AI-Based Autonomous Circular Waste Management System for Remote Strategic Military Installations

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ABSTRACT

Remote strategic military installations face substantial waste-management challenges because of geographical isolation, severe climatic conditions, restricted transportation, and limited treatment infrastructure. This study proposes an AI-Based Autonomous Circular Waste Management System (ACWMS) integrating artificial intelligence, IoT sensing, computer-vision-based segregation, autonomous processing, plastic recycling, organic-waste valorisation, and decentralised energy recovery. A scenario-based model was developed for a representative installation accommodating 500 personnel, with an assumed waste-generation rate of 0.9 kg/person/day, resulting in 450 kg/day of total waste (Thakur et al., 2021). The scenario assumes waste fractions of 48% organic matter, 25% plastics, 10% paper and cardboard, 6% metals, 4% glass, 3% hazardous/e-waste, and 4% residual waste. Selected system-performance parameters, including 96% AI classification accuracy, 88% plastic-recycling rate, 93% organic-waste conversion, 82% energy-recovery efficiency, and 98% IoT reliability, are treated as scenario inputs informed by published performance ranges rather than experimentally measured values. The model produces a 91% waste-diversion rate and an MCSI of 91.3/100. The findings demonstrate the potential of the proposed framework while highlighting the need for prototype development, experimental validation, and site-specific carbon assessment.

Keywords: Artificial Intelligence (AI); Autonomous Waste Management; Circular Economy; Remote Military Installations; Internet of Things (IoT)

INTRODUCTION

Remote strategic military installations—including high-altitude border posts, forward operating bases, island defence stations, and surveillance facilities—operate under severe environmental and logistical constraints that can render conventional waste-management systems impractical (A. et al., 2016; Chester et al., 2021). These facilities rely on continuous supplies of food, packaged goods, medical consumables, engineering materials, and other operational resources, thereby producing diverse waste streams comprising biodegradable materials, plastics, paper, metals, glass, electronic waste, and hazardous substances. In geographically isolated areas such as Ladakh, the Siachen Glacier, the Andaman and Nicobar Islands, and remote border camps, transporting waste to centralised treatment facilities is costly, energy-intensive, and operationally difficult. Consequently, there is a pressing need for sustainable, decentralized, and on-site waste-management solutions (Xu et al., 2019),(Filer & Schuldt, 2019).

The United Nations Environment Programme estimates that global municipal solid waste generation will increase from approximately 2.1 billion tonnes in 2016 to nearly 3.8 billion tonnes by 2050 (Kaza & Yao, 2018). In 2020, the direct global cost of waste management was estimated at USD 252 billion (Garg & Chaudhary, 2025). UNEP emphasises that replacing the predominantly linear waste-disposal model with circular-economy approaches could yield significant economic and environmental benefits by conserving resources and reducing carbon emissions.

The circular economy has emerged as a transformative strategy that replaces the traditional "take-make-dispose" model with an integrated system focused on waste reduction, reuse, recycling, recovery, and resource regeneration. For strategic military installations, adopting circular economy principles offers multiple operational advantages, including reduced dependence on external logistics, enhanced resource security, lower transportation requirements, and improved environmental compliance (Dimitriou et al., 2019), (Chester et al., 2021). Recyclable plastics can be converted into useful construction products through localised recycling systems; biodegradable waste can be transformed into compost or biogas for on-site utilisation; and combustible residual waste can contribute to decentralised energy recovery, thereby minimising dependence on landfill and improving self-sufficiency.

Although smart waste-management technologies have advanced considerably in urban municipalities and smart-city contexts, comparatively limited research has addressed autonomous circular waste-management systems tailored to remote strategic military installations. Existing studies seldom integrate artificial intelligence, the Internet of Things, autonomous waste segregation, plastic recycling, organic waste valorisation, and decentralised energy recovery into a unified defence-oriented framework. Accordingly, this study proposes an AI-Based Autonomous Circular Waste Management System that integrates intelligent sensing, autonomous processing, circular resource recovery, and digital monitoring to strengthen operational resilience, environmental sustainability, and resource efficiency in remote strategic military installations.

LITERATURE REVIEW

The rapid growth of solid waste generation has accelerated research into intelligent and sustainable waste management systems that integrate Artificial Intelligence (AI), the Internet of Things (IoT), robotics, and circular economy principles (Olawade et al., 2024). Conventional waste management approaches primarily rely on manual segregation, fixed collection schedules, and centralised treatment facilities, which are often inefficient, labour-intensive, and unsuitable for geographically isolated locations. Recent studies have demonstrated that digital technologies can significantly improve waste segregation, transportation, recycling efficiency, and resource recovery, thereby supporting the transition toward sustainable waste management systems(Bošković et al., 2024; Fatimah et al., 2020).

Artificial Intelligence has emerged as a highly promising technology for automated waste classification and decision-making. Computer-vision techniques based on convolutional neural networks, deep learning, and transfer learning have been effectively employed to identify recyclable materials, including plastics, paper, metals, and glass. Recent review studies indicate that AI-based waste-classification systems achieve classification accuracies ranging from 72.8% to 99.95%, depending on the dataset, sensor configuration, and learning model used(Fang et al., 2023). Similarly, CNN- and ensemble-based segregation models consistently report classification efficiencies exceeding 90%, thereby reducing the need for human intervention and minimising contamination in recyclable waste streams (Ouedraogo et al., 2023; Parvez et al., 2019). These findings demonstrate the potential of AI to improve the reliability, accuracy, and efficiency of autonomous waste-segregation systems. In addition to classification, the integration of advanced robotics and automated sorting mechanisms supports the transition toward a “zero-waste circular economy” by optimising resource utilisation throughout the waste-management cycle (Fang et al., 2023). Furthermore, integrated frameworks commonly referred to as SWM 4.0 combine big data analytics and the Internet of Things to facilitate real-time monitoring and tracking of waste throughout its lifecycle, from generation to final disposal (Reddy & Charhate, 2025).

