Table of Contents

Exploring AI and Machine Learning in Waste Management: A Case Study of Singapore's Waste Data Analysis

Syedeh Zahra Alavi
48840

ARTICLE INFO

Keywords:
Waste management
Artificial Intelligence
Machine learning
Recycling
Sustainability

ABSTRACT

Artificial Intelligence (AI) and Machine Learning (ML) are revolutionizing waste management by enhancing efficiency, sustainability, and cost-effectiveness. These technologies enable more informed decision-making, improved operational efficiency, and reduced environmental impact through data analysis. This study provides a comprehensive literature review on the application of AI and ML in waste management, highlighting various techniques and their benefits. Additionally, a detailed data analysis of Singapore's waste management from 2003 to 2022 is presented, showcasing practical AI applications in real-world scenarios. The analysis includes waste generation, recycling rates, and the impact on energy and crude oil savings, offering valuable insights into the current state and future potential of waste management in Singapore.

1.Introduction

One of the biggest challenges facing the world today is climate change resulting from global warming (S.I. Zandalinas, et al., 2021)[1]. In recent years, the issue of global warming has attracted considerable attention as the effects of climate change have become increasingly evident (D.I. Armstrong McKay, et al., 2022)[2]. Many governments and organizations are now implementing measures to lower greenhouse gas emissions and mitigate the impacts of global warming (L. Al-Ghussain, 2019)[3]. Managing municipal solid waste offers a chance to reduce greenhouse gas emissions and tackle the global warming challenge (C.B. Agaton, et al., 2020)[4]. Recent statistics show that 2.01 billion tons of municipal solid waste (MSW) were produced in 2016, and this amount is expected to rise to 3.40 billion tons by 2050.Waste management is a critical global issue, as the increasing volume of waste demands innovative and sustainable solutions (Codinhoto, et al., 2023)[5]. Municipal authorities should use new and creative waste management methods to reduce waste and provide sustainable energy solutions. Using waste-to-energy (WtE) techniques is a great way to manage solid waste. These methods turn garbage into useful energy, like electricity or heat (T.-H. Tsui, J.W. Wong, 2019)[6]. There are several WtE methods used for managing solid waste, including incineration, anaerobic digestion, gasification, hydrothermal liquefaction (HTL), refuse-derived fuel (RDF), composting, and fermentation (M.A. Mujtaba, et al., 2024)[7].

On the other hand, there have recently been significant efforts to transform the waste management industry, making it more sustainable and profitable through advanced technologies and smart systems. Artificial Intelligence (AI) is a powerful new technology that can change the way we handle waste and solve many of its problems (Kumari et al., 2023)[8].By using AI's abilities in data analysis, pattern recognition, and decision-making, waste management systems can be optimized to improve efficiency, make better use of resources, and promote environmental sustainability(Aniza, R, et al., 2023)[9]. Recent trends in using AI for waste management show how much it is starting to make a difference and what it could achieve in the future (Pallathadka et al., 2023)[10]. AI technology involves creating computer systems and programs that can imitate human traits like problem-solving, learning, perception, understanding, reasoning, and being aware of their surroundings (Yetilmezsoy et al., 2011)[11]. Currently, in the field of solid waste management (SWM), AI is widely used to predict waste generation patterns, optimize waste collection truck routes, locate waste management facilities, and simulate waste conversion processes, among other applications. However, there have been few reviews of AI research that cover specific waste-related areas such as simulation and optimization of petroleum waste management, waste combustion processes, and biogas generation (Enitan, A.M et al., 2016)[12].

Machine learning and deep learning are two commonly used AI methods. These models are used by individuals, businesses, and government agencies to predict outcomes and gain insights from data (Pallathadka et al., 2023). Machine learning is a part of artificial intelligence where computers learn from data and improve their performance over time based on their experiences (MathWorks, 2024)[13]. In waste management, machine learning plays a crucial role by enabling more efficient sorting of recyclable materials, optimizing collection routes to save time and reduce fuel consumption, predicting waste generation patterns to improve planning and resource allocation, and enhancing the overall efficiency of recycling processes. Additionally, machine learning algorithms analyze vast amounts of data to identify trends and patterns that can inform better decision-making and strategy development, leading to more sustainable and effective waste management solutions.

In this paper, the aim is to review AI techniques in waste management, explore machine learning algorithms, and investigate the potential of machine learning for various waste management tasks. Following the literature review, data from Singapore will be analyzed to demonstrate the practical applications and benefits of these technologies in real-world waste management scenarios.

2.Methodology

The methodology of this paper will be illustrated in Figure 1 as a flowchart for enhanced clarity and understanding.

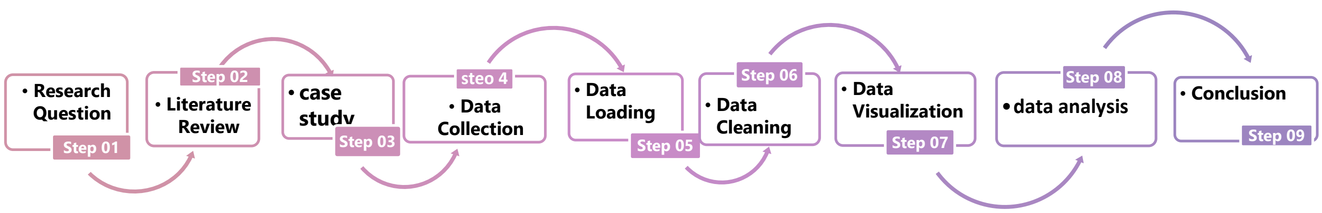

Fig. 1. Flowchart of the methodology adopted in this study

3.Research Question

1) How can AI techniques contribute to improving waste management?
2) In what ways can machine learning benefit waste management practices?
3) What were the total amounts of waste generated and recycled by waste type in Singapore from 2003 to 2022?
4) Which type of waste shows the most significant impact on energy savings in Singapore?

