Image-Based Dry and Wet Waste Recognition with Location-Aware Disposal Guidance: A Deep Learning Web Platform

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Abstract — Rapid urbanisation has increased the volume of municipal waste, while manual segregation at source remains slow, inconsistent and error prone. Citizens also lack immediate guidance on how to dispose of an item and where the nearest suitable bin is. This paper presents Binify ECO Route, a web platform that combines a convolutional neural network (CNN) for image-based waste recognition with a GPS-based dustbin recommendation module. A user uploads or captures a photograph of waste; the image is pre-processed and classified by a TensorFlow model, which returns the waste category, confidence scores, the recommended bin colour and disposal instructions. The platform then reads the user's location, filters a JSON dustbin database by accepted waste type, computes geodesic distances with the Geopy library and lists the nearest suitable bins on an interactive map. A knowledge centre and sign-in module complete the application. The paper describes the architecture, implementation and test plan, shows the working interfaces, and discusses limitations and future work such as sensor-based bin monitoring and wider waste categories.

Keywords: Waste Classification, Convolutional Neural Network, Tensorflow, Geospatial Analysis, Dustbin Recommendation, Flask, Sustainable Waste Management

I. INTRODUCTION

Effective waste management has become a major urban concern because of population growth, higher consumption and expanding cities. Improper handling of waste causes pollution, health hazards and poor recycling rates. Conventional practice depends largely on manual segregation and public participation, which is time consuming and prone to human error, and mixed waste contaminates recyclable material and increases landfill dependence.

Advances in deep learning and geospatial technology offer a way to support citizens at the point of disposal. Convolutional neural networks (CNNs) learn visual features directly from images and are widely used for waste classification [1]–[3]. Location services can then direct the user to a bin that actually accepts that type of waste. Existing map applications can locate places, but dustbin data on them is often incomplete or outdated, bins are not matched to waste type, and users receive no guidance on correct segregation.

This paper presents a web platform that joins these two capabilities. The contributions are: (i) an image-based classifier that labels waste as dry or wet and reports confidence for each class, so that mixed items can be flagged for separation; (ii) a rule-based disposal guidance module that returns the recommended bin colour and instructions; (iii) a dustbin recommendation module that filters bins by accepted waste type and ranks them by geodesic distance from the user; and (iv) a responsive web application, built with Flask, that integrates both modules with an educational knowledge centre. The remainder of the paper reviews related work, describes the system design and implementation, presents the interfaces and test plan, and concludes with future work.

II. RELATED WORK

Surveys of artificial intelligence for solid-waste classification [1], [3] review machine-learning, deep-learning and ensemble methods and the datasets commonly used to validate them. Singh and Azad [5] compare methods including support vector machines, random forests, CNNs, artificial neural networks and decision trees, and relate them to circular-economy goals such as higher recycling rates and less landfill.

Several studies combine learning with Internet of Things (IoT) hardware. Alourani et al. [2] describe an intelligent system with sensor-equipped smart bins, cloud processing and deep learning that classifies plastic, glass, metal and trash and alerts collectors when bins are full. Lakhouit [3] reviews AI and IoT for collection, sorting and recycling, including route optimisation and predictive analytics based on real-time data. Mohabuth and Sunnassy [6] prototype a smart bin that uses IoT and AI to predict waste levels.

Image-based classifiers are reported in [7]–[9]. Lavanya et al. [7] present a CNN-based segregation and collection system. Khetarpal et al. [8] train a CNN for waste categorisation and report an accuracy of 89.88%. Itam et al. [9] improve a CNN with data augmentation (rotation, brightness changes) and hyperparameter optimisation on more than 24,000 labelled images, expanded to over 33,000 samples, and report 94.40% accuracy, outperforming ResNet-50, Inception-V3 and VGG-19 on organic and recyclable classes. Decision-support work such as Soujanya et al. [10], which applies fuzzy AHP and TOPSIS, and Lahcen et al. [11], which studies machine learning for waste collection planning in Morocco, address planning rather than citizen guidance.

Most of this work focuses on classification accuracy or on collection logistics. Few systems give the citizen both an immediate classification and a nearby bin that accepts that category. The present platform addresses this gap with a lightweight web application that needs no special hardware.

