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Sustainable environmental design using circular economy in the plastic manufacturing industry for decarbonization

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ABSTRACT

Plastic waste is one of the most controversial environmental issues because of the poor recyclability and high carbon emissions of traditional plastic production systems. Traditional processes can be inefficient in sorting materials, consume high amounts of energy, and lack lifecycle integration for plastic products. This research proposes a Sustainable Environmental Design Circular Economy (SEDC) framework that overcomes the limitation and provides an entire end-to-end solution from designing the product to recycling processes. The proposed method applies a Novel Convolutional Neural Network- Naive Gradient Boost- Sandpiper Optimization (CNN-NB-SPO) algorithm to determine high-level features that improve the recyclability and modularity of products. SPO is used in refinement stages to improve the decisions and consequently, energy efficiency with regard to recyclability potential is improved at the design stage. Novel Generative Adversarial Network- Artificial Neural Network (GAN-ANNs), improve reverse logistics so that supply chain operations become efficient, and the recycling waste of cyclicality decreases. The framework is applied to the Kaggle Plastic Waste dataset, in which its effectiveness in improving classification accuracy, material recovery, and reduction of carbon emissions is demonstrated. Basic performance parameters—recyclability rate, energy consumption, CO2 emissions, and accuracy—confirm that the proposed model significantly outperforms traditional approaches to plastic production manufacturing for the advancement of the goals of a circular economy. An integrated, data-driven approach from SEDC provides a scalable solution toward sustainable plastic production and waste management for the support of global decarbonization efforts.

1. Introduction

Plastics are part and parcel of our daily life, used for packaging food, textiles, medical products, automotive parts, construction materials, among others (Pires da Mata Costa et al., 2021). The traditional focus of research on plastics in a circular economy has been on the end-of-life phase but can be much more upstream in the production chain. Therefore, an overall framework specifying interventions applicable at every stage of the plastics supply chain is needed (Venkatachalam et al., 2022). One of the main contributors of CO2 emissions and environmental issues is the linear path of plastic from production to disposal. A lot of plastic has been manufactured; most of it is for single-use items and packaging, but unfortunately, little recycling and reuse happen. Meanwhile, 31 percent of the plastic waste still finds its way to the landfills. 39 percent is combusted in Europe; despite landfilling's impending ban, incineration is an increasingly favored trend than recycling. With such scenarios the idea of circular economy increasingly holds its value. Diversed countries, organization as well as business organization advocate for the move toward this system that is known as the reuse and recycle 3.

The circular plastic economies come on this platform as an alternative path toward the linear model towards the increase in plastics

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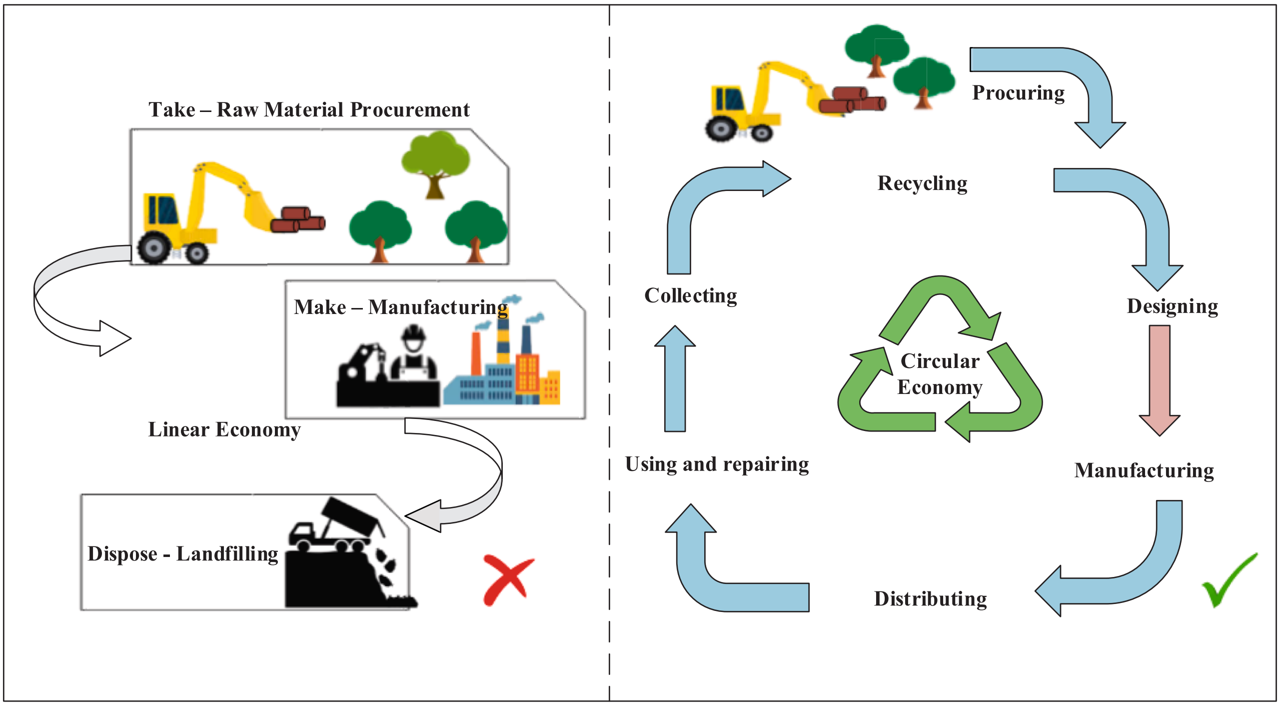

Fig. 1. Linear economy vs circular economy.

delivery in reuse and recycle (Rosenboom et al., 2022). This may reduce a certain share of downcycling and eventually incineration and landfilling, where plastic waste is considered a resource to produce new products in a closed-loop system (Ma et al., 2024). Although the interest grows in the circular economy model, Europe has a recycling collection rate of 30 % of plastic waste. Most them end up as lower value products compared to the original product since much of the supply of downcycling is caused by contamination from various materials and mixed polymers' complexity of products, which makes it complicated for economically viable recycling processes (Eriksen et al., 2020; Wu et al., 2024). Fig. 1: Difference between a linear economy and a circular economy. This kind of economy takes things from nature, uses resources in producing products, then dispose of them as rubbish. In a circular economy, there should be a continuous movement to ensure the procuring, design, manufacturing, use and reuse, collection, or recovery and recycling of resources so as to reduce waste in these economies.

There is post-consumer plastics, a mixture of polymers and additives of short-lived or one-time products that pose quite a challenging task. Researchers have investigated various methods to clean, sort, and recycle mixed plastics but the challenge lies far beyond the recycling stage. Technically and economically, at the design stage, it will be impossible when products are manufactured with several polymers (Bernat, 2023; Antonopoulos et al., 2021). Thus, attaining a circular economy calls for transformative change in dealing with wastes as well as from the design and manufacturing stages. Such a perception goes further by advocating knowledge restructuring besides designing and manufacturing, use, and recycling (Hu et al., 2024; Siltaloppi and Jähi, 2021). Most of the earlier research was directed towards end-of-life solutions to improve plastic waste recycling and recovery rates. However, current emphasis shifts the focus up the value chain. The trends of increased focus at the moment shift to the previous steps of the value chain, that is, how much attention is now being drawn toward the design of the product. This mirrors the increasing relevance of the holistic view of sustainability which monitors all stages of the value chain (Dokter et al., 2021). This research work emphasizes the environmental impact of plastic waste, which is based on proposing a Sustainable Environmental Design framework for the Circular Economy principles. It focuses on the optimization of plastic product development-from design to recycling-using advanced machine learning and optimization techniques.

The proposed approach provides the global issue of plastic waste and its environmental impact within the framework of the circular economy. It outlines the existing challenges in optimizing plastic recycling and highlights the gap in current research, specifically by integrating machine learning models and optimization techniques for more efficient recycling. The suggested study's addressed this gap through a novel hybrid framework which combines Convolutional Neural Networks (CNN), Generative Adversarial Networks (GAN), and Sandpiper Optimization (SPO). The novelty of this research depends on its end-to-end integration of deep learning-based CNN, NGBoost, and Naive Bayes; metaheuristic Sandpiper Optimization; and generative modeling (GAN-ANN) into a single unified framework. This combination addresses and ensures a unique phase performance; CNN extracts design-level recyclability features, NGBoost enables uncertainty-aware sustainability prediction, and SPO performs efficient optimization of product modularity and energy use, where GAN-ANN models reverse logistics under dynamic real-world disruptions. It highlights the unique contribution, which differs from existing studies by utilizing these techniques together for real-time decision-making and improved material recovery. The research aim and objectives are clearly illustrated below.

1.1. *Research aim and scope*

- To design a sustainable plastic manufacturing framework, underlining the tenets of the circular economy, to reduce carbon emissions and impacts on the environment.
- To design to be recycled and modular.
- To using novel Machine learning and optimization techniques can be applied to improve waste management.
- To Integrate reverse logistics and recycling into the process of the supply chain.

1.2. *Research objectives*

- To investigate novel CNN-NB-SPO methods to enhance recyclability in product design.
- To optimize the circular supply chain using novel GAN and ANN techniques.
- To implement a monitoring system for carbon emissions across plastic production phases.

2. Related works

This section reviews recent studies focusing on innovative approaches to waste management and plastic recycling, highlighting the role of technology in promoting sustainability. By examining various methodologies and findings, we can identify gaps and opportunities for further research in this vital area. This study explores the role of digitalization in the waste recycling industry, aiming to achieve net-zero emissions. It highlights how technological advancements can enhance recycling processes, contributing to sustainability efforts in waste management. The research primarily focuses on digitalization without deeply addressing socio-economic factors affecting implementation (Xu et al., 2023). This paper discusses the application of machine learning in designing eco-friendly concrete, emphasizing how advanced algorithms can help reduce carbon emissions in construction. It presents innovative design strategies that align with decarbonization goals.