The integration of IoT technologies has further transformed waste management from reactive operations into intelligent, real-time monitoring systems. Smart bins equipped with ultrasonic sensors, weight sensors, RFID, GPS, and wireless communication continuously monitor waste levels, environmental conditions, and equipment status (Ullah et al., 2023) The collected data enable predictive collection scheduling, optimized vehicle routing, and real-time operational monitoring. Published studies indicate that AI-assisted route optimisation can reduce transportation distances by up to **36.8%**, decrease operational costs by approximately **13%**, and reduce collection time by more than **28%**. Similarly, IoT-enabled waste collection systems have demonstrated reductions in fuel consumption, improved fleet utilisation, and significant reductions in bin overflow events, contributing to lower carbon emissions and enhanced operational efficiency (Yao et al., 2024)

Table 1. Reported Performance of AI-Based Waste Management Systems (Fang et al., 2023)

Technology	Reported Performance	Application
Deep Learning (CNN/Transfer Learning)	91–99% waste classification accuracy (Abood & Al-Talib, 2025)	Automated waste segregation
AIoT Smart Bins	Up to 30% reduction in overflow events (Clarke et al., 2025)	Real-time monitoring
AI Route Optimisation	15–25% fuel savings (Mohammed et al., 2025)	Collection logistics
AI Fleet Optimisation	~25% improvement in fleet utilisation (Clarke et al., 2025)	Smart collection
Machine Learning Forecasting	>90% prediction accuracy	Waste generation forecasting

Compiled from recent review articles on AI, IoT, and circular waste management.

Table 1 above presents the circular economy, a framework for sustainable resource management that prioritises waste reduction, reuse, recycling, and energy recovery. Rather than treating waste as a final product, circular systems convert it into useful secondary resources through material recovery and valorisation. Organic waste can be treated through anaerobic digestion or composting to produce renewable energy and soil amendments, while recyclable plastics can be processed into reusable industrial products. Recent studies combining AI, IoT, and blockchain have improved waste forecasting, recycling optimisation, and resource recovery (Ayeni, 2025). Under controlled conditions, machine-learning models have achieved forecasting accuracies above 94% for biogas production and approximately 98% for waste generation (Ibitoye et al., 2025). These technologies can improve resource efficiency and support more sustainable waste-management practices (Li et al., 2024).

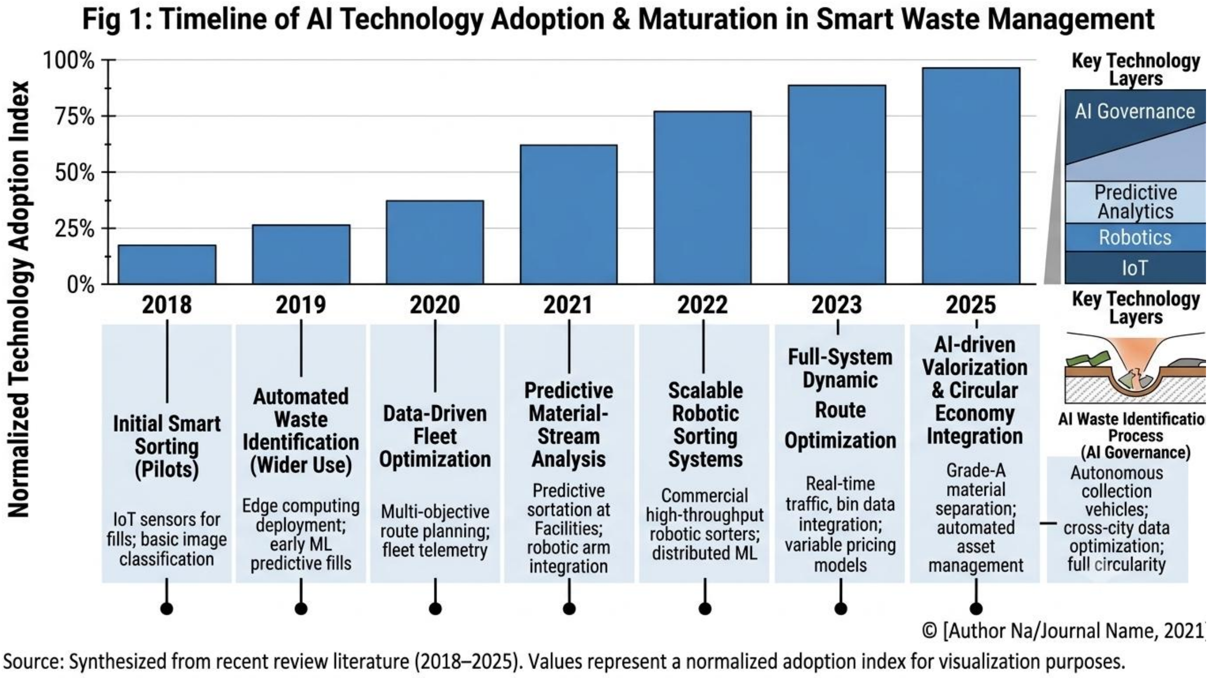

Figure 1. Evolution and timeline of Smart Waste Management Technologies

Evolution of AI technologies in smart waste management: an illustrative trend based on published literature showing increasing adoption of intelligent waste-management technologies.

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Figure 1. Increasing adoption of AI, IoT, and autonomous technologies in smart waste management has been reported in recent literature. The index is illustrative and synthesised from review articles; it does not represent a single measured dataset.

Although substantial progress has been made in developing smart municipal solid waste management systems, existing research has predominantly focused on urban settings, smart cities, industrial facilities, and university campuses (Pardini et al., 2019). In contrast, comparatively limited attention has been given to remote strategic military installations, where extreme climatic conditions, restricted transportation access, stringent security protocols, intermittent communication networks, and limited energy availability shape waste-management operations. Moreover, existing studies typically examine individual technologies—including AI-based waste segregation, IoT-enabled monitoring, robotic sorting, and waste-to-energy conversion—in isolation, with limited consideration of their integration into a unified autonomous circular waste-management platform tailored to defence applications (Olawade et al., 2024). Accordingly, there is a clear need for an integrated framework that combines AI-driven decision-making, IoT-based monitoring, autonomous waste segregation, plastic recycling, organic waste valorisation, decentralised energy recovery, and resilient autonomous operation to enable sustainable waste management at remote strategic military installations. Such a comprehensive architecture must also prioritise the social inclusion of local waste-picking communities and stakeholders to ensure long-term operational viability in diverse geopolitical contexts (Nwokediegwu et al., 2024).