III. PROBLEM STATEMENT AND OBJECTIVES

The problem is the absence of real-time guidance that tells a person what kind of waste they hold, how to dispose of it, and where to take it. The objectives are to: (a) design and train a CNN that classifies waste from images captured or uploaded by users; (b) provide disposal instructions with recommended bin colours; (c) develop a GPS-enabled module that recommends the nearest appropriate dustbin and shows its distance; and (d) deliver the system as a user-friendly web application that works on desktops and smartphones.

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IV. SYSTEM DESIGN

A. Overall Architecture

The platform follows a layered design with a user layer, an application layer, a database layer and an output layer (Fig. 1). The user layer is the browser interface, through which a user uploads or captures an image and grants location permission. The application layer is a Flask server that validates the input, pre-processes the image, runs the TensorFlow classifier and the geospatial engine, and returns a JSON response containing the waste type, confidence, disposal guidance and nearest bins. The database layer stores dustbin records in a JSON file. The output layer renders the results and a map of recommended bins.

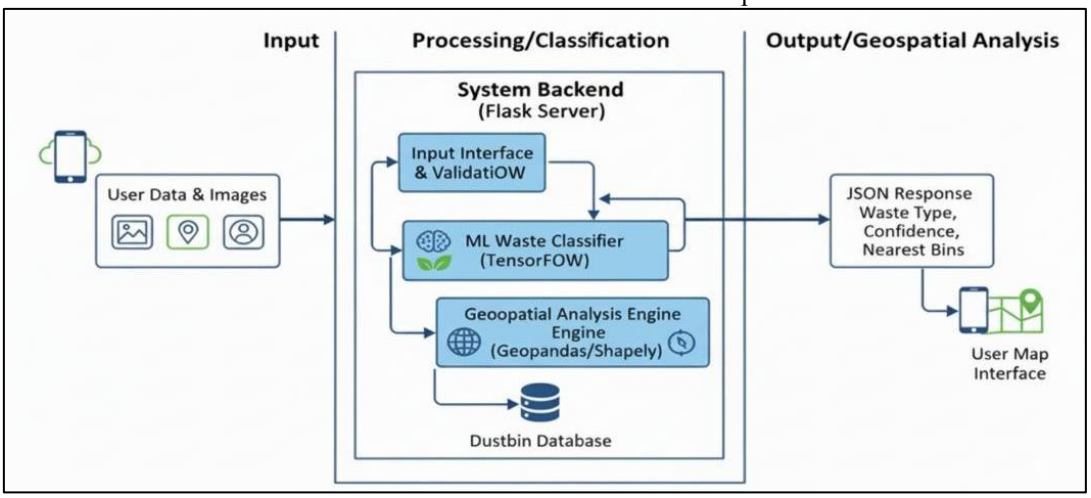


Fig. 1: System architecture of the waste classification and dustbin recommendation platform.

B. Waste Classification Module

The user supplies a photograph from the camera or the file system. The server checks the file type (for example .jpg or .png) and size, then pre-processes the image by resizing to 224 × 224 pixels, noise reduction and colour normalisation. The pre-processed image is passed to a CNN, which extracts hierarchical visual features through convolution, pooling and fully connected layers and outputs a probability for each class. In the implemented classifier the class labels are dry and wet. The result is shown with confidence scores, and when neither class clearly dominates the image is reported as mixed waste and the user is advised to separate the components. Transfer learning with pre-trained networks can be used to improve accuracy when training data is limited.

A rule-based information-retrieval step maps the predicted class to guidance. Wet or organic waste is directed to the green bin for composting or biogas generation, dry or recyclable waste to the blue bin for recycling, and hazardous items such as batteries, chemicals and fluorescent tubes to designated collection points.

C. Dustbin Recommendation Module

Each record in the dustbin database holds an identifier, name, latitude, longitude, address, accepted waste types, bin colours and facilities. After classification the browser obtains the user's coordinates through the Geolocation interface, with permission. The server removes bins that do not accept the detected waste type and computes the geodesic distance d between the user's position and each remaining bin, as in

$$d_j = \text{geodesic}((\varphi_u, \lambda_u), (\varphi_j, \lambda_j)) \quad (1.1)$$

where (φ_u, λ_u) is the latitude and longitude of the user and (φ_j, λ_j) those of bin j. The Geopy library implements this with Karney's algorithms on an ellipsoidal Earth model [12]. The bins are ranked by d_j and the nearest suitable ones, up to five, are returned with their distance in kilometres and shown on the map. A simple spherical formula such as the haversine can be used instead where lower accuracy is acceptable.