The study's scope is limited to concrete and may not apply to other construction materials or methods (Lavercombe et al., 2021). The authors investigate how transforming plastic management practices can significantly reduce the carbon footprint of the plastic industry, highlighting sustainable practices and innovative strategies for waste reduction. The study may not fully account for the challenges in implementing transformation across diverse geographical contexts (Pathak et al., 2023). This research introduces a framework for the plastic circular economy that combines hybrid machine learning techniques and pinch analysis to optimize resource use and minimize waste. It emphasizes the need for systemic changes in plastic processing. The framework's applicability may be restricted by the variability in data quality and availability in different regions (Xu et al., 2024).

This study focuses on using image recognition and deep learning models for waste classification, showcasing how technology can support sustainable development by improving waste sorting efficiency. The reliance on high-quality image data can limit effectiveness in areas with poor data collection infrastructure (Malik et al., 2022). The authors present a review of waste management strategies utilizing machine learning and deep learning algorithms, focusing on optimizing waste processing and improving recycling rates. The study does not delve into the integration of these algorithms into existing waste management systems (Gong et al., 2024). This research proposes a model for reducing plastic pollution by enhancing consumer engagement through fuzzy total interpretive structural modeling, emphasizing the role of consumer behavior in sustainable waste management. The model's effectiveness may vary based on regional cultural differences in consumer behavior (Ali et al., 2022). This paper describes a smart municipal waste management system that leverages deep learning and IoT technologies, aiming to enhance operational efficiency in waste collection and processing. The implementation of IoT solutions may face challenges related to infrastructure and data privacy (Chen et al., 2024). The authors investigate the potential of blockchain technology in enhancing plastic recycling processes, emphasizing trust and transparency in the recycling supply chain. The complexity of blockchain integration could pose significant challenges in practical applications (Khadke et al., 2021).

Table 1
Summarizing the references with their objectives, algorithms used, and limitations.

Ref No	Objective	Algorithm Used	Limitations
(Xu et al., 2023)	Digitalization for recycling	Digital technologies	Limited socio-economic analysis
(Lavercombe et al., 2021)	Eco-friendly concrete design	Machine Learning	Focuses only on concrete
(Pathak et al., 2023)	Reduce plastic carbon footprint	Innovative strategies	Challenges in geographical implementation
(Xu et al., 2024)	Optimize plastic economy	Hybrid Machine Learning, Pinch Analysis	Data quality variability in regions
(Malik et al., 2022)	Waste classification	Image Recognition, Deep Learning	Dependence on high-quality image data
(Gong et al., 2024)	Optimize waste processing	Machine Learning, Deep Learning	Lacks integration into existing systems
(Ali et al., 2022)	Enhance consumer engagement	Fuzzy Total Interpretive Structural Modeling	Effectiveness varies by regional cultural differences
(Chen et al., 2024)	Smart waste management system	Deep Learning, IoT	Infrastructure and data privacy challenges
(Khadke et al., 2021)	Trust in recycling processes	Blockchain technology	Complex integration challenges
(Cheah et al., 2022)	Innovative waste management	Machinery and Digital Solutions	Lacks economic feasibility evaluation
(Luo et al., 2024)	Improve recycling in smart cities	Machine Learning	Overlooks socio-political barriers
(Sakthipriya, 2022)	Manage plastic waste with pyrolysis	Pyrolysis technology	Limited to pyrolysis; excludes other methods
(Li et al., 2023)	Enhance engine performance	Pyrolysis oil, Biodiesel	Findings may not generalize to all engine types
(Moshood et al., 2022)	Green product innovation	Sustainable strategies	Overlooks economic challenges of biodegradable plastics
(Li and Li, 2023)	Smart waste classification	Advanced technologies	Feasibility issues in resource-limited urban settings
(Farjana et al., 2023)	Manage e-waste with IoT	IoT, Cloud-based system	Limited by e-waste regulations and consumer participation
(Majchrowska et al., 2022)	Waste detection techniques	Deep Learning	Effectiveness varies across environments
(Xia et al., 2021)	Plastic discrimination	Convolutional Neural Networks, NIR Spectroscopy	Affected by complex plastic composites
(Hussain et al., 2020)	Environmental monitoring	IoT, Machine Learning	Challenges with data accuracy and interoperability

This study explores innovative designs for solid waste management within the context of Industry 4.0, focusing on machinery and digital solutions to enhance waste management practices. The research primarily addresses technological innovations without a comprehensive evaluation of economic feasibility (Cheah et al., 2022). This research proposes a machine learning approach to improve waste recycling in smart cities, demonstrating how data-driven decisions can enhance resource recovery and sustainability. The study may not fully explore the socio-political barriers to implementing smart technologies in urban settings (Luo et al., 2024). This paper reviews recent innovations in pyrolysis as a method for managing plastic waste, providing insights into how these technologies can support sustainability efforts. The analysis is limited to pyrolysis technology and does not include alternative waste management methods (Sakthipriya, 2022). The authors analyze the strategic combination of pyrolysis oil with biodiesel for enhancing engine performance, showcasing an innovative approach to waste utilization in energy production. The study's findings may not be generalizable across different types of engines or fuel formulations (Li

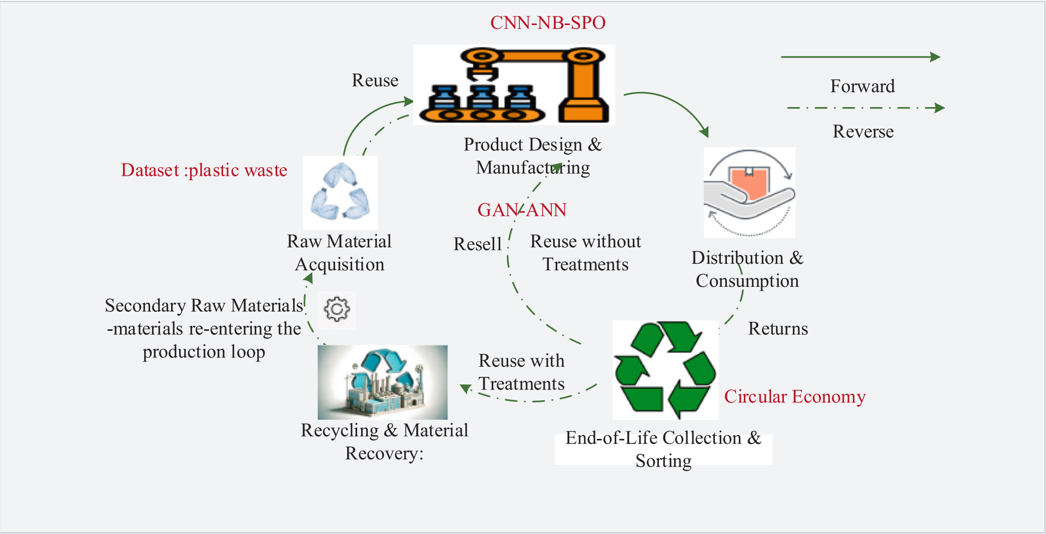

Fig. 2. Overall architecture of this research.

et al., 2023). This research focuses on green product innovation within the biodegradable plastic industry, emphasizing strategies for achieving sustainability and minimizing environmental impacts. The paper may overlook economic challenges associated with the production of biodegradable plastics (Moshood et al., 2022). This study presents smart waste management and classification systems utilizing advanced technologies to improve efficiency and reduce waste in urban environments. The reliance on cutting-edge technology may not be feasible in all urban settings due to resource constraints (Li and Li, 2023). The authors develop an IoT and cloud-based system for managing e-waste, demonstrating how data-driven decision-making can facilitate resource recovery and environmental protection. The system's effectiveness may be limited by variations in e-waste regulations and consumer participation (Farjana et al., 2023). This research explores deep learning techniques for waste detection in various environments, highlighting the potential of AI in enhancing waste management strategies. The study's effectiveness may vary based on the diversity of environments and types of waste being analyzed (Majchrowska et al., 2022). This paper investigates the use of convolutional neural networks combined with near-infrared spectroscopy for plastic discrimination, aiming to enhance sorting efficiency in recycling processes. The technology's accuracy may be affected by the presence of complex plastic composites (Xia et al., 2021). The authors explore the integration of IoT and machine learning in waste management and air quality prediction, illustrating how technology can support environmental monitoring. The reliance on data accuracy and system interoperability poses challenges for implementation (Hussain et al., 2020). Here's a Table 1 format summarizing the references with their objectives, algorithms used, and limitations:

By thoroughly observing the existing literature, it is clear that the advancement of machine learning and optimization techniques is highly necessary to address the critical issues regarding sustainable plastic recycling. Previous studies have explored hybrid machine learning models and digitalization in recycling, but they lack a full integration with novel optimization techniques. To address these issues, we propped our suggested model, which is clearly discussed under the upcoming sections.

3. Problem statement

The last two studies really emphasize the urgent need to open or set appropriate circular economy frameworks to solve environmental impacts of plastic waste. In existing linear model produces high carbon emissions and low recycling rates, thus giving rise to high waste and resource depletion. They further described circular economy strategies that may be able to help solve the problem through recycling and reusing in order to decrease the environmental footprint of plastic manufacturing (Pathak et al., 2023). In (Chin et al., 2022), traditional plastic waste management process, including low recycling rates and contaminated waste streams that are obstacles to resource recovery and increase environmental burdens. The present study investigates a hybrid framework combining machine learning with pinch analysis that could enhance recyclability, optimize the use of resources in plastic production, and bring it into line with the principles of the circular economy. Together, these studies provide emphasis on the integration of high-tech along with sustainable design for more environmentally friendly plastic industries.