4.Literature Review

4-1. AI techniques applied to waste management

Artificial intelligence (AI) techniques have been widely employed to manage and handle waste efficiently. It is capable of processing large volumes of waste data, producing efficient and reliable outcomes, and offering opportunities to automate various processes. Numerous AI techniques are extensively utilized in the waste management sector, encompassing waste collection, waste sorting, bin-level sorting, waste treatment, and waste management planning (Chen,M , et al., 2022)[14]. Over the years, numerous AI techniques have been integrated into waste management, including linear regression; support vector machines (SVMs); decision trees (DTs); artificial neural networks (ANNs); and genetic algorithms (GAs) (David B, et al., 2024)[15]. Table 1 highlights various applications of AI in waste management, including its implementation in waste collection, waste sorting, waste recycling, and waste monitoring.

Table 1: various applications of AI in waste management

AI in:	Applications	References
waste collection	Smart bin systems	Ahmed et al.,2022[16], Dubey et al.,2020[17]
	Route optimization	Ghoreishi and Happonen, 2020[18]
	Dynamic scheduling	Reza, M., 2023[19]
	Demand prediction	Vu et al., 2019a, 2019b[20]
waste sorting	Automated sorting technologies	Yan et al., 2021[21], Mookkaiah et al., 2022[22]
	Image recognition and machine vision	KLONTZA, 2023[23]
	Robotic sorting systems	Sarc et al., 2019[24], Nwokediegwu and Ugwuanyi, 2024[25]
	Sensor-based sorting techniques	Koinig, 2023[26]
waste recycling	Material identification and sorting	Al Duhayyim et al., 2022[27]
	Process optimization	Golbaz et al., 2019[28]
	Quality control and inspection	Araujo-Andrade et al., 2021[29]
	Robotics and automation	Ejimofor et al., 2022[30]
waste monitoring	Real-time monitoring systems	Salman and Hasar, 2023[31]
	Predictive analytics	Liao and Wang, 2020[32]
	Data-driven decision making	Nguyen et al., 2022[33]
	IoT and sensor networks	Aytaç and Korçak, 2021[34]

4-2. Machine learning algorithms for efficient waste management

Machine learning, a specialized branch of artificial intelligence (AI), allows computers to gain knowledge and improve their performance based on experience, without being explicitly programmed. This approach involves teaching computers to learn from data and then using that acquired knowledge to make predictions or take specific actions(Tyagi AK ,et al., 2022)[35]. There are various types of machine learning, including supervised, unsupervised, and reinforcement learning, each of which will be explained in detail.

4-2-1. Supervised learning

Supervised learning is a type of machine learning technique where the algorithm learns from a labeled dataset, which consists of input data (features) and corresponding output data (labels or targets). The goal is to build a model that can make accurate predictions or decisions for new, unseen data based on the patterns learned from the labeled training data. This method is beneficial for tasks such as image classification and speech recognition. Examples of supervised learning techniques include Linear Regression (Azadi, et al., 2016)[36], Logistic Regression(Bernad-Beltran, et al., 2014)[37], Decision Trees(Heshmati R AA, et al., 2014)[38], Random Forest(You H, et al., 2017)[39], Naive Bayes(Mishra R, et al., 2021)[40], k-Nearest Neighbors (k-NN)(Olatunji OO,, et al., 2021)[41], Support Vector Machines (SVMs) (Abbasi M, et al., 2014)[42], Neural Networks (Ma S,et al., 2020)[43], and Deep Learning(Fy O,et al., 2017)[44]. The primary advantage of supervised machine learning is its ability to make accurate predictions based on past data. However, it has several drawbacks, including the risk of overfitting, lack of interpretability, potential bias, limitation to patterns seen in past data, dependence on labeled data, and lack of generalization (Alsharif MH, ET AL., 2020)[45]. Supervised machine learning in waste management predicts waste generation, plans collection routes, and classifies waste materials. By training algorithms on historical waste data and routes, it forecasts future waste trends and enhances route planning. Additionally, it categorizes waste into recyclable, biodegradable, or hazardous types, improving recycling rates. Moreover, supervised learning uses sensor data to anticipate equipment failures and schedule maintenance (Muhammad Tajammal Munir, et al., 2023).

4-2-2. Unsupervised learning

Unsupervised learning is a type of machine learning where a model is trained using data that has not been labeled, meaning the desired output is unknown. This method is utilized for tasks such as clustering, dimensionality reduction, and anomaly detection. Examples of unsupervised learning techniques include (Muhammad Tajammal Munir, ET AL., 2023)[46]:

Clustering: K-means, Hierarchical clustering, Density-based spatial clustering of applications with noise (DBSCAN).

Dimensionality reduction: Principal component analysis (PCA), t-distributed stochastic neighbor embedding (t-SNE), Locally Linear Embedding (LLE).

Anomaly detection: Isolation Forest, and Local Outlier Factor (LOF).