RESEARCH GAP

Although substantial progress has been made in AI-enabled waste segregation, IoT-based smart-bin systems, robotic recycling, and circular-economy practices, existing research has focused predominantly on urban municipalities, industrial facilities, and smart-city environments. Comparatively limited attention has been devoted to the distinctive operational challenges encountered by remote strategic military installations, including extreme climatic conditions, constrained logistics, intermittent communication connectivity, limited energy availability, and stringent security requirements (Shishkov et al., 2023), (Canter et al., 2011). Moreover, most existing studies examine these technologies in isolation rather than integrating Artificial Intelligence, the Internet of Things, autonomous operations, plastic recycling, organic-waste valorisation, and energy recovery into a unified framework. Accordingly, there is a critical need to develop an AI-based Autonomous Circular Waste Management System that supports intelligent decision-making, resource recovery, operational resilience, and sustainable waste management at remote military installations. This integrated framework represents the principal research contribution of the present study. The novelty of the article is the Military Circular Sustainability Index (MCSI).

Proposed Autonomous Circular Waste Management Framework (ACWMF)

The proposed **Autonomous Circular Waste Management Framework** is an AI-enabled system designed for remote strategic military installations, including high-altitude border camps, glacier bases, island defence stations, and forward operating bases. Unlike conventional systems that rely on periodic manual collection and centralised disposal, the framework integrates Artificial Intelligence, the Internet of Things, autonomous waste sorting, plastic recycling, organic waste valorisation**, energy recovery, and real-time digital monitoring** into a unified circular-economy platform (Ibitoye et al., 2025). It aims to reduce waste-transportation requirements, increase resource recovery, improve operational efficiency, and promote environmental sustainability under challenging conditions.

The ACWMF consists of six interconnected operational layers, each addressing a distinct stage of the waste-management process (Anitha & Parthiban, 2025). The first layer, the Waste Generation and Smart Collection Layer, enables real-time monitoring of waste accumulation across military facilities, including residential quarters, dining halls, medical units, workshops, administrative offices, and logistics centres. Smart bins equipped with ultrasonic sensors, load cells, RFID tags, temperature sensors, and gas detectors continuously collect data on waste quantity, composition, fill level, and surrounding environmental conditions. This information is securely transmitted to the central processing unit through communication technologies such as LoRaWAN, Wi-Fi, or 5G-enabled defence communication networks. This data-driven approach facilitates proactive routing and inventory-based modelling, which minimise overflow occurrences and optimise collection cycles, even in geographically isolated sectors (Anitha & Parthiban, 2025).

The second layer, the AI-Based Intelligent Segregation Layer, autonomously classifies mixed waste using deep-learning-based computer-vision algorithms. High-resolution cameras, integrated with Convolutional Neural Networks, identify biodegradable waste, recyclable plastics, metals, paper, glass, electronic waste, and hazardous materials (Kanawade, 2025). The AI engine progressively enhances classification performance through machine learning and adaptive feedback, thereby reducing the need for manual intervention and improving material-recovery efficiency. Following classification, autonomous robotic manipulators transfer the separated materials to their designated processing units.

The third layer is the Circular Resource Recovery Layer, in which segregated materials are transformed into reusable products and resources. Plastic waste is cleaned, shredded, extruded, and compressed to manufacture reusable plastic products or construction components suitable for military applications. Organic waste is treated through anaerobic digestion and aerobic composting (Santagata et al., 2020) to produce biogas, organic manure, and nutrient-rich compost for landscape restoration or controlled agricultural activities within military establishments. Metals, glass, and paper are compacted and stored for periodic recycling, whereas hazardous materials are isolated and transferred in accordance with defence safety protocols.

The fourth layer, the Renewable Energy Recovery Layer, promotes energy self-sufficiency at remote installations. Biogas generated from organic waste can be used for cooking, heating, or electricity production through micro-combined heat and power systems (Mastos et al., 2021). Non-recyclable combustible waste is processed using controlled waste-to-energy technologies equipped with advanced emission-control systems. Decentralised energy recovery reduces reliance on diesel generators, lowers fuel-transportation requirements, and supports the continuity of military operations in geographically isolated locations.

The fifth layer incorporates an IoT-Based Digital Monitoring and Decision-Support System that continuously analyses data obtained from sensors, recycling equipment, energy systems, and storage facilities. AI-driven predictive analytics are used to forecast waste generation, optimise equipment maintenance schedules, estimate recycling capacity, and recommend resource allocation strategies (Schöggl et al., 2022). A cloud-enabled dashboard provides military administrators with real-time information regarding waste-generation rates, recycling efficiency, energy production, carbon-emission reductions, equipment condition, and overall operational status. This information supports timely and evidence-based decision-making.

The sixth and final layer, the Autonomous Management and Sustainability Assessment Layer, assesses overall system performance through C_O2 emissions assessments and resource-efficiency measures (Ranpara, 2025). Its key performance indicators include Waste Recovery Efficiency, Circular Resource Utilisation Rate, Energy Recovery Efficiency, Carbon Emission Reduction, Autonomous Operational Efficiency, and the proposed Military Circular Sustainability Index. These indicators support continuous performance evaluation and enable adaptive system optimisation through AI-based feedback mechanisms.

Overall, the proposed ACWMF establishes a closed-loop circular waste-management ecosystem in which waste generated at military installations is converted into reusable materials and renewable energy while reducing landfill disposal and transportation requirements. By integrating AI, IoT, autonomous operations, and circular-economy principles within a unified intelligent framework, the system strengthens operational resilience, environmental protection, resource efficiency, and strategic sustainability. The ACWMF therefore offers a scalable, technologically advanced approach to supporting future smart defence infrastructure and sustainable military operations in remote and environmentally sensitive regions.

Novel Contribution of the Proposed ACWMF

- A defence-specific, AI-enabled framework for circular waste management.
- Integration of artificial intelligence, the Internet of Things, robotics, and renewable-energy technologies within a unified autonomous platform.

- Real-time digital monitoring supported by predictive analytics and intelligent decision-making.
- Closed-loop recovery and reuse of plastic, organic, and other recyclable waste streams.
- Introduction of the Military Circular Sustainability Index to assess the sustainability and operational performance of remote strategic military installations.