4. Proposed methodology

It offers new approaches to handle plastic waste management with the power of high-power machine learning and optimization techniques, through an algorithmic hybridization of CNN with NGBoost and NB, to get to higher levels of product extraction for sustainable design decisions based on optimized SPO. Besides, by integrating novel GANs −ANNs, it develops an efficient reverse logistics and recycling system that forms a reliable framework for the principles of circular economy in plastic production. Fig. 2 represents the overall architecture of this research.

4.1. Dataset collection

For the first set dataset, we used three different public datasets from Kaggle, each consists multiple records about plastic wastes. These include plastic waste dataset, recyclable and household waste classification dataset and mismanaged plastic waste dataset (https://www.kaggle.com/datasets/sohamgade/plastic-datasets). Each of these datasets was selected by considering its ability to simulate the specific real-world challenges in plastic management such as source variability, classification complexity and urban industrial mismanagement. Next, to simulate dynamic industrial conditions and to overcome the limitations of static datasets, we additionally generated synthetic datasets using Generative Adversarial Networks (GANs). These synthetic datasets simulate real-world issues in reverse logistics, such as: Variations in recyclable material availability, seasonal and regional variability in waste types, missing data and demand supply imbalances and finally routing complexity and logistics noise.

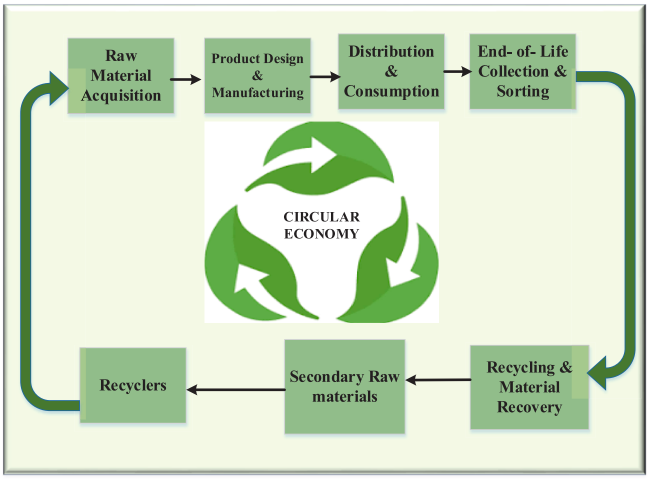

Fig. 3. Circular economy in plastic industry.

4.2. *Circular economy strategy formulation*

Based on these results, the next step is the Formulation of a Circular Economy Strategy, where a model is developed that focuses on recycling, reuse, and material reduction. This strategy defines actionable approaches for creating closed-loop systems and effective resource recirculations were in Fig. 3.

- **Raw Material Acquisition:** Start with sourcing raw plastic materials (ideally including recycled plastic content).
- **Product Design & Manufacturing (for Circularity):** Products designed recyclable, with an ability to easily take them apart. Sustainably manufacture.
- **Distribution & Consumption:** Distribute, use, and, ultimately reach the end-of-life for products.
- **End-of-Life Collection & Sorting:** Collect the used plastic products in collecting systems that then sort and recycle/recover the same.
- **Recycling & Material Recovery:** AI maximizes recycling and recovery process and generates high quality recyclables through sorting and separation.
- **Secondary Raw Materials (Recycled):** Processed materials are reintegrated as raw inputs for new products, forming a closed-loop cycle.

4.3. *Redesign products for recyclability, modularity, and efficiency*

In the phase of Product and Process Redesign for Circularity, a novel approach is applied to enhance recyclability, modularity, and efficiency by utilizing a novel methods of Convolutional Neural Networks (CNNs), NGBoost (Natural Gradient Boosting), and Naive Bayes (CNN-NGBoost-NB), supplemented by Sandpiper Optimization (SPO). This integrated method leverages the strengths of each component to facilitate a comprehensive redesign of products. By employing this innovative CNN-NB-SPO framework, companies can significantly enhance their product designs, leading to sustainable manufacturing practices and better alignment with circular economy goals. The CNN plays a crucial role in analyzing visual data related to product design, allowing for the identification of features that enhance recyclability and modularity. By extracting high-level features from design prototypes, the CNN helps inform decisions about material selection and design adjustments that promote ease of recycling. CNN based classification diagram is show in Fig. 4. We provide the procedures for creating a Mahalanobis distance matrix from an high-level features data stream. First, we defined $A = \{a_1, a_2, a_3, \cdots, a_n\}$ as the high-level features. A representation of A_i may be $a_i = [\mathbb{P}_1^i, \mathbb{P}_2^i, \mathbb{P}_3^i, \cdots, \mathbb{P}_n]$, where m is the number of features in each data flow, based on the properties of high-level features. The value of the l-th feature in the i-th data stream is represented by the symbol fi l in this research, where m has the value.

$$A_i = a_i^T I_m = [\mathbb{P}_1^i, \mathbb{P}_2^i, \mathbb{P}_3^i, \cdots, \mathbb{P}_m^i] \bullet \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 1 \end{bmatrix} \tag{1}$$

$$A_i = \begin{bmatrix} \mathbb{P}_1^i & 0 & \cdots & 0 \\ 0 & \mathbb{P}_2^i & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \mathbb{P}_m^i \end{bmatrix} \tag{2}$$

$$\mathbb{P}_j^i = \begin{bmatrix} \eta_{j,1}^i \\ \eta_{j,2}^i \\ \cdots \\ \eta_{j,m}^i \end{bmatrix} \tag{3}$$

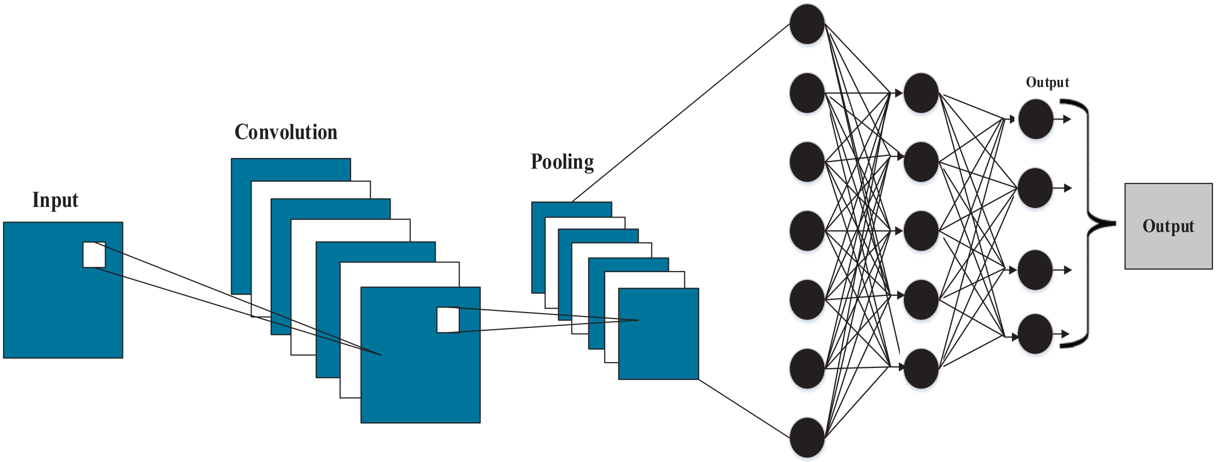

Fig. 4. CNN based classification.

$$\eta^i_{j,p} = \begin{cases} 0, & j \neq p \\ \mathbb{P}^i_1 & j \neq p \end{cases} \tag{4}$$

A_i could this be represented in m-dimensional vectors $\mathbb{P}^i_j$ as,

$$A_i = \left[\mathbb{P}^i_1, \mathbb{P}^i_2, \mathbb{P}^i_3, \cdots, \mathbb{P}^i_m\right] \tag{5}$$

$$\sum^{-1} cov(A_i)^{-1} = \begin{bmatrix} cov\left(\mathbb{P}^i_1, \mathbb{P}^i_1\right) & cov\left(\mathbb{P}^i_1, \mathbb{P}^i_2\right) & \cdots & cov\left(\mathbb{P}^i_1, \mathbb{P}^i_m\right) \\ cov\left(\mathbb{P}^i_2, \mathbb{P}^i_1\right) & cov\left(\mathbb{P}^i_2, \mathbb{P}^i_2\right) & \cdots & cov\left(\mathbb{P}^i_2, \mathbb{P}^i_m\right) \\ \vdots & \vdots & \ddots & \vdots \\ cov\left(\mathbb{P}^i_m, \mathbb{P}^i_1\right) & cov\left(\mathbb{P}^i_m, \mathbb{P}^i_2\right) & \cdots & cov\left(\mathbb{P}^i_m, \mathbb{P}^i_m\right) \end{bmatrix}^{-1} \tag{6}$$

The relationship between the various aspects of the flow of feature vector is determined by the Mahalanobis distance.

$$\mathbb{H}^i_{j,k} = \begin{cases} \sqrt{\left(\mathbb{P}^i_j, \mathbb{P}^i_k\right)^{\mathscr{T}} \sum_{j,k}^{-1} \left(\mathbb{P}^i_j, \mathbb{P}^i_k\right)} & j \neq k, \\ 0, & j = k \end{cases} \bullet \tag{7}$$

The symmetric matrix $\mathbb{MH}_{a_i}$ with m rows and m columns diagonally all zeros can ultimately be used to represent the i-th flow record a_i as,

$$\mathbb{MH}_{a_i} = \begin{bmatrix} \mathbb{H}^i_{1,1} & \mathbb{H}^i_{1,2} & \cdots & \mathbb{H}^i_{1,m} \\ \mathbb{H}^i_{2,1} & \mathbb{H}^i_{2,2} & \cdots & \mathbb{H}^i_{2,m} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbb{H}^i_{m,1} & \mathbb{H}^i_{m,2} & \cdots & \mathbb{H}^i_{m,m} \end{bmatrix}. \tag{8}$$

