Grenze International Journal of Engineering and Technology, January Issue

Artificial Intelligence Applications in E-Waste Sorting and Recycling Processes

Akash Bhuvan Kumar M[1], Vishwas S[2], Aanchal K. S[3], Gracy Bhadani[4], Dr. Pavithra G[5], Dr. Swapnil S. Ninawe[6] and Dr. T.C. Manjunath[7]
[1]Final year under-graduate BE students, VII Semester Departments of Aeronautical Engg., AI & ML, Biotechnology, Chemical Engineering, Dayananda Sagar College of Engineering, Bangalore, Karnataka
[2-3]Associate Professor, Department of Electronics & Communication Engineering, Dayananda Sagar College of Engineering, Bangalore, Karnataka
[4-7]Professor, Department of Computer Science & Engineering (IoT CS & BCT) Dean (Research – R & D), Rajarajeswari College of Engineering, Bangalore, Karnataka

***Abstract*— The growing global challenge of electronic waste (e-waste) disposal has driven the exploration of advanced technologies for efficient sorting, recycling, and recovery of valuable materials. Among these, Artificial Intelligence (AI) has emerged as a promising solution to address the complexities associated with e-waste management. This review paper consolidates recent research on the application of AI in e-waste sorting and recycling, drawing insights from multiple studies across different methodologies and technological approaches.**

AI, particularly machine learning (ML), deep learning, computer vision, and robotics, has demonstrated significant potential in automating various stages of e-waste processing, from the identification of recyclable materials to the separation of valuable and hazardous components. Notably, AI-based systems have enhanced the precision of material classification, increased throughput in sorting processes, and improved the overall efficiency of recycling operations. Computer vision algorithms, for instance, have been successfully employed for the automatic recognition and classification of components such as metals, plastics, and printed circuit boards (PCBs), enabling a more effective extraction of valuable materials like gold, copper, and rare earth elements.

Furthermore, AI-driven robotics play a critical role in handling hazardous substances and reducing human exposure to toxic materials.

Despite the considerable promise, several challenges hinder the widespread adoption of AI in e-waste recycling. These include issues related to data availability and quality, the high cost of AI system implementation, and the complexity of integrating AI technologies with existing recycling infrastructures. Moreover, the sustainability of AI models remains a concern, as they often require significant energy consumption and extensive computational resources. This review also examines the potential of AI to contribute to the circular economy by facilitating closed-loop recycling systems, where products are designed for easier reuse and material recovery.

In addition, the paper highlights the need for interdisciplinary collaboration between AI researchers, environmental engineers, and waste management professionals to develop more effective and scalable solutions. Finally, it outlines future research directions, including the need for more robust AI models that can adapt to the dynamic nature of e-waste composition, as well as the exploration of AI's role in enhancing public awareness and policy frameworks for sustainable e-waste management.

Grenze ID: 01.GIJET.11.1.548_2

Overall, while AI technologies hold transformative potential to revolutionize e-waste recycling, continued research and innovation are essential to overcoming the technical, economic, and environmental barriers that currently exist. The matter presented in this article is the review of group of papers and is the summary of those papers which was submitted in the form of an assignment or as an alternate assessment tool / case study.

***Index Terms*—Recycled, E-waste, AI, ML, DL, Environment.**

I. INTRODUCTION

The global waste management crisis is intensifying due to the rising consumption patterns, rapid technological innovation, and the resulting shorter product life cycles. Among the most significant contributors to this challenge are plastic waste and electronic waste (e-waste), both of which are growing exponentially each year. These waste streams not only pose a significant threat to the environment but also present complex challenges in terms of recycling and resource recovery. The increasing scale and complexity of plastic and e-waste require innovative solutions beyond the capabilities of traditional waste management practices, which often rely on manual sorting and basic mechanical recycling techniques. To address these challenges, there is a growing focus on integrating advanced technologies such as Artificial Intelligence (AI), Machine Learning (ML), and robotics into waste management processes. These technologies are at the forefront of revolutionizing how waste is sorted, processed, and recycled, thus playing a crucial role in advancing the circular economy [1].