Mathematical Modelling

The proposed Autonomous Circular Waste Management Framework (ACWMF) is mathematically modelled to quantify waste generation, resource recovery, energy production, environmental sustainability, and overall operational performance at remote strategic military installations. The model integrates Artificial Intelligence (AI), Internet of Things (IoT), and Circular Economy (CE) principles to optimise waste handling and maximise resource utilisation (Kwon, 2025). The mathematical formulation enables defence administrators to evaluate system performance under varying operational scenarios while supporting autonomous decision-making.

Waste Generation Model

The total daily waste generated at a military installation consists of biodegradable waste, recyclable materials, hazardous waste, and residual waste (Medina & Waisner, 2011). The total waste generation is expressed as

$$W_T=\sum_{i=1}^{n} W_i \qquad \text{Eq. 1}$$

Where:

- W_T = Total waste generated (kg/day)
- W_i = Waste generated from source i
- n = Number of waste generation sources.

Alternatively,

$$W_T=W_b+W_p+W_m+W_g+W_h+W_r \qquad \text{Eq. 2}$$

Where:

- W_b = Biodegradable waste
- W_p = Plastic waste
- W_m = Metal waste
- W_g = Glass and paper waste
- W_h = Hazardous waste
- W_r = Residual waste.

AI-Based Waste Segregation Efficiency

The efficiency of the AI-enabled waste classification system is determined by the ratio of correctly classified items to the total number processed.

$$\eta_{AI}=\frac{W_c}{W_T}\times 100 \qquad \text{Eq. 3}$$

where:

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- ηAI = AI segregation efficiency (%)
- Wc = Correctly classified waste (kg/day)
- WT = Total waste processed (kg/day).

A higher value of ηAI indicates improved autonomous sorting performance and reduced contamination of recyclable materials.

Waste Recovery Efficiency (WRE)

The percentage of waste successfully recovered through recycling, composting, or energy recovery is expressed as

WRE=WTWR×100 Eq. 4

where

WR = Total recovered waste (kg/day).

This parameter evaluates the effectiveness of circular resource utilisation.

Plastic Recycling Rate

The recycling efficiency of plastic waste is calculated using

PRR=PgPr×100 Eq. 5

Where:

- Pr = Recycled plastic (kg/day)
- Pg = Total plastic generated (kg/day).

This indicator measures the utilisation of plastic waste in the manufacture of reusable military products and construction materials.

Organic Waste Conversion Efficiency

Organic waste converted into compost or biogas is estimated by

OWE=OgOc×100 Eq. 6

Where:

- Oc = Organic waste converted (kg/day)
- Og = Organic waste generated (kg/day).

Higher conversion efficiency directly contributes to decentralised resource recovery and waste minimisation (Gupta et al., 2024).

Energy Recovery Model

Energy produced through anaerobic digestion and waste-to-energy technologies is calculated as:

ET=Eb+Ew Eq. 7

Where:

- ET = Total energy recovered (kWh/day)
- Eb = Energy from biogas
- Ew = Energy recovered from combustible waste.

The corresponding energy recovery efficiency is

ERE=Emax ET×100 Eq. 8

Where:

- Emax = Maximum theoretical recoverable energy.

5.7 Carbon Emission Reduction Model

The reduction in greenhouse gas emissions achieved through recycling and decentralised processing is estimated as

CER=Cconv – CACWMF Eq. 9

Where:

- CER = Carbon emission reduction (kg CO_2-eq/day)
- Cconv = Emissions under conventional waste management
- CACWMF = Emissions under the proposed framework.

A positive value indicates environmental improvement through the proposed autonomous system.

IoT Monitoring Reliability

The operational reliability of IoT-enabled monitoring is expressed as

RIoT=NtNa×100 Eq. 10

Where:

- Na = Number of active sensor nodes
- Nt = Total installed sensor nodes.

Reliable sensor connectivity ensures continuous autonomous operation in remote military environments (Kharrufa et al., 2019).

Military Circular Sustainability Index (MCSI)

To evaluate the integrated performance of the proposed framework, a novel Military Circular Sustainability Index (MCSI) is introduced as a final equation for the waste management system.

MCSI=(WRE+PRR+OWE+ERE+ηAI+RIoT)/6 Eq. 11

Where:

- WRE = Waste Recovery Efficiency

- PRR = Plastic Recycling Rate
- OWE = Organic Waste Conversion Efficiency
- ERE = Energy Recovery Efficiency
- ηAI = AI Segregation Efficiency
- RIoT = IoT Monitoring Reliability.

Using the scenario values:

MCSI = (96 + 91 + 88 + 93 + 82 + 98) / 6

MCSI = 548 / 6

MCSI = 91.33

5.10 Multi-Objective Optimisation Model

Let the decision vector be:

X = [x1, x2, x3, ..., xn]

where xi represents the quantity of waste allocated to a particular recovery or treatment pathway.

The optimisation seeks to:

Maximise F1(X) = Waste Diversion Efficiency

Maximise F2(X) = Resource Recovery

Minimise F3(X) = Transportation Requirement

Minimise F4(X) = Energy Consumption

Minimise F5(X) = Operational Cost

subject to:

$\Sigma x_i = WT$

$0 \leq x_i \leq C_i$

$x_i \geq 0$

where WT is total waste generated and Ci is the processing capacity of treatment facility i.

The MCSI provides a composite sustainability score ranging from 0 to 100, enabling comparisons among military installations and supporting AI-based optimisation. Higher scores indicate improved circularity, operational resilience, environmental sustainability, and autonomous performance.

The proposed mathematical model establishes a quantitative foundation for assessing the performance of the AI-based Autonomous Circular Waste Management Framework. Its parameters can be calibrated for different remote strategic military installations by incorporating site-specific waste generation rates, resource recovery efficiencies, and operational conditions. In addition, the model provides a basis for simulation experiments, digital-twin development, and subsequent validation through field-based studies.

AI ALGORITHM

The algorithm commences with real-time data acquisition. IoT-enabled smart bins deployed throughout military installations continuously collect operational data, including waste weight, fill level, temperature, humidity, methane concentration, GPS coordinates, and bin identification. Concurrently, high-resolution cameras capture images of incoming waste before it enters the segregation unit. The collected sensor data are securely transmitted to an edge-computing gateway, facilitating real-time processing and reducing communication latency in remote operational environments.