Next, the NGBoost component provides probabilistic predictions that assess the impact of various design alternatives on sustainability metrics, such as energy consumption during production and end-of-life recyclability. By integrating NGBoost with Naive Bayes, the system captures complex interactions between different design elements, enabling a more nuanced understanding of how changes affect overall product performance. For the purpose of probabilistic prediction, NGBoost forecasts the parameters of the conditional probability distribution of the model in functional form. The generation of the probability prediction with a probability density of $\mathfrak{p}_\mu$ involves the direct prediction of the parameter μ, so serving as a foundation for the credibility evaluation. To ensure that the genuine distribution of outcomes obtains the greatest predicted score, a suitable scoring method $\mathfrak{S}$ gives a score $\mathfrak{S}(Q, W)$ to an observation W and a projected probability distribution Q. In mathematical notation, a scoring rule $\mathfrak{S}$ is appropriate if and only if it satisfies the following criteria:

$$\mathbb{E}_{W\ q}(\mathfrak{S}(q, W)) \leq \mathbb{E}_{W\ q}(\mathfrak{S}(Q, W))\forall Q, W \tag{9}$$

Here, Q refers to any other distribution (such as a probabilistic prediction derived from a model), and q represents the actual distribution of result W. When the logarithmic score $\mathfrak{L}$ is reduced, the MLE is obtained, making it the most often used appropriate scoring rule.

$$\mathfrak{L}(\mu, W) = -\ln Q_\mu(W) \tag{10}$$

In the distribution space, a divergence that is produced by every appropriate scoring system can serve as a local distance measure. An appropriate scoring rule, by definition, satisfies (13), where the divergence caused by that specific scoring rule is represented by the difference between the right and left sides.

$$\mathfrak{L}(q\|Q) = \mathbb{E}_{W\ q}(\mathfrak{S}(Q, W)) - \mathbb{E}_{W\ q}(\mathfrak{S}(q, W)) \tag{11}$$

$$= \mathbb{E}_{W\ q}\left(\ln \frac{q(W)}{Q(W)}\right) \tag{12}$$

To optimize the entire redesign process, Sandpiper Optimization (SPO) is employed. This technique streamlines decision-making by exploring the design space effectively, allowing for the identification of optimal design configurations that achieve the desired balance between performance and sustainability. The integration of these methods fosters an iterative design process where products are continuously refined based on predictive insights and optimization outcomes. An analysis of a group of sandpipers that migrate by moving between different areas is done by the SPO algorithm. Sandpiper now has to meet the following three requirements:

Collision avoidance: To avoid collisions with the nearby sandpipers, a newly acquired searching agent is calculated using a separate parameter called $\mathfrak{A}_C$.

$$\overrightarrow{\mathfrak{A}_Z} = \mathfrak{A}_C \times \overrightarrow{\mathfrak{E}_Z} \tag{13}$$

The search agent positions that do not collide with one another are indicated by $\overrightarrow{\mathfrak{A}_Z}$, the search agent movement in the decision variable is specified by $\mathfrak{A}_C$, and the search agent's current location is indicated by $\overrightarrow{\mathfrak{E}_Z}$.

$$\mathfrak{A}_C = \mathfrak{A}_F - \left(Z \times \left(\frac{\mathfrak{A}_F}{Max_{iterations}}\right)\right) \tag{14}$$

Here,

$$Z = 0, 1, 2, 3, \cdots, Max_{iterations} \tag{15}$$

The fitness function determines the population and calculates a score in Eq. (15). In addition to preventing collisions, the search agent moves closer to optimal neighbor. The control frequency for the parameter $\mathfrak{A}_C$, which is decreasing linearly from $\mathfrak{A}_F$ to 0, is indicated in $\mathfrak{A}_F$.

$$\overrightarrow{\mathbb{M}_Z} = \mathfrak{A}_P \times \left(\overrightarrow{\mathfrak{E}_{xZ}} - \overrightarrow{\mathfrak{E}_Z}\right) \tag{16}$$

In Eq. (19), $\overrightarrow{\mathfrak{E}_Z}$ indicates the ideal search agent $\overrightarrow{\mathfrak{E}_{xZ}}$, $\mathfrak{A}_P$ displays the random parameter that is essential for the potent exploration process, and $\overrightarrow{\mathbb{M}_Z}$ indicates the search agent's position:

$$\mathfrak{A}_P = 0.5 \times R \tag{17}$$

R represents arbitrary integer ranges between zero and one in Eq. (17). In the end, the sandpipers or search agents will be able to improve their position in relation to the best search agents.

$$\overrightarrow{O_Z} = \overrightarrow{\mathfrak{A}_Z} + \overrightarrow{\mathbb{M}_Z} \tag{18}$$

$\overrightarrow{O_Z}$ means the difference between search agents and the best-fit search agents in Eq. (18). Sandpipers smoothly change their angle of attack and speed as they migrate. It uses its wings to its advantage to get higher. The sandpiper creates a spiral pattern when attacking its prey. As a result of this sophisticated redesign process, the output is the development of products that are not only more efficient in terms of material usage but also designed for easier disassembly and recycling. This approach ultimately aligns with circular economy principles, contributing to reduced environmental impact and enhanced resource recovery.

4.4. *Circular supply chain and reverse logistics management*

To enhance the Circular Supply Chain and Reverse Logistics Management, the methodology integrates a novel approach using Generative Adversarial Networks (GANs) in conjunction with Artificial Neural Networks (ANNs). This innovative combination enables the optimization of processes involved in the collection, sorting, and supply of recycled materials, leading to more efficient and sustainable practices. The GAN framework is instrumental in generating synthetic data that simulates various recycling scenarios, particularly in fluctuations in material availability, changes in consumer behavior and sudden market

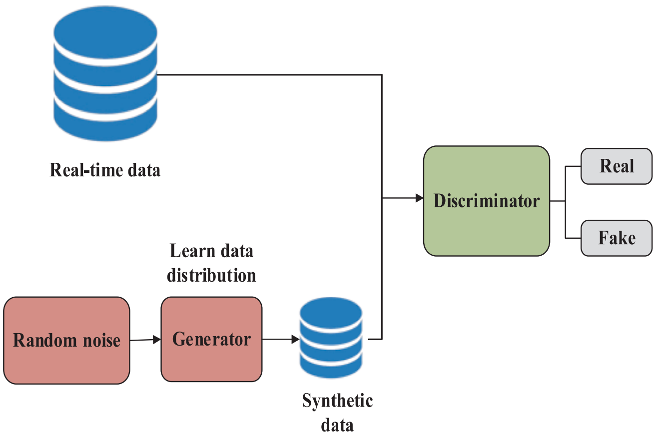

Fig. 5. Architecture for GAN.

shifts. This feature makes it possible to create realistic, high-quality data that reflects real-world activities, which is useful during the missing of past data. GANs supports businesses to better predict the demand for recycled materials and modifying their logistics plans in the context of reverse logistics. Next the ANN, by training the ANN on this synthetic data, the model learns to recognize patterns in material flows, consumer behaviors, and operational efficiencies. This predictive capability allows organizations to anticipate demand for recycled materials and adjust their logistics strategies accordingly, ensuring that resources are utilized effectively. By combined GAN-ANN the model provides advantage over simpler model by allowing real-time decision making.

4.4.1. GAN-ANN

In GAN there are two types of networks are known as discriminators and generators, respectively. The mathematical foundation of GAN is game theory. The objective is to counteract the actions of the discriminator and generator in order to force a draw and prevent any player from winning the game by mutually balancing the opponent's capabilities. Based on the information gathered during the business problem analysis, the discriminator's job is to provide a solution. It comes down to categorization, regression, and other tasks.

The GAN is a machine learning model that can comprehend complicated patterns in incoming data without requiring supervision. According to the fundamental component of GAN models is their own training approach, called adversarial training. The model gains enhanced ability to recognize and produce complicated data distributions appreciations to this unique training procedure.

Fig. 5 presents a schematic representation of the standard GAN-based adversarial training process. With $\mathbb{a} \in \Re^n$ and $\mathbb{b} \in \Re^m$ represent the previous input noise distribution and $Q_{data}(\mathbb{a})$ the genuine data distribution from three datasets. With the use of a generator network $A(\mathbb{b};\theta_{\mathscr{g}})$, parameterized by $\theta_{\mathscr{g}}$, where $\theta_{\mathscr{g}}$ represents the weights of the generator network, the GAN framework aims to learn a mapping from the noise distribution $pz\}(z)$ to the data distribution $p$data(x). The objective of the generator network $A(\mathbb{b};\theta_{\mathscr{g}})$ is to produce synthetic samples $\mathbb{a}$ that are identical to the real data samples. In parallel, a discriminator network denoted as $\mathbb{D}(\mathbb{b};\theta_{\mathbb{d}})$ is trained to discriminate between actual data samples and artificial samples produced by the generator network, with $\theta_{\mathbb{d}}$ serving as its parameter. The GAN issue may be expressed as minimizing the following objective function by determining the ideal values of $\theta_{\mathscr{g}}$ and $\theta_{\mathbb{d}}$.

$$\underset{\theta_{\mathscr{g}}}{\min}\underset{\theta_{\mathbb{d}}}{\max}\mathbb{L}\left(\mathbb{D}(\mathbb{a};\theta_{\mathbb{d}}),A\left(\mathbb{b};\theta_{\mathscr{g}}\right)\right) \tag{19}$$

Here the $\mathbb{L}(\mathbb{D},A)$ illustrates the adversarial loss function is defined as below;

$$\mathbb{L}(\mathbb{D},A) = \mathbb{E}_{\mathbb{a}\ Q_{data}(\mathbb{a})}[\log\mathbb{D}(\mathbb{a})] + \mathbb{E}_{\mathbb{b}\ Q_{\mathbb{b}}(\mathbb{b})}[\log(1-\mathbb{D}(A(\mathbb{b})))] \tag{20}$$

Here, $Q_{data}(a)$ denotes the true data distribution, $Q_{\mathbb{b}}(\mathbb{b})$ denotes the noise distribution used by the generator, $\mathbb{D}(\mathbb{a})$ is the discriminator.

