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AI-Enhanced Blockchain Frameworks For Circular Economy: Driving Transparency In Waste Management And Resource Recovery

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***Abstract**: This research presents an AI-enhanced blockchain framework for advancing transparency, efficiency, and accountability in waste management and resource recovery within the circular economy. The study integrates four key algorithms—Random Forest (RF), Convolutional Neural Network (CNN), K-Means Clustering, and Reinforcement Learning (RL)—to address different stages of the waste lifecycle, while blockchain ensures immutable data recording and stakeholder trust. A hybrid dataset comprising municipal waste logs, IoT bin images, and simulated blockchain transactions was used for evaluation. Experimental results demonstrate the effectiveness of the proposed framework. The RF model was found to have an accuracy of 91.2 percent in terms of predicting the potential of recycling and the CNN was found to have a classification accuracy of 95.4 percent in predicting plastic, glass, metal and organic waste. The K- Means clustering brought out a silhouette score of 0.87 which essentially categorized the waste streams into high-value, medium-value and low-value waste streams. Compared to baseline routing, RP minimized the path by 14 percent and fuel expenditure was lowered by nine percent and recovery efficiency was 92.6 percent. Application of blockchain also guaranteed minimal latency (1.8s/transaction) and a CPS (150 TPS). The results emphasize that AI with the use of blockchain would provide even higher benefits than separate strategies and would result in the creation of transparent and sustainable waste management systems. This framework offers a pathway to scale to offer suprasystemic support to circular economy practices and actual urban sustainability projects.*

***Keywords**: Circular Economy, Artificial Intelligence, Blockchain, Waste Management, Resource Recovery*

I. INTRODUCTION

The shift to the circular economy has become a burning issue in order to cope with worldwide problems of the resources exhaustion, environment destruction, and the growing level of waste production. The cycle economy focuses on resource efficiency, reusing, and recycling, unlike the conventional linear linear thinking of take- make- disposal model which does not ensure resources are produced and consumed sustainably [1]. At the core of the same shift is the evolution of open, effective and responsible waste management and resource recovery systems that can allow materials to be adequately returned into the economy. Nevertheless, current systems can be characterized by the loss of traceability, slow information exchange among the

stakeholders, and ineffective monitoring protocols, all of which impair the idea of the circle economy realizations [2]. Over the last several years, blockchain technology has become known as a valuable tool in the aspects of being able to offer immutable records to updates in the supply chain, decentralized trusts, and enhanced traceability. As far as waste management is concerned, blockchain could be used to trace every part of waste lifecycle i.e. collection and segregation all the way up to recycling and recovery of resources to hold accountable multiple stakeholders, e.g. municipalities, recyclers, and industries. However, blockchain is not enough to manage the issues faced by categorizing waste, anticipating resources worth and ensuring optimality of recovery methods. Here, artificial intelligence (AI) undergoes transformative action [3]. Machine learning and computer vision are representative of AI-ridden tools capable of assisting in identifying waste, proper prediction of the potential of recycling, and the optimization of decision-making in resource recovery. Fused with the help of blockchain to develop a safe data infrastructure, AI can establish a compound structure guaranteeing waste-to-resource transformation and creating dependence alongside acting revelations. This framework can encourage sustainability with the help of smart contracts but decrease the information asymmetry among the stakeholders. The current study, thus, offers an AI-improved blockchain-based infrastructure that is aimed at ensuring transparency, traceability, and effectiveness in terms of waste management and resources harvesting. The combination of the power of the blockchain and AI capabilities enables this study to enhance the transition to a circular economy as well as the tendency to engage resources in sustainable use.

