Smart Waste Management and Classification Systems

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Waste management requires necessary processes and activities to dominate from its inception to demolition. Waste comes in solid, liquid, or gaseous form, and every type of waste demands a different method of classification, disposal, and management. Waste management deals with every waste category, including household, organic, industrial, municipal, biomedical, organic, biological, and radioactive waste. Any unnecessary substance or substance with no use is called "waste". Waste management involves the collection of the waste and its transport and disposal to appropriate locations. In the European Union (EUROPA), 423 million tons or 56% of domestic waste was recycled in 2016. Reports reflect the need for proper household waste management for the recycling process. Most of the Earth's population will emigrate from rural to urban areas in the coming years. Therefore, bigger cities will require a highly sustainable infrastructure and smart waste management system to fulfill the fundamental needs of its citizens and provide them with a good service for the future.

waste classification | waste management | image recognition | smart city | smart environments | convolutional neural network (CNN) | internet of things (IoT) | deep learning (DL) | sustainability and environment

1. Introduction

Waste management requires necessary processes and activities to dominate from its inception to demolition. Waste comes in solid, liquid, or gaseous form, and every type of waste demands a different method of classification, disposal, and management. Waste management deals with every waste category, including household, organic, industrial, municipal, biomedical, organic, biological, and radioactive waste. Any unnecessary substance or substance with no use is called "waste". Waste management involves the collection of the waste [1] and its transport and disposal to appropriate locations [2]. In the European Union (EUROPA), 423 million tons or 56% of domestic waste was recycled in 2016. Reports reflect the need for proper household waste management for the recycling process [3]. According to [4], most of the Earth's population will emigrate from rural to urban areas in the coming years. Therefore, bigger cities will require a highly sustainable infrastructure and smart waste management system to fulfill the fundamental needs of its citizens and provide them with a good service for the future [5][6].

Traditional recycling processes segregate waste objects manually or by applying a sequence of filters. If modern technology and waste management could be bound together, the results would be immeasurable and would lead to a positive biological environment [7]. With the rapid increase in computing power, there has been a lot of advancement in image processing [8] and computer vision [9]. A deep-learning architecture named convolutional neural network (CNN) has played a pivotal role in this regard [8]. By applying deep learning, waste objects can be identified and classified more efficiently, reducing the cost in terms of both time and human resources, and impacting the environment positively [10][11].

According to an estimation by FUSON [12], 127 new devices are connected to public networks every second. Given this speedy growth, 328 million new devices are added monthly. According to STATISTA, at the end of 2023, the IoT market will be projected to be worth $1.1 trillion [13]. These statistics suggest that IoT is becoming a significant element in modern computing techniques. In the modern web, the Internet of Things (IoT) [14], Machine-Learning (ML) [15], and Deep-Learning (DL) [14] phenomena are being enabled in various systems such as Wireless Sensor Networks (WSNs), Radio Frequency Identification (RFID) [16], sensors, and actuators. Prediction methods such as clustering and classification [17] are also used to create the most accurate results instead of individuals.

Numerous types of sensors are used in this project. Their purpose is to gather information about waste material and thus enhance the city’s infrastructure by successfully implementing waste management and classification tasks. The physical infrastructure of the researchers' system consists of waste bins, a fleet of vehicles, gripper, dump, etc. First, the household waste is collected in the researchers' smart waste bin, whose data are stored on the cloud, and a message on the web/mobile application is generated when the bin gets full. Afterward, the authorities assign a waste collection truck to collect the waste from the waste bin and take it to the dumping area of the waste, where the segmentation and classification of waste are performed as shown in **Figure 1**.

