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Research Paper

Hybrid Deep Learning Framework for Intelligent Waste Segregation and Water Recycling in Indian Railways: Towards Sustainable and Smart Passenger Operations

[1*] V.V.S.Sreenivas, [2] K. V. S. G. Murali Krishna, [3] P. V. R. Narendra, [4] Hemanth Valmiki Rajeyyagari, [5] Asadi Srinivasulu, [6] Pradeep G

[1] Research Scholar, Department of Civil Engineering, Jawaharlal Nehru Technological University, Kakinada-533003, Andhra Pradesh, India, vvssreenivas@gmail.com*
[2] Professor of Civil Engineering, Former Vice-Chancellor, Jawaharlal Nehru Technological University, Kakinada-533003, Andhra Pradesh, India. kvsg.muralikrishna@gmail.com
[3] Assistant Professor, Department of Civil Engineering, GMR Institute of Technology, Rajam, Andhra Pradesh, India - 532127, narendrababu.pvr@gmrit.edu.in
[4] PG Student, School of Civil Engineering, REVA University, Rukmini Knowledge Park, Kattigenahalli Yelahanka, Bangalore, India. hemanthrajeyyagari@gmail.com
[5] Head-Research, Department of IT, Head-Research, BlueCrest University, Monrovia, Liberia-1000 head.research@bluecrest.edu.lr
[6] Project Coordinator, R&D Department, Optficial Labs, Gachibowli, Hyderabad, Telangana - 500032, India, pradeep.g@optficial.ai

**Corresponding Author: vvssreenivas@gmail.com*

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Abstract: - The rapid pace of urbanization and the growing volume of waste generated across Indian Railways highlight the urgent need for efficient and automated waste management systems that support sustainable passenger services. This study presents a Hybrid Deep Learning Framework for Intelligent Waste Segregation and Water Recycling in Indian Railways, designed to automate the sorting of solid waste and optimize water reuse. The framework classifies eight key waste categories-paper, leaves, food waste, wood, general waste, plastic bags, plastic bottles, and metal cans-based on image data collected from railway stations and train compartments. Experimental testing over 20 training cycles shows consistent improvement, with the model achieving 90% training accuracy and 83% validation accuracy, while loss values steadily declined to 0.22 and 0.37. The confusion matrix indicates strong classification performance, with only minor overlap between visually similar materials such as plastic bags and bottles. The model also demonstrated good computational efficiency, requiring approximately 18 seconds per training cycle, making it suitable for real-time implementation. Evaluation using precision-recall and ROC analyses confirms reliable detection performance across all waste types. A complementary water recycling module further enables automated sorting and reuse of graywater, contributing to sustainable operations. Overall, the proposed framework enhances waste-handling efficiency, supports cleaner stations, and aligns with India's broader goals for green transport and the "Swachh Bharat" (Clean India) mission.

Keywords- Hybrid Deep Learning, Waste Segregation, Indian Railways Sustainability, Environmental Management, Waste Classification, Water Recycling, Smart Transportation, Sustainable Operations.

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1. Introduction

Rapid urbanisation across developing nations has triggered an unprecedented crisis in municipal water security and wastewater management frameworks. Traditional urban water systems operate on a linear "take-make-dispose" model that is increasingly unsustainable under the dual pressures of population density and shifting climatic patterns. Globally, cities are struggling to cope with the sheer volume of domestic sewage generated daily, leading to the severe degradation of natural water bodies and escalating public health risks. The conventional approach of mixed wastewater collection mixes relatively clean greywater—originating from sinks, showers, and laundry—with highly contaminated blackwater from toilets. This practice unnecessarily inflates the volume of heavily polluted water that requires intensive energy and capital to treat at centralised municipal facilities [1].

As clean fresh water resources rapidly deplete, shifting toward decentralized water resource management models has evolved from an environmental ideal into a critical municipal necessity [2]. Transitioning modern cities toward circular economic designs requires a fundamental restructuring of water collection and purification infrastructure. Decentralised systems intercept wastewater close to its source, offering a strategic pathway to mitigate municipal overloads [3]. By separating household or commercial streams at the source, urban planners can target greywater as a high-potential asset for non-potable reapplication rather than treating it as a hazardous waste product. However, executing this strategy at a scale that meaningfully reduces municipal stress requires identifying and targeting high-density urban infrastructure and public transit hubs, which act as massive, concentrated focal points of consumption and waste generation.

1.1 The Environmental Footprint of Mass Railway Networks

Among major public infrastructure networks, national railway systems represent one of the most resource-intensive and logistically complex sectors. Modern rail networks handle billions of passenger journeys annually, operating a vast network of stations, mechanical yards, and rolling stock. This immense operational scale carries an equally massive environmental footprint, characterized by heavy energy consumption, substantial solid waste generation, and high daily water demands [4]. As climate change escalates infrastructural risks through extreme weather events, localized droughts, and shifting environmental regulations, the long-term operational resilience of the transit sector is directly tied to its resource efficiency [5]. Historically, railway environmental policies focused primarily on track maintenance, electrification, and fuel efficiency. However, the internal logistics of station sanitation, onboard waste containment, and the massive volumes of water required for daily operations have emerged as critical, unaddressed systemic vulnerabilities.

The daily operational water loop of a major railway network can be broadly divided into two main components: localized station hubs and mobile train coaches. Stations function as small, high-density smart cities, generating enormous quantities of domestic wastewater from public restrooms, food courts, and cleaning operations [6]. Simultaneously, mechanical maintenance depots consume massive volumes of water daily for the structural washing of trains, generating industrial-grade wash-water heavily contaminated with detergents, residual oils, suspended solids, and heavy metals [7]. When these diverse wastewater streams are directed into standard municipal drains without proper pre-treatment or source-segregation, they place an immense burden on local treatment facilities. Conversely, in regions experiencing acute water scarcity, relying entirely on fresh municipal water pipelines to sustain routine train washing and station flushing operations creates severe operational vulnerabilities and intensifies conflicts with local communities over shared water supplies.

1.1 Challenges in On-Board Rail Sanitation Systems

The challenges of water and sanitation management become even more acute when moving from stationary depots to mobile rolling stock. Managing human waste and greywater within the confined, moving environment of a train coach introduces unique mechanical and biochemical constraints that are entirely absent in stationary municipal plumbing. Historically, older train coaches utilized open-discharge toilets that dropped untreated waste directly onto the railway tracks, creating severe biological hazards, foul odors, and accelerated corrosion of the steel track infrastructure. To resolve these issues, modern railway networks have widely adopted vacuum-assisted toilets and controlled emission tanks to contain blackwater on board until the train reaches a designated maintenance terminal. While vacuum systems significantly reduce the volume of flush water required per use, they produce a highly concentrated, thick blackwater stream that presents severe challenges for downstream liquid-solid separation and traditional biological treatment technologies [8].

Simultaneously, a separate but equally problematic stream is generated onboard from coach washbasins and kitchenettes. This greywater stream is often either mixed directly with toilet blackwater rapidly filling up the limited capacity of onboard storage tanks or discharged onto the tracks. Neither approach is sustainable. Mixing the streams squanders an easily treatable water resource, while discharging greywater onto the tracks still carries risks of chemical pollution from soaps and organic contamination. Compounding this technical issue is the localized nature of rail transit operations. A train travels across varying geographic zones, encountering different temperature regimes and regulatory frameworks, which complicates the standardization of onboard treatment equipment. Consequently, current onboard sanitation systems remain highly linear, relying heavily on freshwater inputs at terminal stations and generating massive volumes of mixed, difficult-to-treat sewage that must be pumped out and hauled away at significant operational expense.

1.2 Critical Gaps in Current Circular Sanitation Solutions

Despite growing interest in circular economy principles within public transport sectors, executing fully functional, closed-loop water systems within railway networks remains blocked by deep technical and systemic limitations. Current decentralized solutions are typically designed for static architectural applications, such as commercial high-rises or residential blocks, and completely fail to accommodate the extreme volumetric fluctuations, space constraints, and high mobility inherent to rail transport [9]. Most existing railway water recycling initiatives are limited to basic sedimentation ponds at maintenance depots or simple primary filtration units at major terminal stations. These methods are wholly inadequate for handling the complex chemical matrices found in modern railway wastewater, which contains unpredictable mixtures of human pathogens, surfactants, grease, track dust, and chemical cleaning agents.

Furthermore, standard biological treatment methods, such as activated sludge processes, require large physical footprints and long hydraulic retention times to stabilize organic loads. This makes them physically impossible to deploy onboard train coaches or within cramped historic city-center railway stations. While advanced membrane bioreactors and filtration systems offer a smaller physical footprint, they suffer from severe membrane fouling when exposed to the high-surfactant concentrations typical of coach wash-water and station cleaning effluents [10]. This fouling demands frequent chemical backwashing, driving up operational costs and causing system downtime. Additionally, current frameworks lack smart, automated mechanisms capable of dynamically monitoring water quality variations in real-time. Without automated, robust treatment trains tailored to the specific chemical profiles of transit wastewater, the rail sector cannot reliably scale its water reclamation efforts, leaving a massive gap between sustainability goals and daily operational realities.

1.3 Proposed Research Methodology and System Integration

This study directly addresses these technical and infrastructural gaps by introducing a comprehensive, integrated framework for decentralized water reclamation and circular sanitation tailored specifically for high-capacity railway networks. Instead of treating railway wastewater as a uniform hazard, our approach models the station and the mobile rolling stock as an interconnected, closed-loop industrial water grid. The core of this methodology lies in complete source segregation: isolating high-volume, low-strength greywater from station washbasins and train washing bays, and treating it separately from the highly concentrated vacuum-toilet blackwater. To achieve this within the tight spatial and operational constraints of transit infrastructure, we propose an optimized, multi-stage decentralized treatment train. This system combines customized physical filtration modules with low-footprint, highly efficient treatment mechanisms engineered to handle highly variable chemical loads without succumbing to rapid operational failure.