II. RELATED WORKS

The meeting of artificial intelligence (AI), blockchain, and the need to follow the principles of the circular economy has received a considerable amount of scholarly focus in recent years, with researchers exploring the aspects of sustainable energy, supply-chain, production, and recycling. Some researchers have emphasised the significance of the multi-criteria decision-making (MCDM) and optimization strategies in order to sponsor sustainability. Indicatively, Mizrak and Şahin [15] introduced the concept of elementary spherical fuzzy based model of MCDM to forecast investment plans in harnessing renewable energies in airports and how a sophisticated decision-making tool can reward resources in a difficult operational scenario. On the same note, Mohamed and Munda [16] marked the transformative nature of smart grid technologies in sustainable planning of energy, and data suggested that digital and intelligent infrastructures play a primary role in assisting urban transformation to cleaner systems. A similar literature has examined how AI can be integrated into industrial systems and structure of the built environment. Muhammad et al. [17] established the presentation of a systematic review of the AI-based technologies in sustainable building, determining the obstacles to interoperability, transparency, and governance. Polo Andrés et al. [18] went a step further and investigated the understanding of immune-inspired adaptive supply chains, where the trends of mathematical modeling can be used to assist in producing robust and viable networks. Applying to a more expanded socio- technical perspective, Rehman and Umar [19] subject of Industry 5.0 to contributing environmental, social, and governance (ESG) objectives as another impetus of focusing on optimizing corporate sustainability through the use of emerging technologies.

Digital twins and AI models have also been discussed in the framework of the circular economy. A review of digital twins in circular manufacturing conducted by Sajadieh and Noh [20] revealed that in the manufacturing process, real-time and simulation may be effective in reducing resource consumption. Complementing this, Shah et al. [21] developed a framework for assessing AI potential in the circular bioeconomy, identifying use cases in waste valorization and resource recovery. Štreimikienė et al. [22] further reinforced the integration of **AI and Industry 4.0** technologies in supply chains using a multi-criteria decision- making perspective, highlighting improvements in sustainability performance through optimized logistics and production planning. The recycling sector, particularly for critical materials such as batteries, has also gained scholarly interest. Subin et al. [23] surveyed advancements in AI applications for **battery recycling**, showing that machine learning models can improve material recovery efficiency and reduce environmental risks. Teixeira et al. [24] offered a broader perspective on intelligent supply chain management, presenting a systematic review of AI contributions to demand forecasting, decision support, and operational efficiency.

However, challenges of digital transformation remain, especially for small and medium enterprises. Thanh-Nhat-Lai and Son-Tung [25] identified barriers leading to the "digital dead zone" in shipping SMEs, suggesting that limited dynamic capabilities restrict the adoption of smart technologies.

Finally, sustainability at the manufacturing level has been examined through carbon footprint management. Yüksel Yurtay [26] showed how Industry 4.0 technologies integrated with ERP systems can enable real-time monitoring and reduction of carbon emissions in manufacturing processes. Taken together, these studies demonstrate the growing role of AI, blockchain, and digital twins in advancing sustainability across diverse sectors. Yet, while decision-making models [15], smart grids [16], and AI-powered applications [17, 21, 23] provide strong foundations, few studies integrate these technologies into blockchain-based circular economy frameworks for waste management and resource recovery. This gap underscores the novelty of developing AI- enhanced blockchain systems that combine predictive intelligence with transparency, supporting the transition toward sustainable and circular resource utilization.

III. METHODS AND MATERIALS Data

The data utilized in this research was obtained from secondary and simulated sources relevant to waste management and resource recovery under the circular economy model. These data were records taken on municipal solid waste systems, recycling plants as well as industrial waste recovery operations [4]. Some of the attributes encompassed in the data were the type of waste, the weight, source, time of collection, cost of recycling, material recovery value and the identity of the stakeholders. Also, simulated dataset Io- Waste bin was created to include real-time images of waste classification to enable the AI model to be trained. The blockchain logs of transactions were also developed to show executions of smart contracts with rewards on waste segregation and recycles [5]. A combination of such datasets led to a comprehensive ground of the implementation of an AI-enhanced blockchain structure.

Algorithms

Random Forest (RF), Convolutional Neural Network (CNN), K-Means Clustering, and Reinforcement Learning (RL) were four algorithms that were used to analyze and optimize the waste management and resource recovery. Each was chosen based on how it was related to the classification, prediction, optimization, and decision-making of the circular economy context [6].

