

The Use of Artificial Intelligence and Machine Learning in Creating a Roadmap Towards a Circular Economy for Plastics

Sri Charan Yarlagadda,

PhD, Chemical & Biomolecular Engineering, Georgia Institute of Technology, St Louis, Missouri, ysricharanacads@gmail.com

Abstract

The plastic industry and consumer demand have both exploded since the 1950s. Plastic waste in the ocean has also skyrocketed, growing by a factor of 10 since 1980. Many animal species can't survive this kind of pollution. This is probably bad for people. Impacts plankton, which in turn modifies the carbon cycle. Effects global warming by adding to it. This list, by the way, is not comprehensive. Whenscarce resources are used inefficiently and without good planning, a great deal of waste is generated, which has a negative impact on the natural world. The notion of a circular economy (CE) has shown encouraging signs of being adopted at industrial and governmental levels as an alternative for the conventional but wasteful linear manufacturing lines. Through careful planning and subsequent reuse, recycling, and remanufacturing, CE strives to maximise the value of raw materials over a product's entire life cycle. Two cutting-edge technologies that can considerably aid in the widespread acceptance and application of CE in actual practises are artificial intelligence (AI) and machine learning (ML). This research delves into how AI applications are being included into CE.

Key words: Artificial intelligence (AI), Machine learning (ML), Circular Economy (CE), Plastic waste.

1. Introduction

Businesses, educators, and governments around the world who are interested in the future of industrial development have been discussing the Circular Economy (CE) concept for decades. CE is a "system restorative and regenerative by design, which aims to maintain products, components, and materials and their highest utility and value" [1] according to the Ellen Macarthur Foundation. The transition from a "make, use, dispose" strategy to a "make, use, recycle" paradigm requires substantial effort from governments, industry, and consumers, but CE has numerous positive benefits on enterprises. The Macarthur replacement and recovery is high for many businesses, despite the many advantages of circular business models (also known as sustainable business models). Therefore, businesses that potentially create new problems need to adjust their strategies accordingly. To be competitive, businesses today must be able to meet a wide range of challenges, including those related to asset management, supply chain innovation, logistics, the design of manufacturing services, and improvements in quality control [3]. Although doing so adds complexity to the CE workflow, progress towards

circularity can be hastened by focusing on product design development and related business model enhancements [4].

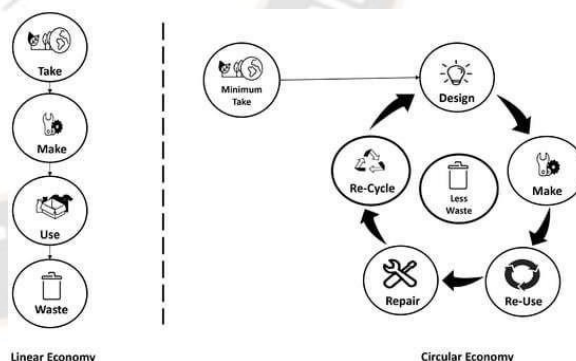


Figure 1. Comparing the Linear and Circular Models of the Economy.

Figure 1 shows how different the operational models of the linear and circular economies are. In addition, the supply chain is widely acknowledged as a crucial aspect in the literature of CE for helping to implement CE. The term "circular economy" (CE) refers to an up-to-date method that prioritises cooperation and integration in its pursuit of greater efficiency through the use of circular practises

including reuse, recycling, and closed-loop systems. Incorporating circular strategies at the outset of product design is crucial for value creation and supply chain [5, 6] because once resources, characteristics, and requirements are assigned for producing a product, it is difficult, if not impossible, to make modifications to the product. Therefore, firms need cutting-edge methods of product design to cut costs and make the most of scarce resources. Bressanelli et al. [7] explain how industries might advance towards circularity with the help of fourth industrial revolution (4IR) technology like Big Data, AI, and the Internet of Things. The Ellen MacArthur Foundation [8] cites artificial intelligence as a key component and a subset of the technologies that aid in bettering product circulation, smart management, and predictive maintenance. In this article, artificial intelligence is discussed as a method to rapidly prototype items for closed-loop applications.