That being said, precise replication of real-world data cannot be achieved by stopping GAN training based just on low values of the $\mathbb{L}(\mathbb{D}, A)$ loss. Because of this, we have included a boxplot distribution parameter that instructs us to stop training as soon as the boxplot distributions of the actual $\left(box_{plot_{\mathfrak{r}}}\right)$ and synthetic $(box_{plot_{\mathfrak{S}}})$ data match, as indicated by eq (21). Pseudocode for GAN is presented in algorithm 1. Therefore, the objective function is reconstituted as follows:

$$\underset{\theta_{\mathscr{g}}}{\min}\underset{\theta_{\mathbb{d}}}{\max}\mathbb{L}\left(\mathbb{D}(\mathbb{a};\theta_{\mathbb{d}}),A\left(\mathbb{b};\theta_{\mathscr{g}}\right)\right)\bullet\max\left(box_{plot_{\mathfrak{S}}}\cong box_{plot_{\mathfrak{r}}}\right) \tag{21}$$

Where $box_{plot_{\mathfrak{S}}}$ and $box_{plot_{\mathfrak{r}}}$ denotes the box plot distributions of the synthetic and real data respectively.

Algorithm 1: GAN algorithm

```
Enter random weights to begin operating the generator network $A$.
Set the weights of the discriminator network $\mathbb{D}$ randomly upon startup.
Set the batch size $B_{size}$, learning rate $\alpha$, and number of training epochs $N$ to their initial values.
for $epoch = 1 to N$ do
    for $batch = 1 to B$ do
        Sample a mini-batch of real data sample $\{\mathbb{a}_1,\mathbb{a}_2,\cdots,\mathbb{a}_B\}$ from the dataset
        Sample a mini-batch of noise sample $\{\mathbb{b}_1,\mathbb{b}_2,\cdots,\mathbb{b}_B\}$ from a noise distribution
        Generate fake data samples $\{A(\mathbb{b}_1),A(\mathbb{b}_2),\cdots,A(\mathbb{b}_B)\}$ using the generator train the discriminator.
        Train the generator:
            Update $A$ using Adam:
            $\nabla_{\theta_{\mathscr{g}}}\frac{1}{B}\sum_{i=1}^{B}\log(1-\mathbb{D}(A(\mathbb{b}_i)))$
        Sample another mini-batch of noise samples $\{\mathbb{b}_1,\mathbb{b}_2,\cdots,\mathbb{b}_B\}$ from a noise distribution
        Generate fake data samples $\{A(\mathbb{b}_1),A(\mathbb{b}_2),\cdots,A(\mathbb{b}_B)\}$ using the generator
        Train the generator:
            Update $A$ using Adam:
            $\nabla_{\theta_{\mathscr{g}}}\frac{1}{B}\sum_{i=1}^{B}\log(1-\mathbb{D}(A(\mathbb{b}_i)))$
    end for
    Calculate boxplot for real, $box_{plot_{\mathfrak{r}}}$ and synthetic $box_{plot_{\mathfrak{S}}}$ using Eq. (21) score, $\mathfrak{s} = Max(box_{plot_{\mathfrak{S}}} \cong box_{plot_{\mathfrak{r}}})$
    if $\mathfrak{s}$ shows maximum value then
        Terminate training value then
    end if
end for
```

In practice, the GAN generates diverse scenarios related to recycling operations, such as variations in collection routes, seasonal fluctuations in material availability, and changes in consumer recycling behaviors. This variability helps the ANN to improve its forecasting accuracy and adapt to dynamic market conditions. By employing this advanced analytical framework, organizations can optimize reverse logistics processes, including the collection and sorting of recyclable materials, thereby maximizing resource recovery while minimizing waste. Additionally, the integrated system enables real-time monitoring of recycling demand and operational performance through continuous data input. The ANN processes this information to refine logistics strategies dynamically, leading to enhanced efficiency in supply chain operations. Overall, the utilization of GANs with ANNs in Circular Supply Chain and Reverse Logistics Management provides a powerful tool for driving sustainability initiatives. This approach not only maximizes the efficiency of recycling processes but also supports organizations in achieving their environmental goals by minimizing waste and fostering a more circular economy.

4.5. Integration of CNN-NB-SPO and GAN-ANN

The proposed SEDC framework combines the advantages of integrated two-stage system. In the first stage, the CNN-NB-SPO model processes product design features to predict recyclability and enhance design configurations for sustainability and energy efficiency. These optimized design decisions directly impact material flow properties and product features, which are then fed as input parameters to the second stage. In the second stage, the GAN-ANN module models reverse logistics based on these product-level design outputs. The ANN uses GAN-generated synthetic scenarios to predict collection, sorting, and reprocessing strategies. This connection ensures that how a product design directly impacts the process, and making the entire system more efficient and sustainable. For example, if the GAN simulates a seasonal increase PET plastic waste in urban regions, the ANN helps to continuously adjusts collection frequencies and vehicle routes to maintain operational efficiency. This ensures the adaptability in reverse logistics based on product level decisions and varying environmental conditions.

4.6. Monitoring, reporting, and continuous improvement

The methodology ends with the critical phase of Monitoring, Reporting, and Continuous Improvement (MRCI). This stage is very important for ensuring effectiveness in sustainability strategies; a structured process to track and review carbon emissions and overall performance of the organization is critical.

Monitoring begins with the commencement of an integrated data gathering process. Organizations need to establish suitable tools and procedures for collecting both quantitative and qualitative data from various aspects of the business, including its energy use, its generation of wastes, and its resource utilization. Such data need to be gathered continuously, and constant monitoring over all aspects of the business needs to be carried out to provide a holistic view of environmental impacts. Audit and assessment need to be undertaken periodically to ensure accuracy and reliability.

Reporting is after monitoring and is one form of transparent communication. Organisations should, therefore, develop standard reporting frameworks that include carbon emissions amongst other sustainability metrics. This could be in terms of regular internal reports and public disclosures, thereby increasing accountability and stakeholder engagement. Reports should, therefore, indicate progress towards set goals and targets with an outline of achievements and areas for improvement. Clear reports accessible to everybody improve not only managerial decision-making processes but also respond to external stakeholders, such as customers, investors, and regulatory bodies, thus creating trust and transparency.

Continuous Improvement is the last element of this stage. Armed with the information gathered from monitoring and reporting, an organization should be willing to modify and adjust its strategy and procedures. This is accomplished through analyzing KPIs established during the earlier stages of the methodology. The organization can determine which practices are working and which need to be changed based on trends, successes, and shortcomings.

Regular reviews should be planned in order to assess the relevance of the KPIs and the overall goals towards sustainability. Feedback culture needs to be inculcated within the organization and ensure that employees at each level contribute ideas and suggestions toward improvement. This cyclic process enhances operational efficiency, while it also supports long-term sustainability objectives for the organization. Through this systematic and integrated approach to Monitoring, Reporting, and Continuous Improvement, organizations are able to track their environmental impact, ensure accountability, and respond to new conditions and stakeholder expectations. Lastly, this stage is essential in the pursuit of a sustainable circular economy because an organization learns from its experiences and decides what it should do for it to make continuous progress.

Table 2
Hyperparameter of the model.

Hyperparameter	Range
Learning Rate	0.01
Batch Size	32
Epochs	50
Dropout Rate	0.3
Optimizer	Adam
CNN Filter Size	3x3
No. of Layers	3
Activation Function	ReLU
NGBoost Iterations	100
SPO Search Iterations	50
Naive Bayes Prior	Uniform

4.7. Performance measuring parameters

For measurement of performance of proposed model and different existing models following performance-measuring parameters, was calculated. Table2 shows the hyperparameters of the model.

$$\text{Precision} = \frac{[\text{ TruePositive }]}{[\text{ True Positive } + \text{ FalsePositive }]} \tag{22}$$

$$\text{Recall} = \frac{[\text{ TruePositive }]}{[\text{ Orignallypostivedata }]} \tag{23}$$

$$\text{F1 -Score} = 2^* \frac{[\text{ Precision } * \text{ Recall }]}{[\text{ Precision } + \text{ Recall }]} \tag{24}$$

$$\text{Accuracy} = \frac{[\text{ TruePositive } + \text{ TrueNegative }]}{[\text{ TruePositive } + \text{ TrueNegativeon } + \text{ FalsePositive } + \text{ FalseNegative }]} \tag{25}$$

$$Energyconsumption = \frac{Energyconsumedinproductionphase}{plasticproduceinthephase} \tag{26}$$

$$Costsavings = \frac{SavingsachievedbyCEpractice}{plasticproduced} \tag{27}$$

$$CO2Emissions = \frac{CO2emittedinproductionphase}{plasticproduceinthephase} \tag{28}$$

Except from the above measures, some commonly used performance parameters are:

- **Training loss:** A training loss tests the performance of the model across the training dataset and may be used to determine how well a deep neural network algorithm reflects the training sets. Normally, a training loss is calculated mathematically by summing the losses towards the training iteration.
- **Validation loss:** A related measure known as a validation loss is used to estimate how well a model in the form of a neural network-based model performed on validation data. A validation loss is