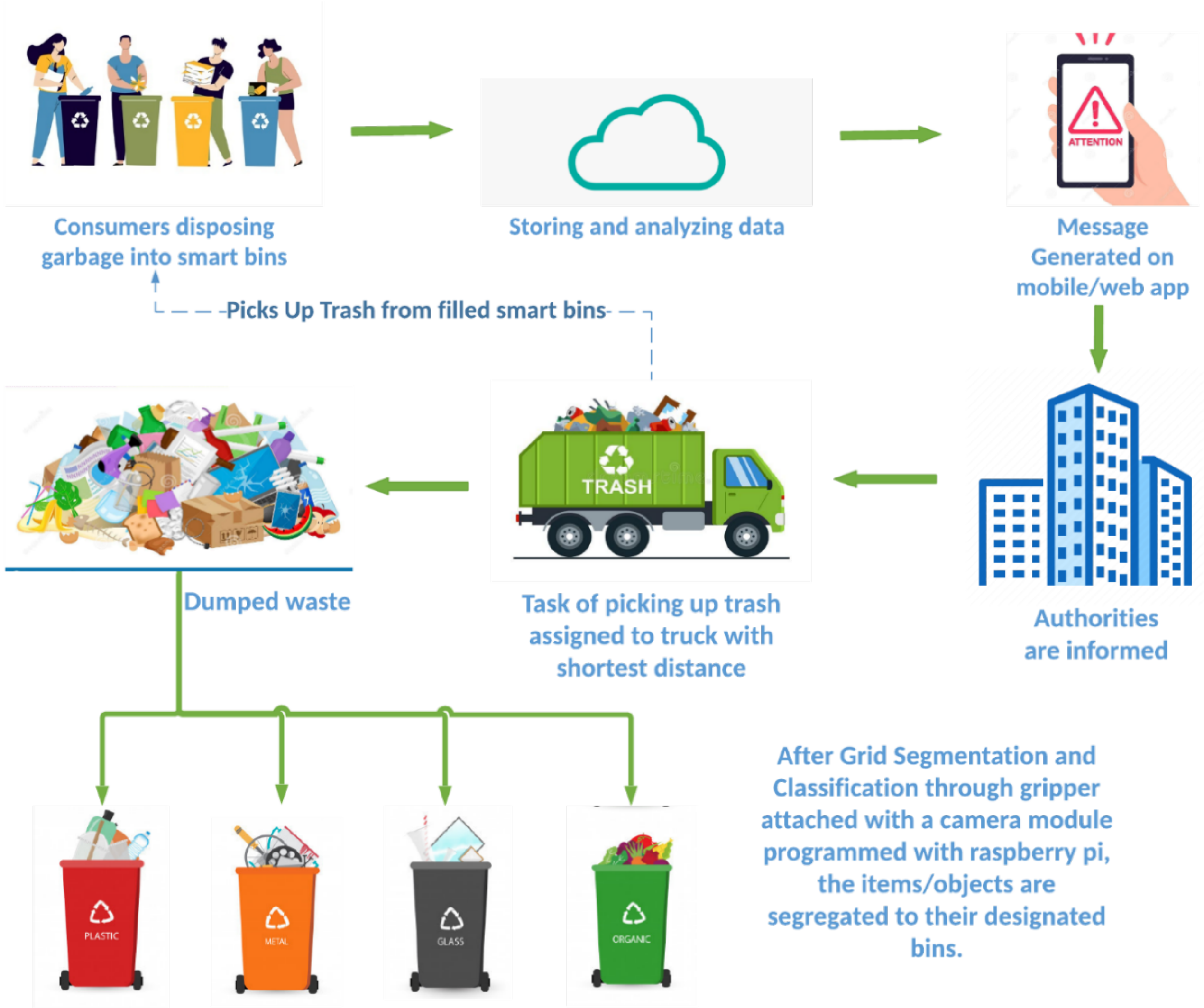

Figure 1. Smart Waste Classification Mechanism.

2. Smart Waste Management and Classification Systems

With the rapid modernization of every sector of society, nowadays, people rely on technology for everything. In this growing age, human lives have changed a lot, and modern technology has taken its place in the heart of every human being. Undoubtedly, there is no field in the researchers' surroundings where technology does not play a vital role. People prefer to live in cities with the latest facilities and technology. As a result, the population in cities is increasing daily, which has many disadvantages and advantages [18][19]. Individuals working in cities have a positive effect on the economy of the country [20][21]. Still, as societies become increasingly congested, many problems related to health, safety, and the environment arise [22][23][24][25]. These problems include medical facilities, security, privacy, and transportation [26][27].

Another huge problem in cities nowadays is waste management, which involves the collection, transportation, and classification of waste, and also helps with recycling waste items [27][28]. Intensive usage of natural resources has become unavoidable [29]. In contrast, due to increasing consumption trends, waste objects have reached levels that endanger human health and the environment in quantity and harmful content. Chemical, manufacturing, physical, and consumption properties are the considerations used to classify waste items [30][31]. Most of the population of growing cities is educated and well aware of the environmental effects of waste, but they dispose of their waste without classifying it. Everything in this universe has two aspects; one is good, and one is bad. Man feels this when it happens to him, or his belongings [3]. Several countries have placed bins with separate compartments for different waste categories. Still, the dwellers are not following the rules, which makes waste management and classification a complex task that needs a specific system to be designed to perform waste classification automatically [32][33].

According to [34][35][36][37], it has been proved that nearly 0.75% of solid domestic waste can be recycled. Therefore, it will be costly to dump it and not recycle it. If these waste items are classified, it will boost the recycling process, which will positively affect the economic boost of the country [38]. It will also provide a much greener environment for future generations to live in [39]. In short, failing to prioritize recycling can cause wastage of natural resources, and financial loss [40][41]. Recycling is a viable solution, though it can be daunting to classify waste accurately. The efficient management of waste has a significant impact on people’s quality of life. The reason is that waste disposal has a clear connection with adverse effects on the environment, and thus, people’s health. Therefore, there is a need for a proper plan for a waste management system for the betterment of the people who want to live in a healthy environment [42][43].