2. Literature review

The world's waste management systems are straining under the weight of ever-increasing amounts of waste plastics (Osman et al., 2023) and cannot keep up. The annual amount of microplastics poured into the oceans is anticipated to be 8 million tonnes (Lau et al., 2020), with a further 1.5 million tonnes being large microplastics. Polymers that have outlived their usefulness can remain in the environment for billions of years. To avoid major ecological and environmental problems caused by inadequate pre- and/or post-user handling and widespread landfilling of discard plastics, pyrolysis can be used as a conversion process. Machine learning methods can be used to forecast the byproducts of scrap plastic pyrolysis's continuous and non-catalytic processes.

Particle size (in millimetres) is used as an input to distinguish between materials including polyethylene, polypropylene, polystyrene, polyvinyl chloride, and polyethylene terephthalate. (Ramya Manikyam 2016) There were also non-flammable

chemical elements like carbon, hydrogen, oxygen, nitrogen, and chlorine present. Sulphur, on the other hand, was not chosen because of how little it is in comparison to the others. (R. Manikyam 2019) For the second reactor, operators thought about feed capacity (in kilogrammes per hour), pyrolysis temperature (in degrees Celsius), and steam residence duration (in seconds). Since only a few reliable sources mentioned heating and carrier gas flow rates, they were not chosen as input parameters. When only ranges were available from reliable sources, we used the midpoints instead (Chenget al., 2023).

Many studies have only looked at one or at most two types of

models, therefore there is a dearth of data to evaluate the prediction accuracy of multiple models using the same trash dataset (Wang et al., 2021). To calculate the relative amounts of biogenic and fossil carbon in trash using a mass basis, the Fourier-transform infrared method can be applied to spectra obtained using reduced total reflection. Using this data, we can calculate the impact that burning solid waste will have on our efforts to cut carbon emissions. This method can produce high-quality outcomes with minimal time and material investment. In this light, the strategy's environmental and commercial financial benefits become clear. The machine learning method can be utilised in bioprocessing to reduce potential environmental concerns and increase the profitability of composting and anaerobic digestion products by distinguishing impurities like plastics and stones from feedstock, compost, and solid digestate (Guo et al., 2021).

Du et al. (2022) have developed a convolutional neural network-based deep learning model to aid in the identification and classification of textile waste. Less than two seconds are needed for recognition, and the model has a 95.4% chance of correctly categorising textile waste into one of 13 material categories. Bobulski and Kubanek (2021a) have shown that plastic trash can be separated into four types according to their composition using a convolutional neural network and the techniques of deep learning. The system is suitable for both industrial and domestic application. Toaçar et al. (2020) provide a garbage classification system that can sort rubbish into recyclable and non-recyclable heaps with a 99.5% accuracy rate using a convolutional neural network. A real-time smartphone app developed by Thumiki and Khandelwal (2022) uses image recognition and a convolutional neural network to sort trash into one of six groups according to its composition and determine whether or not it can be recycled.

3. Methodology

AI Techniques to Advance CE

We explored the potential applications of AI in CE and the part AI plays in these procedures in the preceding section. Important AI approaches for CE will be discussed here, along with their key characteristics. We give some observations on why these methods are good for promoting CE solutions.

- **Machine learning:** Machine learning (ML) is a branch of AI that trains computers to learn independently from data by seeing patterns, drawing conclusions, and generating predictions. Data is fed into ML algorithms, and the algorithms are trained to produce outputs by use of statistical calculations. It is possible to refine the quality of the results by repeating and adjusting

this training process. Significant connections between data aspects of real-time datasets can be detected by ML algorithms, allowing for the identification of potential for circular solutions. The demand for a product, based on consumers' purchase habits, can be predicted using ML techniques. In agricultural settings, ML can be used to predict the best time to sow crops based on factors like as soil quality, weather forecasts, and anticipated demand for the crop.