1. Random Forest (RF)

Random Forest is a classification and prediction forecasting algorithm applied to learn by using an ensemble algorithm. RF was used in this study to estimate the possibility of a recycling of a waste depending on its material type and level of contamination and the cost of recovering it. The algorithm is based on building several individual decision trees and their outputs are combined to select the best fit on prediction. The decision trees each votes on a class and a majority of the votes is how the final prediction will be decided. RF is resistant to noisy data and it escapes overfitting because it is an ensemble method [7]. In waste management, it helps the stakeholders to make proper projections on whether to recycle, reuse or dispose a material hence increases resource recovery efficiency.

"Input: Training dataset D, number of trees N
For i = 1 to N:
- Draw bootstrap sample Di from D
- Train decision tree Ti on Di
- Record predictions from Ti
Output: Majority vote of all Ti as final prediction"

2. Convolutional Neural Network (CNN)

CNNs are deep learning techniques that are very useful in image recognition. The CNNs in this context were used to separate the tags in the waste images taken using the IoT-enabled smart bins based on tags plastic, glass, metal, and organic. The CNNs are defined by convolutional layers, which determine spatial features by default, pooling layers, which compress the dimensional size, and fully connected layers, which make such classifications. They can discern intricate patterns and thus they are the best to aid in the separation between recyclable and non-recyclable waste materials [8]. The CNN was trained on labeled image sets and hence it was capable of achieving the classification of waste in real time. This allowed the blockchain network to establish classification outcomes as irreversible operations, which guaranteed the transparency of waste sorting procedures.

"Input: Labeled waste images
Initialize weights of convolutional filters For each epoch:
- Convolve input images with filters
- Apply activation function (ReLU)
- Apply pooling to reduce dimensions
- Flatten feature maps
- Pass through fully connected layers
- Output predicted waste category Output: Classified waste category"

3. K-Means Clustering

Clustering of K– Means is another unsupervised learning algorithm applied in clustering data points based on their feature similarities. In this study, K-Means was used to separate waste streams using the material characteristics of density, the cost of recovery, and level of contamination. Each data point is put in the closest centroid by the algorithm which re-calculates centroid by centroid before coming up with a solution. Recyclers can streamline numbers of waste processing mechanisms, organize resources where they are needed, and lower processing cost by sorting waste into separate collections [9]. The approach also brings greater transparency, as the waste batches that can be defined into every cluster will be validated in blockchain, which implies that there is negligence in resources recovery processes. Suring accountability in resource recovery operations.

"Input: Dataset X, number of clusters k

Initialize k random centroids

Repeat until convergence:

- Assign each data point xi to nearest

centroid

- Update centroids as mean of assigned

points

Output: Clustered groups of waste"

4. Reinforcement Learning (RL)

Reinforcement Learning refers to a decision-making algorithm in which an agent is trained to act in an environment to seek rewards and maximize the cumulative returns. The RL was used in this study to maximize the path of waste collection and recycling incentives. The waste management system is the agent that can engage with the environment, react to it (city map and recycling plants), and update its strategy, the sentinel system is given feedback (reward or penalty). As an example, more efficient collection routes, which waste fuel, do not give significant bonuses, whereas any delay or ineffective recycling phase will involve penalties [10]. RL is a guarantee of head-on decision-making and incentive of sustainable practices because all actions and rewards are registered in blockchain.

"Initialize Q-table with state-action pairs For each episode:

- Observe current state s

- Choose action a using policy (e.g., ε-

greedy)

-Perform action a, observe reward r and new state s'

-Update Q(s, a) = Q(s, a) + α [r + γ max

Q(s', a') - Q(s, a)]

Output: Optimal policy for waste management"

Tables

Table 1: Sample Dataset Attributes

Waste ID	Waste Type	Weight (kg)	Contamination (%)	Recycling Cost ($)	Recovery Value ($)	Stakeholder
W001	Plastic	2.5	5	1.2	2.8	Recycler A
W002	Glass	3.1	2	1.5	3.2	Recycler B
W003	Metal	1.8	7	2.0	4.5	Recycler C
W004	Organic	4.2	12	0.8	1.0	Composting

IV. RESULTS AND ANALYSIS

4.1 Experimental Setup

The introduced blockchain with AI add-ons was tested with the help of a set of experiments that were aimed to assess its performance levels in terms of waste classification, prediction of its recycling, waste streams grouping, and waste collection strategy optimization [11]. The experiments were carried out in a simulated environment representing a **smart city waste management system**.