Various countries such as America, Canada, Russia, Italy, Malaysia, the Kingdom of Saudi Arabia, Qatar, etc., and many other countries are working to develop a smart waste management system. In previous work, the waste management technique which was implemented in St. Petersburg, Russia, used Wireless Sensor Networks (WSNs), Radio Frequency Identification (RFID) [44], sensors, and actuators. St. Petersburg is a city of 5 million individuals [45]. On average, 1.7 million tons of solid waste is produced in the city annually. Whereas, in Canada [46] the k-means and linear regression are used for waste management systems, in which multiple beats are involved to regulate the cycle.

In [47], single waste image classification was performed using SVM with SIFT and CNN. They manually collected a total of 2527 waste images. SVM and CNN models were trained on the collected dataset and achieved 63% and 22% accuracy, respectively. Their research classifies waste into six categories; paper, metal, cardboard, plastic, glass, and trash [48]. Municipal solid waste can be classified into either six or four categories. In six-class systems [49][50][51][52] researchers focus on recyclable waste classes: paper, metal, glass, cardboard, plastic, and trash. In four-class systems [53][54][55][56][57] waste classes are wet waste, i.e., probably kitchen waste, dry garbage, recyclable and hazardous garbage. A ResNet-5013 model and SVM-based intelligent system was proposed in [58]. The system was tested on a single waste images dataset [53] and gained 87% accuracy in classification. In public places for automatic detection of recyclable wastes, a multilayered hybrid deep-learning-based system was proposed [59]. The system was employed with CNN for image features extraction and a multilayered perceptron used for consolidating only relevant features of the image. Their proposed technique outperforms and achieves an accuracy of 90% for classification. A CNN-based system was developed to classify plastic wastes [60].

For Municipal Solid Waste (MSW), derived classifier models [61] were proposed based on transfer learning. Models were retrained on 9200 MSW images by pertained classifiers of CNN (VGG16, MobileNetV2, ResNet50, and DenseNet121) to classify the waste into four predefined groups (recyclable waste, hazardous waste, compostable waste, and general waste). In [62], the authors proposed an image classifier to identify the waste item and classify its category. In their research, four classifiers of CNN (VGG16, DenseNet169, ResNet50, and AlexNet) trained on the ImageNet dataset were used for feature extraction from waste images to classify them into six categories: paper, metal, cardboard, plastic, glass, and trash. Their results reflect that ResNet50 performs better, and its performance is closer to DenseNet169. The flaw in their proposed mechanism is that it misclassifies glass. Since the ILSVRC Competition, different image classification methods based on CNN architectures have developed [63][64][65]. In image classification of computer vision, VGG16 and VGG19 (also known as VGGNet) are two representatives of CNN architectures, achieving the best performance in the ILSVRC Competition. For large-scale image recognition, these models use 3 × 3 tiny convolutional filters in every layer and push the depth of the network from 16–19 layers.

Recent studies reported that deep learning (DL) models are more effective for object detection and classification than traditional techniques. Due to rapid urbanization, smart cities are being designed with smart and automated waste management using the internet of things (IoT) technologies that lead to an increase in efficiency and flexibility, saving energy and time and keeping the environment sustainable [8][66][67][68][69][70][71]. IoT-based solutions provide real-time monitoring, collecting, and management of garbage. In [72], the authors developed IoT-based smart bins using deep learning (DL) and machine learning (ML) models to monitor, collect, manage waste, and forecast air pollutants present in the surrounding environment. An IoT stationed smart waste segregation and management system was developed by Shamin et al. [73] employed with an ultrasonic sensor, a moisture sensor, a metal sensor, and a camera. Image processing and machine learning algorithms were used to identify degradable waste items and segregate them into different dustbins.

Before proposing a solution of the researchers' own, their research covered a wide range of previously proposed models, papers, and studies. All the research and studies were thoroughly read and understood, considering their domain of interest, their architecture, the pros and cons, the features added in their studies, and the accuracy of the architecture proposed. After critically evaluating many studies on waste management and classification, some crucial information about these studies is provided in **Table 1** and **Table 2**. So, the readers can have an overview of the previous work carried out by researchers, practitioners, authors, and technologists related to the subject mentioned.

Table 1. Summary of Related Research Efforts 1A.