The primary benefit of unsupervised learning is its ability to uncover hidden patterns and relationships within the data that may not be immediately apparent, aiding in the discovery of new insights and understanding the underlying structure. Unlike supervised learning, unsupervised learning algorithms do not require labeled data, which can be challenging or costly to acquire. Moreover, they are more resilient to missing or noisy data (Zhu L-T,et al., 2022)[47]. Unsupervised learning in waste management includes clustering and anomaly detection techniques. Clustering algorithms group similar waste streams based on factors like composition or volume, helping companies optimize collection and processing. Anomaly detection identifies unusual patterns in waste generation, aiding in proactive problem detection. Dimensionality reduction visualizes and analyzes complex data, pinpointing areas for improvement. Moreover, unsupervised learning enhances waste sorting by analyzing sensor data to group similar materials. Effective implementation hinges on ample data and deep understanding of the problem, often combined with supervised learning for optimal outcomes. Overall, unsupervised learning serves as a valuable tool in municipal solid waste management, facilitating pattern identification, waste stream grouping, anomaly detection, data visualization, and sorting enhancements(Muhammad Tajammal Munir, et al., 2023).

4-2-3. Reinforcement learning

Reinforcement learning is a type of machine learning where an agent is trained to make decisions in an uncertain environment. The agent receives rewards or penalties based on its actions and learns to optimize its behavior over time. Examples of reinforcement learning techniques include Q-Learning(Prakash A, et al., 2019)[48],State–action–reward–state–action (SARSA) (Liu Q,, et al.,2022)[49], and Deep Deterministic Policy Gradient (DDPG)(Mason K, 2019)[50]. Reinforcement learning in waste management optimizes collection routes by enabling agents to decide efficient routes based on environmental feedback, like traffic and waste volume. This aids in reducing collection costs. It also optimizes waste processing by prioritizing streams based on resource availability and demand, lowering processing expenses. Additionally, reinforcement learning enhances waste sorting by prioritizing streams based on demand and resource availability. However, successful implementation necessitates substantial data, problem understanding, and well-structured reward systems, alongside significant computational power and expertise. Overall, reinforcement learning serves as a potent tool in municipal waste management, optimizing decision-making across collection routes, processing, and sorting processes(Muhammad Tajammal Munir, et al., 2023).

5. Data Analysis in Waste Management of Singapore

5-1. Data Collection

For data collection, various platforms can be utilized, including Data.gov, the UCI Machine Learning Repository, the Stanford Large Network Dataset Collection, the EU Open Data

Portal, and Kaggle. In this study, the dataset for Singapore's waste management was sourced from Kaggle and the National Environment Agency's website. Three different Excel files were downloaded from Kaggle, and data from 2021 and 2022 were obtained from the NEA website[51]. The data, which spans from 2003 to 2022, includes information about waste generated and recycled from different types of waste. Additionally, it provides details on the amount of energy and crude oil saved by recycling specific types of waste, including plastic, glass, ferrous metal, non-ferrous metal, and paper. The analysis will be conducted using Python.

5-2. Data Loading

In this section, the key libraries and data input methods used in the Python code for analysis will be briefly explained:

The pandas library is essential for data manipulation and analysis, providing efficient data structures like DataFrames. Plotly is used for creating interactive visualizations that dynamically explore data trends. Numerical operations and array handling are supported by numpy, which is fundamental for scientific computing. For creating static visualizations, seaborn and matplotlib are utilized; seaborn offers attractive statistical graphics while matplotlib allows detailed customization. Statistical modeling and hypothesis testing are performed using statsmodels and scipy, which offer a wide range of statistical tests and models. Scikit-learn, a comprehensive machine learning library, is used for data preprocessing, model training, evaluation, and feature selection. Mlxtend extends scikit-learn with additional feature selection tools to enhance model performance. Additionally, the warnings module is used to manage warning messages, making the output cleaner.

For data input, CSV files are loaded into pandas DataFrames using the pd.read_csv function. Specifically, datasets on waste statistics and energy saved are imported for analysis. Using these libraries and datasets enables comprehensive data analysis, visualization, statistical modeling, and machine learning. To access the complete code, you can use this link:

https://colab.research.google.com/drive/1bPAHHjb-zPDyVo19RkiEkjb-miv5vuiN?usp=sharing.

5-3. Data Cleaning

In the data cleaning process, the following steps were undertaken: First, the columns in the 2018-2020 and 2021-2022 datasets were renamed to match those in the 2003-2017 dataset to ensure consistency. Second, numbers were converted to tonnes by multiplying by 1000, and recycling rates were calculated and rounded accordingly. Additionally, waste disposed of from 2003 to 2022 was computed. Third, the columns in the 2018-2020 and 2021-2022 files were sorted to match the column order of the 2003-2017 dataset. Fourth, data from the 2003-2017, 2018-2020, and 2021-2022 periods were merged into a single DataFrame for comprehensive analysis. Finally, the waste_type column was converted to lowercase to avoid case sensitivity issues. After completing the data visualization, I discovered two data points that were out of range. One was the total amount of food waste generated in 2019, initially recorded as 7440 tonnes, which I verified against other sources and found to be 744 tonnes. The second discrepancy was in the total amount of metal recycled in 2018, which I corrected during the data cleaning process. As a result of these steps, we now have a clean dataset that is ready for visualization.

5-4. Data Visualization

In the visualization section, several analyses were conducted.