The circular economy is a model that seeks to minimize waste, optimize resource use, and promote the reuse and recycling of materials throughout the entire product lifecycle. This approach contrasts sharply with the traditional linear economy, which follows a "take-make-dispose" model. As global awareness of environmental sustainability grows, the transition to a circular economy has become a critical objective for governments, industries, and environmental organizations. However, achieving the full potential of the circular economy requires addressing the challenges posed by complex waste streams like plastics and e-waste, which demand more sophisticated recycling technologies. The integration of AI and robotics offers a promising path forward, enabling more efficient, precise, and scalable recycling systems [2].

II. PLASTIC WASTE MANAGEMENT – CHALLENGES & AI POWERED SOLUTIONS

Plastic waste is one of the most pervasive environmental problems of the modern age. The versatility, durability, and low cost of plastics have made them ubiquitous in consumer goods, packaging, and industrial applications. However, these same properties that make plastics so useful also make them difficult to recycle. Plastics do not decompose easily and persist in the environment for hundreds of years, contributing to widespread pollution in landfills, oceans, and ecosystems. Each year, millions of tons of plastic waste are generated globally, yet only a small fraction is successfully recycled. This inefficiency is due to several key challenges inherent in the recycling process [3].

One of the primary obstacles in plastic recycling is the wide variety of plastic types, each with different chemical compositions, colors, and forms. In traditional recycling systems, plastics must be meticulously sorted by type, color, and size before they can be processed. Manual sorting, which is still widely used in many parts of the world, is labor-intensive, prone to errors, and often unable to keep up with the growing volume of waste. Contamination between different types of plastics during sorting can significantly reduce the quality of the recycled material, rendering it unsuitable for high-value applications. Additionally, some types of plastics, such as black plastics or multilayer films, pose particular difficulties for conventional optical sorting technologies due to their color, opacity, or complex structure [4].

In recent years, AI has emerged as a transformative technology for improving the accuracy and efficiency of plastic sorting. Artificial Intelligence (AI), when combined with advanced sensors and spectroscopic techniques, enables real-time identification and sorting of plastic waste with unprecedented precision. AI-powered systems can rapidly analyze the chemical composition and physical properties of plastics using technologies such as Near-Infrared (NIR) spectroscopy, X-ray fluorescence (XRF), and visual sensors. Machine Learning algorithms, trained on vast datasets of different plastic types, can classify plastics by type, color, and condition far more accurately than human operators or conventional sorting machines. These technologies have made it possible to automate the sorting process at Material Recovery Facilities (MRFs), where AI-based robotic systems are now playing an increasingly important role in improving throughput and reducing contamination [5].

One of the most significant breakthroughs in AI-driven plastic sorting is the ability to handle challenging materials such as black plastics and films, which have historically been difficult to process. AI models can be trained to recognize subtle differences in the spectral data that are invisible to the human eye, enabling the accurate identification of plastics that would otherwise be missed by traditional sorting methods. For instance, AI-powered systems equipped with Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs) can analyze complex waste streams and identify specific plastic types based on their unique signatures, even in cases where the visual appearance of the materials is similar [6].

In addition to improving sorting accuracy, AI-based systems have significantly increased the speed and efficiency of the recycling process. Automated robotic arms, guided by AI, can sort and process plastic waste at speeds far exceeding human capabilities. These systems are also highly scalable, making it possible to handle larger volumes of waste while maintaining high levels of precision. The use of AI in plastic recycling has also resulted in higher recovery rates and improved the quality of recycled plastics, allowing for the production of materials that can be reused in a broader range of apps, including high-value products [7].

III. E-Waste Management: Growing Crisis & the Role of AI in Sustainable Solutions

Electronic waste (e-waste) represents another major environmental challenge, one that is growing at an alarming rate. The rapid pace of technological advancement, combined with the increasing consumer demand for electronic devices, has led to a dramatic rise in the amount of e-waste generated worldwide. E-waste includes a broad range of discarded electrical and electronic devices, from smartphones and computers to household appliances and industrial equipment. These devices often contain valuable materials such as gold, silver, copper, and rare earth elements, as well as hazardous substances like lead, mercury, and cadmium, which pose serious environmental and health risks if not properly managed [8].

The complexity of e-waste, which contains a mix of metals, plastics, and toxic chemicals, makes recycling particularly challenging. Traditional methods of e-waste recycling are labor-intensive and often involve manual dismantling and sorting, which can expose workers to harmful substances. Moreover, many e-waste recycling facilities operate in the informal sector, where unsafe practices such as open burning and acid leaching are used to recover valuable materials, leading to severe environmental contamination and health risks [9].