- Artificial Neural Networks:** Artificial neural networks (ANNs) are a type of computational model that mimics the behaviour of real neural networks. ANNs are programmed to mimic the functioning of human neurons. Learning algorithms are used in ANNs so that the systems can improve or learn on their own as new data is added and investigated. This makes ANNs useful for solving a wide variety of challenging issues. Artificial neural networks (ANNs) are a widely-used AI technology. In the field of CE, there are numerous existing instances. Applications of ANNs trained with ML algorithms include recycling stream classification, material end-of-life traceability tracking and forecasting, and product demand forecasting.

- Convolutional Neural Networks:** Since convolutional neural networks (CNNs) are capable of complex digital image processing, they are frequently utilised for analysing visual data. In the CE, convolutional neural networks (CNNs) can be used to process input images, label them with importance (learnable weights and biases), and establish object differentiation. In order to sort recyclables from trash, CNNs can be utilised. They can be used to monitor urban waste management, including the automatic detection of full trashcans and other uses that help maximise food output.
- Timeseries Analysis:** The artificial intelligence method of Timeseries Analysis can handle variables that change over time. This strategy is outstanding for discovering significant trends in data sets for use in future forecasting. One very sophisticated Deep Learning (DL) model is the Long Short-Term Memory (LSTM). Methods such as autoregression, moving average, and lines of best fit are also available. Food waste can be reduced by using consumption patterns to estimate demand, and equipment maintenance costs can be reduced and the lifespan of the equipment increased through the use of predictive maintenance.

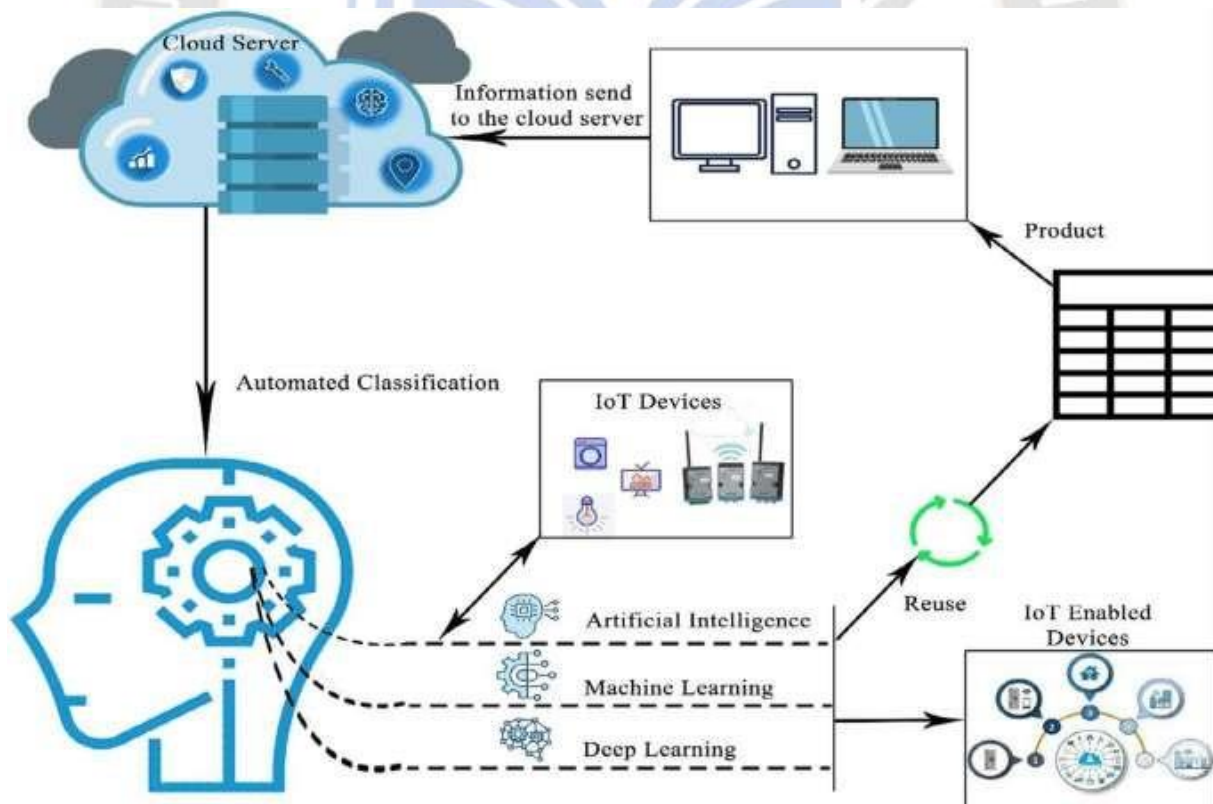


Fig 2: Management of electronic waste framework using artificial intelligence.