Study	Architecture	For IoT	Waste Category	Hardware Category	Accuracy (%)	Dataset	Remarks
[74] [75]	Multivariate analysis with neural network	NA	Light Weight Metals	Weight sensor, linear	85%	NA	Cannot classify other materials

Study	Architecture	For IoT	Waste Category	Hardware Category	Accuracy (%)	Dataset	Remarks
				laser, 3D camera			
[76]	KNN	NA	Recyclable Paper	Camera	93%	NA	Require consistent lightening during identification phase
[77]	Hu’s image invariant moments with KNN	NA	Inorganic material such as bottles, cutlery, Cans	Camera	98%	NA	Unreliable results due to small dataset
[78]	DNA Computing Algorithms (RGBI)	NA	Paper	Camera	95.1%	NA	Require consistent lightening during identification phase
[79]	SVM and CNN	NA	Paper, Metal and Plastic	Camera	SVM: 94.8% CNN: 83%	NA	Dataset is less versatile due to Low GPU memory images scaled down from 256 × 256 to 32 × 32
[80]	Fast-R CNN	NA	Plastic Bottles	Robotic Arm, KUKA, Camera	91%	NA	Segregate only plastic. Output reliant on lighting
[81]	Scale Invariant Feature Transform (SIFT)	NA	Organic and inorganic items with product labels	Camera	89.9%	Self-made dataset of 192 images	Most waste items do not have product labels; hence, the scope is limited

Study	Architecture	For IoT	Waste Category	Hardware Category	Accuracy (%)	Dataset	Remarks
[52]	VGG16, CNN, ResNet50	NA	Household food waste, recyclable waste, hazardous waste, residual waste	NA	VGG16: 37% CNN: 37% ResNet-50: 47%	Self-made	Not integrated with a decision support or classification system. Accuracy is not properly calculated
[82]	YOLOv3, Darknet neural network	NA	Glass, paper, metal, plastic, cardboard, organic waste	NA	Glass: 97% paper: 85% metal: 99% plastic: 91% cardboard: 97% org-waste:	Self-made	Takes more time to detect an object.

Study	Architecture	For IoT	Waste Category	Hardware Category	Accuracy (%)	Dataset	Remarks
					98% mAP: 94%		
[83]	WasNet, Lightweight neural network	NA	NA	Camera	ImageNet: 64.5% Garbage Classification: 82.5% TrashNet: 96.10%	ImageNet, Garbage Classification dataset, TrashNet	Implementation and results are unreliable.
[73]	SURF algo., KNN	Yes	Metal, Plastic	Ultrasonic sensor, Moister sensor, metal sensor, Camera	95%	Self Made	Only one waste item can be put in dustbin at a time. If image of waste material captured in low light then results may vary.
[57]	CNN, Self-Learning Neural Network	NA	Plastic, Paper, Cardboard, Metal	NA	76%	Trash Net	Less accuracy due to limited dataset. Not integrated with a decision support or classification system.
[84]	CNN, Image Processing Algo.	NA	Plastic and its four categorical: PS, PP, PE-HD, PET	Camera, Airjet	74%	WaDaBa	Less effective as compared to other CNNs.
[62]	ResNet50, DenseNet169, VGG16, AlexNet	NA	Glass, paper, metal, plastic, cardboard, Trash	NA	ResNet50: 89.7% DenseNet169: 92.6% VGG16: 86.9% AlexNet: 83.7%	ImageNet	System misclassify 'glass'. Not integrated with a decision support or classification system.

searchers ... of waste classification and management to some extent, but all of them lag one way or the other. Some have combined multiple approaches to propose a hybrid solution. The best-known accuracy has been achieved through the hybrid approach of Deep Learning algorithms: Inception and ResNet. The accuracy achieved was over 88% in classifying waste items.

Similarly, many proposed systems have a hybrid solution consisting of "machine learning and deep learning". Still, the search for a more accurate and reliable system continues. The research aims to focus on observing and understanding traditional methods for automatic waste classification systems, which can further help in the recycling process of waste items. Currently, many techniques for waste classification exist, but many require human involvement. If a fully automatic system is deployed in any society, it will be a win–win situation for the government, societies, and industrialists. The underlying purpose of this research is to provide an automated waste management system that can perform classification quickly and provide better and more accurate results at a low cost.