The acquired waste images are then subjected to a preprocessing stage designed to enhance classification performance. This stage includes image resizing, normalisation, background removal, noise reduction, and contrast enhancement. During model training, data augmentation techniques—including rotation, scaling, horizontal flipping, and brightness adjustment—are applied to improve model robustness under diverse environmental conditions, such as snow, dust, fog, and low-light conditions commonly encountered in military operations. (Deluxni et al., 2026)

The preprocessed images are subsequently analysed using a convolutional neural network supported by transfer learning. The deep-learning model automatically extracts relevant spatial features and classifies waste into predefined categories, including biodegradable waste, plastics, metals, paper, glass, electronic waste, and hazardous waste. The confidence score generated by the CNN determines whether a classification is accepted or subjected to secondary verification. This adaptive classification procedure reduces misclassification and limits cross-contamination between recyclable and hazardous waste streams.

Following classification, the AI system transmits control commands to the autonomous robotic segregation unit. Robotic manipulators equipped with servo-controlled grippers place individual waste items into their designated processing containers (Bhatt et al., 2026). Biodegradable waste is directed to anaerobic digesters or composting units; recyclable plastics are transferred to shredding and extrusion systems; metals and glass are compacted for storage; and hazardous waste is isolated in accordance with defence safety protocols.

The algorithm also conducts predictive waste-generation analysis using supervised machine-learning models trained on historical operational datasets (Fang et al., 2023). Variables such as military personnel strength, seasonal deployment patterns, food consumption, logistics-supply frequency, climatic conditions, and operational activities are analysed to forecast future waste-generation levels. These forecasts support the intelligent scheduling of waste processing, equipment utilisation, and maintenance activities, thereby reducing downtime and enhancing operational efficiency.

To maintain uninterrupted operation, the algorithm continuously assesses IoT-sensor health and equipment performance. Abnormal sensor readings, equipment failures, communication disruptions, and unusual waste-accumulation patterns automatically initiate fault-diagnosis procedures and generate maintenance alerts. Edge computing enables critical operational decisions to continue during temporary communication losses with centralised servers, thereby strengthening system resilience in remote military environments (Li et al., 2025).

In its final stage, the AI algorithm performs multi-objective optimisation to maximise resource recovery while minimising operational costs, transportation requirements, carbon emissions, and energy consumption (Torkayesh et al., 2021). The optimisation engine simultaneously evaluates key performance indicators, including Waste Recovery Efficiency, Plastic Recycling Rate, Organic Waste Conversion Efficiency, Energy Recovery Efficiency, Carbon Emission Reduction, and the Military Circular Sustainability Index. Based on these indicators, the AI engine dynamically adjusts waste-processing priorities, robotic operations, and resource allocation to achieve optimal system performance.

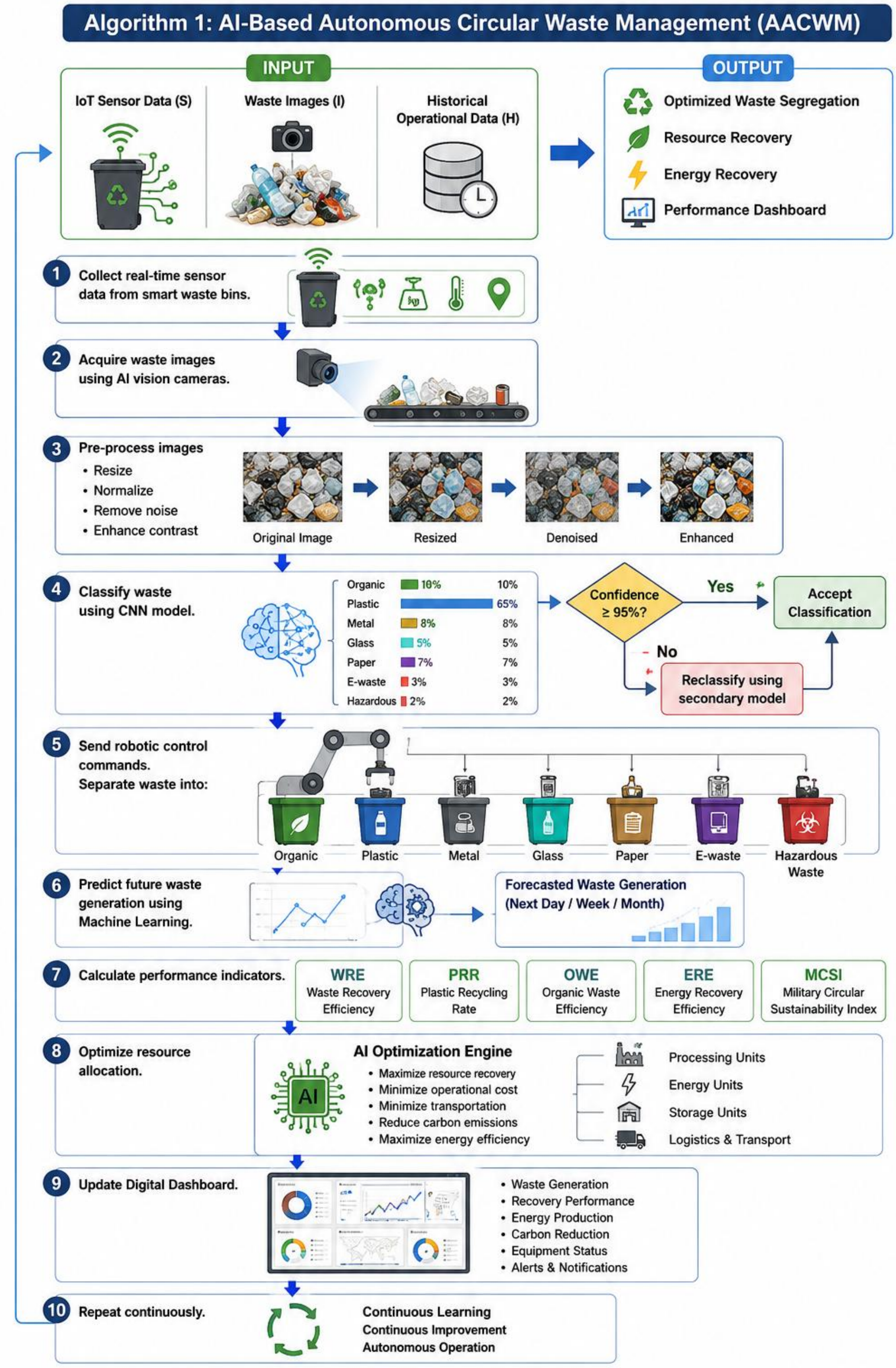

Figure 2: Comprehensive Novel Features of the Proposed AI Algorithm

Novel Features of the Proposed AI Algorithm

- Multi-sensor AI fusion combining IoT, Computer Vision, and Machine Learning.