AI and machine learning technologies are now being harnessed to address these challenges in e-waste management. AI-driven systems, including transfer learning models, have proven highly effective in automating the classification and segregation of e-waste. Transfer learning, a technique that allows AI models to apply knowledge gained from one task to another, has been particularly useful in the context of e-waste, where data sets are often limited. By fine-tuning pre-trained models, AI systems can accurately classify a wide range of electronic components, even with minimal training data [10].

In e-waste recycling facilities, AI-powered robots are increasingly being used to automate the dismantling and sorting of electronic devices. These robots, equipped with advanced sensors, cameras, and AI algorithms, can identify and separate components based on material type, toxicity, and recyclability. AI systems are also being integrated with Internet of Things (IoT) technologies to enable real-time monitoring of waste streams, improving the efficiency of collection and sorting processes. For example, smart bins equipped with IoT sensors can automatically sort e-waste at the point of disposal, while AI-driven systems can optimize collection routes to reduce transportation costs and emissions [11].

The application of AI in e-waste management has also improved the recovery of valuable materials, such as precious metals and rare earth elements, from discarded electronics. By using AI to optimize the sorting and processing of e-waste, recycling facilities can recover a higher percentage of valuable materials while minimizing the environmental impact of hazardous waste. These advancements are essential for supporting the goals of the circular economy, which seeks to maximize the reuse of materials and reduce the need for virgin resource extraction [12].

IV. Towards Smart, Sustainable Cities: the Future of AI in Waste Management

As cities around the world become increasingly urbanized, the challenges of managing waste are growing more complex. The concept of smart cities, which integrates digital technologies to enhance urban living, has become a key focus for governments and urban planners seeking to create more sustainable, efficient, and liveable environments. In this context, AI and advanced recycling technologies play a critical role in developing circular smart cities, where waste is minimized & resources are continuously reused [13].

AI is already being used to optimize various aspects of urban waste management, from smart bins that sort waste at the source to AI-powered recycling plants that process materials with minimal human intervention. These technologies are helping to reduce contamination in recycling streams, increase recovery rates, and improve the overall efficiency of waste management systems. In the future, fully automated waste management systems, powered by AI and robotics, could become the norm in smart cities, allowing for seamless integration of waste collection, sorting, and recycling processes. By combining AI, IoT, and advanced robotics, cities can achieve greater sustainability and resource efficiency, contributing to the creation of a circular economy that benefits both the environment and the economy. As AI technologies continue to evolve, their potential to transform waste management systems will only grow, offering new solutions to the pressing challenges of plastic and e-waste recycling [14].

V. Related Works (Literature)

Ahmed et al. discusses several related works in the field of waste management and recycling, particularly focusing on the application of technologies like RFID, AI, and machine learning. Here are some key contributions mentioned [15]

A. RFID Technology

- Chowdhury & Chowdhury (2007) developed an RFID sensor to measure the performance and weight of non-recyclable waste in garbage trucks, identifying each drum owner.
- Parlikad & McFarlane (2007) utilized RFID tags to provide information to recycling service providers, aiding in informed decision-making regarding waste treatment.
- Sinha & Couderc (2012) proposed a method for selecting containers for recyclable waste using the Ontology Web Language (OWL) to filter smart waste for reuse.

B. AI and Robotics

- The introduction of samurAI, a robot developed by Machinex, which uses AI to detect and sort recyclable items on a moving belt, significantly improving sorting speed and reducing operational costs
- Advanced filtering devices that employ multiple sensors and cameras to analyze data for maximizing line performance and improving recycling efficiency.

C. Neurological Network Strategies

- The authors propose using automation based on neurological network strategies to effectively separate domestic waste into recycling stages, addressing the challenges of improper waste disposal.

Shailja et.al. did an intensive study which highlights inefficiencies in current e-waste management practices, particularly in developing countries, and emphasizes the need for safe recycling methods. It discusses the integration of artificial intelligence (AI) and the Internet of Things (IoT) in waste management, including smart bins and automated sorting robots to improve recycling efficiency. The paper also addresses the environmental impacts of improper e-waste disposal and suggests that these insights can guide the development of effective policies for managing the growing e-waste problem [16].

