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AI-Powered Circular Economy Tracker for Intelligent Waste Management

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Abstract:
The shift in the linear economic system to a circular economy (CE) has turned into an international necessity, as resources exploitation, pollution of the environment, and the unreliability of waste management systems have increased. Artificial intelligence (AI) has become one of the most important facilitators of operationalizing the principles of the circular economy, offering information-oriented insights, analytics, and smart decision support. In this paper, the author suggests an AI-based circular economy tracker that designs waste monitoring as the supervised classification problem that seeks to detect manufacturing facilities with an abnormally high waste generation. Based on a real-world industrial data, which combines the production, material use, energy use and water usage, operational efficiency and recycling indicators, several machine learning models are created and tested, such as the Logistic Regression, Support Vector Machines (SVM), XGBoost, and Neural Networks. According to the experimental results, ensemble-related methods, especially XGBoost, have a higher predictive accuracy and almost perfect generalization. The proposed framework offers a scalable and practical solution to intelligent waste tracking by integrating strong preprocessing pipelines and an equal split of data as well as detailed evaluation metrics. The research is relevant to the field of the circular economy as it provides the empirically confirmed AI system, which has the potential to support the sustainability governing system, industrial optimization, and policy-driven environmental interventions.

Keywords: *Artificial Intelligence; Circular Economy; Waste Management; Machine Learning; Sustainability Analytics; XGBoost; Smart Manufacturing.*

نظام تتبع الاقتصاد الدائري المدعوم بالذكاء الاصطناعي لإدارةٍ ذكيةٍ للنفايات

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ملخص:

أصبح التحول من النظام الاقتصادي الخطي إلى الاقتصاد الدائري ضرورة دولية ملحة، نظرًا لتزايد استغلال الموارد وتلوث البيئة وعدم موثوقية أنظمة إدارة النفايات. وقد برز الذكاء الاصطناعي كأحد أهم العوامل المساعدة في تطبيق مبادئ الاقتصاد الدائري، إذ يوفر رؤى تحليلية ومعلوماتية ودعمًا ذكيًا لاتخاذ القرارات. في هذه الدراسة، يقترح الباحثون نظامًا لتتبع الاقتصاد الدائري قائمًا على الذكاء الاصطناعي، يصمم عملية مراقبة النفايات كمسألة تصنيف مُشرف عليها، بهدف الكشف عن المنشآت الصناعية التي تُنتج كميات غير طبيعية من النفايات. استنادًا إلى بيانات صناعية واقعية، تجمع بين مؤشرات الإنتاج واستخدام المواد والطاقة والمياه، وكفاءة التشغيل، وإعادة التدوير، تم إنشاء واختبار العديد من نماذج التعلم الآلي، مثل الانحدار اللوجستي، وآلات المتجهات الداعمة (SVM)، وXGBoost، والشبكات العصبية. ووفقًا للنتائج التجريبية، تتمتع الطرق القائمة على التجميع، وخاصة XGBoost، بدقة تنبؤية أعلى وقدرة تعميم شبه مثالية. يقدم الإطار المقترح حلاً عملياً وقابلاً للتطوير لتتبع النفايات بذكاء، وذلك من خلال دمج مسارات معالجة مسبقة قوية وتوزيع متساوٍ للبيانات، بالإضافة إلى مقاييس تقييم مفصلة. تُعدّ هذه الدراسة ذا صلة بمجال الاقتصاد الدائري، إذ يوفر نظام ذكاء اصطناعي مُثبت تجريبياً، يتمتع بإمكانية دعم نظام إدارة الاستدامة، وتحسين الصناعة، والتدخلات البيئية الموجهة بالسياسات.

الكلمات المفتاحية: *الذكاء الاصطناعي؛ الاقتصاد الدائري؛ إدارة النفايات؛ التعلم الآلي؛ تحليلات الاستدامة؛ تعزيز التدرج الفائق؛ التصنيع الذكي.*

1. Introduction

The currently dominant paradigm of the linear economy, in which people use take- make- Dispose models, has turned out to be unsustainable by the natural environment, which results into overexploitation of the resources, growth of greenhouse gases in the atmosphere, and more than ever before people create a lot of wastes (Shennib et al., 2024). In turn, the circular economy (CE) has been suggested as a regenerative approach to the economy, that is, it focuses on the efficiency of resources, the reduction of wastes, reuse, recycling, and the closed-loop flows of materials (Oladapo et al., 2024).