E-waste can be effectively managed in line with correct reuse and recycle procedures, as shown in figure 2.

Artificial intelligence and machine learning can be used to significantly speed up the process of creating a plastics circular economy plan. The purpose of the circular economy is to increase the number of times materials like

plastics are reused and recycled while simultaneously decreasing waste. Here's how AI and ML can be applied in this context:

Waste Sorting and Recycling Optimization:

1. *Optimized data collection and processing:* Cloud computing has been used for data collection and analysis in the current framework. At this stage, we'll be conducting e-waste surveys, as well as monitoring, reporting, and establishing a notification system. It's able to process mobile app requests for e-waste collection from a variety of users. It is responsible for collecting and verifying information, such as the identity of the requestor and details about e-waste items like metal and reusable
2. *Machine intelligence* this stage, automated techniques based on machine intelligence can be

analysis, extraction, engineering, labelling, and classification.

3. Third, we suggest an Internet of Things (IoT)-based e-waste container to manage the sensing and notification mechanism. This structure may separate the valuable metal from the reused parts as well.
4. Finally, if the requested parts are necessary, the requester will receive

AI-powered robots and machines can be used to automate the sorting of plastics in recycling facilities. ML algorithms can identify and classify different types of plastics, making the sorting process more efficient.

- Predictive analytics can help optimize recycling operations by forecasting material flows, machine maintenance needs, and production schedules.

Supply Chain Management:

The recycling plastics supply chain can be improved with the help of AI. It can predict demand, manage inventory, and optimize transportation routes to reduce emissions and costs.

When combined with AI, the transparency and traceability provided by blockchain can verify the genuineness of recycled materials along the whole supply chain.

Product Design and Material Selection:

AI and ML can assist in the design of products that are

easier to recycle or upcycle. They can analyze the environmental impact of different material choices and designs, helping manufacturers make more sustainable choices.

Design optimization tools can be used to create products with minimal waste and longer lifecycles.

Consumer Engagement:

Consumers may get advice on plastic recycling and disposal from chatbots and virtual assistants driven by artificial intelligence.

Personalized recommendations and incentives can encourage consumers to choose products with less plastic or made from recycled materials.

Monitoring and Compliance:

AI can be used to monitor and enforce compliance with recycling and waste reduction regulations. Image recognition and sensors can identify illegal dumping or

improper disposal.

ML models can analyze data from monitoring systems to identify trends and areas for improvement in waste management practices.

Marketplace for Recycled Materials:

AI-based platforms can connect buyers and sellers of recycled plastics, making it easier for manufacturers to source sustainable materials.

ML algorithms can predict market trends and pricing for recycled materials, incentivizing more businesses to participate in the circular economy.

Research and Innovation:

AI can accelerate materials research by simulating chemical reactions and properties, helping scientists discover new, more sustainable plastics.

ML can analyze vast datasets of scientific literature to identify emerging trends and research opportunities in the field of plastics and recycling.

Quality Control:

ML can be used for quality control in the manufacturing of products made from recycled plastics, ensuring that they meet the required standards.

Environmental Impact Assessment:

AI models can assess the environmental impact of different recycling and disposal methods, helping policymakers make informed decisions.

Predictive Maintenance:

AI can be applied to maintenance processes in recycling facilities to predict when equipment needs servicing, reducing downtime and improving efficiency.