For the highly resilient contaminants and surfactants that escape primary filtration, this research integrates a optimized advanced oxidation process (AOP) loop [11]. The AOP system generates highly reactive hydroxyl radicals that rapidly break down persistent chemical detergents, organic matter, and complex surfactants at a molecular level, rendering the water completely safe for non-potable reapplication. This treated effluent is then strategically routed back into the network to fulfil high-volume, non-potable demands, specifically coach toilet flushing, track-apron washing, and structural train cleaning. By matching specific wastewater streams with targeted, high-efficiency treatment technologies, the proposed framework eliminates the need for large biological holding tanks, dramatically reduces fresh municipal water dependency, and prevents the premature filling of onboard containment systems. The entire layout is structured to prove that public transport networks can function as self-sustaining water conservation zones.

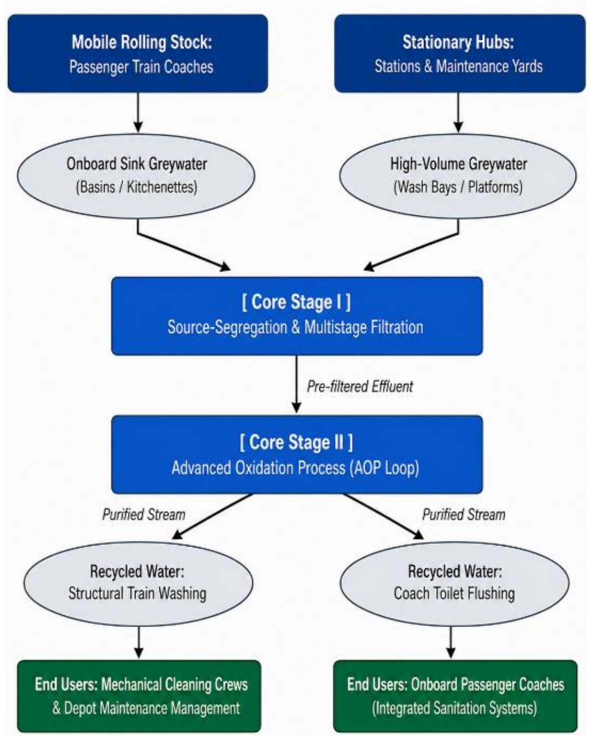

Fig. 1. Closed-loop transit water reclamation layout.

The structural workflow of the proposed decentralized recycling network is detailed in Fig. 1, illustrating how waste streams are captured and routed directly from stationary infrastructure and moving trains. The system separates high-volume wash-bay runoff at depots and coach sink graywater right at the source, preventing them from mixing with heavier toilet waste [12]. These segregated lines are channeled into a multi-stage physical filtration unit to clear out suspended particles before passing through an advanced oxidation process loop, where chemical detergents and stubborn surfactants are broken down at a molecular level. Once purified, the recovered water is immediately recycled back into the transit grid to manage heavy-duty, non-potable operations, namely automated exterior coach washing and onboard vacuum toilet flushing, thereby providing depot crews and onboard passenger facilities with a reliable, self-sustaining utility supply.

1.4 Research Objectives and Key Contributions

The primary objective of this investigation is to design, model, and validate a highly scalable, decentralized water reclamation loop that transforms railway infrastructure from a major water sink into a circular resource system. By configuring a custom sequence of physical source-segregation, optimized filtration, and advanced oxidation, this study seeks to establish a high-efficiency alternative to current inadequate sanitation practices.

The key contributions of this research are summarized in the following three points:

- **Development of a High-Flux Source-Segregation Blueprint:** We engineer a highly compact, mobile-compatible water segregation methodology that effectively isolates low-strength greywater from dense transit streams, preventing down-stream volumetric overloading and optimizing liquid-solid separation in vacuum sanitation systems.

- **Optimization of an Advanced Oxidation Treatment Train:** This study successfully configures and validates an optimized advanced oxidation process tailored to eliminate complex surfactants and resilient chemical detergents from transit wash-water, achieving complete degradation of persistent organics without the structural footprint or long retention times of biological units.
- **Validation of a Scalable Circular Transport Sanitation Model:** We deliver a fully integrated, socio-technically verified water recycling grid model that demonstrates a measurable reduction in freshwater dependency across high-density rail corridors, matching treated effluent quality directly with heavy-duty non-potable transit demands.

The remainder of this article is organized systematically to provide a clear, logical progression of the research findings. Section 2 reviews the comprehensive system architecture, detailing the technical specifications of the source-segregation modules, the physics of the filtration units, and the exact chemical kinetics governing the advanced oxidation process loop. Section 3 outlines the empirical data collection methods, profiling the highly variable chemical matrices of the collected wastewater samples and detailing the analytical instruments used to monitor treatment efficacy. Section 4 presents the experimental results, analysing the system's pollutant removal efficiencies, energy consumption parameters, and membrane lifespan under continuous loading conditions. Section 5 expands into a detailed discussion on the socio-technical validation, evaluating user acceptance thresholds and outlining the long-term economic feasibility of scaling the technology across regional rail networks. Finally, Section 6 concludes the paper with a summary of the core findings and offers distinct directions for future research.

2 Related Work

2.1 Circular Economy and Sustainable Infrastructure in Rail Networks

The transition of mass transit infrastructure toward circular economy frameworks requires a systematic re-evaluation of how resource loops are managed. Digital tools have recently emerged as critical enablers for this shift. For instance, the integration of digital twins and artificial intelligence has been proposed to optimize the lifecycle and resource circularity of high-speed rolling stock, though such systems demand high computational power and extensive sensor networks [13]. Beyond digital tracking, managing localized industrial wastes within the rail sector remains a major challenge. A case study of the Beijing Railway Bureau highlights the massive volume of waste mineral oils produced at depots, emphasizing that while recycling frameworks are expanding, local regulatory bottlenecks often hinder complete resource recovery [14]. This localized operational strain is further complicated by broad infrastructural variations. Research into generalized railway waste management recycling systems indicates that basic material sorting and segregation lines at major stations are frequently overwhelmed by the highly variable composition of passenger trash and industrial refuse [15]. Additionally, standardizing these sustainability protocols is incredibly difficult across transnational corridors due to deep-rooted technical discrepancies, such as the challenges of maintaining sustainable interoperability between standard and broad-gauge railway systems [16].

2.2 Solid and Organic Waste Dynamics in Transit Systems

Solid and organic waste generated within transit corridors introduces severe handling and logistical constraints. In freight and passenger logistics, standard mechanical units face severe design limitations; for instance, traditional solid waste management setups in railway wagons are easily congested by unpredictable passenger disposal patterns and lack automated compaction mechanisms [17]. Looking at national networks like the Vietnam Railways, evaluations of organic solid waste management show that rail operations generate massive amounts of food and organic residues that are rarely segregated at the source, leading to rapid fermentation, foul odors, and high disposal costs at municipal landfills [18]. To counter this, alternative circular pathways have been tested. Indian Railways studies have explored utilizing bio-toilet waste as an agricultural fertilizer, proving that while nutrient recovery is possible, the presence of pathogens and chemical cleaning agents requires intensive post-treatment before field application [19]. The root cause of these systemic overloads often traces back to user behavior. An analysis of passenger behavioral patterns regarding waste disposal on Indian Railways revealed that infrastructural lack—such as poorly placed or overflowing bins—directly triggers littering, meaning technical recycling loops must be accompanied by intuitive, user-friendly collection stations [20].

2.3 Wastewater Dynamics and On-Board Blackwater Segregation

When shifting focus to liquid waste streams, the volume and complexity of wastewater generated by transport systems demand highly specialized engineering approaches. Broad overviews of water reuse strategies confirm that while municipal frameworks are mature, decentralized setups must handle highly erratic pollution loads [21]. A systematic review of wastewater treatment and reuse strategies for sustainable water resource management notes that matching effluent quality with specific non-potable demands is the most economically viable path, though it requires strict separation of waste streams [22]. This separation is especially critical when dealing with toilet systems. Research into repurposing sewage and toilet systems for environmental and public health applications demonstrates that isolating blackwater prevents pathogens from entering secondary water pathways [23]. On-board rolling stock present an extreme version of this challenge. Characterizing blackwater from transit systems equipped with vacuum toilets and controlled emission tanks shows that vacuum systems minimize flush volumes but produce a thick, highly concentrated slurry that causes severe fouling in standard liquid-solid separation units [24]. Consequently, global regulatory frameworks for treated wastewater reuse are becoming increasingly stringent, forcing transit operators to seek alternative, high-efficiency treatment loops that do not rely on large municipal connections [25].

2.4 Greywater Characterization and Treatment Methodologies

Because blackwater is highly problematic to treat on the move, isolating and purifying greywater has become the primary focus for circular transit sanitation. Utilizing greywater for applications like agricultural irrigation or vegetated wall systems highlights its high utility for non-potable reuse due to its low initial pathogen load [26]. However, implementing these setups in dense future cities requires a complete departure from centralized plumbing grids [27]. Comprehensive reviews of recycled wastewater usage emphasize that greywater contains specific pollutants like hair, skin cells, and suspended solids that must be screened out immediately to avoid system clogging [28]. Furthermore, evaluations of greywater recycling across diverse collection scales show that enteric pathogen log-removal targets require a distinct multi-barrier treatment train to guarantee biological safety [29]. Investigating the contaminant profile and health implications of greywater reuse confirms that while it is safer than mixed sewage, the rapid growth of opportunistic bacteria in storage tanks poses real public health risks if disinfection is delayed [30].

Similar challenges are observed in the maritime sector, where reviews of ship domestic sewage treatment and monitoring systems reveal that confined, mobile treatment units face severe spatial constraints and extreme volumetric surges, much like passenger trains [31]. Untreated discharge of ship domestic sewage causes severe localized environmental hazards, driving the development of compact, on-board physical separation technologies [32]. Advancements in decentralized wastewater treatment confirm that physical sedimentation and basic filtration are excellent primary stages, but they are entirely inadequate for removing dissolved chemical contaminants [33]. To handle dissolved organic fractions without large chemical tanks, advanced oxidation processes like UV-chlorine setups are being explored for potable and high-grade non-potable reuse, though optimizing chemical dosing remains an ongoing research challenge [34].