Although circular economy strategies have a conceptual promise, they have significant operational issues. These entail the existence of fragmented data ecosystems, low levels of transparency throughout the chain of supply and inadequate monitoring systems that can detect inefficiencies in time (Jose et al., 2020). With the increase in complexity of industrial systems, the previous methods of waste management, which were based on rules or manual efforts, are not sufficient to guarantee the achievement of the goals of circularity.

The concept of artificial intelligence (AI) has been welcomed as a ground-breaking technology that can eliminate these constraints. AI-based systems allow the analysis of massive heterogeneous data to help identify non-linear trends and create actionable information that fosters sustainable management of resources (Lanzalonga et al., 2025). Previous studies emphasize the use of AI to increase the efficiency of recycling, reverse logistics, product design to achieve a more circular design, and environmental cost management (Shennib & Schmitt, 2021; Ghoreishi & Happonen, 2020; Ali et al., 2025).

Early detection of abnormal and excessive production of waste is one of the most important processes in waste management. Detection of high-waste facilities enables organizations and regulators to take initiative before the environments are damaged and enhance recovery of the materials (Wilts et al., 2021). Nevertheless, current AI uses in this field are mostly dedicated to robotic sorting or smart-city implementations and very little to waste classification on the facility level, using integrated operational data (Chen et al., 2022).

Furthermore, Shennib and Schmitt (Wilson et al., 2022; Wilson et al., 2022; Ranpara, 2025) focus on the fact that most AI-based CE projects are not open, scalable, and applicable to resource-constrained settings. This deficiency highlights the necessity of data-centric, model-driven frameworks, which can be implemented into various industrial settings.

Based on these obstacles, this study suggests an AI-based circular economy tracker to operationalize the problem of waste monitoring as a binary classification issue. The framework uses supervised machine learning models that are trained on actual manufacturing data in order to detect high-waste facilities, hence aiding in making sustainability decisions based on data.

2. Literature Review

Recurrence In the framework of AI and Circular Economies

2.1 Will be the basis of the foundations.

The artificial intelligence has been identified as one of the major facilitators of the transition to a circular economy. According to Jose et al. (2020), digital technologies powered by AI are necessary in order to manage energy sustainably and reduce carbon emissions, especially now that energy consumption in the world keeps growing. On the same note, Bag [16] underscores the role of big data analytics and AI in driving sustainability in manufacturing in Industry 4.0 ecosystems.

Roberts et al. (2024) further the discussion with reference to the ethical considerations of AI implementation on the systems of the circular economy. They claim that AI can hasten circular transitions, but it should be developed in a responsible manner to prevent further strengthening of environmental or social disparities.

2.2 Waste and Resource Tracking the AI in Waste Management.

A significant area of application of AI in the circular economy is waste management, which is one of the most mature applications. Wilts et al. (2021) show that the AI-based sorting systems with robots can increase the recycling rates and the quality of the materials in the municipal waste systems. Lanzalonga et al. (2025) even indicate that AI can have a positive impact on the decision-making process within waste utilities, as it allows taking a proactive approach in engaging users and provides economically effective waste separation.

The article by Shennib et al. (2024) presents OpenWasteAI, an open-data and IoT-compatible platform that can be used to monitor waste in resource-limited communities. In their conclusions, they show that open data sharing with AI analytics can significantly increase waste governance and accountability.

2.3 Circularity of Industry based on AI.

A number of studies address the use of AI in industrial circles of the economy. Quantitatively, the study by Oladapo et al. (2024) shows that recycling waste can be decreased by up to 25 percent and recycling can be optimized through AI-assisted circular strategies. Chen et al. (2022) use decision tree algorithms to control costs in the environmental, which validates the fact that AI-based classification aids in making sustainable decisions in manufacturing.

Ghoreishi and Happonen (2020), Roberts et al. (2024) note that in product design AI can be utilized to reduce waste of materials by means of intelligent design optimization and rapid prototyping. Wilson et al. (2022) scale AI in the reverse logistics, and the authors single out the specific AI paradigms that can benefit various logistical functions.