1. A bar chart was created to visualize waste generation, waste recycled, and recycling rates over time. To achieve this, rows in the merged data where waste_type was 'Total' were filtered.
2. Two pie charts were generated to show the proportion of total waste generated by waste type (excluding 'Total') and the proportion of total waste recycled by waste type.
3. Bar charts for energy saving and oil saving amounts per year were created. These quantities were calculated based on the provided data. Energy-saving amounts were assigned to different types of waste, detailing the energy saved in kilowatt-hours (kWh) and crude oil saved (in barrels) by recycling 1 metric tonne of each waste type. Since 1 barrel of oil is approximately 159 liters, crude oil savings were calculated accordingly.
4. The time series trends of 'waste generation', 'recycling', and 'recycling rate' for six different waste types were also visualized.

These analyses provided comprehensive insights into waste management trends and resource savings over time, which will be discussed in the following section.

5-5. Data analysis and interpretation

From Figure 2, depicting waste generated, waste recycled and the rate of waste recycled, it can be observed that there was a continuous sharp increase in the amount of waste generated in Singapore, from around 5 million tonnes to 8 million tonnes between 2003 and 2013. During those years, the recycling rate increased from 0.41 to 0.61. From 2014 to 2018, waste generation fluctuated, but the recycling rate remained steady at 0.61. In 2020, there was a significant decrease in waste generated, reaching just under 6 million tonnes. However, it began to rise again, reaching 7.385 million tonnes in 2022. The recycling rate in 2022 was 0.57.

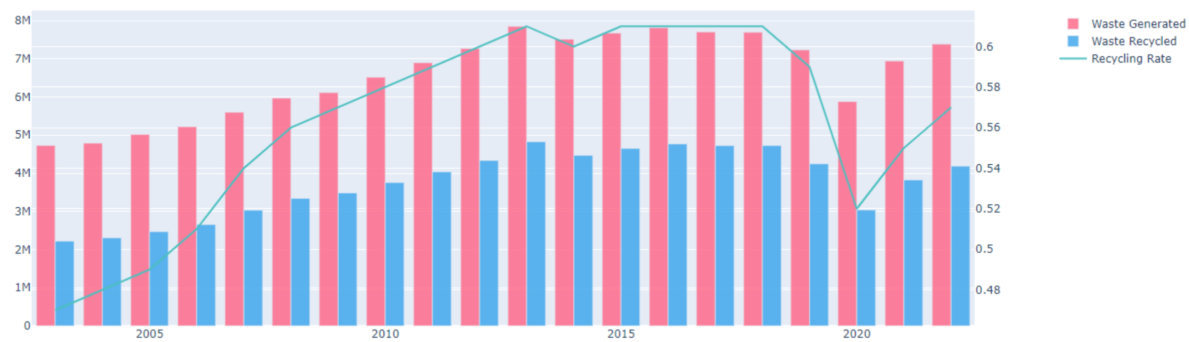

Fig. 2. Waste Generated, Waste Recycled, and the Rate of Waste Recycled in Singapore (2003-2022)

From Figure 3, the pie chart depicting waste generation in Singapore from 2003 to 2022 by waste type shows that the majority of waste is composed of paper (17%), cardboard (16.2%), followed closely by ferrous metals, construction debris, food, and plastics with 16.1%, 14.7%, and 11.4% respectively. These proportions highlight the significant contribution of these waste types to the overall waste generation in Singapore.

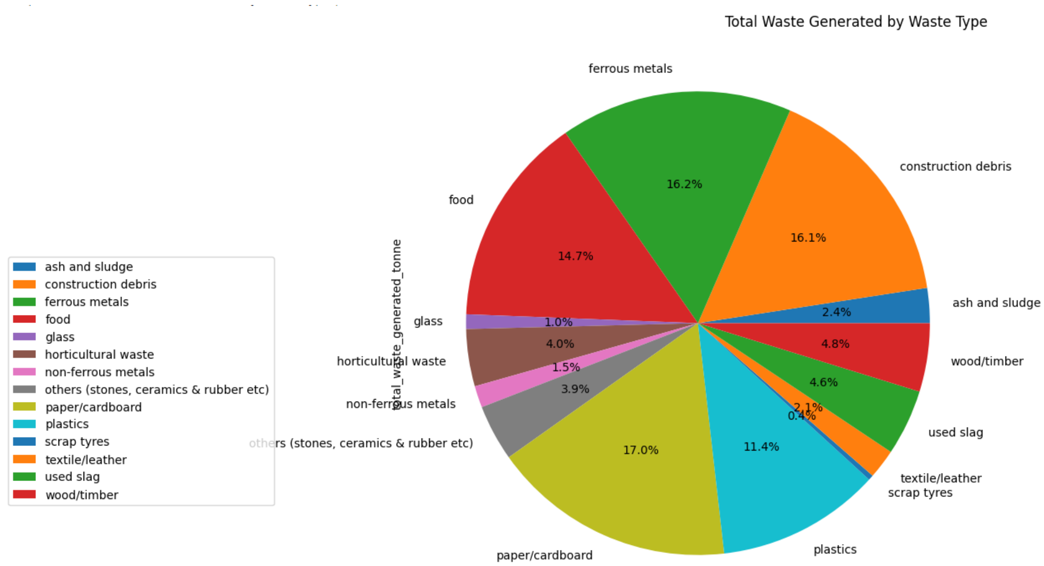

Fig. 3. Total Waste Generated by waste type in Singapore (2003-2022)

Figure 4 illustrates the pie chart depicting waste recycling by type in Singapore. It highlights the city-state's strong recycling capabilities for construction debris (29.7%) and ferrous metals (27.7%), as well as moderate rates for paper and cardboard (15.5%). In contrast, despite being a major contributor to waste generation, only a small fraction (2.5%) of food waste is recycled, indicating room for improvement in food waste recycling efforts.