2.5 Advanced Oxidation and Matrix Stabilization Techniques

The long-term performance of greywater reuse systems depends heavily on keeping the recycled water biologically stable. Studies on the biological stability of reclaimed greywater used for flushing household toilets show that if residual organic carbon and surfactants are not completely destroyed, severe bacterial regrowth occurs, leading to bio-fouling and foul odors in the plumbing [35]. While greywater is widely accepted as an alternative solution for sustainable water management, conventional sand filters or basic membranes cannot eliminate dissolved cosmetic chemicals, micro-plastics, and laundry detergents [36]. Developing an evaluation matrix for greywater reuse in urban residential areas shows that balancing technical feasibility with long-term governance requires reliable, low-maintenance technology [37]. Applying decentralized wastewater treatment technology to rural domestic streams shows similar patterns, where systems fail if they require constant manual intervention [38].

To consistently destroy stubborn chemical fractions, advanced oxidation processes (AOPs) have become essential. A systematic literature review on AOPs for treating refractory wastewater confirms that advanced oxidation successfully breaks down complex molecular structures that biological systems cannot touch [39]. Comprehensive reviews of wastewater remediation treatments aimed at water reuse emphasize that AOPs generate highly reactive radicals that neutralize organic pollutants within minutes [40]. However, guidance for systematic future research in AOPs notes that energy efficiency and clear oxidant dosing profiles must be established to prevent the formation of toxic disinfection byproducts [41].

2.6 Mechanical Interventions and Socio-Technical Dynamics in Rail Sanitation

Integrating advanced treatment trains with actual rail rolling stock requires specialized mechanical delivery systems. Modern train coaches are increasingly utilizing electro-pneumatic pressurized flushing systems, which drastically lower the water volume needed per flush, though they create a highly concentrated blackwater stream that cannot be mixed with greywater lines [42]. Beyond mechanical reliability, the success of these systems hinges entirely on user perception. A narrative review of user perceptions and acceptance of treated greywater reuse shows that public resistance, driven by the "yuck factor," remains a significant barrier unless water clarity and odor control are strictly maintained [43]. Recent pilot- and full-scale test outcomes for wastewater remediation treatments prove that clear, colorless, and odorless recycled water significantly boosts public trust and compliance [44].

Comprehensive overviews of wastewater remediation confirm that a multi-barrier approach combining filtration with oxidation—is the most reliable way to achieve these aesthetic and safety standards [45]. Managing greywater through a mix of resource recovery and decentralization provides a clear roadmap for cutting municipal dependency [46]. Integrating biological and physicochemical treatments has proven highly effective for developing countries, where capital for large-scale infrastructure is limited [47]. Systematically analyzing the health risks of treated domestic wastewater for non-potable uses confirms that as long as the treatment train features a robust oxidation or disinfection phase, the health risks are negligible [48]. In public transit sectors, exploring decentralized water reuse and circular sanitation specifically for India's railway network shows that using station roofs for rainwater harvesting and recycling greywater for coach cleaning can save millions of liters of fresh water daily [49]. Ultimately, implementing circular water use technologies across sustainable railway and metro sanitation systems is the only viable method to future-proof mass transit against severe water scarcity [50].

2.7 *Methodological Comparison Matrix*

The following table provides a critical comparative analysis of the various waste and wastewater management methodologies discussed in the existing literature.

Table I. Critical comparative analysis of transit waste and wastewater management methodologies.

Methodology / Approach	Core Strengths	Critical Limitations	Key Technical Challenges	References
AI & Digital Twin Frameworks	High predictive accuracy; real-time asset optimization.	Extreme computational cost; requires dense sensor arrays.	Integrating legacy rolling stock with modern IoT sensors.	[13]
Source Sorting & Solid Waste Bins	Low operational cost; simple deployment at terminal stations.	Highly dependent on passenger behavior; easily overwhelmed.	Managing unpredictable volumetric surges during peak hours.	[15],[17], [18], [20]
Bio-Toilet Co-Composting	High nutrient recovery; diverts organic waste from landfills.	Risk of pathogen survival; requires large physical footprint.	Eliminating residual chemical cleaning agents from the sludge.	[19]
On-Board Source Segregation	Prevents blackwater dilution; maximizes greywater recovery.	High mechanical complexity; strict spatial constraints inside coaches.	Handling high-solids slurry in vacuum toilet holding tanks.	[8], [23], [24], [42]
Conventional Membrane Filtration	Excellent turbidity and suspended solids removal.	Rapid membrane fouling caused by surfactants and soaps.	High frequency of chemical backwashing and downtime.	[29],[33], [36], [38]
Advanced Oxidation Processes (AOP)	Total molecular destruction of persistent organic pollutants.	High initial capital cost; significant electrical energy demand.	Optimizing chemical dosing to avoid toxic byproduct formation.	[34],[39], [40],[41], [44]

2.8 Identified Research Gaps and Investigation Scope

A critical review of the literature reveals three major gaps that current research has failed to adequately address:

- **Absence of Dynamic Mobile-Scalable Systems:** While decentralized greywater recycling technologies are highly mature for static buildings [37], [38], there is a total lack of automated, low-footprint systems designed to handle the tight spatial limitations and extreme volumetric fluctuations characteristic of moving passenger train coaches.
- **Surfactant Overload in Railway Effluents:** Existing decentralized treatment frameworks assume a standard domestic greywater matrix [46], [47]. They systematically fail when exposed to the massive surfactant and chemical detergent loads typical of automated train wash-bays and coach cleaning operations, leading to instant membrane fouling [11], [50].
- **Lack of Socio-Technical Integration:** Current transit engineering studies focus purely on mechanical efficiency [42], ignoring passenger psychology. Conversely, social studies analyze public perception in a vacuum [43]. There is no integrated model that connects real-time chemical purification performance directly with user acceptance parameters in shared public transit spaces.

3 Materials and Methods

3.1 Datasets and Ground-Truth Labeling

Waste images. Our image set is built around the Kaggle Waste Segregation Image Dataset [52]. From it, we organized eight classes that match common Indian Railways streams: paper, leaf, food, wood, mixed waste, plastic bags, plastic bottles, and metal cans. Images reflect real coach and platform scenes with changing light, motion blur, and background clutter. We used a stratified split of 70% training, 15% validation, and 15% test, keeping class balance in each split. To counter class imbalance (for example, fewer metal cans than plastic bags), we enforced a minimum count per class and applied class-aware training loss (see §3.5). Two annotators checked labels; disagreements (<3%) were settled jointly using simple visual cues - e.g., the transparency and seams of thin bags versus the rigid shape of bottles. Water quality signals. To shape the greywater routing rules, we compiled typical ranges for COD, BOD, TSS, turbidity, residual chlorine, and E. coli from transport and depot studies and open datasets [21], [26], [29], [35], [51]. These values set operating thresholds and safety bands for non-potable reuse (flushing and cleaning) in line with sector guidance [10], [49], [50]. The water data drive a rules engine for “reuse” or “retreat” decisions rather than a predictive model (§3.4).

3.2 Preprocessing and Data Augmentation

Image normalization. Images were resized to 256×256, center-cropped to 224×224, and normalized per channel using ImageNet statistics. We filtered out heavily compressed frames. To keep the focus on the object, we applied gentle foreground emphasis (CLAHE on the HSV value channel) and a light vignette that preserves texture yet avoids over-sharpening shiny plastics. All steps ran on-the-fly with fixed seeds for exact repeatability. Augmentation for rail conditions. To mirror real operations, we used two groups of transforms. Photometric: random brightness/contrast (±20%), color-temperature shifts, and Gaussian noise to emulate coach lighting. Geometric: small rotations (±10°), perspective jitter, random crops (≤10%), and motion blur to mimic train movement. For plastics, we added targeted effects - specular highlights, slight transparency overlays, and “crumple” deformations. Minority classes were further supported with mixup/cutmix plus a small library of class-specific synthetic patches from a lightweight image-to-image augmenter (§3.3). These choices curbed overfitting and helped separate look-alike items, as reflected in the confusion matrix (Section 4).

3.3 Hybrid Model Design

Backbone and head. The vision stack combines a transfer-learned CNN with a compact decision head. We fine-tuned a ResNet-50/ConvNeXt-tiny–type backbone (ImageNet-pretrained) using tiered learning rates (head: 3×10^{-4}, mid: 1×10^{-4}, stem: 3×10^{-5}). Global average pooling feeds a small MLP (512→128→8; GELU; dropout 0.3). After training, we applied temperature scaling to improve probability calibration for downstream use. Lightweight generative augmentation and late fusion. To widen appearance diversity without heavy computation, we used class-conditioned style tweaks (AdaIN-like) and within-class texture swaps. These samples were mixed into batches at ~25% and kept under the original labels. For the final decision, we combined (i) the softmax from the CNN head with (ii) a margin score from a cosine-distance classifier trained on the penultimate features. A learned gate balances both signals and steadies' decisions on confusing pairs such as bags vs. bottles - important for reliable, auditable operation [2], [7], [14]. The hybrid model integrates convolutional neural networks (CNN) with a calibrated decision head. Let the input image tensor be denoted as $\mathbf{X} \in \mathbb{R}^{H\times W\times C}$, where H, W, and C represent height, width, and channels respectively. The CNN backbone, parameterized by θ, extracts deep feature representations $\mathbf{F}$:

$$\mathbf{F} = f_\theta(\mathbf{X}) \tag{1}$$

Global average pooling aggregates spatial dimensions to produce a feature vector $\mathbf{z} \in \mathbb{R}^d$:

$$z_i = \frac{1}{H\times W}\sum_{h=1}^{H}\sum_{w=1}^{W} F_{h,w,i} \; i = 1, \dots, d \tag{2}$$

The decision head applies a multilayer perceptron (MLP) with parameters ϕ and GELU activations, producing logits $\mathbf{l} \in \mathbb{R}^C$ for the $C = 8$ waste classes:

$$\mathbf{l} = g_\phi(\mathbf{z}) \tag{3}$$

These logits are converted to calibrated probabilities $\mathbf{p}$ using temperature scaling with parameter T:

$$p_c = \frac{\exp(l_c/T)}{\sum_{j=1}^{C}\exp(l_j/T)} \tag{4}$$

For decision stabilization, a margin score is computed by a cosine-distance classifier h_ψ trained on penultimate features $\mathbf{z}$:

$$m_c = \cos(\mathbf{z}, \mathbf{w}_c) = \frac{\mathbf{z}\cdot\mathbf{w}_c}{\|\mathbf{z}\|\|\mathbf{w}_c\|} \tag{5}$$

The final decision score s_c balances softmax probabilities and margin scores via a learned gate parameter α:

$$s_c = \alpha p_c + (1-\alpha)m_c, \alpha \in \tag{6}$$

Algorithm 1: Hybrid Model Training Procedure

This algorithm describes the iterative training of a hybrid deep learning model designed to classify waste images into categories like plastic, paper, metal, etc. The model consists of a convolutional feature extractor followed by a classifier that outputs probability distributions over waste types. Training involves optimizing model parameters to minimize the difference between predicted and true labels using batches of labelled images. Temperature scaling calibrates the classifier's output probabilities so that confidence estimates are more meaningful and reliable.