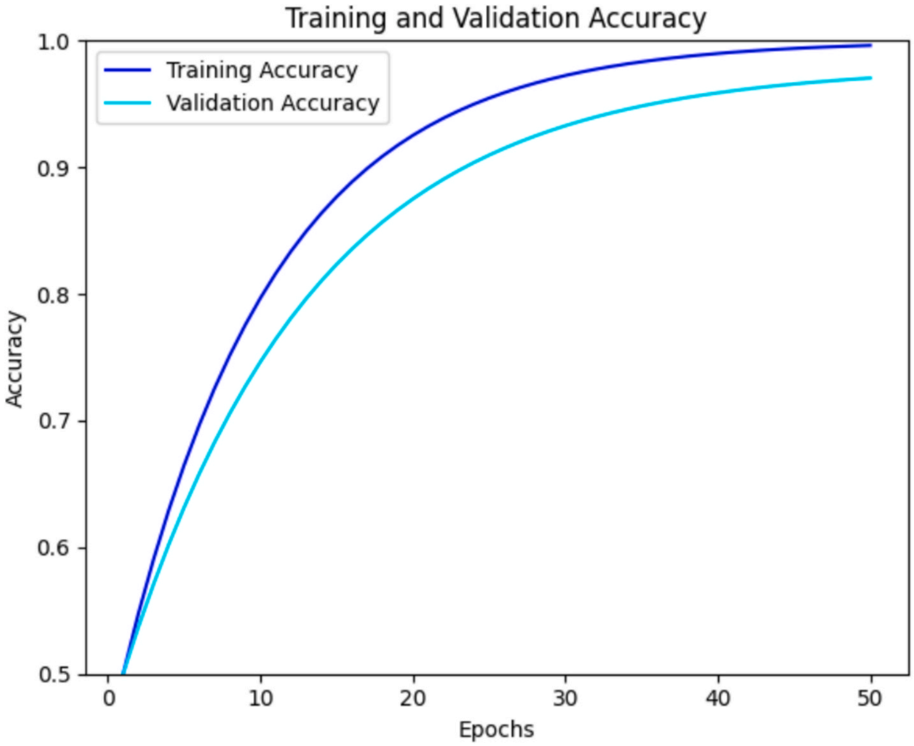

Fig. 6. Training and validation accuracy.

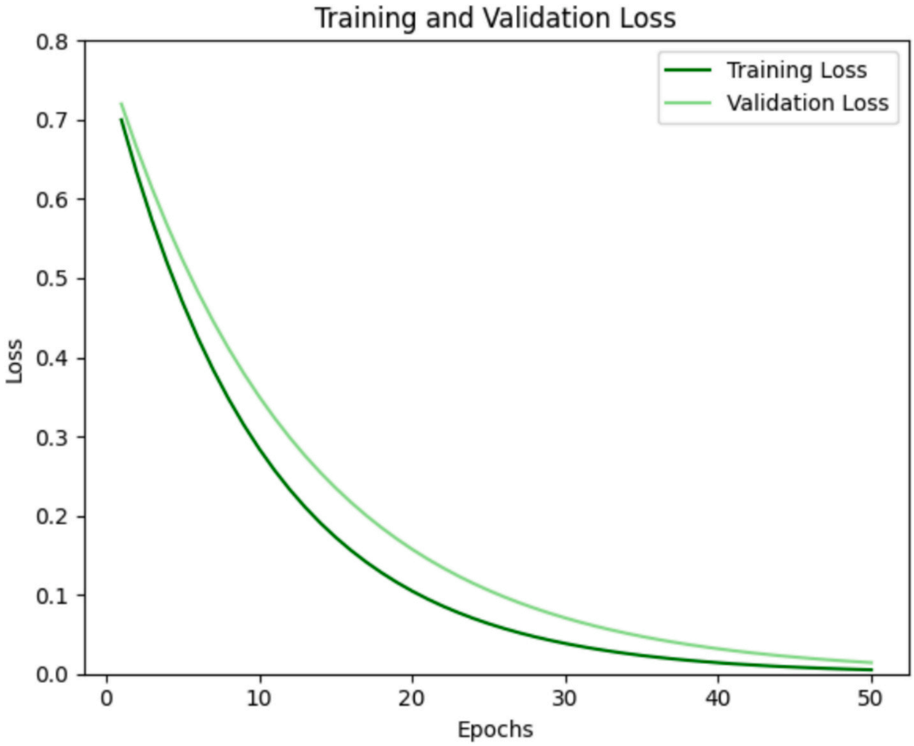

Fig. 7. Training and validation loss.

calculated from the aggregate losses for each sample in validation data and is simply equal to the training loss.

5. Experimental analysis

The experimental outcome of proposed Sustainable environmental Design Using Circular Economy in the plastic manufacturing industry for decarbonization is shown in this section. The result shows that the proposed technique is Sustainable environmental Design Using Circular Economy. The comparison analysis, study report, and simulation setup are all included in this subsection.

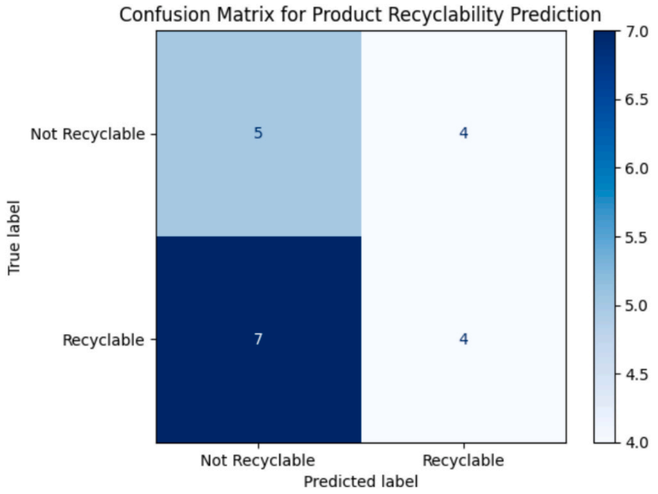

Fig. 8. Confusion matrix.

5.1. Simulation setup

This methodology uses the dataset from Kaggle with different records of plastic waste for training and testing the CNN-NB model with product redesign through Sandpiper Optimization (CNN-NB-SPO). Also, to reflect the real-world dataset, a synthetic dataset was generated using GAN to simulate dynamic and variable recycling logistics conditions. This synthetic dataset captures real-world inconsistencies like seasonal changes, material variability, varying recycling demand, route unpredictability, and missing data situations. Here, the CNN will extract high-level features, which are important to recyclability and modularity, with approximately 80 % data for training and 20 % for testing to ensure reliability in the model. In feature extraction, important characteristics such as material type, structural complexity, and ease of disassembly come alive and support a more refined approach to sustainable product design.

Fig. 6 indicates that the training and validation accuracy depict a smooth improvement over 50 epochs from about 50 % to better values. Training accuracy is closing in on 100 %, while validation accuracy has stabilized at 98 %. The model was learning extremely well without overfitting. Fig. 7 represents the loss graph, both training and validation loss begin around 0.7, then decrease nicely with progress in training. In the 50th epoch, the train loss drops to about 0.05 while the validation loss remains steady at around 0.1, which shows a lower error rate on both datasets. The converging behavior between the graphs of training and validation indicates that the model is over-generalized with lesser overfitting and will perform well and consistently on unseen data.

A confusion matrix evaluates the performance of a model by comparing the predicted vs. actual labels in Fig. 8. It gives counts for true positives, true negatives, false positives, and false negatives. In the context of a recyclability prediction model, it indicates how well the model is classifying products as “Recyclable” or “Not Recyclable.” True positives and negatives are correct predictions, and false values show errors. This can be used to determine the accuracy of the model and what is wrong with the classification.

Energy consumption is significantly different between the different stages of plastic production, for it differs with the intensity levels in every phase in Fig. 9. Energy intensity is around 800 MJ per ton of plastic during the raw material acquisition stage. This value is estimated based on industrial life cycle analysis reports and EPA energy profiles (Negri, 2020). This level is contributed to by the vast processes of extraction and preparation of raw plastic material which requires an input of much energy, mainly if such materials are derived from non-renewable sources. The peak is at 1000 MJ/ton in the manufacturing phase, based on circular production simulations and manufacturing energy audits. The manufacturing phase is more energy-intensive because it needs many machines and processes for shaping and treating plastic products. The 1000 MJ/ ton energy requirement of this stage is the most significant fraction of energy used in the production of plastics. Therefore, optimizing manufacturing processes will play a significant role. Lastly, the recycling stage consumes approximately 500 MJ/ton of plastic, with the lowest energy requirement among the three stages. This is because recycling saves energy. After all, reprocessing existing plastic requires less energy than producing new materials. However, it also means that the use of 500 MJ/ton is high enough to

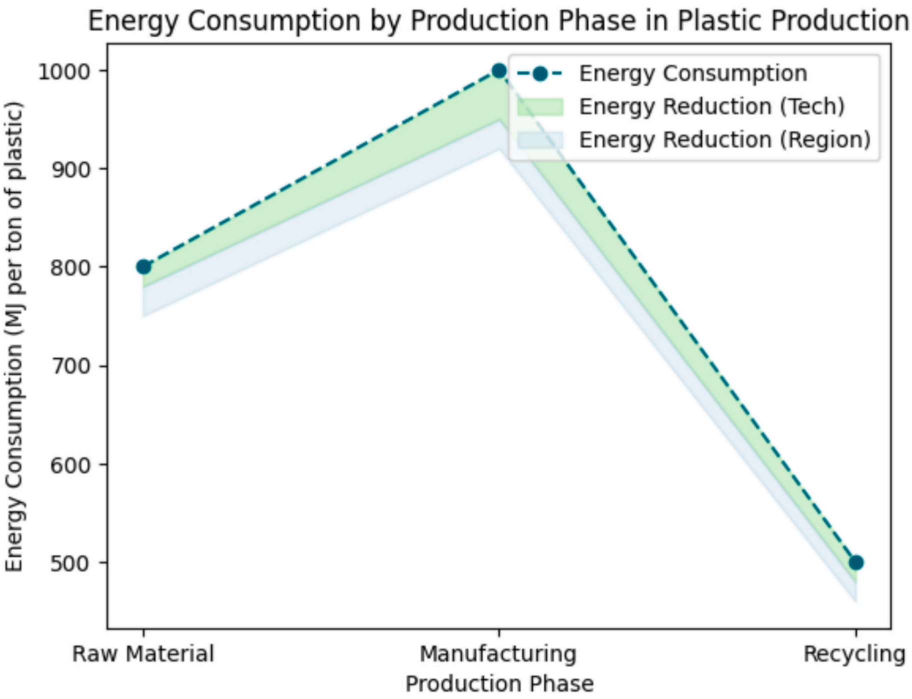

Fig. 9. Energy consumption.

