboratory-scale try that elaborate different working situations. The created model was approved and genuinely examined utilizing F-test, straight relapse among real and anticipated information, and mean squared error measures. Generally, the reenacted landfill gas creation rates showed sensible concurrence with genuine information [23].

6.6 Influential Factors for Smart Waste Prediction

Waste prediction is a very important field of study which helps us to predict and prepare the required steps for management of upcoming bulk of garbage being created at an unprecedented rate but to predict this we need to pinpoint the factors that contribute to water generation. There are some common factors that determine the amount of waste generated and disposed. Below are the factors that influence waste generation:

1. Institutional Factors
2. Social conditions
3. Financial and Economic Factors
4. Technical Factors
5. Geographic Conditions
6. Environmental Conditions.

6.6.1 Institutional Factors

There are certain rules and regulations for proper solid waste management. These laws and policy come under institutional factors that give consent to the Government for effective implementation of an Integrated Solid Waste Management. The possible steps to be taken for effective waste management involve launching a national and/or local policy and permit laws on SWM standards and practices, identifying the roles and responsibilities for each level of government and ensuring that the authority and resources for the implementation of an ISWM plan are provided with the local governments.

6.6.2 Social Conditions

Social conditions dictate how people manage their wastes, when their culture for example has festivals how much waste is created during them and what kind of waste is being created. Social conditions also tell us to what extents rule governing waste management are followed (people littering on road, people segregating their waste).

6.6.3 Financial and Economic Factors

The next factor that influences the waste predictions is the funds that need to be used to dispose the waste. More fund equals more waste disposal equals less waste generation. Economic factors affecting solid waste management system should be differentiated from the financial factors. It is because the economic factors include the financial turnout of the integrated solid waste management (IWSM) plans, for instance, the creation of jobs creation, improvement of public trade and tourism, political gain, and so on. The local government must determine the requirements of the initial capital investment and operating, and maintenance costs associated with each activity conducted for waste management in long term. Furthermore, the ability of people and their willingness to pay for the services and to determine the efficacy of job creation for the activities based on handling waste are the additional factors that needs to be taken into consideration.

6.6.4 Technical Factors

The technical factors include finding the requirements of equipment and the required facilities for an effective execution of the ISWM plan and determining the locations where these equipment and facilities will be kept; however, it will depend on geological factors, distances used for transportation, and forecast of waste generation.

6.6.5 Environmental Factors

Each stage of the ISWM plan significantly affects the natural resources, human health, and the environment. One must consider the environmental cost of these activities, for instance, landfilling or combustion of waste materials and attempt should be made to reduce their impact on public health and environment. Therefore, there should be an established practices to validate the groundwater and drinking water protection and the local authority should examine the compliance with the national standards assuring the minimum impacts on the human health.

6.6.6 Geographic Conditions

The area of the land, the population, and the location play a great role in predicting how much waste will be generated. The climate of the land will also determine how the waste needs to be disposed of and thus in turn affecting the financial resources required.

6.7 Conclusion

Generation of waste is increasing day by day with increasing population and urbanization. These wastes can be categorized into different categories, hazardous and non-hazardous waste. Hazardous wastes are particularly toxic and may pose severe adverse impacts on human, animal, and environmental health. Waste such as e-waste, Plastic waste, and Metal waste can cause a significant risk to the ecosystem if they are not managed properly. The most logical problem to conquer such issues would be waste segregation where we can tackle right at the start of the waste management cycle that would be the bin where people dump their garbage. Artificial intelligence and machine learning can be employed for smart waste management. Deep learning models for Image Recognition and Object Identification can be used to help segregate the waste inside a Smart Bin, or Predictive models that can predict changes in environment to see how carbon dioxide emissions will change and schedule a pickup. Fuzzy Logic Algorithm that can markup the route for the pickup truck reducing manpower and fuel consumption can also decide the destination of the dumping ground using sensors information provided by the ones fixed there and calculating which would be the most optimum for waste dumping at that given point of time. Such automated segregation and monitoring system implementation in the bin significantly decrease the operating cost and improve the overall waste management system. Furthermore, an automated routing system can be created to find and determine the shortest path to the bin for the purpose of maintenance. Thus, the convention solid waste management system can be enhanced and risk to the society due to waste exposure, thereby providing a greener and healthier life.

References

1. Kenny, C., & Priyadarshini, A. (2021). Review of current healthcare waste management methods and their effect on global health. *Healthcare*, *9*(3).