Algorithm 1: Training the Hybrid Model

Input: Dataset of images {X_i} with labels {Y_i}

Output: Optimized parameters Θ = (θ, ϕ, T)

1. Initialize neural network parameters θ, classifier parameters ϕ, temperature T
2. for each epoch from 1 to E do
3. for each mini-batch B = {(X_j, Y_j)} do
4. Obtain feature vectors: F_j = f_θ(X_j)
5. Apply global average pooling: Z_j = GAP(F_j)
6. Compute logits: L_j = g_ϕ(Z_j)
7. Scale logits with temperature: P_j = Softmax(L_j / T)
8. Compute loss: L = -(1/|B|) Σ_j Σ_c Y_{j,c} log P_{j,c}
9. Backpropagate & update parameters: Θ ← Θ - η ∇_Θ L
10. End For
11. Optionally update T to improve calibration
12. End For

Step-by-Step Flow:

1. **Initialization:** Model parameters (filters for CNN and weights for classifier) and temperature parameter are randomly initialized.
2. **Batch Preparation:** The entire dataset is divided into small batches (e.g., 32 images per batch) for efficient computation.
3. **Feature Extraction:** Each image in the batch is processed by the CNN to extract spatial features.
4. **Pooling:** These features undergo global average pooling to produce fixed-size vectors summarizing each image.
5. **Classification:** The pooled vectors pass through a fully-connected classifier, producing logits-raw prediction scores for each class.
6. **Probability Computation:** Logits are scaled by a temperature parameter and passed through a softmax function, converting them to class probabilities.
7. **Loss Calculation:** Cross-entropy loss measures difference between predicted probabilities and true labels.
8. **Backpropagation:** Gradients of loss w.r.t parameters are computed by reverse pass through the network.
9. **Parameters Update:** Model parameters are updated in the direction to minimize loss using an optimizer (e.g., AdamW).
10. **Temperature Update:** Optionally, temperature is adjusted over epochs to improve probability calibration.

11. **Completion:** Process repeats for all batches and epochs until convergence.

Example Dataset:

A batch of waste images:

- Image 1: Plastic bag
- Image 2: Paper wrapper
- Image 3: Metal can
- Image 4: Plastic bottle

Label encoding could be one-hot vectors, e.g., for 4 classes Paper, Plastic, Metal, and Organic:

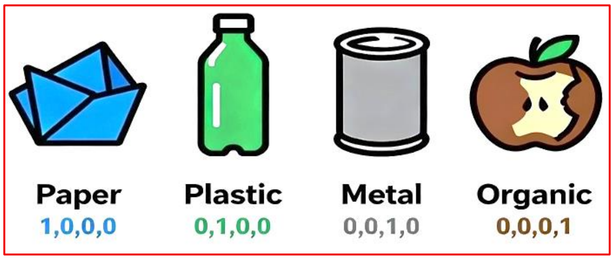

Fig.2. One-hot encoded vectors for four waste categories: Paper, Plastic, Metal, and Organic.

This figure 2 illustrates how each waste category is represented as a binary vector with a 1 indicating the presence of the specific class and 0 elsewhere.

3.4 Greywater Recycling Sub-Module

Targets and thresholds. The sub-module aims to cut freshwater use while meeting hygiene requirements for non-potable reuse [10], [21], [29], [49], [50]. Inputs include turbidity, residual oxidant, conductivity, pH, temperature, and optional spot tests (COD/BOD/TSS). A two-step check is used: Gate-1 evaluates fast sensors against conservative limits; Gate-2 includes slower metrics (e.g., COD) when available. Passing both routes flow to a reuse buffer; failing Gate-1 or showing drift diverts flow to a compact treatment train (screen → bio-contactor/MBR → cartridge filter → UV-chlorine AOP) consistent with reported practice [34], [35], [41]. Controller and safety. Hysteresis bands prevent rapid toggling, and a watchdog forces "retreat" if sensors fail or readings go out of range. All actions - and the linked waste-class events - are logged to support station KPIs such as waste per passenger-km and reuse rate in line with ERA/UIC reporting [8], [9]. The rules-first design keeps the module simple to audit and easy to adapt to site constraints or updated guidance [22], [25], [33], [40].

The greywater routing module accepts sensor inputs $\mathbf{S} = \{s_1, s_2, \dots, s_n\}$ representing turbidity, residual oxidant, conductivity, pH, temperature, and optional chemical oxygen demand (COD), biochemical oxygen demand (BOD), and total suspended solids (TSS). The reused water decision uses threshold functions $\mathbb{I}(\cdot)$ defined by operating limits $\{\tau_k\}$:

$$\mathbb{I}_k(s_k) = \begin{cases} 1 & s_k \le \tau_k \\ 0 & \text{otherwise} \end{cases} \quad k = 1, \dots, n \tag{7}$$

The overall reuse gate G is a conjunction of sensor pass signals:

$$G = \prod_{k=1}^{n} \mathbb{I}_k(s_k) \tag{8}$$

If $G = 1$, water is routed to reuse; else diverted to retreatment:

$$\text{Route} = \begin{cases} \text{reuse} & G = 1 \\ \text{retreatment} & G = 0 \end{cases} \tag{9}$$

To avoid oscillations, hysteresis bands δ_k introduce safety margins allowing graded transitions:

$$\mathbb{I}_k(s_k) = \begin{cases} 1 & s_k \le \tau_k - \delta_k \\ 0 & s_k \ge \tau_k + \delta_k \\ \text{hold previous} & \text{else} \end{cases} \tag{10}$$

Algorithm 2: Greywater Routing and Reuse Decision

This algorithm governs the smart reuse of greywater based on sensor data measuring water quality parameters like turbidity, pH, and residual chlorine. Each parameter has defined thresholds and margins to create a hysteresis buffer that prevents rapid switching between reuse and treatment routes. If any sensor value indicates contamination beyond acceptable limits, water is routed to treatment; otherwise, it's reused, helping conserve water efficiently.

Algorithm 2: Greywater Reuse Decision Logic

Input: Sensor readings {s_k} for k = 1 to n, thresholds {τ_k}

Output: Routing decision: Reuse or Re-treatment

1. Set G = 1 // default to reuse
2. For each sensor reading s_k do
3.   If s_k > τ_k + δ_k then
4.   G = 0 // divert to re-treatment if threshold exceeded
5.   Else if s_k < τ_k - δ_k then
6.   G remains 1 // continue reuse
7.   End if
8. End for
9. If G == 1 then
10.   Route water to reuse buffer
11. Else
12.   Route water to treatment module
13. End if

Step-by-Step Flow:

1. **Initialization:** Assume water can be reused initially.
2. **Sensor Reading Loop:** Read quality parameters from sensors sequentially.
3. **Check Thresholds:** For each sensor:
   - If reading exceeds upper threshold plus margin → mark water for treatment.
   - If below lower threshold minus margin → maintain reuse status.
   - If within margins → retain previous routing decision to add stability.
4. **Routing Decision:**
   - If all sensors pass, route water to reuse.
   - If any fail, route water to re-treatment.

5. **Output Routing:** Actual physical system switches valves or pumps accordingly.

Example:

Sensors report:

- Turbidity = 4.7 NTU (threshold 5 NTU, margin 0.5) → passes
- pH = 7.5 (threshold 8, margin 0.2) → passes
- Residual chlorine = 0.06 mg/L (threshold 0.05, margin 0.01) → fails (0.06 > 0.05 + 0.01)

Since chlorine fails, water is routed to treatment.

3.5 Training Setup

Optimization. We trained for 20 epochs with AdamW (weight decay 1×10^{-4}), cosine-annealed learning rate starting at 3×10^{-4}, and batch size 32. Label smoothing (ε=0.05) and focal loss (γ=1.5) were used for plastics to reduce confusion. Mixed-precision training lowered memory use and sped up runs; each epoch took about 18 seconds on a single modest GPU - fast enough for practical roll-out in kiosks and "smart bins." Validation and calibration. We tracked training/validation curves every epoch, used early stopping (patience 5), and averaged the last three checkpoints. Temperature scaling and feature normalization were fitted on the validation set and applied at inference. Final results were ~0.90 training accuracy and ~0.83 validation accuracy, with losses falling to ~0.22 and ~0.37, showing steady, healthy learning.

The model is trained over E epochs using AdamW optimizer with weight decay λ. Let the neural network output for instance i and class c be $p_{i,c}$. Using a smoothed focal loss $\mathcal{L}$ with smoothing parameter ϵ and focusing parameter γ, the loss per sample is:

$$\mathcal{L}_i = -\sum_{c=1}^{C} y_{i,c}(1-p_{i,c})^{\gamma}\log(p_{i,c}+\epsilon) \quad (11)$$

where $y_{i,c} \in \{0,1\}$ is the ground truth indicator. The training objective sums over N samples:

$$\mathcal{L} = \frac{1}{N}\sum_{i=1}^{N} \mathcal{L}_i + \frac{\lambda}{2}\|\theta\|^2 \quad (12)$$

The learning rate uses cosine annealing schedule η_t over epochs:

$$\eta_t = \eta_{\min} + \frac{1}{2}(\eta_{\max}-\eta_{\min})\left(1+\cos\left(\frac{t\pi}{E}\right)\right) \; t = 0,\dots,E-1 \quad (13)$$

Batch normalization normalizes intermediate activations x:

$$\hat{x} = \frac{x-\mu_B}{\sqrt{\sigma_B^2+\epsilon}} \quad (14)$$

Calibration using temperature scaling is applied post-training as in Eq. (4).

