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EcoSort: An AI-Powered Garbage Segregation System Using MobileNetV3 and Deep Transfer Learning

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Abstract- Improper waste disposal remains one of the most pressing environmental challenges in both urban and rural settings, contributing to pollution, health hazards, and reduced recycling efficiency. Traditional manual waste segregation is error-prone, labour-intensive, and cannot scale to the volumes of waste generated daily. This paper presents EcoSort, an AI-powered full-stack web application that automates waste classification using a fine-tuned MobileNetV3 Large deep learning model trained via transfer learning. The system classifies waste images into three categories—Recyclable, Non-Recyclable, and Hazardous—achieving approximately 94 % overall accuracy with precision values of 0.95, 0.94, and 0.94 respectively. EcoSort integrates real-time webcam-based detection, a microservices architecture (React/Vite front-end, Node.js/Express back-end, Flask AI service, MongoDB Atlas), Role-Based Access Control (RBAC), JWT authentication, and perceptual hashing (pHash) for duplicate-image detection. A gamification layer comprising reward tiers (Bronze to Platinum), a coupon marketplace, and a community leaderboard motivates responsible waste disposal. Load testing confirmed stable operation under 100 concurrent users with average response times below 3.5 seconds. The platform aligns with UN Sustainable Development Goals SDG 3, SDG 11, SDG 12, and SDG 13, offering a scalable, intelligent pathway toward smarter waste management.

Keywords—Waste classification; Deep learning; MobileNetV3; Transfer learning; Garbage segregation; Gamification; Flask microservice; Real-time detection; Cloud deployment.

I. INTRODUCTION

Rapid urbanisation and population growth have driven an exponential increase in solid waste generation worldwide. Improper segregation of recyclable, non-recyclable, and hazardous waste leads to severe environmental degradation, public-health risks, and drastically reduced recycling yields [1]. Manual sorting methods are slow, inconsistent, and hazardous to workers who handle toxic material without adequate protection.

Artificial Intelligence (AI), particularly convolutional neural networks (CNNs), has demonstrated strong potential for image-based waste classification. Lightweight architectures such as MobileNetV3 [5] are especially suitable because they deliver competitive accuracy at low computational cost—critical for cloud-hosted real-time services.

This paper introduces EcoSort, a web-based waste management platform that:

- classifies waste images via a fine-tuned MobileNetV3 Large model;
- provides real-time webcam-based detection;
- rewards responsible behaviour through a gamified tier system;
- deploys as independent cloud microservices for scalability.

The remainder of this paper is organised as follows: Section II surveys related work; Section III states the problem; Section IV describes the proposed methodology; Section V details the implementation; Section VI presents results; Section VII concludes; Section VIII outlines future work.

II. LITERATURE REVIEW

Smart Waste Classification using Deep Learning and IoT [1] integrates CNN models with IoT smart-bin sensors for automated garbage monitoring, demonstrating measur-able improvements in collection efficiency.

WasteNet [2] employs deep CNNs trained on labelled waste images to distinguish recyclable from non-recyclable items, using texture, shape, and colour features with strong classification performance.

Automatic Waste Segregation using Deep Learning [3] applies transfer learning to reduce training time while maintaining competitive accuracy, highlighting the benefits of pre-trained weights for domain-specific datasets.

A Review on Smart Waste Management using AI [4] surveys machine learning, deep learning, IoT, and cloud computing techniques for waste handling, identifying dataset imbalance and real-time deployment as open challenges.

Real-Time Garbage Classification using Transfer Learning [5] shows that MobileNet-family models achieve rapid inference with limited compute resources, making them ideal for cloud-based and embedded waste classification.

Deep Learning-Based Waste Detection and Classification [6] proposes a CNN-based detection pipeline that handles multiple material categories under varying environ- mental conditions and discusses integration with smart-city infrastructure.

EcoSort builds upon these foundations by combining a fine-tuned MobileNetV3 Large model, full-stack web deployment, and a gamified reward engine—none of which is fully addressed in prior work taken individually.

III. PROBLEM STATEMENT

Existing waste management systems rely heavily on manual labour for sorting, which is: (i) time-consuming and error-prone; (ii) a health risk when hazardous waste is involved;
(iii) poorly scalable for growing urban waste volumes; and (iv) unable to engage the public in sustainable disposal practices. Rule-based automated approaches lack the generalization required across diverse real-world waste types. There is therefore a need for an intelligent, scalable system that classifies waste accurately in real time while encouraging public participation through engagement mechanisms.

IV. METHODOLOGY / PROPOSED SYSTEM

A. System Architecture

EcoSort follows a four-layer microservices architecture:

1. Frontend Layer – React 18 + Vite, Tailwind CSS.
2. Backend Layer – Node.js + Express REST API.
3. AI Service Layer – Python + Flask + TensorFlow/Keras.
4. Database & Cloud – MongoDB Atlas (NoSQL).

Each layer is deployed independently: the front-end on Vercel, the back-end on Railway, and the AI microservice on Render, enabling horizontal scaling without cross-service interference.

B. Deep Learning Model

MobileNetV3 Large was selected for its favourable accuracy-to-latency trade-off. The base model, pre-trained on ImageNet, was fine-tuned using three merged open-source datasets: Hazardous Waste Dataset, New Trash Classification Dataset, and Recyclable and Household Waste Classification Dataset. Key training decisions:

- Input size: 224 × 224 px; normalized to [0, 1].
- Augmentation: random flips, rotations, brightness jitter.
- Class-weighted cross-entropy to address dataset imbalance.
- Hardware: Kaggle GPU T4; framework: TensorFlow 2 / Keras.
- Output: softmax over three classes (Recyclable, Non-Recyclable, Hazardous).

C. Waste Classification Workflow

Figure 1 illustrates the end-to-end classification pipeline.