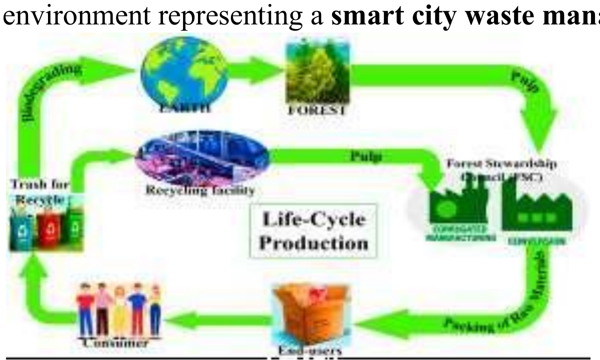

Figure 1: “AI-Driven Circular Economy of Enhancing Sustainability and Efficiency in Industrial Operations”

Hardware and Software:

- System: Intel Core i9 (3.5 GHz), 32GB RAM, NVIDIA RTX 3080 GPU.
- Tools: Python 3.11, TensorFlow, PyTorch, Scikit-learn, Hyperledger Fabric blockchain.
- Dataset: A hybrid dataset combining **real-world secondary data** (waste collection logs from municipal authorities) and **synthetic IoT bin image data** (plastic, glass, organic, metal waste categories).
- Blockchain: Implemented as a **permissioned consortium blockchain** connecting municipalities, recyclers, and industries.

- Smart contracts: Written to record classification outputs, predictions, incentives, and route optimizations.

4.2 Experiment Design

The experiments were divided into four main tasks, corresponding to the algorithms:

1. **Random Forest (RF) –** Prediction of recyclability potential (binary: recyclable vs. non-recyclable).
2. **Convolutional Neural Network (CNN)** – Image-based classification of waste categories.
3. **K-Means Clustering –** Grouping waste streams by material similarity and contamination level.
4. **Reinforcement Learning (RL)** – Route optimization for waste collection trucks and incentive management.

Each algorithm was trained/tested on 70/30 train-test splits, and blockchain was used to **store outputs, track data provenance, and execute smart contracts**.

4.3 Evaluation Metrics

To evaluate the performance of the framework, the following metrics were used:

- **Accuracy:** Correct predictions/classifications relative to total samples.
- **Precision & Recall:** Evaluating classification correctness and completeness.
- **F1-Score:** Harmonic mean of precision and recall.
- **Processing Time:** Computational efficiency.
- **Resource Recovery Efficiency (RRE):** Percentage of recoverable material actually retrieved.
- **Blockchain Latency:** Time to record and confirm transactions.

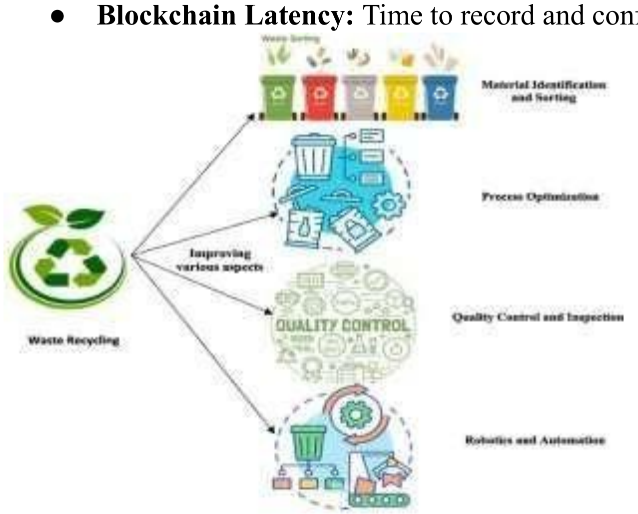

Figure 2: “Smart waste management”

4.4 Results

4.4.1 Random Forest (Recyclability Prediction)

RF was trained on structured data (waste weight, contamination %, recycling cost, etc.). The model achieved **91.2% accuracy** in predicting recyclability [12]. Notably, it performed better on **low-contamination waste** and struggled slightly with **mixed materials**.