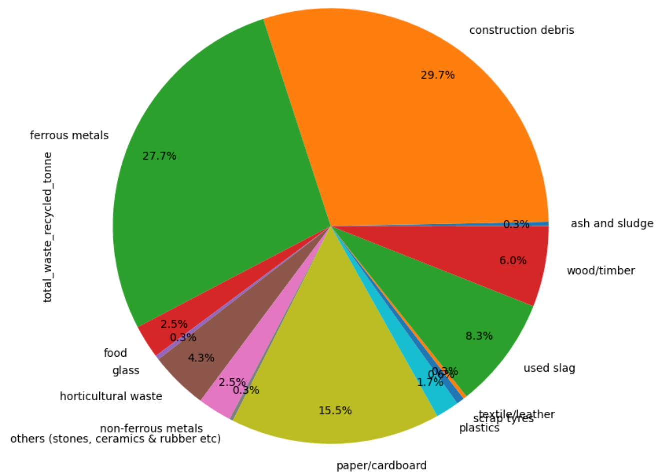

Fig. 3. Total Waste Recycled by waste type in Singapore (2003-2022)

In Figure 5, the bar chart illustrates the energy savings achieved through recycling different types of waste in Singapore. The data shows that recycling paper/cardboard provides the highest energy savings, followed by non-ferrous metals. Notably, recycling glass waste does not yield significant energy savings. This pattern is also observed in Figure 6 for oil savings. It's important to note that there is no available data on the amount of energy saved from food recycling and oil savings through this method in Singapore.

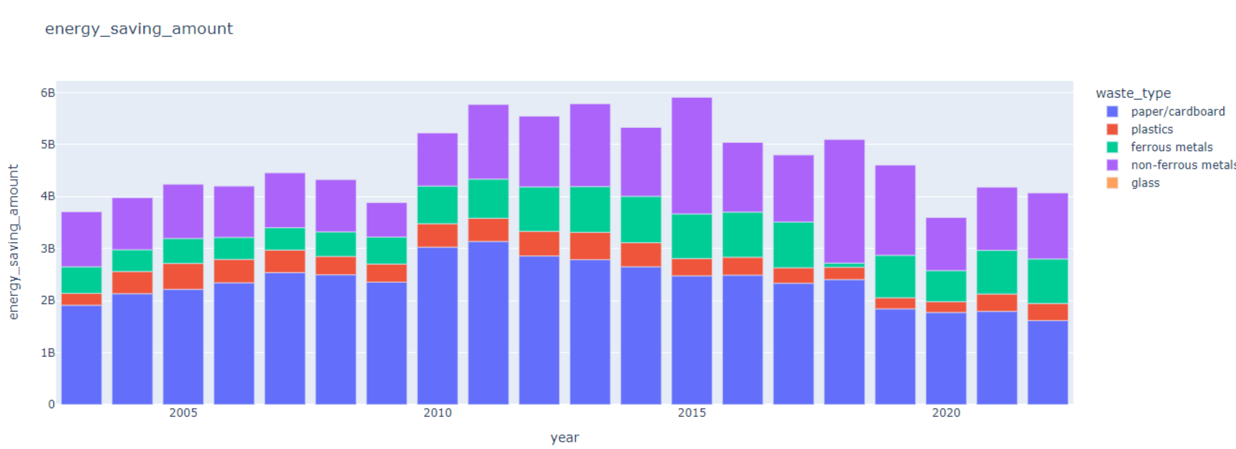

Fig. 5. Energy Savings by Waste Type in Singapore (2003-2022)

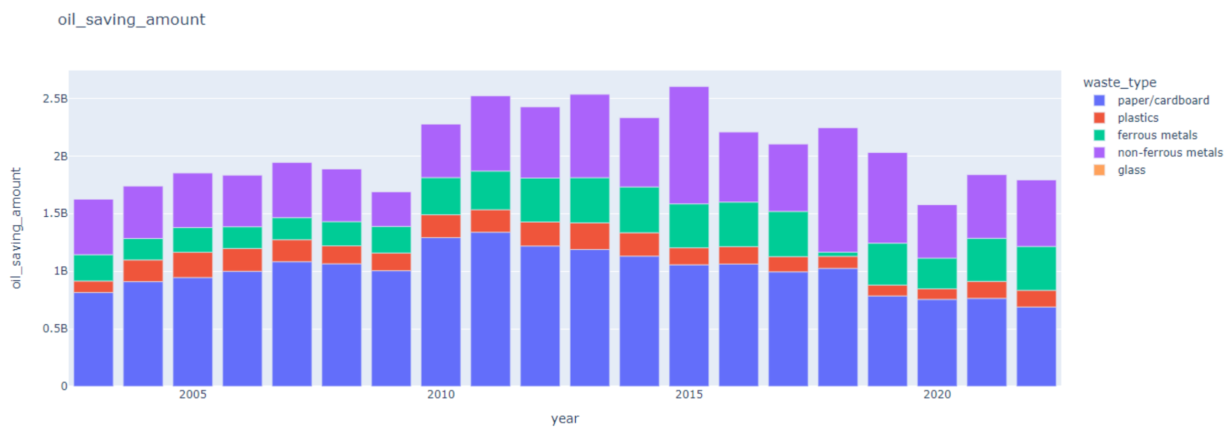

Fig. 5. Oil Savings by Waste Type in Singapore

Although plastic has a high potential for energy savings in kilowatt hours (kWh) and significant crude oil savings (in barrels) when recycling 1 metric tonne (1000 kilograms) per waste type, as shown in Figure 6 its recycling rate is very low. Consequently, its overall impact on energy savings is quite limited.