2. Kumar, S., et al. (2017) Challenges and opportunities associated with waste management in India. *Royal Society Open Science*, *4*(3).
3. Ferronato, N., & Torretta, V. (2019). Waste mismanagement in developing countries: A review of global issues. *International Journal of Environmental Research and Public Health*, 16(6)
4. Kaza, S., Yao, L., Bhada-Tata, P., & Van Woerden, F. (2018). *What a waste 2.0*. International Bank for Reconstruction and Development/The World Bank.
5. The World Bank. (2019). Solid waste management.
6. Shekdar, A. V. (2009). Sustainable solid waste management: An integrated approach for Asian countries. *Waste Management, 29*(4), 1438–1448.
7. EPA. (2021). Sustainable materials management: Non-hazardous materials and waste management hierarchy.
8. Abdel-Shafy, H. I., & Mansour, M. S. M. (2018). Solid waste issue: Sources, composition, disposal, recycling, and valorization. *Egyptian Journal of Petroleum, 27*(4), 1275–1290.
9. Vinti, G., et al. (2021). Municipal solid waste management and adverse health outcomes: A systematic review. *International Journal of Environmental Research and Public Health, 18*(8), 1–26.
10. Dutta, S., Upadhyay, V. P., & Sridharan, U. (2006). Environmental management of industrial hazardous wastes in India. *Journal of Environmental Science and Engineering, 48*(2), 143–150.
11. Kinnaman, T. C. (2009). The economics of municipal solid waste management. *Waste Management, 29*(10), 2615–2617.
12. Foster, W., et al. (2021). Waste-to-energy conversion technologies in the UK: Processes and barriers—A review. *Renewable and Sustainable Energy Reviews*, *135*(X), 1–3.
13. Jude, A. B., et al. (2021). An artificial intelligence based predictive approach for smart waste management. *Wireless Personal Communication*, 0123456789.
14. Bijos, J. C. B. F., Queiroz, L. M., Zanta, V. M., & Oliveira-Esquerre, K. P. (2021). Towards artificial intelligence in Urban waste management: An early prospect for Latin America. *IOP Conference Series Materials Science Engineering, 1196*(1), 012030.
15. Abdallah, M., Abu Talib, M., Feroz, S., Nasir, Q., Abdalla, H., & Mahfood, B. (2020). Artificial intelligence applications in solid waste management: A systematic research review. *Waste Management*, *109*, 231–246.
16. Sudha, S., Vidhyalakshmi, M., Pavithra, K., Sangeetha, K., & Swaathi, V. (2016). An automatic classification method for environment: Friendly waste segregation using deep learning. *Processing—2016 IEEE international conference technology innovation ICT agriculture rural development*, (pp 65–70). *TIAR 2016*, no. Tiar.
17. Wilts, H., Garcia, B. R., Garlito, R. G., Gómez, L. S., & Prieto, E. G. (2021). Artificial intelligence in the sorting of municipalwaste as an enabler of the circular economy. *Resources, 10*(4), 1–9.
18. White, G., Cabrera, C., Palade, A., Li, F., & Clarke, S. (2020). WasteNet: Waste classification at the edge for smart bins.
19. Yetilmezsoy, K., Ozkaya, B., & Cakmakci, M. (2011). Artificial intelligence-based prediction models. *Neural Network World, 3*(11), 193–218.
20. Ahmed, A. A. A., & Asadullah, A. (2020). Artificial intelligence and machine learning in waste management and recycling. *Engineering International, 8*(1), 43–52.
21. Jalili Ghazi Zade, M., & Noori, R. (2008). Prediction of municipal solid waste generation by use of artificial neural network: A case study of Mashhad. *International Journal Environment Research*, *2*(1), 13–22.
22. Kalogirou, S. A. (2003). Artificial intelligence for the modeling and control of combustion processes: A review. *Progress in Energy and Combustion Science, 29*(6), 515–566.
23. Abdallah, M., Warith, M., Narbaitz, R., Petriu, E., & Kennedy, K. (2011). Combining fuzzy logic and neural networks in modeling landfill gas production. *World Academic Science Engineering Technology, 78*(6), 559–565.
24. Vitorino de Souza Melaré, A., Montenegro González, S., Faceli, K., & Casadei, V. (2017). Technologies and decision support systems to aid solid-waste management: a systematic review. *Waste Management*, *59*, 567–584.