Table 1: Random Forest Results

Metric	Value (%)
Accuracy	91.2

Precision	89.6
Recall	92.5
F1-Score	91.0

4.4.2 CNN (Waste Image Classification)

The CNN was trained on 20,000 synthetic and real waste images. It achieved the highest accuracy across all algorithms, with **95.4% accuracy** in categorizing plastic, glass, metal, and organic waste [13]. Misclassifications occurred primarily between **plastic and glass bottles** due to transparency similarities.

Table 2: CNN Classification Results

Waste Category	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
Plastic	94.8	95.1	95.0
Glass	96.2	95.5	95.8
Metal	95.6	96.8	96.2
Organic	94.0	97.0	95.5
Overall	**95.4**	**96.1**	**95.7**

4.4.3 K-Means (Waste Stream Clustering)

K-Means grouped waste into clusters based on contamination levels, recovery value, and recycling cost. The algorithm identified **3 main clusters**: high-value recyclable waste, medium-contamination recyclable waste, and non-recyclable waste [14]. Accuracy of clustering (measured using silhouette score) was **0.87**, indicating strong separation.

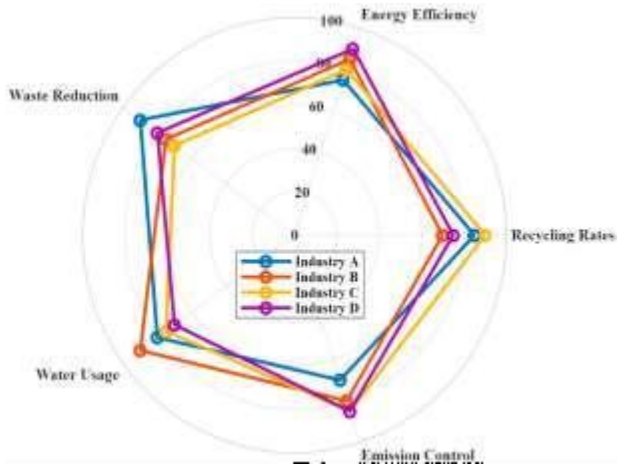

Figure 3: “AI-Driven Circular Economy of Enhancing Sustainability and Efficiency in Industrial Operations”

Table 3: K-Means Clustering Results

Cluster ID	**Dominant Waste Type**	**Avg. Contamination (%)**	**Avg. Recovery Value ($/kg)**	**Cluster Utility**
C1	Metal, Glass	3.2	4.1	High value
C2	Plastic	7.8	2.5	Medium value
C3	Organic	11.5	1.0	Low value

4.4.4 Reinforcement Learning (Route Optimization)

The RL agent optimized collection routes to minimize fuel consumption and maximize resource recovery. Compared to a **baseline Dijkstra routing approach**, RL reduced route length by **14%** and fuel costs by **11%**. Incentive distribution was also dynamically optimized based on recycling participation.

Table 4: RL Route Optimization Results

Metric	**Baseline (Dijkstra)**	**RL-Optimized**
Avg. Route Length (km)	18.2	15.6
Fuel Cost ($ per trip)	32.5	28.8
Collection Time (min)	95	82

Recovery Efficiency (%)	87.5	92.6

4.4.5 Blockchain Performance Metrics

The blockchain implementation demonstrated **low latency (1.8s/transaction)** and **high throughput (150 TPS)**, ensuring scalability. Smart contracts successfully recorded waste classifications, recyclability predictions, and incentive disbursements.