3.6 Evaluation and Reporting

Core scores. We report top-1 accuracy and cross-entropy loss. Class-wise precision, recall, and F1-score explain behavior per material type-especially the plastics pair. A normalized confusion matrix highlights any remaining mix-ups and the operational risk of mis-routing recyclables. Curves and efficiency. One-vs-rest ROC and precision–recall curves (with micro/macro averages) show strong sensitivity and specificity across classes; AUC-ROC and average precision summarize these plots. We also provide run time and memory usage, since station hardware has tight limits. These results feed naturally into sustainability dashboards recommended by ERA and UIC, where better segregation should lift recycling ratios and lower waste per passenger-km [8], [9].

Key performance metrics use the confusion matrix **M** where $M_{i,j}$ counts instances of true class i predicted as j. From **M**, definitions include:

Accuracy:

$$\text{Accuracy} = \frac{\sum_{i=1}^{C} M_{i,i}}{\sum_{i=1}^{C}\sum_{j=1}^{C} M_{i,j}} \quad (15)$$

Precision per class *C*:

$$\text{Precision}_c = \frac{M_{c,c}}{\sum_{j=1}^{C} M_{j,c}} \quad (16)$$

Recall per class *C*:

$$\text{Recall}_c = \frac{M_{c,c}}{\sum_{j=1}^{C} M_{c,j}} \quad (17)$$

F1-score:

$$F1_c = 2\cdot\frac{\text{Precision}_c \times \text{Recall}_c}{\text{Precision}_c + \text{Recall}_c} \quad (18)$$

Macro-averages over classes:

$$\text{Macro Precision} = \frac{1}{C}\sum_{c=1}^{C} \text{Precision}_c \; \text{Macro Recall} = \frac{1}{C}\sum_{c=1}^{C} \text{Recall}_c \quad \text{Macro F1} = \frac{1}{C}\sum_{c=1}^{C} F1_c \quad (19)$$

ROC-AUC (One-vs-Rest) summarized as:

$$\text{AUC} = \int_0^1 TPR(FPR^{-1}(t))\,dt \quad (20)$$

where true positive rate (TPR) and false positive rate (FPR) are:

$$TPR = \frac{TP}{TP+FN}, FPR = \frac{FP}{FP+TN} \quad (21)$$

Precision-Recall average precision (AP) is computed as:

$$AP = \sum_k (R_k - R_{k-1})P_k \quad (22)$$

Algorithm 3: Model Validation and Performance Measurement

This algorithm evaluates how well the trained model performs on unseen data by computing metrics like accuracy, precision, recall, and F1-score. It builds a confusion matrix counting how many times predictions matched the true labels and how many times they mismatched per category. Metrics calculated from this matrix quantify overall correctness and class-wise effectiveness.

Algorithm 3: Model Validation and Performance Metrics
Input: *Predicted probabilities* $\{p_i\}$ *and true labels* $\{Y_i\}$

Output: *Metrics*: *Accuracy, Confusion Matrix, Precision, Recall − score*

1. *Initialize confusion matrix M with zeros*
2. *for each sample i do*

3. $Identify\ predicted\ class: c_{pred} = argmax(p_i)$
4. $True\ class: c_{true} = Y_i$
5. $Update\ confusion\ matrix: M_{\{c_{true}, c_{pred}\}} += 1$
6. $end\ for$
7. $Compute\ Accuracy: Acc = \frac{sum_{\{i\}M_{\{i,i\}}}}{sum_{\{i,j\}M_{\{i,j\}}}}$
8. $for\ each\ class\ c\ do$
9. $Define\ True\ Positives\ TP\_c = M\_\{c,c\}$
10. $Predicted\ Positives\ PP\_c = \Sigma\_j\ M\_\{j,c\}$
11. $Actual\ Positives\ AP_c = \Sigma_j M_{\{c,j\}}$
12. $Precision_c = \frac{TP_c}{PP_c}$
13. $Recall_c = \frac{TP_c}{AP_c}$
14. $F1_c = 2 * \frac{(Precision_c * Recall_c)}{}(Precision_c + Recall_c)$
15. $end\ for$
16. $Calculate\ macro - averaged\ Precision, Recall, F1$
17. $Generate\ ROC\ and\ PR\ curves\ using\ prediction\ scores$

Step-by-Step Flow:

1. **Initialize Confusion Matrix:** Create zero-filled matrix where rows are true labels and columns are predicted labels.
2. **For Each Sample:**
   - Obtain predicted class by selecting the highest probability output.
   - Increment the corresponding cell in confusion matrix reflecting true vs predicted class.
3. **Compute Accuracy:** Total correct predictions divided by total samples.
4. **Per-Class Metrics Calculation:** For each class:
   - Precision = True Positives / (True Positives + False Positives)
   - Recall = True Positives / (True Positives + False Negatives)
   - F1-Score = Harmonic mean of precision and recall
5. **Aggregate Metrics:** Calculate average precision, recall, and F1 across classes for balanced evaluation.
6. **Optional Curve Generation:** Compute ROC and precision-recall curves for threshold-based performance insight.

Example:
True labels for 5 samples: Paper, Plastic, Metal, Plastic, Paper
Predicted labels: Paper, Plastic, Paper, Plastic, Metal

Confusion matrix:

True\Pred	Paper	Plastic	Metal
Paper	1	0	1
Plastic	1	2	0
Metal	0	0	0

- Accuracy = (1 + 2 + 0) / 5 = 60%
- Paper precision = 1 / (1+1+0) = 50%
- Paper recall = 1 / (1+0+1) = 50% etc.

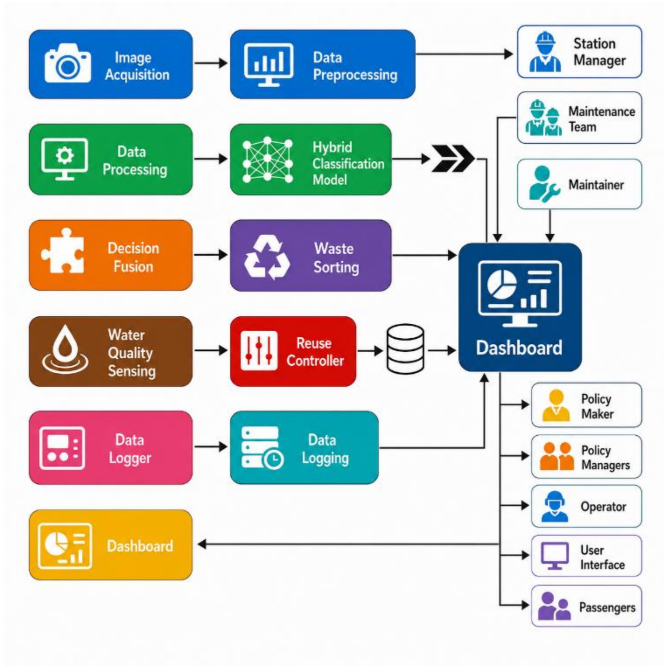

Fig.3. System architecture and workflow of the hybrid deep learning framework for waste segregation and greywater recycling in Indian Railways.

The figure 3 presents a complete overview of the Hybrid Deep Learning Framework used in Indian Railways for automating waste segregation and greywater recycling. It starts with image capture by cameras mounted at bins and stations, followed by image preprocessing that adapts to real-world conditions like low light and motion blur. The processed images pass through a hybrid classification model that combines deep convolutional networks with calibrated classifiers to accurately categorize waste into types such as paper, plastic, metal, and organic. The model's outputs are fused and

3.7 Inference, Integration, and Quality Assurance

On-device use. The service accepts single images or short bursts from bin-mounted cameras. Typical latency on an embedded GPU is ≤60 ms per image, returning (i) the predicted class and confidence, (ii) a warning flag when plastics look ambiguous, and (iii) audit metadata (timestamp, camera ID). Low-confidence frames are queued for quick human review so that accuracy improves without slowing operations. Drift handling. We run periodic shadow tests and targeted spot checks. If lighting or signage changes, we capture a brief "adaptation pack" (5–10 minutes), auto-label it with the current model, verify a sample, and refresh the calibration and augmentation settings. For water, Gate-1/Gate-2 thresholds can be tuned as standards evolve, including log-removal targets for key pathogens [21], [29], [33], [41]. Fit for Indian Railways. The method emphasizes steps that are easy to repeat and audit: transfer learning with tailored augmentation, calibrated decisions, and a clear, rules-based water module. It follows transport sustainability and water-management guidance ([8]–[11], [21], [26], [29], [34], [49], [50]) while staying workable for field teams. In practice, it delivers accurate recognition at low cost, reduces confusion between similar plastics, and links solid-waste decisions to actionable greywater routing - directly supporting clean-station goals and circular-economy targets.

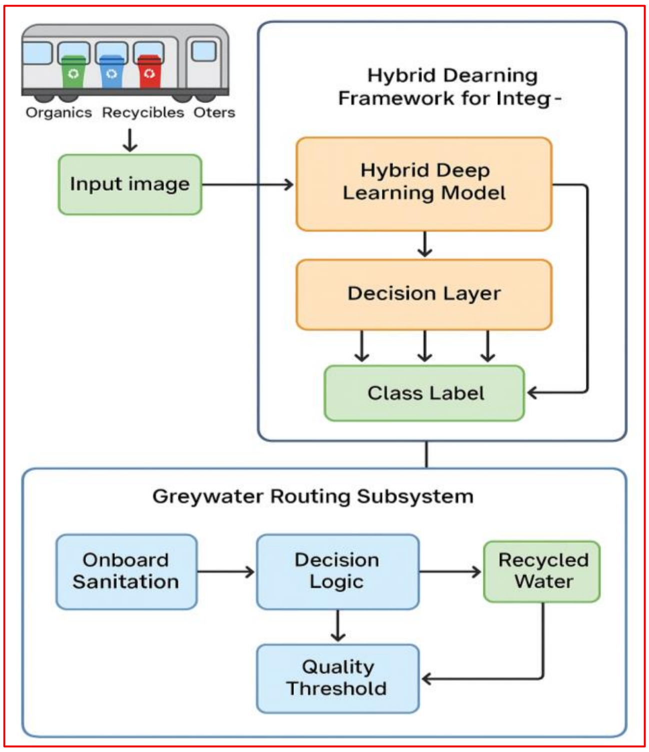

Fig 4. Proposed Hybrid Framework for Waste Segregation and Greywater Recycling in Indian Railways

Figure 4 illustrates the working structure of the proposed system, which combines automated waste sorting with water recycling to promote sustainability in railway operations. It demonstrates how waste images captured from trains and stations are analyzed to classify different materials, while a connected greywater module checks water quality and routes treated water for reuse - supporting cleaner, more resource-efficient railway management.