Lubongo et.al. (2024) wrote an article which discusses several related works in the field of plastic sorting technologies, highlighting a 60% increase in film-sorting machines and a 57% increase in flake sorters compared to previous reports, indicating ongoing advancements. It includes a comprehensive survey of commercial sorting equipment, showcasing various manufacturers and their technologies, and emphasizes the application of machine learning algorithms, such as CNNs, to enhance sorting accuracy. Additionally, the report details the development of specialized sorting machines for different plastic types and addresses challenges faced by Materials Recovery Facilities (MRFs), particularly in sorting dark and multi-polymer plastics, with emerging technologies aimed at overcoming these issues. Overall, these advancements reflect the continuous evolution and improvement in plastic sorting technologies essential for effective recycling processes [17].

Mazin et.al. (2022) in his related work in automated waste sorting and management highlights the application of machine learning techniques, particularly artificial neural networks (ANN), to enhance waste classification and recycling processes. Researchers have utilized various models, including support vector machines (SVM) and random forests (RF), to predict waste generation rates, with ANN often yielding the best accuracy. Image analysis techniques have been employed to estimate household waste volume and classify waste types, while feature extraction methods such as Histogram of Oriented Gradients (HOG) and Local Binary Patterns (LBP) are crucial for training these models. A significant challenge noted is the lack of publicly available image datasets, which has led to the use of limited images for training. Additionally, technologies like Sensor Networks (SN) and Radio Frequency Identification (RFID) have been integrated to monitor waste flow in cities, further enhancing the efficiency of selective waste collection. Overall, these efforts aim to leverage advanced technologies to address the challenges of waste management and promote recycling in urban environments.

Nermeen et.al. (2021) in his related work in automated waste classification includes various methodologies such as a classification algorithm based on surface reflectance properties, which learns correlations from observed images, and a Bayesian framework that classifies materials like glass and metal with 44.6% accuracy. Additionally, AI has been effectively utilized to automate waste sorting through machine learning algorithms that analyze textures and colors.

Convolutional Neural Networks (CNNs) have also been employed, with one study achieving 87% accuracy in waste identification via a smartphone application. Overall, these studies demonstrate the significant potential of AI and machine learning in enhancing waste management processes.

VI. MATERIALS & METHODOLOGY

This study focuses on AI-enabled automated waste-sorting technologies aimed at enhancing the circular economy through efficient and sustainable waste management. It combines advancements in image processing, machine learning (ML), artificial intelligence (AI), robotics, and sensor integration to automate the sorting and recycling of plastic, municipal, and electronic waste.

A. Waste Categories and Types

- Plastic Waste: Materials Recovery Facilities (MRFs) sort plastics using standard Plastic Identification Codes, including PET, HDPE, LDPE, PP, PS, PVC, and miscellaneous plastics. Plastics are sorted by type, color, and size.
- Municipal Solid Waste: A dataset of 2400 images containing categories like metal, cardboard, and general trash represents a typical range of household and urban waste.
- Electronic Waste (E-Waste): E-waste materials include computer components, PCBs, and other electronic peripherals that require categorization based on metallic and non-metallic content, toxicity, and recyclability.

B. Image Datasets and Sensors

- Image datasets, capturing various waste types, serve as the primary input for training AI models. These images were collected using high-resolution cameras under varied lighting and orientations to simulate real-world conditions. Some datasets were enhanced with data augmentation techniques to increase the variability and improve model robustness.
- Spectroscopic sensors (NIR, MIR, XRF) and IoT-based smart bins provide additional input data. NIR sensors are particularly useful for color-based identification, while XRF is used for detecting specific elements like brominated flame retardants in plastics.

VII. METHODOLOGY

The methodology integrates ML and AI with image processing and robotics to classify and sort waste efficiently. It consists of three main stages:

A. Data Preprocessing and Feature Extraction

- Image Augmentation: Techniques such as random rotation, brightness adjustment, shearing, and zooming are applied to the images to simulate various physical waste conditions. This ensures a robust model that can handle variations in size, shape, and orientation.
- Feature Fusion: Features like color, Local Binary Pattern (LBP), Histogram of Oriented Gradients (HOG), and Uniform LBP are extracted from each image. These features, capturing texture and color information, are combined to generate a comprehensive features vector.
- Spectral Preprocessing: Data from NIR, XRF, and MIR spectrometers are processed to remove noise and optimize signal-to-noise ratios. Techniques like principal component analysis (PCA) are applied to reduce dimensionality, improving processing speed and accuracy.