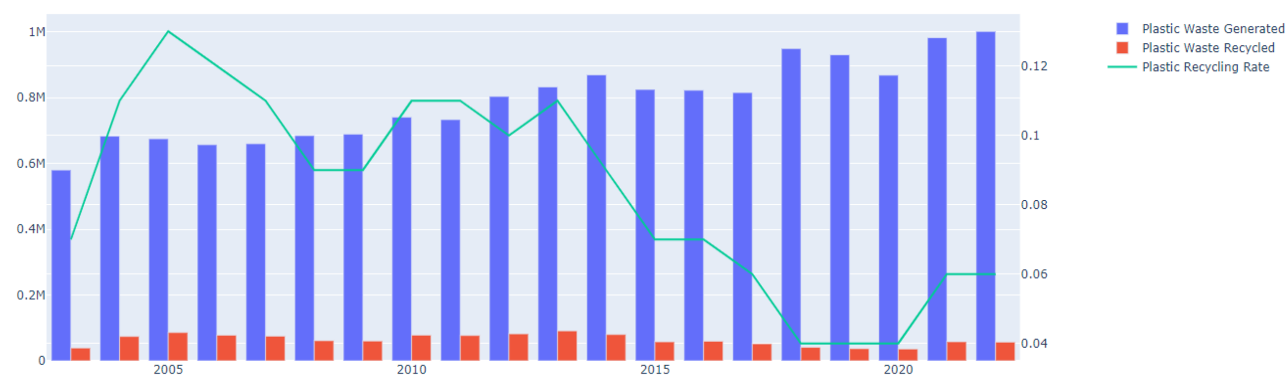

Fig.5. Plastic waste generated, recycled and recycling rate (2003-2022)

These findings highlight the importance of targeted efforts to improve recycling rates for key waste types, particularly plastics and food waste, to enhance overall energy savings and resource efficiency in Singapore's waste management system. One way to achieve this is by investing in advanced recycling technologies and infrastructure, as well as implementing robust public awareness campaigns to encourage proper waste segregation and recycling practices among residents and businesses.

6.Conclusion

This study underscores the transformative potential of AI and Machine Learning in waste management. By leveraging these technologies, waste management practices can become more efficient, sustainable, and cost-effective. The literature review revealed a wide range of AI techniques being employed across various aspects of waste management, including waste collection, sorting, recycling, and monitoring. The data analysis of Singapore's waste management from 2003 to 2022 highlighted significant trends and insights, such as the continuous increase in waste generation, fluctuations in recycling rates, and the notable impact of specific waste types on energy and crude oil savings. These findings demonstrate the importance of integrating AI and ML into waste management strategies to achieve better environmental and operational outcomes.