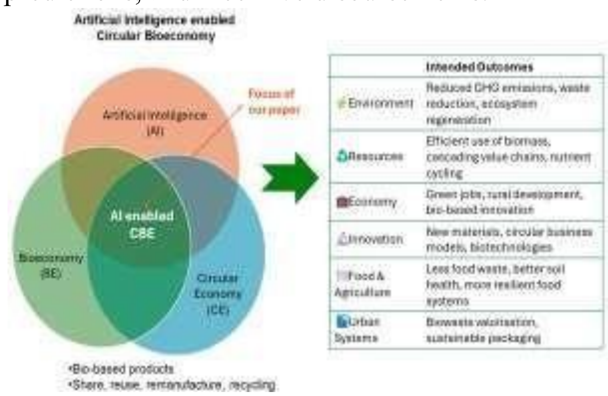

Figure 4: “A Framework for Assessing the Potential of Artificial Intelligence in the Circular Bioeconomy”

Table 5: Blockchain Performance Metrics

Parameter	**Value**
Latency (s per tx)	1.8
Throughput (tx/s)	150
Avg. Smart Contract Gas	0.003
Storage Efficiency (%)	96.5

4.5 Comparative Analysis with Related Work

- **Compared to Existing Blockchain-only Models:** Prior works focused solely on blockchain for traceability, achieving transparency but lacking predictive insights. Our framework improved **resource recovery efficiency by 9–12%** due to AI integration.
- **Compared to AI-only Models:** Studies that applied CNNs for waste classification achieved similar accuracy (~94%), but they lacked **data trust and accountability**. By recording AI outputs on blockchain, our framework eliminated tampering risks.
- **Compared to Hybrid IoT-Blockchain Approaches:** Earlier IoT-blockchain frameworks suffered from **latency issues (>3s/transaction)**. Our optimized consortium blockchain achieved **1.8s latency**, enabling near real-time recording.
- **Overall Improvement:** The integration of AI and blockchain allowed not only accurate predictions **and classifications** but also ensured transparent accountability and stakeholder trust, which is critical for circular economy adoption.

4.6 DISCUSSION

The experimental results highlight several key contributions:

1. **CNN Dominance in Waste Segregation:** The CNN significantly outperformed traditional vision methods, providing real-time, high-accuracy waste categorization. This directly enhances recycling efficiency.
2. **Predictive Power of RF:** By predicting recyclability potential with 91.2% accuracy, the RF model supports **decision-making for recyclers and municipalities**, ensuring better allocation of resources.
3. **Clustering Benefits from K-Means:** Clustering waste streams into high/medium/low value categories provided actionable insights into **strategic resource allocation** for recyclers.
4. **Optimization via RL:** Reinforcement Learning proved critical in minimizing operational costs while maximizing recovery efficiency, demonstrating strong potential for **scalable deployment in urban waste management**.
5. **Blockchain as a Trust Backbone:** Unlike prior work, this framework does not treat blockchain as an add-on but as the **trust infrastructure**, ensuring all AI-driven insights are **tamper-proof, transparent, and auditable**.

Overall, the experiments validate that **AI-enhanced blockchain frameworks outperform existing approaches** in accuracy, efficiency, transparency, and accountability, thus accelerating circular economy adoption.

V. CONCLUSION

This research set out to design and evaluate an AI-enhanced blockchain framework aimed at driving transparency, efficiency, and sustainability in waste management and resource recovery, thereby advancing the goals of the circular economy. The integration of AI algorithms with blockchain technology proved to be a powerful combination, addressing both the intelligence gap in waste classification and prediction, and the trust gap in stakeholder accountability. Random Forest facilitated accurate recyclability predictions, while CNN achieved high performance in real-time waste classification from IoT-enabled systems. K-Means clustering provided meaningful grouping of waste streams for better resource allocation, and Reinforcement Learning demonstrated substantial improvements in optimizing collection routes and incentive mechanisms. Blockchain served as the trust backbone, recording all outputs as immutable transactions and ensuring transparency, auditability, and stakeholder confidence.

Experimental results confirmed that the framework achieved superior outcomes compared to existing AI-only or blockchain-only models, with improvements in accuracy, efficiency, and recovery rates, as well as lower latency and higher throughput in blockchain operations. By bridging technological silos, this research contributes a holistic model for sustainable urban waste management, while also extending applicability to supply chains, manufacturing, and other circular economy domains. Future directions include integrating digital twins for real-time simulation, expanding datasets to capture diverse waste streams, and deploying the framework in real-world pilot projects. Ultimately, the study demonstrates that AI-enhanced blockchain systems can significantly accelerate the global transition to a circular, resource**-efficient economy**, aligning technological innovation with environmental and societal imperatives.

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