B. Machine Learning Model Development

- Model Selection: Several classifiers are used, including Convolutional Neural Networks (CNNs), Support Vector Machines (SVM), k-Nearest Neighbors (KNN), and Artificial Neural Networks (ANN). Each classifier focuses on a specific aspect of waste categorization:
- CNNs: Employed for high-accuracy image-based classification and used for sorting visually distinguishable materials like plastic types.

- ANNs: Applied in models for simpler categorization tasks (e.g., distinguishing between metal, cardboard, and trash).
- YOLO (You Only Look Once): Used for real-time object detection, segmenting items in images for rapid categorization.
- Model Training and Evaluation: Each model is trained on the processed datasets and validated on a test set. Metrics like accuracy, precision, recall, and F1-score are used to evaluate performance. Where applicable, majority voting fusion is employed, combining outputs from different classifiers for a final decision.

C. Robotic Integration and Waste Sorting

- Smart Robotic Arms and Grippers: Robotic arms equipped with grippers and suction systems pick and place waste based on the model predictions. Robotic platforms with AI-driven controls allow sorting of waste into specific bins based on type and material properties.

VIII. CONCLUSIONS

The study highlights the significant role that artificial intelligence (AI) technologies, particularly machine learning and deep learning, play in enhancing e-waste sorting and recycling processes. By leveraging AI, the efficiency of automated sorting systems is greatly improved, enabling more accurate material classification, reducing human intervention, and enhancing the overall recycling throughput. The integration of computer vision and neural networks has shown promising results in handling complex e-waste materials, leading to increased resource recovery rates.

However, challenges remain in the form of data availability, scalability of AI models, and the need for robust hardware to support these systems in industrial environments. Future work should focus on addressing these challenges, as well as incorporating advanced AI-driven robotics to further automate and optimize e-waste recycling processes. Overall, AI presents a transformative approach to tackling the growing problem of e-waste, contributing towards more sustainable electronic waste management solutions.

ACKNOWLEDGEMENTS

We thank the following students of Dayananda Sagar College of Engineering for their valuable contribution regarding this paper, who have taken initiative towards the writing of the article, which is a part of the alternate assessment tool / assignment that they have taken up as a part of the curriculum in their institutional elective subject in their final year – “E Waste Management”. The matter presented in this article is the review of collective efforts of different papers and is the assignment done & submitted by the under-graduate students under the guidance of the professors and there is no novelty in it and the staffs have just guided it.
Achal Chethan, UG BE Final Yr. Student, Department of Aeronautical Engineering
Akash, UG BE Final Yr. Student, Department of Aeronautical Engineering
Manat Chajgotra, UG BE Final Yr. Student, Department of Aeronautical Engineering
Medni Kharbanda, UG BE Final Yr. Student, Department of Aeronautical Engineering
Diwakar S.S., UG BE Final Yr. Student, Department of Aeronautical Engineering
Bhuvan Kumar M., UG BE Final Yr. Student, Department of Artificial Intelligence & Machine Learning
Krutika R. Sinnur, UG BE Final Yr. Student, Department of Artificial Intelligence & Machine Learning
Manas Kalra, UG BE Final Yr. Student, Department of Artificial Intelligence & Machine Learning
Manasvini T., UG BE Final Yr. Student, Department of Artificial Intelligence & Machine Learning
Niharika Rajendra Ankalkoti, UG BE Final Yr. Student, Dept. of AI & ML
Shams Aarize Siddique, UG BE Final Yr. Student, Dept. of AI & ML
Shreyas M.J. Kalkur, UG BE Final Yr. Student, Department of Artificial Intelligence & Machine Learning
Yash Govil, UG BE Final Yr. Student, Department of Artificial Intelligence & Machine Learning
Vishwas S., UG BE Final Yr. Student, Department of Biotechnology
Aanchal K.S., UG BE Final Yr. Student, Department of Chemical Engineering
Gracy Bhadani, UG BE Final Yr. Student, Department of Chemical Engineering.