2.4 New Trends: Green AI and Digital Twins.

The recent literature has turned towards having the AI systems themselves supportive of sustainability objectives. Ranpara (2025) suggests Green AI architectures that operate at low energy levels and enhance classification of waste management missions. Ali et al. (2025) show that AI and technologies of digital twins can assist in circular transitions in the agricultural industry and help in achieving several UN Sustainable Development Goals.

According to these improvements, the current literature is usually abstract or industry-focused. The empirically validated AI frameworks that use integrated industrial data to treat the waste monitoring as a classification problem are lacking significantly. This gap is directly addressed by this research.

3. Methodology

3.1 Problem Formulation

The suggested system describes waste monitoring as a binary classification issue, with the target variable (high waste flag) representing a facility of abnormally high waste production on a particular day (1 = high waste, 0 = normal).

3.2 Dataset Description

The data would be a collection of daily operation logs in manufacturing plants that would be run on a circular economy system. It incorporates measures of production, flow of materials, energy and water use, operational efficiency indicators and recycling performance variables. It has both numerical and categorical features to represent operational diversity by region, sector and facility.

3.3 Data Preprocessing

Strong preprocessing pipeline was employed in order to guarantee data quality and stability of models. Median values were utilized to impute the numerical features to reduce the effects of outliers and standardization then occurred. The most common category was used to impute categorical variables and one-hot encoding was used to transform them. Model training did not include non-informative identifiers and time fields.

3.4 Data Splitting

Stratified sampling was used to divide the dataset into training and testing subsets (80 and 20 percent respectively) to ensure the balance of classes. The method will guarantee a high level of generalization and fair assessment.

3.5 Machine Learning Hyperparameters and Models.

To predict the high-waste facilities within a circular economy framework, four supervised machine learning classifiers were tested in this study. Logistic Regression was taken as a baseline model since it is quite simple and easy to interpret, and it gives a simple point of reference with which the other simpler models can be compared. Although it has linear assumptions, it can be used in predicting overall trends in the data.

The radial basis function kernel was used to run the Support Vector Machine and it enables the model to pick up non-linear associations of the input features. The regularization parameter was tuned to balance the maximization of the margin and the minimization of the classification error and the gamma parameter was also tuned to magnify the effect of the individual data points. With this setup, the model can be generalized to unknown data.

XGBoost is a sophisticated ensemble learning tool that was employed to define a more intricate pattern within the data. In the model, all the parameters were set to 200 decision trees, maximum depth of the tree was six, the learning rate was set to 0.1, and the subsampling ratio was set to avoid overfitting. These hyperparameters will make sure that the model is able to effectively learn the non-linear interactions between features and provide predictions that are very accurate.

Lastly, a design of the Neural Network model was made with three hidden layers consisting of 128, 64, and 32 neurons, respectively. The hidden layers had the ReLU activation function applied to introduce non-linearity and dropout regularization preventing overfitting. The output layer was used to produce the binary classification probabilities through the use of a sigmoid activation function. This architecture allows the network to learn complex features representations despite the training being stable and the generalization being robust.

3.6 Evaluation Metrics

Accuracy, precision, recall, and F1-score were used to evaluate the model performance on the training and testing data.

4. Results

Table 1 summarizes the performance of the four machine learning models namely Logistic Regression (LR), Support Vector Machine (SVM), XGBoost, and Neural Networks (NN) models based on their evaluation metrics on both the training and the testing dataset. These metrics are accuracy, precision, recall and F1-score.

Table 1: Study Results

		LR	SVM	XGBoost	NN
Accuracy	Train	0.998	0.998	1.0	0.9975
	Test	0.998	0.993	0.999	0.9950
Precision	Train	0.997	0.996	1.0	0.9959
	Test	0.996	0.986	0.999	0.9893
Recall	Train	0.997	0.996	1.0	0.9943
	Test	0.997	0.988	1.0	0.9908
F1-Score	Train	0.997	0.996	1.0	0.9951
	Test	0.997	0.987	0.999	0.9900

The findings show that each of the models scored very high in all the metrics, meaning that the preprocessing pipeline is well-built and the features chosen are predictive. XGBoost was the best performing model, achieving almost flawless precision of 0.999 on the test set. Logistic Regression and the Neural Networks also did very well with a score of above 0.995 and SVM with a lower score, but with good predictive power, did a very good job.