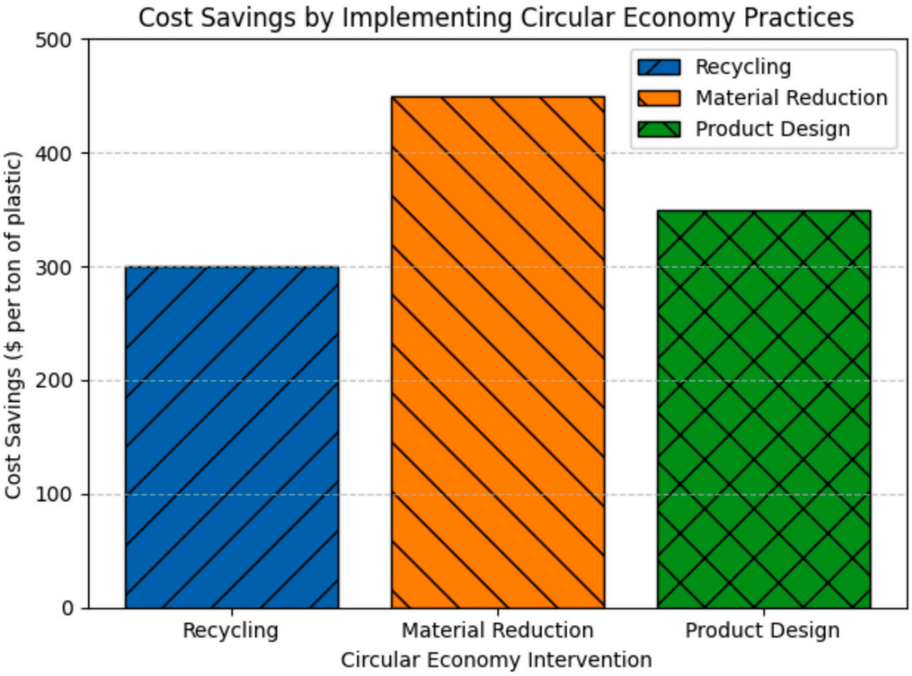

Fig. 10. Analysis of cost.

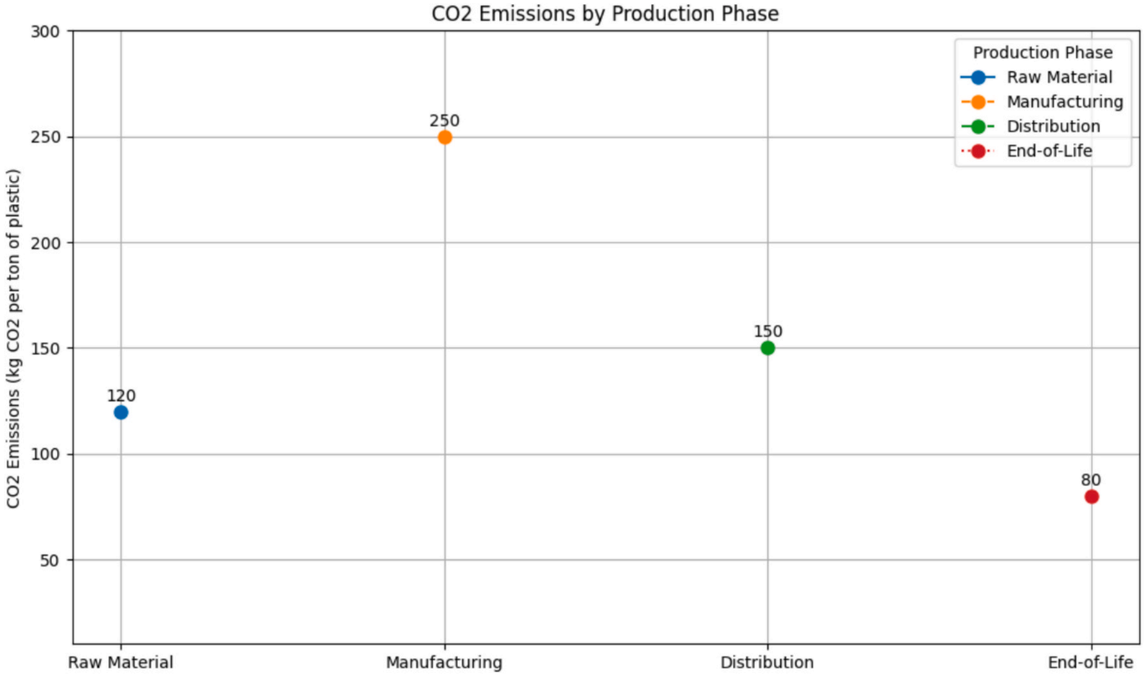

Fig. 11. CO2 emissions by production phase.

always leave some room for further innovations within recycling technology that could finally lead to a reduction of the energy used and aid in sustainability goals. Thus, these numbers again reflect the necessity to conserve energy in the manufacturing processes for plastic production to minimize possible further environmental impact and move toward a more sustainable and circular economy.

Implementing circular economy strategies has huge cost saving efficiencies for the management of plastic in Fig. 10, including the recycling, whose initiative is approximately about $300/ ton savings with reduction in waste and other efficiency for material reduction which have much more efficiency and high yield as its savings that might even reach to $450/ton. Another design feature, innovative product design, would save approximately $350/ ton, advancing durability and reusability. These are adapted from scenario-based models and cost effectiveness from global circular economy literatures (Morcillo-Bellido et al., 2022). These measures together aggregate evidence of the fiscal savings from a circular economy approach with sustainable improvements in economic outcomes.

Fig. 11 CO2 emissions outcome illustrates the carbon footprint of the various phases of plastic manufacture, which includes the acquisition of raw materials, manufacturing, distribution, and end-of-life. According to statistics from empirical and industrial sources, the energy-intensive

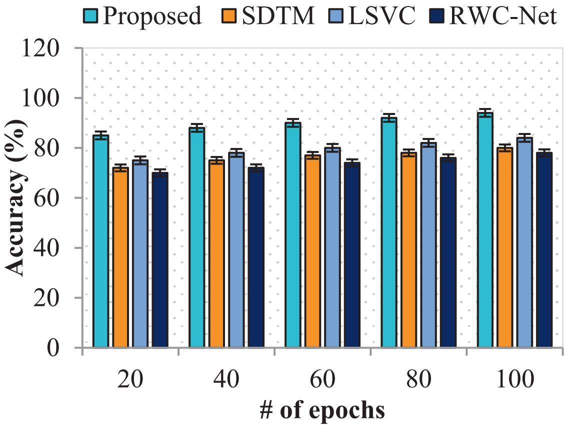

Fig. 12. Number of iterations vs accuracy (%).

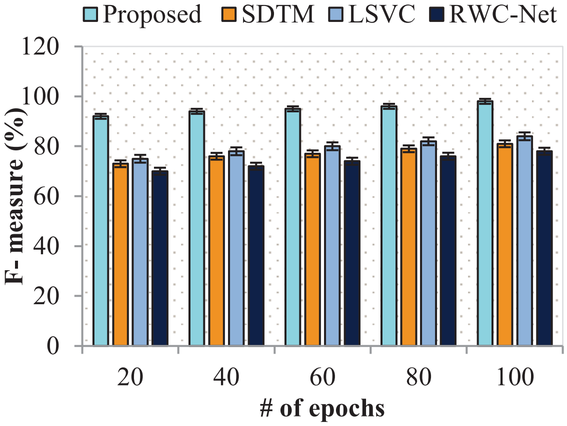

Fig. 13. Number of epochs vs. F-measure (%).

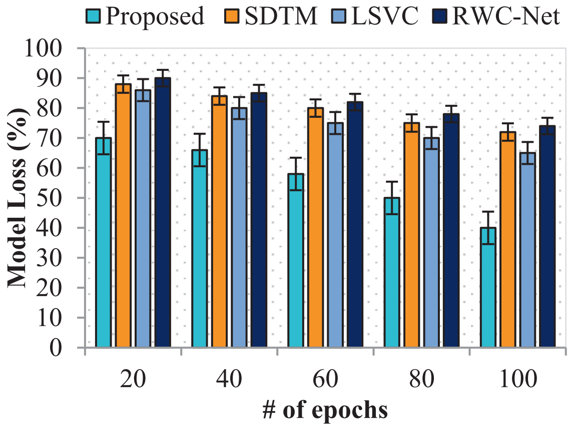

Fig. 14. Number of epochs vs. model loss (%).