4. RESULTS AND STUDY

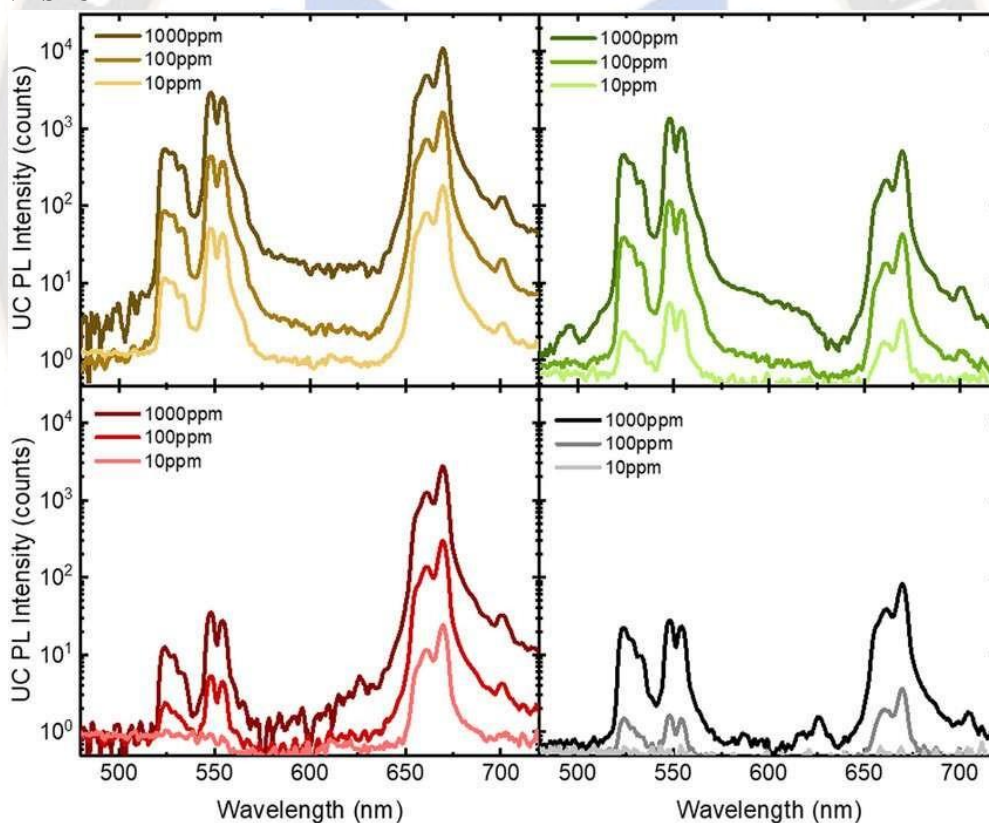


Fig. 3. UC PL spectra of semi-transparent plastics with varying concentrations of a Yb³⁺/Er³⁺ - based marker ((a) - yellow, (b) - green, (c) - red, and (d) - black). Longitudinal 980 nm excitation. 10 W/cm² of excitation power.

Embedded in a semi-opaque plastic film, the up-conversion spectra of the Yb³⁺/Er³⁺ -based marker are displayed in Fig. 3. In the up-conversion spectra, the emission peaks of Er³⁺ can be detected at 540 and 670 nm.