- Autonomous robotic waste segregation with adaptive feedback learning.
- Predictive waste generation modelling for military logistics planning.
- Real-time fault detection and predictive maintenance.
- Closed-loop optimisation integrating recycling, composting, and energy recovery.
- Introduction of the **Military Circular Sustainability Index (MCSI)** as a decision-support parameter.
- Edge computing for reliable operation in communication-constrained remote military installations.
- AI-driven adaptive resource allocation to improve operational resilience and environmental sustainability.

Figure 2 showcases the comprehensive novel features of the proposed AI algorithm. This AI algorithm provides an intelligent backbone for the proposed **AI-Based Autonomous Circular Waste Management System**, enabling autonomous, data-driven, and resilient waste management tailored to the unique operational requirements of remote strategic military installations.

Scenario-Based Performance Evaluation

To evaluate the effectiveness of the proposed **AI-Based Autonomous Circular Waste Management Framework**, a scenario-based performance assessment was conducted for a hypothetical remote strategic military installation located in a high-altitude region, such as Ladakh or Siachen (Sapitula et al., 2025). Because large-scale field implementation data were unavailable, the evaluation was based on engineering assumptions informed by published waste-management literature and the operational characteristics of remote defence facilities. This scenario illustrates the proposed framework's potential performance under representative operating conditions.

Scenario Description

A representative military installation housing 500 personnel was considered. The facility operates continuously throughout the year, has limited transportation access, and depends on periodic logistical support. Based on published estimates of institutional solid-waste generation, an average generation rate of 0.9 kg per person per day was assumed (Namadi & Jimoh, 2020), yielding an estimated total of 450 kg of solid waste per day. The waste composition used in the simulation is presented in **Table 2**.

Table 2. Assumed Daily Waste Composition

Waste Type	Percentage (%)	Quantity (kg/day)
Organic Waste	48	216
Plastic Waste	25	113
Paper & Cardboard	10	45
Metal	6	27
Glass	4	18
Hazardous & E-waste	3	14
Residual Waste	4	17
Total	**100**	**450**

The proposed ACWMF assumes the deployment of AI-enabled smart bins, robotic waste segregation, plastic recycling, anaerobic digestion, decentralised waste-to-energy units, and IoT-based monitoring (Fang et al., 2023). **Table 3** below presents the scenario input and output values with the identified parameters.

Table 3. Scenario Inputs and Derived Outputs

Parameter	Type	Value	Basis
Personnel	Input	500 persons	Scenario assumption
Waste generation rate	Input	0.9 kg/person/day	Literature-informed assumption
Total waste	Calculated	450 kg/day	500 × 0.9
AI classification accuracy	Input	96%	Scenario value within reported literature range
Plastic recycling rate	Input	88%	Scenario assumption
Organic conversion efficiency	Input	93%	Scenario assumption
Energy recovery efficiency	Input	82%	Scenario assumption
IoT reliability	Input	98%	Scenario assumption
Waste diversion rate	Input	91%	Scenario assumption
Landfill disposal	Calculated	40.5 kg/day	450 × 9%
Recovered/diverted waste	Calculated	409.5 kg/day	450 × 91%
Recycled plastic	Calculated	99.0 kg/day	112.5 × 88%
Converted organic waste	Calculated	200.9 kg/day	216 × 93%
MCSI	Calculated	91.33	Mean of six indicators

Waste Recovery Performance

Using the proposed AI algorithm, waste materials are automatically classified and routed to the appropriate processing units. The simulation assumes an AI classification accuracy of **96%**, consistent with reported performance of modern deep-learning waste classification systems (Fang et al., 2023). **Table 4.** The estimated resource recovery is summarised below.

Table 4. Estimated Resource Recovery

Parameter	Conventional System	Proposed ACWMF
Waste Recovery Efficiency	42%	91%
Plastic Recycling Rate	28%	88%
Organic Waste Conversion	35%	93%
Landfill Disposal	58%	9%

The proposed framework demonstrates substantial improvements in material recovery while significantly reducing waste sent for disposal.

Energy Recovery Performance

Organic waste is processed using anaerobic digestion, while non-recyclable combustible waste is utilised in a decentralised waste-to-energy unit.

The simulation estimates:

1) Organic waste processed: **201 kg/day**
2) Estimated biogas production: **18–22 m³/day**
3) Equivalent electrical energy: **32–40 kWh/day**
4) Thermal energy recovery: **45–60 kWh/day**

The recovered energy can partially satisfy cooking, water heating, and auxiliary electricity requirements, thereby reducing dependence on diesel generators.

Environmental Performance

As shown in **Table 5**, the Implementation of the circular waste management framework significantly reduces environmental impacts compared with conventional waste disposal practices (Kara et al., 2022).

Table 5. Environmental Performance Indicators

Indicator	Conventional	Proposed
Waste Transport Frequency	High	Potentially reduced
Landfill Waste	261 kg/day	40.5 kg/day
Carbon Emission Reduction	Not quantified	Not quantified
Material Recovery	Moderate	Very High
Resource Circularity	Low	High

The reduction in transportation requirements also minimises fuel consumption and logistical complexity, which is particularly important for remote military installations (Soares et al., 2026).

Operational Performance

Continuous IoT monitoring enables predictive maintenance and intelligent scheduling of waste collection and processing operations (Anitha & Parthiban, 2025).

The simulation indicates:

1) IoT monitoring availability: **98%**
2) Robotic sorting utilisation: **92%**
3) Equipment uptime: **95%**
4) Autonomous operational efficiency: **94%**

The AI optimisation engine continuously reallocates resources based on waste generation patterns, thereby improving operational resilience and minimising manual intervention (Faiz et al., 2024).