References

[1] S.I. Zandalinas, F.B. Fritschi, R. Mittler, Global warming, climate change, and environmental pollution: recipe for a multifactorial stress combination disaster, Trends Plant Sci. 26 (6) (2021) 588–599.
[2] D.I. Armstrong McKay, et al., Exceeding 1.5 C global warming could trigger multiple climate tipping points, Science 377 (6611) (2022) eabn7950
[3] L. Al-Ghussain, Global warming: review on driving forces and mitigation, Environ. Prog. Sustain. Energy 38 (1) (2019) 13–21
[4] C.B. Agaton, et al., Economic analysis of waste-to-energy investment in the Philippines: a real options approach, Appl. Energy 275 (2020) 115265.
[5] Codinhoto, R., Becher, O., Heron, J.N., Donato, V., 2023. BIM Bin: Waste Management Through BIM and Digital Twin, in: Research Anthology on BIM and Digital Twins in Smart Cities. IGI Global, pp. 504–532. DOI: 10.4018/978-1-6684-7548-5.ch023.
[6] T.-H. Tsui, J.W. Wong, A critical review: emerging bioeconomy and waste-to-energy technologies for sustainable municipal solid waste management, Waste Disposal Sust. Energy 1 (2019) 151–167.
[7] M.A. Mujtaba et al., Evaluating sustainable municipal solid waste management scenarios: A multicriteria decision making approach, Heliyon 10 (2024) e25788
[8] Kumari, N., Pandey, S., Pandey, A.K., Banerjee, M., 2023. Role of artificial intelligence in municipal solid waste management. Br. J. Multidiscip. Adv. Stud. 4, 5–13. https:// doi.org/10.37745/bjmas.2022.0180.
[9] Aniza, R., Chen, W.-H., P´etrissans, A., Hoang, A.T., Ashokkumar, V., P´etrissans, M., 2023. A review of biowaste remediation and valorization for environmental sustainability: Artificial intelligence approach. Environ. Pollut. 324, 121363 https://doi.org/ 10.1016/j.envpol.2023.121363.
[10] Pallathadka, H., Mustafa, M., Sanchez, D.T., Sekhar Sajja, G., Gour, S., Naved, M., 2023. IMPACT OF MACHINE learning ON Management, healthcare AND AGRICULTURE. Materials Today: Proceedings, SI:5 NANO 2021 80, 2803–2806. DOI: 10.1016/j. matpr.2021.07.042.
[11] Yetilmezsoy, K., Ozkaya, B., Cakmakci, M., 2011. Artificial intelligence-based prediction models for environmental engineering. Neural Netw. World 3, 193–218.
[12] Enitan, A.M., Adeyemo, J., Swalaha, F.M., Kumari, S., Bux, F., 2016. Optimization of biogas generation using anaerobic digestion models and computational intelligence approaches. Rev. Chem. Eng. 33, 2–27. https://doi.org/10.1515/ revce-2015-0057
[13] MathWorks, What is machine learning?. https://www.mathworks.com/discover y/machine-learning.html, 2024.
[14] Chen, M., Liu, Q., Huang, S., Dang, C., 2022. Environmental cost control system of manufacturing enterprises using artificial intelligence based on value chain of circular economy.
Enterprise Inform. Syst. 16, 1856422. https://doi.org/10.1080/17517575.2020.1856422
[15] David B. Olawade , Oluwaseun Fapohunda , Ojima Z. Wada , Sunday O. Usman , Abimbola O. Ige , Olawale Ajisafe , Bankole I. Oladapo, Smart waste management: A paradigm shift enabled by artificial intelligence, Waste Management Bulletin 2 (2024) 244–263
[16] Ahmed Chowdhury, T., Jahan Sinthiya, N., Sajid Hasan Shanta, S.M., Tasbiul Hasan, Md., Habib, M., Rahman, R.M., 2022. Object Detection Based Management System of Solid Waste Using Artificial Intelligence Techniques, in: 2022 IEEE 13th Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON). Presented at the 2022 IEEE 13th Annual Ubiquitous Computing,
[17] Dubey, S., Singh, M.K., Singh, P., Aggarwal, S., 2020a. Waste Management of Residential Society using Machine Learning and IoT Approach, in: 2020 International Conference on Emerging Smart Computing and Informatics (ESCI). Presented at the 2020 International Conference on Emerging Smart Computing and Informatics (ESCI), pp. 293–297. DOI: 10.1109/ESCI48226.2020.9167526.
[18] Ghoreishi, M., Happonen, A., 2020. Key enablers for deploying artificial intelligence for circular economy embracing sustainable product design: Three case studies. AIP Conf. Proc. 2233, 050008 https://doi.org/10.1063/5.0001339.
[19] Reza, M., 2023. AI-driven solutions for enhanced waste management and recycling in urban areas. Int. J. Sustain. Infrastruct. Cities Soc. 8 (2), 1–13
[20] Vu, H.L., Bolingbroke, D., Ng, K.T.W., Fallah, B., 2019a. Assessment of waste characteristics and their impact on GIS vehicle collection route optimization using ANN waste forecasts. Waste Manag. 88, 118–130. https://doi.org/10.1016/j. wasman.2019.03.037.
Vu, H.L., Ng, K.T.W., Bolingbroke, D., 2019b. Time-lagged effects of weekly climatic and socio-economic factors on ANN municipal yard waste prediction models. Waste Manag. 84, 129–140. https://doi.org/10.1016/j.wasman.2018.11.038.
[21] Yan, B., Liang, R., Li, B., Tao, J., Chen, G., Cheng, Z., Zhu, Z., Li, X., 2021. Fast identification and characterization of residual wastes via laser-induced breakdown spectroscopy and machine learning. Resour. Conserv. Recycl. 174, 105851 https:// doi.org/10.1016/j.resconrec.2021.105851.
[22] Mookkaiah, S.S., Thangavelu, G., Hebbar, R., Haldar, N., Singh, H., 2022. Design and development of smart Internet of Things–based solid waste management system using computer vision. Environ. Sci. Pollut. Res. 29, 64871–64885. https://doi.org/ 10.1007/s11356-022-20428-2
[23] KLONTZA, D.E., 2023. Artificial Intelligence with Earthworm Optimization Assisted Waste Management System for Smart Cities [WWW Document]. URL https://journal.gnest.org/publication/gnest_04712 (accessed 5.27.23).

[24] Sarc, R., Curtis, A., Kandlbauer, L., Khodier, K., Lorber, K.E., Pomberger, R., 2019. Digitalisation and intelligent robotics in value chain of circular economy oriented waste management – A review. Waste Manag. 95, 476–492. https://doi.org/ 10.1016/j.wasman.2019.06.035.

[25] Nwokediegwu, Z.Q.S., Ugwuanyi, E.D., 2024. Implementing ai-driven waste management systems in underserved communities in the USA. Eng. Sci. Technol. J. 5 (3), 794–802.

[26] Koinig, G., 2023. Sensor-Based Sorting and Waste Management Analysis and Treatment of Plastic Waste With Special Consideration of Multilayer Films, Dr.mont., Montanuniversitaet Leoben (000). DOI: 10.34901/mul.pub.2023.58.

[27] Al Duhayyim, M., Abdalla Elfadil Eisa, T., N. Al-Wesabi, F., Abdelmaboud, A., Ahmed Hamza, M., Sarwar Zamani, A., Rizwanullah, M., Marzouk, R. ,2022. Deep Reinforcement Learning Enabled Smart City Recycling Waste Object Classification. Computers, Materials & Continua 71, 5699–5715. DOI: 10.32604/ cmc.2022.024431

[28] Golbaz, S., Nabizadeh, R., Sajadi, H.S., 2019. Comparative study of predicting hospital solid waste generation using multiple linear regression and artificial intelligence. J. Environ. Health Sci. Eng. 17, 41–51. https://doi.org/10.1007/s40201-018-00324- z

[29] Araujo-Andrade, C., Bugnicourt, E., Philippet, L., Rodriguez-Turienzo, L., Nettleton, D., Hoffmann, L., Schlummer, M., 2021. Review on the photonic techniques suitable for automatic monitoring of the composition of multi-materials wastes in view of their posterior recycling. Waste Manag. Res. 39 (5), 631–651.