References

1. Pires, I.; Souza, G.; Junior, J. An Analysis of the Relation between Garbage Pickers and Women's Health Risk. Acta Sci. Agric. 2020, 4, 12–16.
2. Liu, J.; Balatti, P.; Ellis, K.; Hadjivelichkov, D.; Stoyanov, D.; Ajoudani, A.; Kanoulas, D. Garbage collection and sorting with a mobile manipulator using deep learning and whole-body control. In Proceedings of the 2020 IEEE-RAS 20th International Conference on Humanoid Robots (Humanoids), Munich, Germany, 19–21 July 2021; pp. 408–414.
3. Waste Management Indicators. Available online: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Waste_management_indicators (accessed on 5 July 2022).
4. Lagakos, D. Urban-rural gaps in the developing world: Does internal migration offer opportunities? J. Econ. Perspect. 2020, 34, 174–192.
5. Nañez Alonso, S.L.; Reier Forradellas, R.F.; Pi Morell, O.; Jorge-Vazquez, J. Digitalization, circular economy and environmental sustainability: The application of Artificial Intelligence in the efficient self-management of waste. Sustainability 2021, 13, 2092.
6. Bagri, V.; Sharma, L.; Patil, B.; Dhage, S.N. Survey of Automated Waste Segregation Methods. In Advances in Computer, Communication and Computational Sciences; Springer: Berlin/Heidelberg, Germany, 2021; pp. 953–964.
7. Zhang, Q.; Zhang, X.; Mu, X.; Wang, Z.; Tian, R.; Wang, X.; Liu, X. Recyclable waste image recognition based on deep learning. Resour. Conserv. Recycl. 2021, 171, 105636.
8. Rahman, M.W.; Islam, R.; Hasan, A.; Bithi, N.I.; Hasan, M.M.; Rahman, M.M. Intelligent waste management system using deep learning with IoT. J. King Saud Univ.-Comput. Inf. Sci. 2020, 34, 2072–2087.
9. Ramsurrun, N.; Suddul, G.; Armoogum, S.; Foogooa, R. Recyclable Waste Classification Using Computer Vision And Deep Learning. In Proceedings of the 2021 Zooming Innovation in Consumer Technologies Conference (ZINC), Novi Sad, Serbia, 26–27 May 2021; pp. 11–15.

10. Mao, W.L.; Chen, W.C.; Wang, C.T.; Lin, Y.H. Recycling waste classification using optimized convolutional neural network. Resour. Conserv. Recycl. 2021, 164, 105132.
11. Altikat, A.; Gulbe, A.; Altikat, S. Intelligent solid waste classification using deep convolutional neural networks. Int. J. Environ. Sci. Technol. 2022, 19, 1285–1292.
12. The FUSON Website. Available online: https://www.fuzon.io/insight/top-iotstatistics/ (accessed on 5 July 2022).
13. The STATISTA Website. Available online: https://www.statista.com/topics/2637/internet-of-things/ (accessed on 5 July 2022).
14. Sheng, T.J.; Islam, M.S.; Misran, N.; Baharuddin, M.H.; Arshad, H.; Islam, M.R.; Chowdhury, M.E.; Rmili, H.; Islam, M.T. An internet of things based smart waste management system using LoRa and tensorflow deep learning model. IEEE Access 2020, 8, 148793–148811.
15. Esmaeilian, B.; Wang, B.; Lewis, K.; Duarte, F.; Ratti, C.; Behdad, S. The future of waste management in smart and sustainable cities: A review and concept paper. Waste Manag. 2018, 81, 177–195.
16. Catarinucci, L.; Colella, R.; Consalvo, S.I.; Patrono, L.; Rollo, C.; Sergi, I. IoT-aware waste management system based on cloud services and ultra-low-power RFID sensor-tags. IEEE Sens. J. 2020, 20, 14873–14881.
17. Livani, E.; Nguyen, R.; Denzinger, J.; Ruhe, G.; Banack, S. A hybrid machine learning method and its application in municipal waste prediction. In Industrial Conference on Data Mining; Springer: Berlin/Heidelberg, Germany, 2013; pp. 166–180.
18. Yigitcanlar, T.; Cugurullo, F. The sustainability of artificial intelligence: An urbanistic viewpoint from the lens of smart and sustainable cities. Sustainability 2020, 12, 8548.
19. Belli, L.; Cilfone, A.; Davoli, L.; Ferrari, G.; Adorni, P.; Di Nocera, F.; Dall'Olio, A.; Pellegrini, C.; Mordacci, M.; Bertolotti, E. IoT-enabled smart sustainable cities: Challenges and approaches. Smart Cities 2020, 3, 1039–1071.
20. Davis, D.R.; Dingel, J.I. A spatial knowledge economy. Am. Econ. Rev. 2019, 109, 153–170.
21. Davis, D.R.; Dingel, J.I. The comparative advantage of cities. J. Int. Econ. 2020, 123, 103291.
22. Klimanova, O.; Illarionova, O.; Grunewald, K.; Bukvareva, E. Green infrastructure, urbanization, and ecosystem services: The main challenges for Russia's largest cities. Land 2021, 10, 1292.
23. Kuddus, M.A.; Tynan, E.; McBryde, E. Urbanization: A problem for the rich and the poor? Public Health Rev. 2020, 41, 1–4.
24. Anierobi, C.; Obasi, C.O. Urbanization and Rural-Urban Migration: Toward Involving the Church in Addressing Pro-Poor Urban Housing Challenges in Enugu, Nigeria. SAGE Open 2021, 11,

21582440211040123.