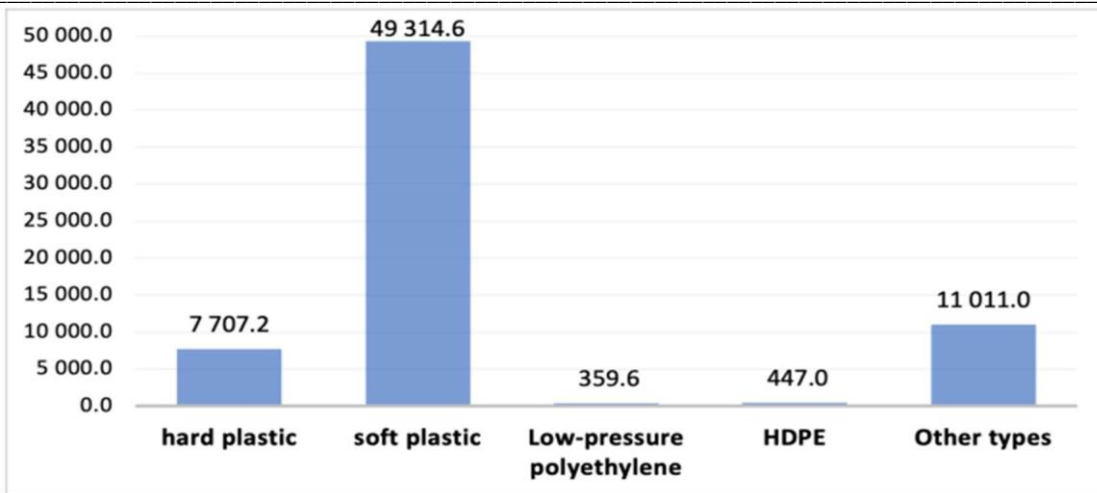


Fig 4. Volume of plastic waste for 2022.

Figure 4 presents the available statistics showing that soft plastics account for the majority of plastic volume.

Table 1. The amount of waste generated from MSW and plastic waste combination.

Year	MSW million t	Waste polymers (plastics) million t
2020	4.6	0.51
2021	4.2	0.47

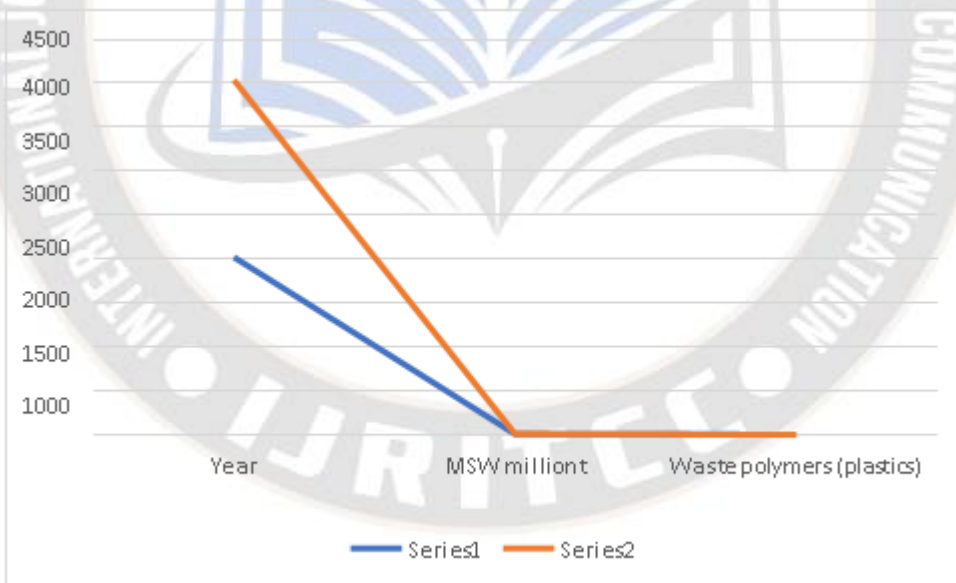


Fig 5: Total amount of plastic generated from cities, including garbage and plastic waste.

Table 2 presents the calculated total volume of plastic garbage, and figure 5 displays the associated graph.