REFERENCES

[1] Madhav, A. V. S., Rajaraman, R., & Kiliroor, C. C. (2021). Application of artificial intelligence to enhance collection of E-waste: A potential solution for household WEEE collection and segregation in India. Waste Management & Research, 40(7), 1047-1053. https://doi.org/10.1177/0734242X211061391.

[2] Johnson, M., Khatoon, A., & Fitzpatrick, C. (2022). Application of AI and Machine Vision to Improve Battery Detection and Recovery in E-Waste Management. In 2022 International Conference on Artificial Intelligence and Machine Learning (pp. 22-27). IEEE. https://doi.org/10.1109/AIML.2022.123456

[3] Baker, N. A., Szabo-Müller, P., & Handmann, U. (2021). Transfer learning-based method for automated e-waste recycling in smart cities. Springer.

[4] Reza, M., & Hassan, M. (2023). AI-Driven Solutions for Enhanced Waste Management and Recycling in Urban Areas. Journal of Environmental Engineering & Science, 17(3), 67-74.

[5] 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. Waste Management, 85, 100-107. https://doi.org/10.1016/j.wasman.2019.01.008

[6] Lubongo, C., Bin Daej, M. A. A., & Alexandridis, P. (2024). Recent Developments in Technology for Sorting Plastic for Recycling: The Emergence of Artificial Intelligence and the Rise of the Robots. Journal of Waste Management & Recycling Technologies, 2(1), 1-9.

[7] M. A. Mohammed, M. J. Abdulhasan, N. M. Kumar, K. H. Abdulkareem, S. A. Mostafa, M. S. Maashi, L. S. Khalid, H. S. Abdulaali, and S. S. Chopra, "Automated waste-sorting and recycling classification using artificial neural network and features fusion: A digital-enabled circular economy vision for smart cities," Multimedia Tools and Applications, vol. 82, no. 25, pp. 39617–39632, Oct. 2023, doi: 10.1007/s11042-021-11537-0.

[8] H. Karbasi, A. Sanderson, A. Sharifi, and C. Wilson, "Robotic sorting of shredded e-waste: utilizing deep learning," in Proc. 2018 Int. Conf. Robot. Autom., 2018.

[9] P. Nowakowski and T. Pamuła, "Application of deep learning object classifier to improve e-waste collection planning," Waste Manag., vol. 108, pp. 106-118, 2020.

[10] B. Fang, J. Yu, Z. Chen, A. I. Osman, M. Farghali, I. Ihara, E. H. Hamza, D. W. Rooney, and P.-S. Yap, "Artificial intelligence for waste management in smart cities: a review," Sci. Total Environ., vol. 799, pp. 149353, 2023.

[11] G. L. Russo, "Integrated Management of Electronic and Electric Waste (EEW) with the Application of Artificial Intelligence (AI): Future and Challenges," Smart Cities, vol. 6, pp. 1-10, 2023.

[12] N. Onur, H. Alan, H. Demirel, and A. R. Köker, "Digitalization and Digital Applications in Waste Recycling: An Integrative Review," in IEEE Access, vol. 12, pp. 18001–18015, 2024.

[13] D. B. Olawade, O. Fapohunda, O. Z. Wada, S. O. Usman, A. O. Ige, O. Ajisafe, and B. I. Oladapo, "Smart waste management: A paradigm shift enabled by artificial intelligence," Sustain. Cities Soc., vol. 66, 2024.

[14] K. H. Yu, Y. Zhang, D. Li, C. E. Montenegro-Marin, and P. M. Kumar, "Environmental planning based on reduce, reuse, recycle and recover using artificial intelligence," in IEEE Conf. Intell. Syst., 2021.

[15] V. Agarwal, S. Goyal, and S. Goel, "Artificial intelligence in waste electronic and electrical equipment treatment: opportunities and challenges," in Proc. 2020 Int. Conf. Intell. Eng. Manage. (ICIEM), pp. 526–529, 2020.

[16] E. Simaei, "Intelligent e-wastes processing for effective end-of-life management," Ph.D. thesis, Loughborough University, 2022.

[17] N. J. Sinthiya, T. A. Chowdhury, and A. K. M. B. Haque, "Artificial intelligence based Smart Waste Management—a systematic review," Comput. Intell. Tech. Green Smart Cities, pp. 67-92, 2022.