D. Use Cases

Two actors interact with the system. The *user* uploads a waste image, receives the classification, reads the disposal instructions, obtains nearby bin recommendations and views them on a map. The *system administrator* maintains the waste image dataset used for training and the dustbin database, adding, updating or removing records so that recommendations stay accurate.

V. IMPLEMENTATION

A. Technology Stack

The classifier is built with TensorFlow [4] and Keras in Python. A WasteClassifier class loads a saved model file when it exists and otherwise creates a new model, using an input size of 224 × 224. OpenCV and the Python Imaging Library handle image reading, conversion to RGB, resizing and normalisation. Flask exposes the functions as web routes and returns JSON. Front-end pages are written in HTML, CSS and JavaScript, user sign-in uses Firebase authentication scripts, and mapping uses an interactive map component. Table I summarises the environment.

Component	Technology
Model	TensorFlow / Keras CNN, 224 × 224 input
Image handling	OpenCV, Pillow, NumPy
Backend	Python, Flask, JSON responses
Location	Browser GPS, Geopy geodesic
Data store	JSON dustbin file
Front end	HTML, CSS, JavaScript
Hardware	Core i5, 8 GB RAM

Table I: Implementation Environment

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B. Web Application

The application has a landing page, a home dashboard, the image classifier page, the dustbin tracking page and a knowledge centre. The home page links to the waste classifier, nearby dustbin tracking, an AI chat assistant, the knowledge centre and a motivation and rewards section. Users register and log in with an e-mail address and password.

VI. RESULTS AND DISCUSSION

A. Waste Classification

The classifier page provides upload and camera options and an Analyze Waste button. Fig. 2 shows a photograph of mixed household waste (plastic cups, straws, bags, paper cups and food residue). The system reports 40% wet-waste confidence and 60% dry-waste confidence, labels the item as mixed waste, advises separating the wet and dry parts, and recommends the green bin for wet components and the blue bin for dry components, followed by a written analysis. This demonstrates the complete path from image to disposal guidance.

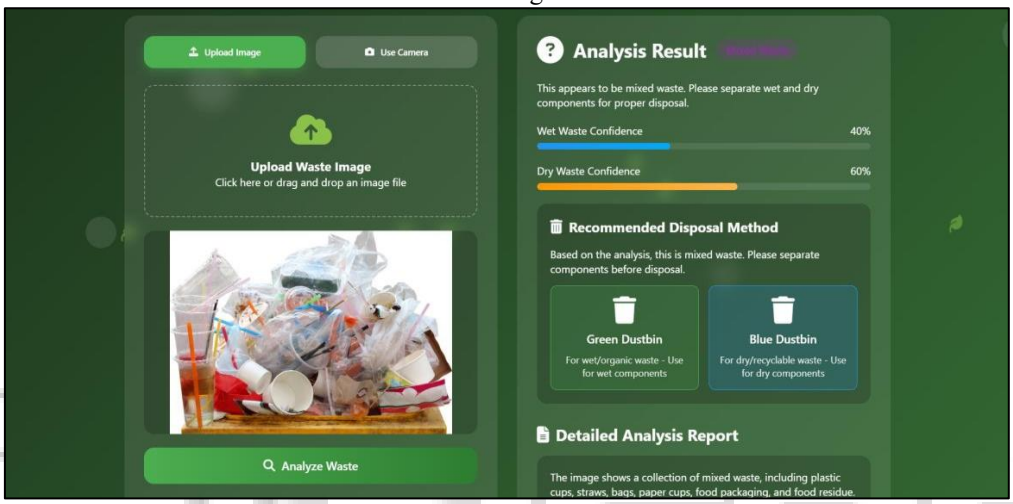


Fig. 2: Classification output with confidence scores and bin recommendation.