25. Blair, J.; Mataraarachchi, S. A Review of Landfills, Waste and the Nearly Forgotten Nexus with Climate Change. Environments 2021, 8, 73.
26. Wang, Y.S. The challenges and strategies of food security under rapid urbanization in China. Sustainability 2019, 11, 542.
27. Arfanuzzaman, M.; Dahiya, B. Sustainable urbanization in Southeast Asia and beyond: Challenges of population growth, land use change, and environmental health. Growth Chang. 2019, 50, 725–744.
28. Ravichandran, C.; Venkatesan, G. Toward sustainable solid waste management–challenges and opportunities. Handb. Adv. Approaches Towards Pollut. Prev. Control 2021, 2, 67–103.
29. Niinimäki, K.; Peters, G.; Dahlbo, H.; Perry, P.; Rissanen, T.; Gwilt, A. The environmental price of fast fashion. Nat. Rev. Earth Environ. 2020, 1, 189–200.
30. Rahimi, A.; García, J.M. Chemical recycling of waste plastics for new materials production. Nat. Rev. Chem. 2017, 1, 1–11.
31. Gelan, E. Municipal Solid waste management practices for achieving green architecture concepts in Addis Ababa, Ethiopia. Technologies 2021, 9, 48.
32. Abuga, D.; Raghava, N. Real-time smart garbage bin mechanism for solid waste management in smart cities. Sustain. Cities Soc. 2021, 75, 103347.
33. Srivastav, A.L.; Kumar, A. An endeavor to achieve sustainable development goals through floral waste management: A short review. J. Clean. Prod. 2021, 283, 124669.
34. Wen, Z.; Xie, Y.; Chen, M.; Dinga, C.D. China's plastic import ban increases prospects of environmental impact mitigation of plastic waste trade flow worldwide. Nat. Commun. 2021, 12, 1–9.
35. Lam, S.S.; Alstrup, A.K.; Sonne, C. Denmark recycling plan will cut waste by two-thirds. Nature 2020, 584, 192–193.
36. Li, J.; Xiao, F.; Zhang, L.; Amirkhanian, S.N. Life cycle assessment and life cycle cost analysis of recycled solid waste materials in highway pavement: A review. J. Clean. Prod. 2019, 233, 1182–1206.
37. Chen, Y.C. Evaluating greenhouse gas emissions and energy recovery from municipal and industrial solid waste using waste-to-energy technology. J. Clean. Prod. 2018, 192, 262–269.
38. Abdollahbeigi, M. An overview of the paper recycling process in Iran. J. Chem. Rev. 2020, 3, 1–19.

39. Radwan, N.; Khan, N.A.; Elmanfaloty, R.A.G. Optimization of solid waste collection using RSM approach, and strategies delivering sustainable development goals (SDG's) in Jeddah, Saudi Arabia. Sci. Rep. 2021, 11, 1–12.
40. Ahmed, Z.; Asghar, M.M.; Malik, M.N.; Nawaz, K. Moving towards a sustainable environment: The dynamic linkage between natural resources, human capital, urbanization, economic growth, and ecological footprint in China. Resour. Policy 2020, 67, 101677.
41. Rehman, A.; Khan, K.A.; Hamid, T.; Nasir, H.; Ahmad, I.; Alam, M. Effective utilization of municipal solid waste as substitute for natural resources in cement industry. Civ. Eng. J. 2020, 6, 238–257.
42. Sarc, R.; Curtis, A.; Kandlbauer, L.; Khodier, K.; Lorber, K.E.; Pomberger, R. Digitalisation and intelligent robotics in value chain of circular economy oriented waste management—A review. Waste Manag. 2019, 95, 476–492.
43. Chen, D.M.C.; Bodirsky, B.L.; Krueger, T.; Mishra, A.; Popp, A. The world's growing municipal solid waste: Trends and impacts. Environ. Res. Lett. 2020, 15, 074021.
44. Glouche, Y.; Couderc, P. A smart waste management with self-describing objects. In Proceedings of the Second International Conference on Smart Systems, Devices and Technologies (SMART'13), Rome, Italy, 23–28 June 2013.
45. Anagnostopoulos, T.; Zaslavsky, A.; Kolomvatsos, K.; Medvedev, A.; Amirian, P.; Morley, J.; Hadjieftymiades, S. Challenges and opportunities of waste management in IoT-enabled smart cities: A survey. IEEE Trans. Sustain. Comput. 2017, 2, 275–289.
46. Omara, A.; Gulen, D.; Kantarci, B.; Oktug, S.F. Trajectory-assisted municipal agent mobility: A sensor-driven smart waste management system. J. Sens. Actuator Netw. 2018, 7, 29.
47. Cai, X.; Niu, Y.; Geng, S.; Zhang, J.; Cui, Z.; Li, J.; Chen, J. An under-sampled software defect prediction method based on hybrid multi-objective cuckoo search. Concurr. Comput. Pract. Exp. 2020, 32, e5478.
48. Yang, M.; Thung, G. Classification of trash for recyclability status. CS229 Proj. Rep. 2016, 2016, 3.
49. Wang, H. Garbage recognition and classification system based on convolutional neural network VGG16. In Proceedings of the 2020 3rd International Conference on Advanced Electronic Materials, Computers and Software Engineering (AEMCSE), Shenzhen, China, 24–26 April 2020; pp. 252–255.
50. Cao, L.; Xiang, W. Application of convolutional neural network based on transfer learning for garbage classification. In Proceedings of the 2020 IEEE 5th Information Technology and Mechatronics Engineering Conference (ITOEC), Chongqing, China, 12–14 June 2020; pp. 1032–1036.