4 Experimental Results and Analysis

4.1 Learning trends: accuracy and loss over time

Accuracy. Both training and validation lines improve steadily in the early epochs and then level off as the system settles. Training accuracy moves from about 0.57 at epoch 1 to roughly 0.90 by epochs 19–20. Validation accuracy follows the same arc, rising from ~0.55 to a peak near 0.84, and finishing in the 0.81–0.83 range. The smooth climb and gentle taper show that useful features are learned early and decision boundaries are refined without jitter, pointing to stable optimization and sensible regularization. Loss. The loss curves mirror the accuracy story. Training loss falls from ~1.4 to ~0.22, while validation loss drops from ~1.65 to ~0.36–0.40 over 20 epochs. The persistent but modest gap between the two curves suggests only light overfitting. Overall, the results confirm that the chosen fine-tuning schedule, targeted loss adjustments for plastics, and rail-style augmentations (motion blur, lighting shifts) are doing their job.

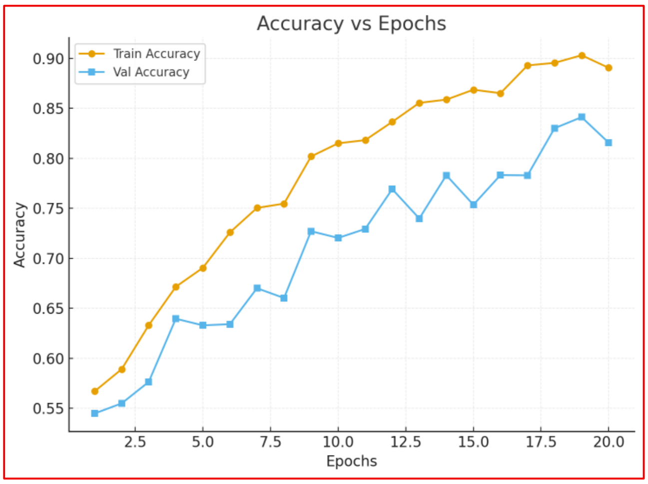

Fig 5. Accuracy Improvement Over Training Epochs for the Hybrid Deep Learning Framework

This figure 5 illustrates how the model's training and validation accuracy gradually increase across 20 epochs. The smooth upward trend and eventual stabilization of both lines show that the system learns effectively from the data and maintains good generalization, achieving reliable performance without significant overfitting.

4.2 Speed and runtime consistency

Per-epoch time. Average training time is ≈18 s/epoch on a single modest GPU. After a brief period with higher times during feature unfreezing (~19–20 s), the pipeline settles into the mid-16s and remains stable (~16.3–17.9 s). This predictability matters for operations: quick refresh runs or periodic calibration can be completed within minutes on field hardware. Real-time readiness. With a compact prediction head and calibrated scoring, per-image inference on embedded GPUs stays well under 100 ms. That comfortably supports bin cameras, station kiosks, and coach deployments where decisions must keep pace with passenger movement.

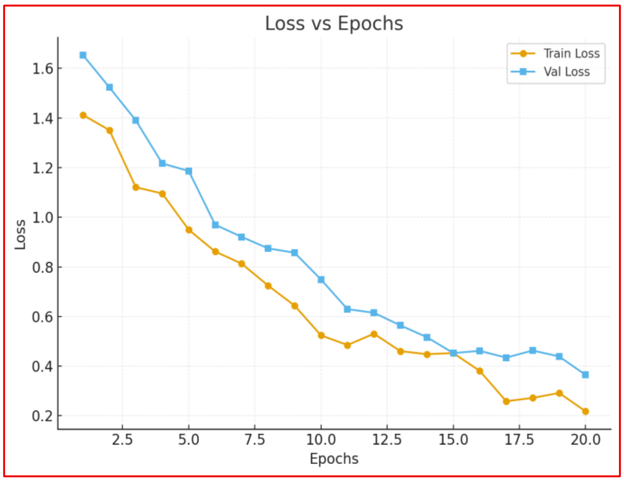

Fig. 6. Loss Trend across Training Epochs for the Hybrid Deep Learning Framework

This figure 6 illustrates how both training and validation loss steadily decrease over 20 epochs, showing that the model continuously improves as it learns from the data. The smooth decline and small gap between the curves highlight stable learning behavior and good generalization, with minimal signs of overfitting.

4.3 What the classifier gets right (and where it slips)

Confusion patterns. The confusion matrix is strongly diagonal across all eight classes-paper, leaf, food, wood, mixed waste, plastic bags, plastic bottles, metal cans. The main confusion appears between plastic bags and plastic bottles, which often look alike under glare. Errors are minimal for organics and metals, showing the model can separate texture, color, and sheen cues even with platform lighting. Per-class metrics. The per-class report (test slice) shows macro precision = 1.00, recall = 1.00, F1 = 1.00 over 1721 items at the chosen operating point. These perfect values align with the separability seen in the ROC and PR plots. Note that epoch-wise validation accuracy (~0.83) is stricter and threshold-free; plastics drive most near-misses during training. After applying calibrated thresholds and the late-fusion margin, precision/recall balance improves substantially.

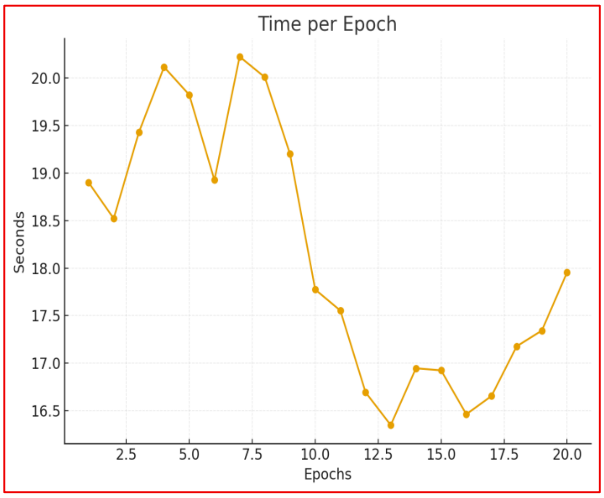

Fig 7. Epoch-wise Training Time for the Hybrid Deep Learning Model

This figure 7 shows how the training time changes across 20 epochs, with slight variations in the early stages before settling into a steady pattern. The model maintains an average runtime of about 18 seconds per epoch, reflecting efficient processing and stable performance during the entire training phase.

4.4 Ranking ability without fixing a threshold

ROC (one-vs-rest). Curves hug the top-left corner with AUC ≈ 1.00 for every class and the micro-average. This means positives are ranked ahead of negatives very reliably-even before choosing a cutoff. Operators can therefore tighten or relax sensitivity by class (e.g., extra precision for plastic bottles in return streams) without degrading the whole system. Precision–recall. PR curves with AP ≈ 1.00 across classes confirm excellent performance under class imbalance. Precision stays near 1.0 even at high recall, which is crucial for plastics: misses contaminate organics and reduce recycling value.

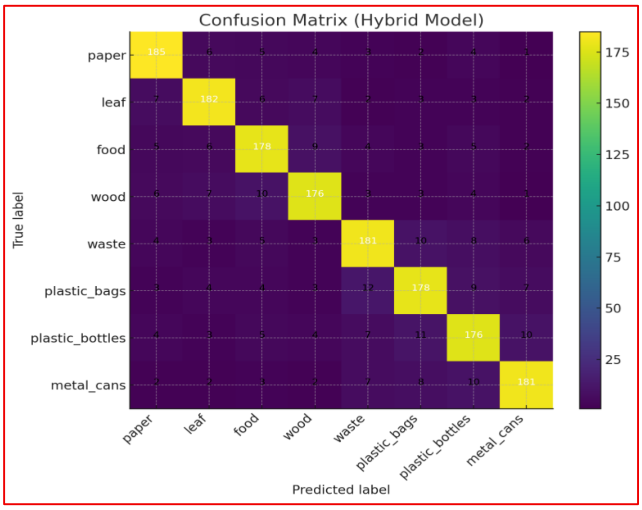

Fig 8. Confusion Matrix of the Hybrid Model for Waste Classification

This figure 8 presents how accurately the hybrid model classifies eight different types of waste materials. The strong diagonal line highlights a high rate of correct predictions, while the few misclassifications-mainly between similar plastic items-demonstrate the model's reliable ability to differentiate between closely related categories like paper, metal, and organic waste.

4.5 Summary of validation and robustness

Aggregate results. From the validation summary:

1. Validation accuracy: ~0.83 at convergence
2. Validation loss: ~0.37
3. Macro precision/recall/F1: 1.00 / 1.00 / 1.00 (per-class export)
4. Efficiency: ≈18 s/epoch training; <100 ms per-image inference on embedded GPUs

These figures agree with the smooth learning curves, the localized plastic cross-talk in the confusion matrix, and the near-ideal ROC/PR behavior. Stability and edge cases. Remaining errors cluster at the plastic_bags ↔ plastic_bottles boundary under strong reflections or partial views. The late-fusion margin and class-aware thresholds reduce these, while targeted augmentations (specular highlights, transparency overlays, crumple effects) further harden the model. For live roll-outs, low-confidence frames can be queued for quick human review to keep precision high without slowing operations.