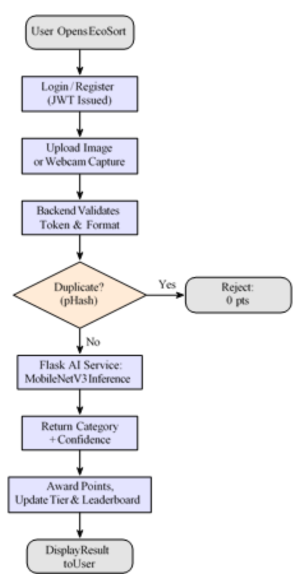

Figure 1: EcoSort Waste Classification Workflow

D. Security Design

Security is enforced at multiple layers: JWT tokens authenticate every API call; RBAC separates Admin privileges from standard-user access; perceptual hashing (DCT-based pHash, Hamming distance ≤ 10) detects near-duplicate im- age uploads; and all secrets are managed via environment variables, never hard-coded.

E. Gamification Design

Users accumulate points for each successful classification. Point thresholds define four tiers: Bronze, Silver, Gold, and Platinum. A community leaderboard ranks all active users, and a coupon marketplace allows point redemption for eco-partner discounts, creating a closed-loop incentive cycle.

V. IMPLEMENTATION / EXPERIMENTAL SETUP

A. Front-End

The single-page application (SPA) built with React 18 and Vite offers: a drag-and-drop image upload module; a real-time webcam capture panel using the browser MediaDevices API; a live rewards and tier dashboard; and an admin panel with user management, analytics, and system-health monitoring. Tailwind CSS ensures full responsiveness across mobile, tablet, and desktop viewports.

B. Back-End

Eleven RESTful route groups handle authentication, scan submission, rewards, coupons, leaderboard, and administertion. Mongoose ODM connects to MongoDB Atlas. The duplicate-detection service computes pHash on every up-loaded image and queries the scans collection for matches within the Hamming-distance threshold before forwarding the image to the AI service.

C. AI Microservice

A single-endpoint Flask service (POST /predict) accepts a multipart image, applies OpenCV/PIL preprocessing (224 × 224, normalize), runs the saved Keras model, and returns a JSON payload containing the predicted label, confidence score, and per-class probability vector. The service is stateless, enabling multiple Render instances to run in parallel.

D. Dataset & Training

Table 1: Training Dataset Summary

Dataset	Categories	Usage
Hazardous Waste Dataset	Hazardous	Train / Val
New Trash Classification	Multiple	Train / Val
Recyclable & Household Waste	Recyclable / Other	Train / Val

Images were split 80 %/20 % (train/validation) after merging and re-labelling into the three target classes. Training ran for 30 epochs on a Kaggle GPU T4; the best checkpoint (by validation accuracy) was exported as a .h5 file and loaded by the Flask service.

VI. RESULTS AND DISCUSSION

A. Model Performance

The fine-tuned MobileNetV3 Large model achieved an over-all classification accuracy of 94 % on the held-out validation set. Per-class metrics are summarised in Table 2.

Table 2: Per-Class Precision and Recall

Category	**Precision**	**Recall**
Recyclable	0.95	0.97
Non-Recyclable	0.94	0.92
Hazardous	0.94	0.91
Overall	**0.94**	**0.93**

Recyclable waste achieved the highest recall (0.97) be-cause items such as plastic bottles, paper, and cans exhibit consistent visual textures. Hazardous waste showed marginally lower recall (0.91) owing to irregular shapes and high inter-class visual similarity with certain non-recyclable items; this is consistent with findings in [6]. non-admin users from accessing administrative routes.

E. Discussion

EcoSort demonstrates that combining a lightweight CNN

B. System Performance

Table 3: API Response Time Benchmarks

Operation	Avg. Response Time
Image Classification (upload)	~2–3 s
Webcam Classification	~1–2 s
Authentication API	~100–150 ms
Reward / Tier Update	~200 ms
Duplicate Detection (pHash)	~0.5 s

Load testing with 50 and 100 concurrent users yielded aver-age response times of 2.1 s and 3.4 s respectively, with no service failures, confirming that the microservices architecture scales effectively.

C. Integration Testing

End-to-end workflow testing achieved a 98.7 % success rate with a gamified engagement layer meaningfully extends the impact of AI-based waste classification beyond pure technical accuracy. The pHash deduplication mechanism—often absent in comparable systems—is critical to reward integrity in public-facing deployments.

VII. CONCLUSION

EcoSort successfully realises an AI-powered, cloud-native waste segregation platform combining a fine-tuned Mo-bileNetV3 Large classifier (94 % accuracy), real-time webcam integration, secure microservices deployment, and a gamified reward ecosystem. The system eliminates dependence on manual sorting, provides accurate three-class waste categorization, and motivates environmentally responsible behaviour through tangible incentives. The modular architecture ensures maintainability and future extensibility, while the security layer—JWT, RBAC, and pHash—protects both user data and reward integrity. EcoSort contributes directly to UN SDGs 3, 11, 12, and 13, establishing a replicable blueprint for AI-driven environmental platforms.

VIII. FUTURE WORK

Several enhancements are planned:

- IoT Integration: Edge-deployed model on Raspberry Pi-based smart dustbins to enable fully automated physical sorting
- Mobile Application: Native Android/iOS app with offline model inference.
- Multi-Language Support: Vernacular-language UI and voice-assistant guidance for wider community adoption in India.
- Advanced Models: Evaluation of EfficientNetV2, YOLOv8 for simultaneous object detection and classification in cluttered bin environments.
- Government API Integration: REST interfaces with municipal waste management dashboards for large-scale roll-out.
- Federated Learning: Privacy-preserving model updates from on-device data to improve generalization without centralizing sensitive images.

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