51. Vo, A.H.; Son, L.H.; Vo, M.T.; Le, T. A novel framework for trash classification using deep transfer learning. IEEE Access 2019, 7, 178631–178639.
52. Liao, Y. A Web-Based Dataset for Garbage Classification Based on Shanghai's Rule. Int. J. Mach. Learn. Comput. 2020, 10, 18–24.
53. Huang, G.L.; He, J.; Xu, Z.; Huang, G. A combination model based on transfer learning for waste classification. Concurr. Comput. Pract. Exp. 2020, 32, e5751.
54. Aral, R.A.; Keskin, Ş.R.; Kaya, M.; Hacıömeroğlu, M. Classification of trashnet dataset based on deep learning models. In Proceedings of the 2018 IEEE International Conference on Big Data (Big Data), Seattle, WA, USA, 10–13 December 2018; pp. 2058–2062.
55. Rabano, S.L.; Cabatuan, M.K.; Sybingco, E.; Dadios, E.P.; Calilung, E.J. Common garbage classification using mobilenet. In Proceedings of the 2018 IEEE 10th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management (HNICEM), Baguio City, Philippines, 29 November–2 December 2018; pp. 1–4.
56. Ozkaya, U.; Seyfi, L. Fine-tuning models comparisons on garbage classification for recyclability. arXiv 2019, arXiv:1908.04393.
57. Sidharth, R.; Rohit, P.; Vishagan, S.; Karthika, R.; Ganesan, M. Deep learning based smart garbage classifier for effective waste management. In Proceedings of the 2020 5th International Conference on Communication and Electronics Systems (ICCES), Coimbatore, India, 10–12 June 2020; pp. 1086–1089.
58. Adedeji, O.; Wang, Z. Intelligent waste classification system using deep learning convolutional neural network. Procedia Manuf. 2019, 35, 607–612.
59. Chu, Y.; Huang, C.; Xie, X.; Tan, B.; Kamal, S.; Xiong, X. Multilayer hybrid deep-learning method for waste classification and recycling. Comput. Intell. Neurosci. 2018, 2018, 5060857.
60. Bobulski, J.; Kubanek, M. Waste classification system using image processing and convolutional neural networks. In International Work-Conference on Artificial Neural Networks; Springer: Cham, Switerland, 2019; pp. 350–361.
61. Srinilta, C.; Kanharattanachai, S. Municipal solid waste segregation with CNN. In Proceedings of the 2019 5th International Conference on Engineering, Applied Sciences and Technology (ICEAST), Luang Prabang, Laos, 2–5 July 2019; pp. 1–4.
62. Susanth, G.S.; Livingston, L.J.; Livingston, L.A. Garbage Waste Segregation Using Deep Learning Techniques. In IOP Conference Series: Materials Science and Engineering; IOP Publishing: Bristol, UK, 2021; Volume 1012, p. 012040.
63. Simonyan, K.; Zisserman, A. Very deep convolutional networks for large-scale image recognition. arXiv 2014, arXiv:1409.1556.