[30] Ejimofor, M.I., Aniagor, C.O., Oba, S.N., Menkiti, M.C., Ugonabo, V.I., 2022. Artificial intelligence in the reduction and management of land pollution, in: Current Trends and Advances in Computer-Aided Intelligent Environmental Data Engineering. Elsevier, pp. 319–333. DOI: 10.1016/B978-0-323-85597-6.00009-4

[31] Salman, M.Y., Hasar, H., 2023. Review on environmental aspects in smart city concept: Water, waste, air pollution and transportation smart applications using IoT techniques. Sustain. Cities Soc. 94, 104567 https://doi.org/10.1016/j. scs.2023.104567

[32] Liao, B., Wang, T., 2020. Research on industrial waste recovery network optimization: Opportunities brought by artificial intelligence. Math. Probl. Eng. 2020, e3618424.

[33] Nguyen, V.T., Ta, Q.T.H., Nguyen, P.K.T., 2022. Artificial intelligence-based modeling and optimization of microbial electrolysis cell-assisted anaerobic digestion fed with alkaline-pretreated waste-activated sludge. Biochem. Eng. J. 187, 108670 https:// doi.org/10.1016/j.bej.2022.108670.

[34] Aytaç, K., Korçak, O., ¨ 2021. IoT based intelligence for proactive waste management in Quick Service Restaurants. J. Clean. Prod. 284, 125401 https://doi.org/10.1016/j. jclepro.2020.125401

[35] Tyagi AK, Chahal P. Artificial intelligence and machine learning algorithms. Res Anthol Mach Learn Techn Methods Applications, IGI Global 2022:421–46

[36] Azadi S, Karimi-Jashni A. Verifying the performance of artificial neural network and multiple linear regression in predicting the mean seasonal municipal solid waste generation rate: a case study of Fars province, Iran. Waste Manag 2016;48: 14–23

[37] Bernad-Beltran ´ D, Simo´ A, Bovea MD. Attitude towards the incorporation of the selective collection of biowaste in a municipal solid waste management system. A case study. Waste Manag 2014;34(12):2434–44

[38] Heshmati R AA, Mokhtari M, Shakiba Rad S. Prediction of the compression ratio for municipal solid waste using decision tree. Waste Manag Res 2014;32(1):64–9.

[39] You H, Ma Z, Tang Y, Wang Y, Yan J, Ni M, et al. Comparison of ANN (MLP), ANFIS, SVM, and RF models for the online classification of heating value of burning municipal solid waste in circulating fluidized bed incinerators. Waste Manag 2017;68:186–97

[40] Mishra R, Singh E, Kumar A, Kumar S. Artificial intelligence models for forecasting of municipal solid waste generation. In: Soft Computing Techniques in Solid Waste and Wastewater Management. Elsevier; 2021. p. 289–304.

[41] Olatunji OO, Akinlabi S, Madushele N, Adedeji PA. Property-based biomass feedstock grading using k-Nearest Neighbour technique. Energy 2020;190: 116346

[42] Abbasi M, Abduli M, Omidvar B, Baghvand A. Results uncertainty of support vector machine and hybrid of wavelet transform-support vector machine models for solid waste generation forecasting. Environ Prog Sustain Energy 2014;33(1): 220–8

[43] Ma S, Zhou C, Chi C, Liu Y, Yang G. Estimating physical composition of municipal solid waste in China by applying artificial neural network method. Environ Sci Tech 2020;54(15):9609–17.

[44] Fy O, Jet A, O A, Jo H, O O, J A. Supervised machine learning algorithms: classification and comparison. Int J Comput Trends Technol (IJCTT) 2017;48(3): 128–38

[45] Alsharif MH, Kelechi AH, Yahya K, Chaudhry SA. Machine learning algorithms for smart data analysis in internet of things environment: taxonomies and research trends. Symmetry 2020;12(1):88.

[46] Muhammad Tajammal Munir , Bing Li , Muhammad Naqvi, Revolutionizing municipal solid waste management (MSWM) with machine learning as a clean resource: Opportunities, challenges and solutions, Fuel 348 (2023) 128548

[47] Zhu L-T, Chen X-Z, Ouyang B, Yan W-C, Lei H, Chen Z, et al. Review of machine learning for hydrodynamics, transport, and reactions in multiphase flows and reactors. Ind Eng Chem Res 2022;61(28):9901–49.

[48] Prakash A, AgarwallaN, Priyadarshini R, Misra R. A Novel Approach Towards Industrial Waste Management Using Q-Learning. In: 2019 International Conference on Intelligent Computing and Remote Sensing (ICICRS), IEEE; 2019

[49] Liu Q, Cui C, Fan Q. Self-adaptive constrained multi-objective differential evolution algorithm based on the state–action–reward–state–action method. Mathematics 2022;10(5):813

[50] Mason K, Grijalva S. A review of reinforcement learning for autonomous building energy management. Comput Electr Eng 2019;78:300–12.

[51] https://www.nea.gov.sg/our-services/waste-management/waste-statistics-and-overall-recycling