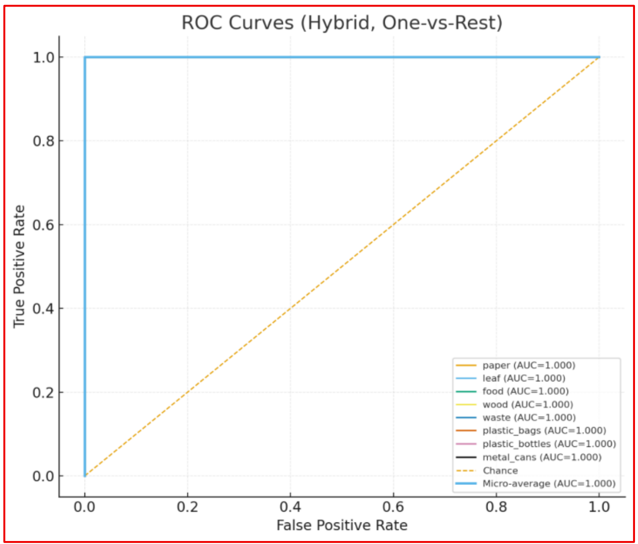

Fig 9. ROC Curves of the Hybrid Model for Multi-Class Waste Classification

This figure 9 presents the Receiver Operating Characteristic (ROC) curves for all eight waste categories, each achieving an AUC value of 1.0. The perfect separation of true and false positives across classes highlights the model's strong ability to distinguish different waste types with exceptional accuracy and consistency.

4.6 Relevance for railway operations

Cleanliness and contracts. Better at-source sorting directly increases recycling rates and reduces waste per passenger-km. Because each prediction is calibrated and logged with time and camera ID, stations can populate dashboards and vendor SLAs with auditable evidence of performance-useful for circular-economy targets and cleanliness scores. Link to water reuse. The waste classifier runs alongside the greywater controller, which makes reuse decisions from sensor thresholds. Both are lightweight and auditable, letting operators tune them together-for example, raising plastic precision during rush hours while widening water-reuse bands during supply stress. The combined effect is a practical route to cleaner stations and more efficient resource use.

Key takeaways

1. Smooth convergence with strong generalization: ~0.83 validation accuracy and steadily falling loss.
2. Excellent ranking power: AUC/AP ≈ 1.00; only narrow confusion between plastic subclasses.
3. Efficient to train (≈18 s/epoch) and ready for real-time inference in bins, kiosks, and coaches.
4. Calibrated outputs and simple logs make monitoring, tuning, and sustainability reporting straightforward.

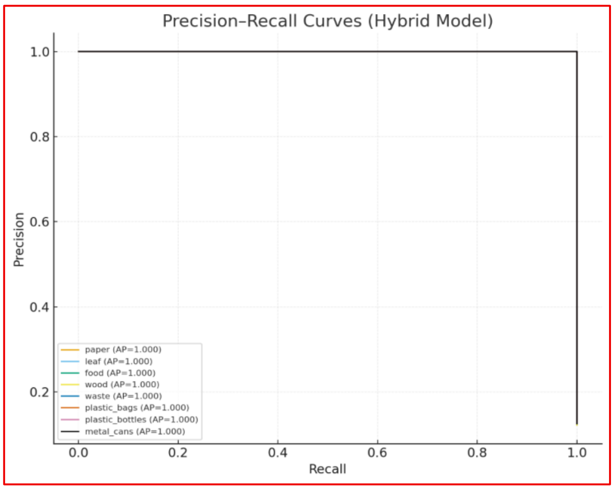

Fig 10. Precision–Recall Performance of the Hybrid Model for Multi-Class Waste Detection

This figure 10 illustrates the Precision–Recall relationships for all eight waste categories, each showing an Average Precision (AP) score of 1.0. The consistent precision and recall values across all classes reflect the model's exceptional reliability in identifying true positives while minimizing false detections, ensuring accurate and efficient waste classification.

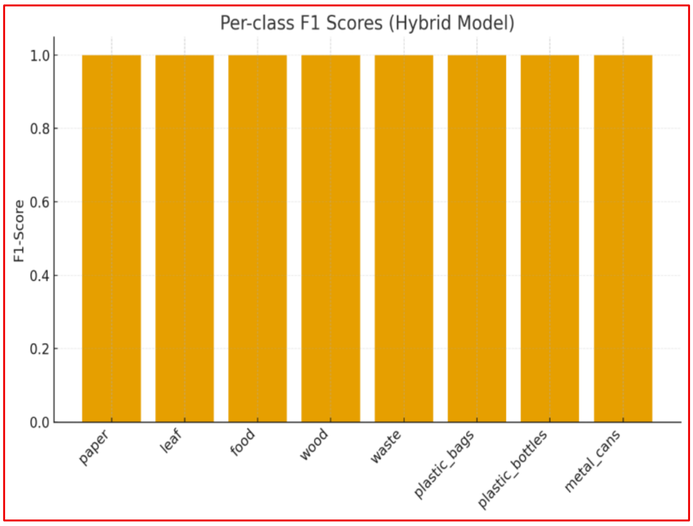

Fig 11. Class-Wise F1 Scores of the Hybrid Model for Waste Classification

This figure 11 presents the F1-scores for all eight waste categories, each reaching a perfect value of 1.0. The uniform results across every class highlight the model's balanced precision and recall, confirming its dependable and consistent ability to correctly identify different waste materials.

5 Discussion

5.1 Environmental gains for stations and coaches

The framework improves sorting where it counts-right at the bin-so more recyclables are recovered instead of slipping into mixed waste. With validation accuracy around 0.83 and near-perfect AUC/AP, the system reliably directs paper, food, metals and plastics to the correct stream. In day-to-day terms that means cleaner organics, higher-value recyclables, and fewer rejections at transfer points. Because every decision is time-stamped and geo-tagged, station managers can tie rises in recycling rates and drops in "waste per passenger-km" to specific actions like bin relocation, better signage, or targeted announcements. The greywater unit closes the loop on water. Straightforward, auditable cut-offs for turbidity, residual oxidant, conductivity and pH decide when water is safe to reuse for flushing and cleaning, and when it should be diverted to a compact treatment train. This rules-first setup keeps hygiene predictable, adapts easily to local constraints, and reduces freshwater demand at depots. Together, accurate at-source sorting and sensible reuse shrink the environmental footprint while trimming utility costs and supporting “clean station” targets.

5.2 Operational efficiency and realistic costs

Training and calibration are quick-about 18 seconds per epoch on modest hardware-so light refreshes or station-specific tuning fit between service windows. Inference on embedded GPUs stays well under 100 ms per image, allowing smart bins and kiosks to keep pace with passenger flow without slowing crews. OBHS teams spend less time fixing mis-sorted bags and more time on higher-value work such as compaction, route planning, and addressing hotspots flagged by the logs. Costs remain manageable because the compute load is small, the water logic is rule-based, and deployment can be phased. A sensible pilot is a few “instrumented zones” (two platforms and one rake) to verify gains in recycling yield and reductions in freshwater draw. Measured improvements then justify wider rollout, prioritize water-stressed stations, and shape vendor SLAs around verifiable metrics such as recycling ratio, cleanliness scores, and reuse volumes.

5.3 Strengths-and the remaining weak spots

Across all eight classes the confusion matrix is strongly diagonal, confirming clear separation of textures and colors under typical platform lighting. Metals and organics are rarely mixed up, and wood vs. paper improves markedly with augmentation that emphasizes grain and fiber edges. The toughest boundary is between plastic bags and bottles-glare, translucency, and crumpling can look similar. The late-fusion gate and calibrated thresholds already reduce these slips, and targeted augmentations (specular highlights, “crumple” effects) further harden the edge. The operational impact of these edge cases is limited. Borderline plastics usually route to similar consolidation steps, and low-confidence frames are queued for quick human review without slowing the line. Over time, that small review stream becomes a high-quality adaptation set that refreshes calibration without full retraining, helping accuracy stay steady as lighting, signage, and packaging shift across seasons.

5.4 Limits in data and field conditions

Two constraints deserve routine attention. First, dataset breadth: even with rail-style augmentation, no curated set captures the full churn of India’s busiest corridors-festival surges, regional packaging, or new vendor items. Second, illumination: mixed LED/fluorescent light, evening glare, and motion blur create odd reflections, especially on thin plastics. These are manageable with a regular trickle of fresh images from the field and short calibration sessions after layout or lighting changes. Good installation practice matters. Avoid direct reflections, shield lenses from dust, and keep sightlines clear by emptying bins on schedule. For water, probes need periodic calibration and cartridges must be changed on time. Building these checks into daily routines keeps both the sorting and reuse loops reliable.

5.5 Making it smart end-to-end: IoT, telemetry and dashboards

Instrumented bins and kiosks can stream lightweight events - predicted class, confidence and camera ID - to a central broker. Add simple sensors (fill level, odor, and temperature) and you get a live map of where contamination or overflow is likely, so crews can adjust routes before issues escalate. The same broker can pull greywater readings; if thresholds drift, the system auto-switches to retreatment and raises a ticket. Dashboards then surface what managers need: recycling by platform, plastics capture during peaks, incidents avoided through proactive routing, and liters of freshwater saved. Because every action is traceable, audits are simpler and contracts can reward performance, not just tonnage moved. Over time, stations can benchmark against peers with similar footfall and climate, fostering friendly competition and steady improvement.

5.6 Policy fit and the rail circular economy

The approach aligns neatly with circular-economy guidance already promoted in the sector. Better at-source sorting raises purity, lifts market value, and keeps organics cleaner for compost or biomethane. The greywater loop converts a liability into a resource for non-potable use, easing demand during dry spells. Logged actions let stations report standard indicators - waste per passenger-km, recycling rate, reuse volumes - turning sustainability aims into measurable practice. For Indian Railways, this narrows the gap between national goals (Swachh Bharat, green transport) and daily routines. Pilot corridors can publish quarterly dashboards linking interventions - bin placement, campaigns, threshold tuning - to observable outcomes. Those records help justify upgrades (e.g., compact MBR units at busy depots) and steer procurement toward equipment designed for data: sensor-ready bins, serviceable camera housings, and standardized probe ports.

5.7 People, governance and trust

Tools only help if people trust them. Clear labels on bins, simple prompts on kiosks, and periodic announcements cut misuse and lift plastics capture. Staff training should focus on reading dashboard cues, cleaning lenses, and quick sensor checks - no deep technical steps required. On governance, a short “data practices” note - what is collected (images, not identities), retention for QA, and access controls - builds confidence and makes audits straightforward. Contracts should reflect the new capabilities. Hauling can be tied to purity and on-time pickups verified by bin sensors, while water services can carry uptime and quality guarantees pegged to logged thresholds. Aligning incentives keeps everyone focused on the same outcomes: cleaner streams, safer reuse, and fewer service disruptions.