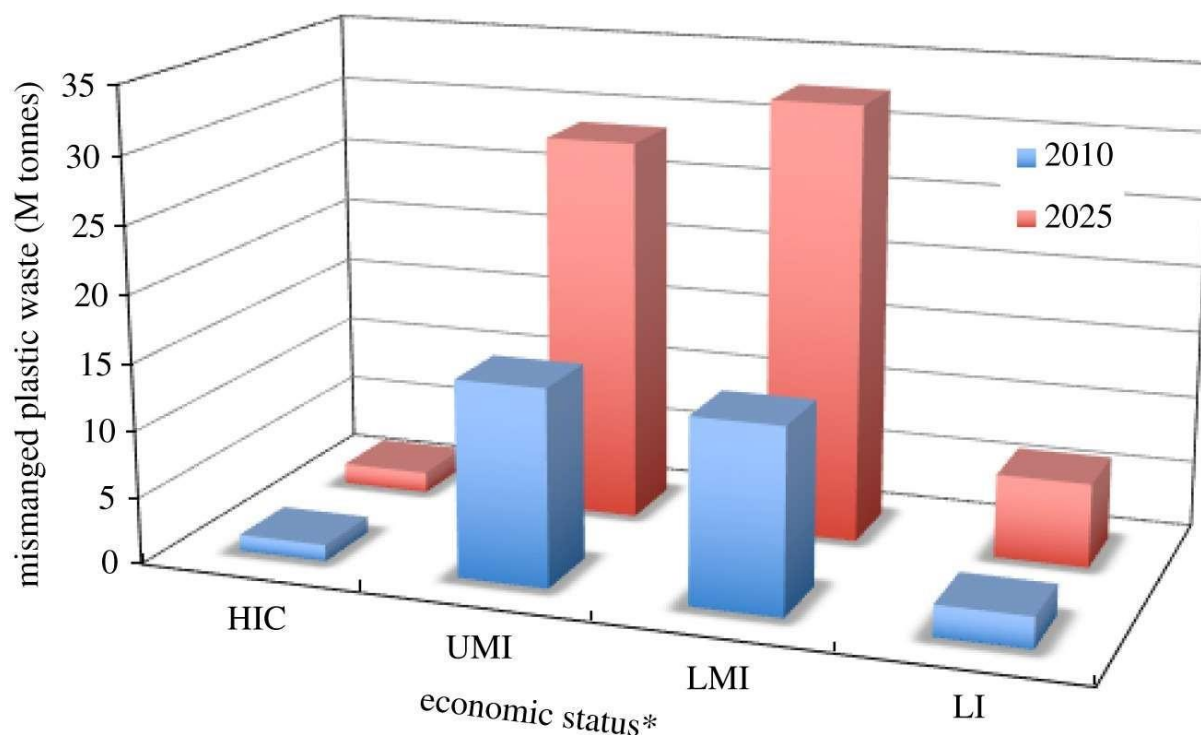


Figure 6. Annual mismanaged waste plastics amounts by World Bank economic status.

A similar strategy in the West led to decades of huge waste exports to developing countries in Asia and Africa. There is no way for these nations to process the large quantities of plastic trash they collect. Figure 6 shows that the top countries contributing to the problem of trash in the ocean are all located in Asia.

CONCLUSION

AI and ML have the potential to revolutionize the way we approach the circular economy for plastics by enhancing efficiency, reducing waste, and enabling more sustainable practices across the entire lifecycle of plastic products. Collaboration among governments, industries, and researchers is essential to leverage these technologies effectively and address the challenges of plastic waste. The goal of a circular economy is to increase the value of raw materials by using them several times. A significant and promising technology that can help steer the transition from linear to circular CE is artificial intelligence. Our research incorporates a wide range of topics related to the circular economy, including sustainable development, reverse logistics, waste management, supply chain management, recycling & reuse, and the creation of industrial processes based on artificial intelligence and machine learning.

REFERENCES

1. E. Macarthur, Towards the Circular Economy”, Journal

of Industrial Ecology, 10, pp. 4–8. (2012)
 2. E. M. & C. Macarthur Foundation, Towards the Circular Economy : Accelerating the scale-up across global supply chains, World Economic Forum Reports, 64(2014)
 3. T. S. Ramadoss, H. Alam, and P. R. Seeram, Artificial Intelligence and Internet of Things enabled Circular economy, The International Journal of Engineering and Science (2018)
 4. C. Kraaijenhagen, C. Van Oppen, and N. Bocken, in Circular Collaboration”, Circular Business: Collaborate and Circulate (Amersfoort, the Netherlands), (2016)
 5. N. M. P. Bocken, M. Farracho, R. Bosworth, and R. Kemp, The front-end of eco-innovation for ecoinnovative small and medium sized companies, Journal of Engineering and Technology Management - JET-M, Elsevier B.V. 31, 43 (2014)
 6. M. Saidani, B. Yannou, Y. Leroy, F. Cluzel, A. Kendall, M. A taxonomy of circular economy indicators, Journal of Cleaner Production, 542-559 542 (2019), hal-01954800
 7. G. Bressanelli, F. Adrodegari, M. Perona, and N. Saccani, The role of digital technologies to overcome Circular Economy challenges in PSS Business Models: An exploratory case study, Procedia CIRP, Elsevier B.V. 73,216 (2018)
 8. Ellen MacArthur Foundation, Artificial intelligence and