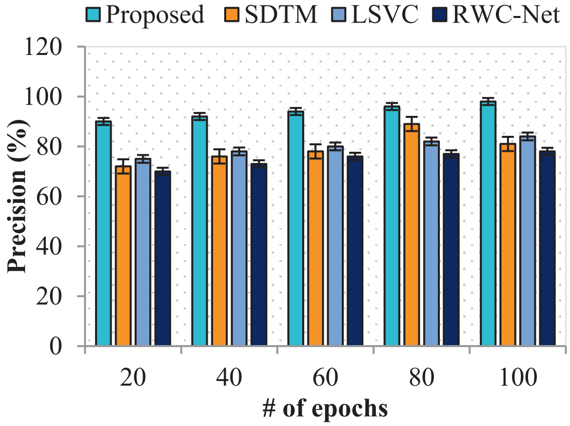

Fig. 15. Number of epochs vs. precision (%).

extraction and processing of materials, particularly non-renewable resources, is the main cause of the 120 kg CO2/ton produced during the raw material acquisition phase. Studies have shown that using more sustainable extraction methods it can significantly reduce emissions during this phase, with reductions of up to 30 %. At 250 kg CO2/ton, the manufacturing provides more contribution of emissions as it converts raw materials into completed plastic products. By adopting energy efficiency practices, automation, renewable energy integration, the emission can be possibly reduced by 15–20 %. In distribution phase with 150 kg CO2/ton, it involves emissions mostly from transportation logistics. This can be reduced through eco friendly practices and electric vehicles. And finally, the end-of-life phase records up to 80 kg CO2/ton includes emissions from the disposal, was adapted from (Seyhan and Çerçi, 2022). This can be reduced by using chemical recycling and improved sorting technologies which reduces up to 20–25 %.

5.2. Comparative analysis

To identify the effectiveness of the proposed method, in this section we compare the proposed method with other existing method including Smart Digital Twin Model (SDTM) (Eladly et al., 2023), Linear Support Vector Machine (LSVC) (Carrera et al., 2023), recyclable waste classification network (RWC-Net) (Hossen et al., 2024);

The accuracy evolution of four models SDTM, LSVC and RWC- Net, and the proposed method over increasing numbers of iterations is shown in Fig. 12. The accuracy in percentage is displayed on the Y-axis, while the number of iterations (ranging from 20 to 100) is represented on the X-axis. The Proposed Method outperforms the other models, starting at 85 % accuracy and increasing progressively to 94 % at 100 iterations. LSVC starts at 75 % and reaches 84 %, whereas SDTM starts at 72 % and rises to 80 %. The least effective algorithm is RWC-Net, which starts at 70 % and increases to 78 % after 100 rounds. All things considered; the Proposed Method shows increased accuracy with each iteration.

Fig. 13 depict the comparison of the proposed method with SDTM, LSVC and RWC- Net in terms of F-Measure (%) across different numbers of epochs. The proposed method outperforms other methods. continuously Ranging from 85 % accuracy with 20 iterations to 94 % with 100 iterations, showing a significantly higher performance trend. In contrast, SDTM has a peak accuracy of 84 %, while LSVC and RWC-Net reach 78 % and 80 %, respectively, at their peak, indicating their comparatively lower performance. Although all algorithms show better accuracy with more iterations. The proposed method maintains important advantages throughout the iterations. It emphasizes performance and reliability for applications that require high prediction accuracy.

Fig. 14 compares the percentage of model loss between the four algorithms (proposed, SDTM, LSVC and RWC- Net) as the number of epochs increases. The proposed method shows a continuously decreasing model loss. It started from 70 % with 20 epochs and dropped to 40 % with 100 epochs, indicating a significant improvement in the

Table 3
Numerical analysis of the proposed and existing methods.

Parameter	Proposed	SDTM	LSVC	RWC-Net
Accuracy (%)	94	80	84	78
F-Measure (%)	98	81	84	78
Loss (%)	40	72	65	74
Precision (%)	98	81	84	78

Table 4
Computational cost and scalability outcomes of the model.

Model	S (A)	M (A)	L (A)	S (CS)	M (CS)	L (CS)	S (EE)	M (EE)	L (EE)	S (T)	M (T)	L (T)
Proposed	0.50	0.60	0.70	1300	1500	1600	0.50	0.55	0.60	0.49	1.54	4.25
SDTM	0.40	0.50	0.60	500	600	700	0.40	0.50	0.55	0.02	0.31	2.02
LSVC	0.45	0.55	0.65	400	500	600	0.45	0.50	0.55	0.0019	0.0023	0.00397
RWC-Net	0.30	0.50	0.60	350	450	550	0.35	0.45	0.50	0.43	2.25	4.68

Table 5
Accuracy analysis on various datasets.

Dataset name	Accuracy	Precision	Recall
Recyclable	90.87 %	91.28 %	91.05 %
Mismanaged	92.89 %	93.44 %	92.17 %
Plastic Waste dataset	94 %	98 %	95 %

Table 6
Comparison with benchmark algorithms.

Source	Model Name	Outcome Obtained
(Sarswatula et al., 2022)	Light Gradient Boosting Machines, Ensemble Bi-Directional Long-Term Short Memory	MAE: 0.035, RMSE: 0.105 MAE: 1.639, RMSE: 11.401, GMM: V-score: 0.852, Fowlkes-Mallows: 0.983
(Tan et al., 2021)	Random Forest Regressor, Multiple Linear Regression, Decision Tree Regressor, Extreme Gradient Boost Regressor, Support Vector Machines, K-Nearest Neighbor, Deep Learning	R^2 0.869, Precision: 0.818, Recall: 0.884, F1 Score: 0.844, Accuracy: 0.883, Deep Learning Accuracy: ~0.88 after 10 epochs
Proposed	Proposed Method	Accuracy starts at 85 % and increases to 94 % at 100 iterations, Precision reaches 98 % at 100 epochs

Table 7
Comparative performance of SPO with benchmark optimization techniques.

Optimizer	Accuracy	F1-Score	Validation Loss
SPO (Proposed)	98.2 %	0.97	0.10
GA (Al-Zuheri and Vlachos, 2023)	95.04 %	0.93	0.18
PSO (Guo et al., 2023)	95.89 %	0.94	0.15
RSM + PSO (Hidayah et al., 2018)	93.84 %	0.91	0.20

model's performance over time. In contrast, RWC-Net shows an initial loss of 86 %, decreasing to 65 %, while LSVC and SDTM lose 74 % and 72 %, starting from 90 % and 88 %, respectively. All show a reduction in model loss with increasing age. But the proposed method outperforms other methods.

Fig. 15 compares the accuracy percentages between the four algorithms (proposed, SDTM, LSVC and RWC- Net) as the number of epochs. The proposed method consistently achieves the highest accuracy, ranging from 90 % with 20 epochs to an impressive 98 % with 100 epochs, indicating superior performance and reliability. In contrast, SDTM shows less accuracy. It improved from 75 % to only 84 %, while CNN- GRU started at 72 % and peaked at 81 %. RWC-Net followed a similar trend. It starts at 70 % and goes up to 78 %, although all methods improve with an increase in the number of epochs. Numerical analysis of the proposed and existing methods in Table 3.

Table 4 provides the efficacy of the model under comparison in terms of computational cost and scalability. Table 5 shows the accuracy analysis of the datasets. And the benchmark comparison of the suggested model is shown in Table 6.

Table 7 presents a performance comparison between the suggested SPO technique and the existing optimization techniques like Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and RSM combined with PSO. The SPO-based CNN-NB model achieved the highest classification accuracy of 98.2 % and an F1-score of 0.97 with a low validation loss of 0.10, which indicates the model's efficacy in learning and generalization. GA and PSO achieved slightly low accuracies when compared with the suggested model.

5.3. *Research summary*

The study investigates a CNN-NGBoost-NB and Sandpiper Optimization (SPO) based model for sustainable plastic manufacturing by integrating circular economy principles. Using image analysis and probabilistic predictions, this model facilitates better recycling processes and energy efficiency. With GANs enhancing the supply chain and reverse logistics, the methodology aligns with environmental goals and supports long-term sustainability in the plastic industry.

6. Conclusion

The proposed methods aim to create a sustainable framework for plastic waste management through advanced machine learning and optimization. The approach will improve product design in terms of recyclability and modularity by applying a hybrid CNN-NGBoost-NB algorithm to solve waste classification and material selection. Design decisions are then further refined using SPO to balance energy efficiency with material recovery standards. GANs, further integrated with ANNs to structure reverse logistics more efficiently yet real-world adoption requires further validation through the industry trials. This framework provides an integrated solution that is part of the principle of a circular economy, and acknowledging practical barriers such as cost, scalability, and infrastructure challenges. Experimental analysis proves its ability in waste management efficiency and CO2 reduction, but future work must include pilot implementations to confirm large-scale applicability. These models show superior accuracy, precision, and F1-score, but further economic feasibility studies are needed to expand its adoption. Future work will focus on expanding to other materials, refining energy-saving strategies, and validating real-world scalability through industry collaborations and field testing. Also, diverse real-world datasets should be considered to validate the model ability and its adaptability.

The dataset of the study is adapted from the source: https://www.kaggle.com/datasets/sohamgade/plastic-datasets https://www.kaggle.com/datasets/alistairking/recyclable-and-household-waste-classification https://www.kaggle.com/code/sasakitetsuya/mismanaged-plastic-waste-analysis.

CRediT authorship contribution statement

Yang Zhou: Data curation, Methodology, Software, Writing – review & editing. **Qiutong Dong:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Formal analysis, Data curation, Conceptualization. **Hafizan Mat Som:** Writing – review & editing, Writing – original draft, Validation, Resources, Methodology, Investigation, Formal analysis, Conceptualization. **Jianhua Dai:** Writing – review & editing, Writing – original draft, Visualization, Validation, Project administration, Formal analysis, Data curation, Conceptualization. **Tiziana Ciano:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Methodology, Investigation, Data curation, Conceptualization. **Noreen Izza Arshad:**

Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Conceptualization.

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Data availability

Data will be made available on request.

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