The accuracy scores of the models were between 0.986 and 0.999 on the testing set implying that the models were very effective in accurately identifying the facilities with the highest level of waste production and also reducing the number of false positives. This is especially the case in industrial real-world scenarios when false alerts may result in unnecessary interventions and wastage of resources.

All models had a value of above 0.988 in terms of recall, which illustrates that they would identify virtually all cases of high-waste facilities. High recall will capture the critical sustainability risks and gives an opportunity to take an action and make decisions in time. The F1-score, a combination of the precision and recall, also helps to prove the reliability of the models as XGBoost scores almost perfect F1-score of 0.999 on the test set. It means that the model can be successfully used to compromise between identifying high-waste facilities and reducing errors that are essential to the operational deployment.

In general, the experimental outcomes emphasize that ensemble-based systems and deep learning models are very useful in predictive waste monitoring in the framework of a circular economy environment, to deliver practical information on sustainability governance.

5. Discussion

The This study reinforces the prevailing literature that highlights the effectiveness of the state-of-the-art machine learning methods, especially ensemble models, to be applied in the context of the circular economy (Oladapo et al., 2024; Lanzalonga et al., 2025; Chen et al., 2022). The improved performance of XGBoost is similar to other previous studies which have indicated that XGBoost can easily deal with non-linear and heterogeneous data that is typical of industrial operations (Oladapo et al., 2024). The values of recall are high, which means that the system is specifically appropriate when it comes to detecting high-risk facilities, allowing taking proactive measures to decrease waste and increase recycling performance.

Additionally, the paper shows the feasible benefits of AI-based integrations with facility-level data about the circular economy. Whereas the current literature tends to concentrate on smart-city implementations or theoretical applications of AI (Shennib et al., 2024; Jose et al., 2020), this framework is a scaled, empirically tested solution to industrial settings. The system will help in making decision-making that is data driven through the use of real time operational information including energy consumption, water use, material recovery, and production volumes which will improve resource efficiency and sustainability.

The results are also in line with the concepts of Green AI and energy-efficient modeling (Ranpara, 2025), because correct classification minimizes the unnecessary monitoring, interventions based on resources are avoided, and optimization of operational processes is provided. Furthermore, the research adds to the existing debate about AI-based sustainability by demonstrating how predictive analytics can enhance the level of circularity and operational transparency of various sectors of the industrial industry (Ghoreishi & Happonen, 2020; Wilts et al., 2021).

Notably, the findings indicate the complementing nature of AI and human control. Although the models are accurate in predictions, there is still a need to incorporate the expertise and domain specific policies so as to have ethical, responsible, and contextually correct interventions (Bag, 2020). This underscores the importance of mixed strategies that integrate data insights with managerial skills in order to have its implementation to work.

6. Conclusion

This study introduced an artificial intelligence-based circular economy sensor that analyzes the manufacturing factories that produce a lot of waste. The presented framework can use Logistic Regression, SVM, XGBoost, and Neural Networks to analyze the real industrial information including production data, energy and water usage, and recycling rates by presenting the waste monitoring as a binary classification problem. The experimental analysis proves that ensemble and deep learning models, especially XGBoost, attain the near perfect accuracy, precision, recall, and F1-score, which highlights the reliability and scalability of the framework. The paper offers an intelligent waste monitoring AI conversion that is practical and scientifically proven, and which can aid in the efficiency of operations, sustainability governance, and data-based circular economy actions.

7. Recommendations

Future research is needed to investigate the use of multi-task learning to integrate classification of high-waste facilities with regression-based circularity scoring to offer sustainability benchmarking in full. Also, incorporation of real-time IoT data streams can improve model responsiveness, which would allow intervention strategies that are dynamic. Increasing transparency through the use of explainable AI methods would also enable industrial managers to have an understanding of and trust model decisions. Lastly, the framework might be extended to a cross-sectoral implementation so as to encourage the best practice industry-wide in terms of resources optimization, waste minimization and the adoption of the principles of a circular economy at large.

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