- the circular economy -AI as a tool to accelerate the transition,<http://www.ellenmacarthurfoundation.org/publications> (2019)
9. Osman AI, Hosny M, Eltaweil AS, Omar S, Elgarahy AM, Farghali M, Yap P-S, Wu Y-S, Nagandran S, Batumalaie K, Gopinath SCB, John OD, Sekar M, Saikia T, Karunanithi P, Hatta MHM, Akinyede KA (2023) Microplastics sources, formation, toxicity and remediation: a review. *Environ Chem Lett*. <https://doi.org/10.1007/s10311-023-01593-3>
 10. Lau WWY, Shiran Y, Bailey RM, Cook E, Stuchtey MR, Koskella J, Velis CA, Godfrey L, Boucher J, Murphy MB, Thompson RC, Jankowska E, Castillo Castillo A, Pilditch TD, Dixon B, Koerselman L, Kosior E, Favoino E, Gutberlet J, Baulch S, Atreya ME, Fischer D, He KK, Petit MM, Sumaila UR, Neil E, Bernhofen MV, Lawrence K, Palardy JE (2020) Evaluating scenarios toward zero plastic pollution. *Science* 369:1455–1461. <https://doi.org/10.1126/science.aba9475>
 11. Cheng Y, Ekici E, Yildiz G, Yang Y, Coward B, Wang J (2023) Applied machine learning for prediction of waste plastic pyrolysis towards valuable fuel and chemicals production. *J Anal Appl Pyrol* 169:105857. <https://doi.org/10.1016/j.jaap.2023.105857>
 12. Wang D, Tang Y-T, He J, Yang F, Robinson D (2021) Generalized models to predict the lower heating value (LHV) of municipal solid waste (MSW). *Energy* 216:119279. <https://doi.org/10.1016/j.energy.2020.119279>
 13. Guo H-N, Wu S-B, Tian Y-J, Zhang J, Liu H-T (2021) Application of machine learning methods for the prediction of organic solid waste treatment and recycling processes: a review. *Biores Technol* 319:124114. <https://doi.org/10.1016/j.biortech.2020.124114>
 14. Du W, Zheng J, Li W, Liu Z, Wang H, Han X (2022) Efficient recognition and automatic sorting technology of waste textiles based on online near infrared spectroscopy and convolutional neural network. *Resour Conserv Recycl* 180:106157. <https://doi.org/10.1016/j.resconrec.2022.106157>
 15. Bobulski J, Kubanek M (2021a) Deep learning for plastic waste classification system. *Appl Comput Intell Soft Comput* 2021:6626948. <https://doi.org/10.1155/2021/6626948>
 16. Toğaçar M, Ergen B, Cömert Z (2020) Waste classification using autoencoder network with integrated feature selection method in convolutional neural network models. *Measurement* 153:107459. <https://doi.org/10.1016/j.measurement.2019.107459>
 17. Thumiki M, Khandelwal A (2022) Real-time mobile application for classifying solid waste material into recyclable and non-recyclable using Image recognition and convolutional neural network. 2022 IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS). 1–6. <https://doi.org/10.1109/SCEECS54111.2022.9740863>
 18. Ramya Manikyam, J. Todd McDonald, William R. Mahoney, Todd R. Andel, and Samuel H. Russ. 2016. Comparing the effectiveness of commercial obfuscators against MATE attacks. In Proceedings of the 6th Workshop on Software Security, Protection, and Reverse Engineering (SSPREW'16).
 19. R. Manikyam. 2019. Program protection using software based hardware abstraction. Ph.D. Dissertation. University of South Alabama.