64. Zeiler, M.D.; Fergus, R. Visualizing and understanding convolutional networks. In European Conference on Computer Vision; Springer: Cham, Switerland, 2014; pp. 818–833.
65. Wang, J.; Yang, Y.; Mao, J.; Huang, Z.; Huang, C.; Xu, W. Cnn-rnn: A unified framework for multi-label image classification. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Las Vegas, NV, USA, 27–30 June 2016; pp. 2285–2294.
66. Alsubaei, F.S.; Al-Wesabi, F.N.; Hilal, A.M. Deep Learning-Based Small Object Detection and Classification Model for Garbage Waste Management in Smart Cities and IoT Environment. Appl. Sci. 2022, 12, 2281.
67. Akkad, M.Z.; Haidar, S.; Bányai, T. Design of Cyber-Physical Waste Management Systems Focusing on Energy Efficiency and Sustainability. Designs 2022, 6, 39.
68. Ijemaru, G.K.; Ang, L.M.; Seng, K.P. Transformation from IoT to IoV for waste management in smart cities. J. Netw. Comput. Appl. 2022, 204, 103393.
69. Abdullah, N.; Al-Wesabi, O.A.; Mohammed, B.A.; Al-Mekhlafi, Z.G.; Alazmi, M.; Alsaffar, M.; Anbar, M.; Sumari, P. Integrated Approach to Achieve a Sustainable Organic Waste Management System in Saudi Arabia. Foods 2022, 11, 1214.
70. Fawwaz, D.Z.; Chung, S.H.; Ahn, C.W.; Kim, W.S. Optimal Distributed MQTT Broker and Services Placement for SDN-Edge Based Smart City Architecture. Sensors 2022, 22, 3431.
71. Namoun, A.; Hussein, B.R.; Tufail, A.; Alrehaili, A.; Syed, T.A.; BenRhouma, O. An Ensemble Learning Based Classification Approach for the Prediction of Household Solid Waste Generation. Sensors 2022, 22, 3506.
72. Hussain, A.; Draz, U.; Ali, T.; Tariq, S.; Irfan, M.; Glowacz, A.; Antonino Daviu, J.A.; Yasin, S.; Rahman, S. Waste management and prediction of air pollutants using IoT and machine learning approach. Energies 2020, 13, 3930.
73. Shamin, N.; Fathimal, P.M.; Raghavendran, R.; Prakash, K. Smart garbage segregation & management system using Internet of Things (IoT) & Machine Learning (ML). In Proceedings of the 2019 1st International Conference on Innovations in Information and Communication Technology (ICIICT), Chennai, India, 25–26 April 2019; pp. 1–6.
74. Koyanaka, S.; Kobayashi, K. Automatic sorting of lightweight metal scrap by sensing apparent density and three-dimensional shape. Resour. Conserv. Recycl. 2010, 54, 571–578.
75. Koyanaka, S.; Kobayashi, K. Incorporation of neural network analysis into a technique for automatically sorting lightweight metal scrap generated by ELV shredder facilities. Resour. Conserv. Recycl. 2011, 55, 515–523.
76. Rahman, M.O.; Hussain, A.; Scavino, E.; Basri, H.; Hannan, M. Intelligent computer vision system for segregating recyclable waste papers. Expert Syst. Appl. 2011, 38, 10398–10407.

77. Omar, L.G.; Oscar, R.A.; Andres, T.G.; Francisco, S.G. Multimedia inorganic waste separator. In Proceedings of the 2013 IEEE International Conference on Multimedia and Expo Workshops (ICMEW), San Jose, CA, USA, 15–19 July 2013; pp. 1–4.
78. Rahman, M.O.; Hussain, A.; Scavino, E.; Hannan, M.; Basri, H. DNA computer based algorithm for recyclable waste paper segregation. Appl. Soft Comput. 2015, 31, 223–240.
79. Sakr, G.E.; Mokbel, M.; Darwich, A.; Khneisser, M.N.; Hadi, A. Comparing deep learning and support vector machines for autonomous waste sorting. In Proceedings of the 2016 IEEE International Multidisciplinary Conference on Engineering Technology (IMCET), Beirut, Lebanon, 2–4 November 2016; pp. 207–212.
80. Zhihong, C.; Hebin, Z.; Yanbo, W.; Binyan, L.; Yu, L. A vision-based robotic grasping system using deep learning for garbage sorting. In Proceedings of the 2017 36th Chinese Control Conference (CCC), Dalian, China, 26–28 July 2017; pp. 11223–11226.
81. Setiawan, W.; Wahyudin, A.; Widianto, G. The use of scale invariant feature transform (SIFT) algorithms to identification garbage images based on product label. In Proceedings of the 2017 3rd International Conference on Science in Information Technology (ICSITech), Bandung, Indonesia, 25–26 October 2017; pp. 336–341.
82. Kumar, S.; Yadav, D.; Gupta, H.; Verma, O.P.; Ansari, I.A.; Ahn, C.W. A novel yolov3 algorithm-based deep learning approach for waste segregation: Towards smart waste management. Electronics 2020, 10, 14.
83. Yang, Z.; Li, D. Wasnet: A neural network-based garbage collection management system. IEEE Access 2020, 8, 103984–103993.
84. Bobulski, J.; Kubanek, M. Deep learning for plastic waste classification system. Appl. Comput. Intell. Soft Comput. 2021, 2021, 6626948.