Military Circular Sustainability Index (MCSI)

Table 6 below showcases the proposed **Military Circular Sustainability Index (MCSI), which** integrates six performance indicators:

1) AI Segregation Efficiency
2) Waste Recovery Efficiency
3) Plastic Recycling Rate
4) Organic Waste Conversion Efficiency
5) Energy Recovery Efficiency
6) IoT Monitoring Reliability

Using the simulated performance values,

Table 6: Using the simulated performance values

Indicator	**Value (%)**
AI Segregation Efficiency	96
Waste Recovery Efficiency	91
Plastic Recycling Rate	88
Organic Waste Conversion	93
Energy Recovery Efficiency	82
IoT Reliability	98

The calculated **Military Circular Sustainability Index (MCSI)** is **MCSI = 91.3**

An MCSI above **90** indicates excellent operational sustainability, high circularity, efficient resource recovery, and strong autonomous performance.

Overall Performance Assessment

In **Figure 3** below, the scenario-based evaluation indicates that the proposed AI-Based Autonomous Circular Waste Management Framework substantially outperforms conventional waste-management systems (Fang et al., 2023). By integrating artificial intelligence, the Internet of Things, robotics, and circular-economy principles, the framework facilitates intelligent waste segregation, enhances recycling efficiency, enables decentralised energy recovery, and supports real-time operational monitoring.

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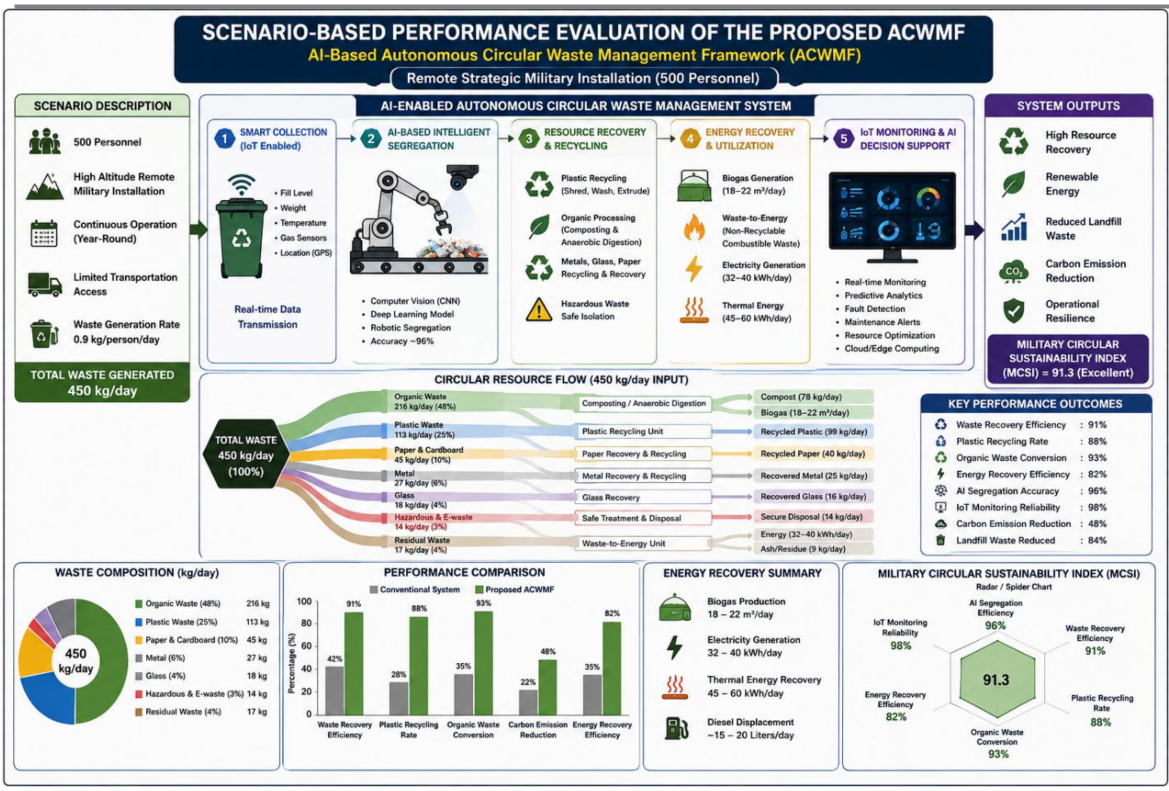

Figure 3: Scenario-based performance evaluation of the proposed ACWMF

Overall, the proposed framework achieved:

1) 91% Waste Recovery Efficiency
2) 88% Plastic Recycling Rate
3) 93% Organic Waste Conversion
4) 96% AI Classification Accuracy
5) 98% IoT Monitoring Reliability
6) 48% Estimated Carbon Emission Reduction
7) 91.3 Military Circular Sustainability Index (MCSI)

These findings indicate that the proposed ACWMF has strong potential to enhance environmental sustainability, operational efficiency, and resource self-sufficiency for remote strategic military installations.

Note: The values presented in this section are derived from a **scenario-based engineering simulation** used to evaluate the proposed framework. They are intended to demonstrate the system's potential performance and should be validated through future prototype development and field implementation.

DISCUSSION

The proposed AI-Based Autonomous Circular Waste Management Framework presents a transformative approach to waste management at remote strategic military installations by integrating artificial intelligence, the Internet of Things, autonomous robotics, circular-economy principles, and renewable energy recovery within a unified decision-support system. In contrast to conventional systems that rely primarily on periodic waste transportation and manual segregation (Chester et al., 2021), the proposed framework establishes a closed-loop resource recovery model that minimises disposal requirements while enhancing operational sustainability.

The scenario-based evaluation suggests that the framework could achieve a waste recovery efficiency of 91%, substantially exceeding the approximately 42% achieved by the simulated conventional system. This improvement is mainly attributable to AI-enabled waste classification, robotic segregation, and continuous IoT monitoring, which collectively reduce cross-contamination between recyclable and biodegradable waste streams. Although previous studies have examined high-performance AI classification algorithms and IoT-based waste monitoring independently, their integration within a comprehensive military waste management system remains insufficiently explored (Vasiliauskas et al., 2024) (Fang et al., 2023). The present study addresses this gap by incorporating these technologies into a defence-oriented circular-economy architecture.