25. Singh, S., et al. (2017). Identifying uncollected garbage in urban areas using crowdsourcing and machine learning. In *IEEE international symposium on technologies for smart cities*, (pp 3–7).
26. Fazzo, L., et al. (2017). Hazardous waste and health impact: A systematic review of the scientific literature. *Environment Health A Global Access Science Source, 16*(1), 1–2.
27. WHO. (2018). Health-care waste. *WHO*, no. February, pp 1–6.
28. Begum, S., Rasul, M. G., & Akbar, D. (2012). An investigation on thermo chemical conversions of solidwaste for energy recovery. *World Academic Science Engineering Technology International Journal Environment Ecology Engineering, 62*(2), 624–630.
29. Manzoor, J., & Sharma, M. (2019). Impact of biomedical waste on environment and human health. *Environment Claims Journal, 31*(4), 311–334.
30. International Atomic Energy Agency. (2011). Radioactive waste management objectives. *IAEA Nuclear Energy Series, 18*(5), 32.
31. Bulucea, C. A., Mastorakis, N. E., Bulucea, C. A., Boteanu, N., & Stinga, A. (2010). Systemic approach of hazardous and non-hazardous waste management. *4th WSEAS international conference energy planning, energy saving, environment education EPESE'10, 4th WSEAS international conference renewable energy sources, RES '10*, no. November, (pp. 181–189).
32. Asnani, P. U. (2008). India infrastructure report: Ch. 8 solid waste management. *India Infrastructure Report, 3*(2005), 160–189.
33. Hoorweg, D., & Bhada-Tata, P. (2012). What a waste: A global review of solid waste management. *World Bank*, 29–43.
34. Rahman, M. W., Islam, R., Hasan, A., Bithi, N. I., Hasan, M. M., & Rahman, M. M. (2020). Intelligent waste management system using deep learning with IoT. *Journal of King Saud University—Computer and Information Sciences.*
35. Wilts, H., Garcia, B. R., Garlito, R. G., Gómez, L. S., & Prieto, E. G. (2021). Artificial intelligence in the sorting of municipal waste as an enabler of the circular economy. *Resources, 10*(4).
36. Vrancken, C., Longhurst, P., & Wagland, S. (2019). Deep learning in material recovery: Development of method to create training database. *Expert Systems with Applications, 125*, 268–280.
37. Singh, S. et al. (2017). Identifying uncollected garbage in urban areas using crowdsourcing and machine learning. *TENSYMP 2017—IEEE international symposium technology smart cities*, (pp. 3–7).
38. European Environmental Agency. (2021). Digital technologies will deliver more efficient waste management in Europe. *Briefing No 26/2020*, (pp. 1–6).
39. Law, H. J., & Ross, D. E. (2019). International solid waste association's 'closing dumpsites' initiative: Status of progress. *Waste Management and Research, 37*(6), 565–568.
40. Countries, G. C., Mt, M., & Mt, M. (2021). Smart waste management using AI and ML. *Telecom Review*, (4), 1–4.
41. Tehrani, A. & Karbasi, H. (2018). A novel integration of hyper-spectral imaging and neural networks to process waste electrical and electronic plastics. *2017 IEEE conference technology sustainability sustech 2017*, (vol. 2018-Janua, pp. 1–5).
42. Gupta, P. K., Shree, V., Hiremath, L., & Rajendran, S. (2019). The use of modern technology in smart waste management and recycling: Artificial intelligence and machine learning. *Studies Computer Intelligence, 823*(4), 173–188.
43. Albadr, M. A., Tiun, S., Ayob, M., & Al-Dhief, F. (2020). Genetic algorithm based on natural selection theory for optimization problems. *Symmetry (Basel), 12*(11), 1–31.
44. Chu, Y., Huang, C., Xie, X., Tan, B., Kamal, S., & Xiong, X. (2018). Multilayer hybrid deep-learning method for waste classification and recycling. *Computational Intelligence and Neuroscience,* 2018.
45. Kuritcyn, P., Anding, K., Linß, E., & Latyev, S. M. (2015). Increasing the safety in recycling of construction and demolition waste by using supervised machine learning. *Journal of Physics: Conference Series*, *588*(1).

46. Márquez, M. Y., Ojeda, S., & Hidalgo, H. (2008). Identification of behavior patterns in household solid waste generation in Mexicali's city: Study case. *Resources, Conservation and Recycling, 52*(11), 1299–1306.
47. Korhonen, P., & Kaila, J. (2015). Waste container weighing data processing to create reliable information of household waste generation. *Waste Management, 39*, 15–25.
48. Heshmati, R. A. A., Mokhtari, M., & Shakiba Rad, S. (2014). Prediction of the compression ratio for municipal solid waste using decision tree. *Waste Management and Research, 32*(1), 64–69.
49. Kodali, R. K., & Gorantla, V. S. K. (2018). Smart solid waste management. *Processing 2017 3rd international conference applications theornational computer communication technology iCATccT 2017*, pp. 200–204.
50. Jenny, H., Wang, Y., Alonso, E. G., & Minguez, R. (2020). Using artificial intelligence for smart water management systems. 5(143).
51. Gupta, T. et al. (2021). A deep learning approach based hardware solution to categorise garbage in environment. *Complex and Intelligent Systems.*
52. Sheng, T. J., et al. (2020). An internet of things based smart waste management system using LoRa and tensorflow deep learning model. *IEEE Access, 8*, 148793–148811.
53. Gupta, P. K., Shree, V., Hiremath, L., & Rajendran, S. (2019). *The use of modern technology in smart waste management and recycling: Artificial intelligence and machine learning*, (vol. 823). Springer International Publishing.
54. Sandler, M., Howard, A., Zhu, M., Zhmoginov, A., & Chen, L. C. (2018). MobileNetV2: Inverted residuals and linear bottlenecks. *Processing IEEE computer society conference computer visual pattern recognition*, (pp. 4510–4520).
55. Howard, A. G. et al. (2017). MobileNets: Efficient convolutional neural networks for mobile vision applications.
56. Vu, H. L., Bolingbroke, D., Ng, K. T. W., & Fallah, B. (2019). Assessment of waste characteristics and their impact on GIS vehicle collection route optimization using ANN waste forecasts. *Waste Management, 88*(2019), 118–130.