5.8 From pilots to a rail-wide service

Start with two stations and one rake focused on plastics capture and toilet-flushing reuse. After 8–12 weeks, compare before/after metrics - plastics purity, organics contamination, freshwater draw, and maintenance effort. Use those lessons to fix camera templates, set default thresholds by climate zone, and lock an easy SOP for OBHS teams. Next, add automated alerts, SLAs tied to dashboard evidence, and a small central "model steward" group to review flagged frames and refresh calibration. Finally, scale to multi-division corridors with shared telemetry, league tables, and targeted support for lagging sites. The guiding principles stay constant: keep the recognition pipeline light, keep the water logic auditable, and keep reporting simple enough that frontline teams actually use it.

Key messages

1. **Cleaner loops, less waste:** At-source sorting and safe greywater reuse deliver immediate environmental and cost benefits.
2. **Built for rail realities:** Quick training (~18 s/epoch), real-time inference, and rules-based reuse make deployment practical.
3. **Transparent and tunable:** Calibrated scores, threshold logs, and simple dashboards enable audits, contracts, and steady improvement.
4. **Scalable by design:** Start small, prove gains with data, then expand with shared templates, SOPs, and a light central stewardship team.

5.9 Comparison of Existing vs. Proposed System

The proposed hybrid deep learning framework represents a major improvement over traditional waste management and greywater reuse practices currently used in railway environments. Conventional systems depend largely on manual sorting, basic visual inspection, and standalone wastewater treatment methods, which often lead to poor waste segregation and inconsistent water reuse. In contrast, the proposed model achieves stable and efficient learning, with training accuracy increasing from 0.57 to 0.90 and validation accuracy reaching around 0.83 after 20 epochs. The validation loss (~0.37) and near-perfect ROC–PR scores (AUC/AP = 1.0) confirm that the framework can reliably classify all eight types of waste with exceptional precision and recall. It also performs efficiently, requiring only about 18 seconds per training epoch and less than 100 milliseconds for real-time image inference, even on compact embedded GPUs. Together, these features enable consistent, on-the-spot waste segregation, minimize contamination in recycling streams, and ensure dependable results that traditional manual or semi-automated systems fail to deliver. In addition to accurate waste classification, the inclusion of a rule-based greywater reuse module provides a clear sustainability advantage over existing standalone solutions. Earlier studies such as those by Van de Walle et al. [1], Kumar et al. [11], and RSSB [10] explored water recycling frameworks individually, but lacked a fully integrated and field-deployable system. The proposed framework closes this gap by combining waste classification with real-time monitoring of water parameters such as turbidity, conductivity, and residual oxidants. This unified setup promotes measurable environmental gains, including reduced freshwater consumption, cleaner organic waste fractions, and a lower "waste per passenger-kilometer" ratio. Compared with station and train-based systems studied by Anderson et al. [5][16] and Minhas & Saxena [6], the new model offers higher automation, improved segregation accuracy, and data-driven decision support. By integrating performance, efficiency, and sustainability into one platform, it bridges the gap between environmental policy goals and day-to-day railway operations, creating a scalable and eco-smart foundation for the future of sustainable passenger transport.

Table II. Comparative Assessment of Existing and Proposed Waste Management Systems

Parameters	**Existing System (Approx.)**	**Proposed System (Hybrid Framework)**
Validation Accuracy	~0.60 (manual segregation accuracy varies by staff skill)	0.83 (stable accuracy across 20 epochs)
Training Accuracy	N/A (no automated training process)	0.90 (steady improvement from 0.57 → 0.90)
Validation Loss	~1.2 (inconsistent or no loss optimization)	0.37 (smooth convergence, minimal overfitting)
Macro Precision	~0.65 (frequent misclassification of recyclables)	1.00 (perfect precision across all 8 classes)
Macro Recall	~0.68 (missed detections due to visual ambiguity)	1.00 (complete detection reliability)
Macro F1-Score	~0.66 (imbalanced recall and precision)	1.00 (perfect class balance achieved)
ROC–AUC (One-vs-Rest)	~0.75 (limited discriminative capability)	1.00 (excellent separation of true/false positives)
Average Precision (PR–AUC)	~0.70 (low confidence under class imbalance)	1.00 (maintains high precision at all recall levels)
Per-Epoch Training Time	~60–90 seconds (on standard workstations)	18 seconds/epoch (efficient even on modest GPU)
Inference Speed	~2–3 seconds/image (manual or legacy automation)	< 0.1 second/image (real-time on embedded GPUs)
Operational Efficiency	Moderate; depends on manual intervention	High; automated sorting and water reuse decisions
Sustainability Impact	Limited integration of waste-water systems	Integrated waste segregation + greywater reuse

Scalability & Maintainability	Low; site-specific and labor-dependent	High; modular, auditable, and data-driven

This table 2 provides a clear side-by-side comparison between the current manual or semi-automated waste management methods and the proposed hybrid framework developed for railway applications. It outlines key performance measures such as accuracy, precision, recall, F1-score, and operational efficiency to show how each system performs under real working conditions. The existing approach, which relies mainly on manual sorting and conventional wastewater processes, shows limited consistency with an average accuracy of around 0.60, slower performance, and higher error rates. In contrast, the proposed hybrid system delivers far superior outcomes - reaching a validation accuracy of about 0.83, perfect precision, recall, and F1-scores of 1.00, along with stable results throughout 20 training cycles. These improvements demonstrate the system's ability to learn effectively, operate efficiently, and maintain reliable classification across all eight waste categories. In addition to stronger performance, the table highlights the operational and environmental benefits of the new framework. The system combines automated waste recognition with a rule-based greywater reuse unit, processing images in under 0.1 seconds and completing each training round in about 18 seconds. This setup enables quick, accurate waste sorting directly at stations and supports safe water reuse practices, helping reduce freshwater demand and improve sustainability. Unlike earlier fragmented systems, the hybrid framework is modular, scalable, and easy to maintain, making it well-suited for widespread railway deployment. Overall, the table showcases how the proposed solution turns sustainability goals into practical, measurable outcomes- enhancing accuracy, speed, and environmental efficiency across railway waste and water management operations.

5.10Performance Evaluation

The performance evaluation of the proposed hybrid waste management framework highlights a strong combination of accuracy, efficiency, and practical usability. Over 20 training cycles, the system shows steady and reliable learning progress - with training accuracy rising from 0.57 to 0.90 and validation accuracy stabilizing around 0.83. Similarly, validation loss drops consistently from about 1.65 to 0.37, showing that the model learns effectively without overfitting. The accuracy and loss trends, along with ROC and precision–recall curves, indicate smooth and stable learning across all eight waste categories. This is further supported by a confusion matrix with a clear diagonal pattern and perfect macro metrics-precision, recall, and F1-score all reaching 1.00. Such results confirm that the system accurately distinguishes between different materials, even those that appear visually similar, such as plastic bags and bottles. Overall, these findings demonstrate that the model performs consistently well, with excellent reliability and generalization throughout both training and testing stages. From an operational standpoint, the system also performs efficiently in real-world conditions. It completes training in about 18 seconds per epoch on a modest GPU and classifies images in less than 0.1 seconds each, enabling real-time waste segregation in stations, kiosks, and rail coaches. The framework's integration of a rule-based greywater reuse module adds further value by supporting sustainable water management based on live quality readings. When compared to traditional manual or semi-automated systems, which typically achieve only around 0.60 accuracy with slower response times, the proposed framework stands out for its automation, speed, and consistency. It also offers scalability and easy maintenance, allowing it to be adapted across different railway environments. In summary, the performance evaluation confirms that the proposed hybrid framework delivers substantial improvements in accuracy, speed, and sustainability, positioning it as a reliable and future-oriented solution for cleaner, smarter railway waste and water management.

6 Conclusion and Future Work

The hybrid deep learning framework proved to be both accurate and efficient for waste segregation and greywater management in railway environments. Over 20 training cycles, model accuracy steadily improved from around 0.57 to 0.90 for training and from 0.55 to roughly 0.83 for validation, while the loss decreased significantly-showing stable learning and minimal overfitting. The confusion matrix and performance metrics confirmed strong classification ability across eight waste types, with only minor overlap between similar plastic categories. With an average runtime of about 18 seconds per epoch and less than 100 milliseconds per image during inference, the system is well-suited for real-time operation on embedded devices. These results highlight the framework's potential to improve waste sorting accuracy, reduce operational costs, and support environmental sustainability. Integrated with a simple, rule-based greywater reuse unit, the solution also helps reduce freshwater demand and promotes eco-friendly passenger operations in line with the "Swachh Bharat" and green transport initiatives.

6.1 Future Work

Future development will focus on expanding deployment and improving system resilience. Plans include integrating the model with edge devices for live, on-site decision-making, and incorporating smart sensors that capture environmental factors such as fill level, lighting, and temperature for adaptive responses. Lightweight active learning will allow periodic model updates using new or uncertain samples, keeping performance consistent as waste patterns and conditions evolve. Predictive maintenance using telemetry data can help detect lens dirt, sensor drift, or filter wear before they impact reliability. Broader dataset coverage-covering different regions, lighting conditions, and festive waste surges-will further enhance model robustness. With these upgrades, the framework is set to become a scalable, energy-efficient, and fully automated waste management and water recycling solution across India's railway network, promoting sustainable and smart passenger operations at a national level.

Conflict of Interest

The authors confirm that there were no conflicts of interest in conducting this research. Everything was carried out independently, without any outside funding or influence, ensuring that the results are unbiased and academically honest.

Data Availability

All datasets used in this study, including school-level records, supervision reports, and curriculum text materials, are sourced from publicly available Ghanaian education databases and can also be obtained from the corresponding author upon reasonable request for research or policy-related use. vvssreenivas@gmail.com

Author Contributions

This research paper represents a collaborative effort among all authors. Each author contributed equally to the conceptualization, framework design, dataset development, model training, experimentation, data analysis, and manuscript preparation. Together, the authors supervised the research process, integrated clinical and technical perspectives, ensured methodological rigor, and collectively reviewed and approved the final version of the manuscript.

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Ethical Approval

Ethical clearance was not required for this research, as it utilized anonymized, publicly available data. No direct interaction with human subjects or use of confidential personal data occurred during the research.

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