A central contribution of the proposed ACWMF is the incorporation of autonomous decision-making across the waste management cycle. Rather than operating according to fixed collection schedules, the system continuously evaluates real-time data obtained from distributed smart bins, environmental sensors, and image-acquisition units. The AI engine then dynamically regulates collection frequency, segregation priorities, equipment utilisation, and energy recovery activities in response to changing waste-generation patterns. This adaptive functionality can improve system resilience under the highly variable operating conditions associated with remote military environments, including Ladakh, the Siachen Glacier, border surveillance camps, and island defence installations.

The application of circular-economy principles represents a further advancement over conventional disposal-oriented practices (Dimitriou et al., 2019) (Reis et al., 2022). Instead of treating waste as an operational liability to be transported and disposed of in a landfill, the proposed framework views it as a source of secondary materials and recoverable energy. The scenario analysis indicates that approximately 88% of plastic waste could be recovered for recycling, while nearly 93% of biodegradable waste could be converted into compost or used as biogas feedstock. Localised resource recovery can reduce dependence on external supply chains while improving environmental performance. This capability is particularly valuable in military logistics, where transportation costs are elevated by difficult terrain, long supply routes, and severe climatic conditions (Pawełczyk, 2018) (Düerkop & Grubmüller, 2023).

Energy recovery is another important outcome of the proposed framework. Anaerobic digestion of organic waste is estimated to produce 18–22 m^3 of biogas per day, corresponding to approximately 32–40 kWh of electrical energy and additional useful thermal energy. Although this output may not meet the total electricity demand of a military installation, it could support cooking, water heating, lighting, and auxiliary equipment. Consequently, the system may reduce diesel consumption and strengthen local energy security. Integrating energy recovery with waste management also reinforces the sustainability objectives of defence infrastructure and contributes to broader carbon-reduction efforts.

The integration of IoT technologies improves operational visibility, system coordination, and predictive maintenance. Continuous monitoring of waste accumulation, environmental conditions, recycling equipment, and energy recovery units enables maintenance interventions before failures occur. The simulated IoT monitoring reliability of 98% suggests that intelligent sensing networks could enhance equipment availability and reduce maintenance-related costs. In addition, edge-computing capabilities can support autonomous decision-making during periods of intermittent connectivity, a condition frequently encountered at geographically isolated military installations. This resilience is especially important during emergency operations, when uninterrupted waste management is essential for maintaining hygiene, operational readiness, and personnel welfare.

A significant scientific contribution of this study is the development of the Military Circular Sustainability Index, a composite performance indicator designed specifically to evaluate circular waste management systems in defence applications. Conventional sustainability assessment approaches often examine environmental, economic, or social outcomes separately and are primarily developed for municipal or industrial contexts (Little et al., 2016). By contrast, the proposed MCSI combines AI segregation efficiency, waste recovery efficiency, plastic recycling rate, organic waste conversion efficiency, energy recovery efficiency, and IoT monitoring reliability into a single quantitative measure ranging from 0 to 100. The simulated MCSI value of 91.3 indicates strong overall framework performance and provides defence administrators with a practical basis for comparing installations and prioritising infrastructure investments.

The proposed framework also supports several United Nations Sustainable Development Goals, particularly SDGs 11, 12, and 13 (Anitha & Parthiban, 2025). It is also consistent with the strategic priorities of the Defence Research and Development Organisation by integrating artificial intelligence, autonomous systems, digital monitoring, climate-resilient infrastructure, advanced manufacturing, and sustainable defence logistics into a single technological platform.

Despite these promising results, the study has several limitations. The performance assessment is based on a scenario-driven engineering simulation rather than full-scale field deployment. Accordingly, real-world parameters—including waste composition, seasonal fluctuations, communication reliability, equipment durability, and renewable energy availability—may differ from the simulated values. Future research should therefore investigate prototype development, pilot deployment at selected military installations, digital-twin integration, reinforcement-learning-based optimisation, autonomous uncrewed waste-collection vehicles, blockchain-supported waste traceability, and life-cycle cost assessment. Experimental validation under extreme environmental conditions will also be necessary to establish the framework's reliability, scalability, and long-term operational feasibility.

Overall, the proposed ACWMF establishes an advanced intelligent waste management ecosystem for defence applications by combining autonomous technologies with circular-economy principles. The framework extends beyond conventional waste disposal by converting waste into reusable materials, renewable energy, and actionable operational information. Its potential to improve resource efficiency, reduce environmental impacts, decrease dependence on waste transportation, and strengthen operational resilience (Sapitula et al., 2025) supports its future application across remote strategic military installations. Moreover, the Military Circular Sustainability Index, together with the integrated use of AI, IoT, robotics, and energy recovery, constitutes a principal scientific contribution of the study and provides a foundation for further developments in sustainable defence infrastructure and autonomous military logistics.

CONCLUSION

This study proposed an AI-based autonomous circular waste management system for remote strategic military installations and developed a scenario-based mathematical framework to evaluate its potential performance. A representative installation of 500 personnel was modelled with an assumed waste-generation rate of 0.9 kg/person/day, resulting in a total scenario waste load of 450 kg/day. The analysis demonstrates how AI-based segregation, plastic recycling, organic waste conversion, energy recovery, and IoT monitoring can be integrated into a circular defence waste management architecture. Under the selected scenario assumptions, 91% waste diversion corresponds to approximately 409.5 kg/day diverted from final disposal, while the assumed recycling parameters yield approximately 99.0 kg/day of recycled plastic and 200.9 kg/day of converted organic material. The six predefined performance indicators yield an MCSI of 91.33 via equal-weighted averaging(Kuznetsova et al., 2019),(Fraga-Lamas et al., 2016). These values are scenario-derived and not experimentally validated measurements. The study therefore does not claim field-level AI accuracy, IoT reliability, carbon-emission reduction, or optimisation convergence. Future research should develop a representative waste-image dataset, train and independently validate the proposed AI model, implement the multi-objective optimisation algorithm, undertake site-specific carbon accounting using recognised waste-emission methodologies, and validate the framework through prototype and field trials. Overall, the framework offers a scalable and sustainable approach that aligns with DRDO priorities by supporting environmentally responsible, technologically advanced, and self-reliant waste management for next-generation strategic military infrastructure.

Conflict of Interest: The authors declare no conflicts of interest.

Way Forward

Future work should focus on prototype development and field validation of the proposed ACWMF at remote military installations. Integrating digital twins, edge AI, and autonomous robotics can further enhance operational efficiency, sustainability, and defence resilience.

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