B. Dustbin Tracking

The tracker page detects the user's position (the sample session shows latitude 12.9565 and longitude 77.6208), reports 47 facilities across 9 cities with 3 near the user, and lets the user filter by waste type (plastic, organic, e-waste, construction, hazardous). The map in Fig. 3 marks facilities with coloured bin icons, and the result list in Fig. 4 shows each facility's name, city, distance (for example 3.30 km for the nearest bin), daily handling capacity and recycling rate.

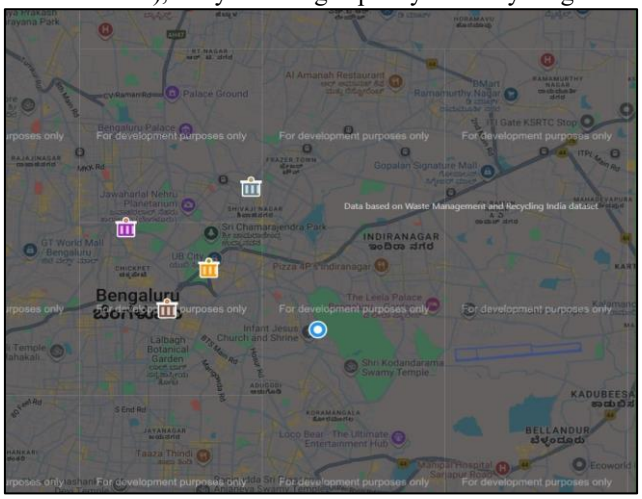


Fig. 3: Map view of nearby dustbins and the user location.

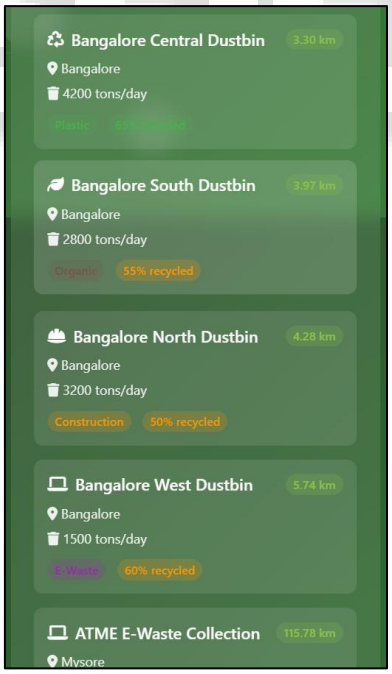


Fig. 4: List of nearest dustbins with distance and capacity.

C. Testing

The test plan covers four levels. *Classification testing* uses images with varied lighting, background and orientation and a held-out test set, and checks that preprocessing does not distort the image and that the correct disposal method is returned. *Recommendation testing* validates GPS capture on different devices and browsers, correct storage of bin records,

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distance accuracy, ranking, and edge cases such as no nearby bin, equidistant bins and full bins. *Web interface testing* checks functionality, responsiveness on desktops, tablets and smartphones, usability and error messages for invalid input, network loss or unsupported files. *Integration testing* follows the whole path from image upload to bin recommendation under typical and peak load.

D. Discussion and Limitations

The prototype shows that image classification, disposal guidance and location-based recommendation can be delivered in one browser application. The report that this paper is based on does not provide measured accuracy or response-time figures for the trained model, so none are claimed here; for context, published CNN classifiers achieve 89.88% [8] and 94.40% [9] on their own datasets, and the target for this system is above 90%. The classifier currently separates dry from wet waste, so categories such as e-waste or hazardous waste are handled only through guidance text and the facility filter. Bin data depends on the maintained database, and the system cannot yet detect whether a bin is full.

VII. Conclusion and Future Work

This paper presented a web platform that classifies waste from images, tells the user how to dispose of it, and recommends the nearest bin that accepts that waste using geodesic distance. By combining a CNN with location services it reduces dependence on manual sorting and supports correct segregation at the source.

Future work includes native Android and iOS applications with offline support, IoT fill-level sensors for real-time bin status and predictive collection, more waste categories (e-waste, hazardous waste, construction debris and sub-types of recyclables), larger and augmented training sets with reported accuracy, precision, recall and F1-score, gamification to encourage participation, integration with municipal systems for collection scheduling and routing, and multilingual support.

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