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CLASSIFICATION OF RECYCLABLE WASTE USING DEEP LEARNING

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Abstract: When recyclables and biological waste are not properly segregated, recycling cannot happen. ecological pollution. Unsystematic decision-making occurs due to labour-intensive manual sorting. SortWise is a web application for waste classification that uses deep learning and disposal wisdom. The experiment uses transfer-learned MobileNetV2 neural network for the two-class task (organic (biodegradable) and recyclable waste) On a held-out test set of 4,512. the model correctly classified the images achieving 92.04% accuracy with a macro-averaged F1-score of 0.92. The software uses Python and Flask for backend, HTML CSS and Javascript for frontend, and MongoDB Atlas for user and scan records. Provided. The images presented show capabilities for uploading images, displaying the prediction results, awaiting disposal instructions, accessing user account, scanning history, eco-point, leaderboard, and a chatbot. The new interface contains three labels E-Waste Non-Recyclable. In contrast, the reported quantitative assessment is binary. Thus, the three-label interface is characterized as a prototype function and not as a verified three-class version.

Keywords: Waste classification, recyclable waste, biodegradable waste, deep learning, computer vision, convolutional neural network, transfer learning, MobileNetV2, Flask.

1. INTRODUCTION

Thanks to advances in technology, public transit systems are now able to operate more efficiently and economically. When improperly disposed of, waste can end up spoiling our air, water and soil, damaging public health. Effective waste management starts with segregation at the source through waste separation. Paper, plastic, glass, metal etc. may be recycled. Food scraps and plant matter are generally termed as biodegradable waste.

In many settings, waste sorting still depends on manual inspection. A person must judge the shape, colour, texture and likely material of an item. This process requires time and effort, and the result may vary between individuals. Similar-looking materials, mixed waste and poor lighting can make the decision more difficult. A simple image-based tool can assist users by providing a preliminary category and disposal guidance.

Deep learning has become a useful approach for image classification because convolutional neural networks can learn visual features directly from image data. Transfer learning makes it possible to adapt a model pretrained on a large image collection to a smaller waste-classification dataset. In this project, MobileNetV2 is used as the selected model and is connected to a browser-based application named SortWise.

The main contributions of this work are: (1) a documented image-classification pipeline for organic and recyclable waste; (2) an evaluation of the selected MobileNetV2 model using a held-out test set; and (3) a web application that connects prediction results with disposal instructions, user history and engagement features. The current interface also displays an e-waste category, but the supplied quantitative report does not include a separate three-class evaluation.

2. RELATED WORK

Yang and Thung introduced TrashNet, an image collection used to study waste classification across six categories: glass, paper, cardboard, plastic, metal and trash [1]. The dataset provides a foundation for image-based waste recognition, although its categories do not cover every real-world disposal condition.

Divakar's Kaggle waste-classification dataset [2] is identified in this project as a source of waste images. The E-Waste Image Dataset published by akshat103 [3] is relevant to the extension of a classifier towards electronic waste. The available project records do not provide a complete source-wise image count, licence audit or exact data split for these collections; such details should be documented in a reproducible dataset manifest.

Dabhane [7] studied organic and recyclable waste classification using deep learning and reported results for a customized VGG16 model. Özyurt and Sevinç [8] compared deep-learning architectures for recyclable waste classification. Adedeji and Wang [9] presented a waste-classification system using a convolutional neural network. These studies show the

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usefulness of deep learning for visual waste categorisation. However, their datasets, class definitions and evaluation procedures differ, so their reported metrics should not be directly compared with the present experiment.

MobileNetV2, introduced by Sandler et al. [5], uses inverted residual blocks and linear bottlenecks to reduce computation while maintaining useful representational capacity. This makes it a practical candidate for applications where model size and inference cost matter. Transfer learning allows the model to reuse features learned during large-scale image pretraining and adapt them to the target waste categories.

Table 1 summarises selected literature relevant to the present work.

Table 1. Summary of selected literature relevant to the present work.

Study / Source	Method / Focus	Relevance and limitation
Yang and Thung [1]	TrashNet; image classification across six waste classes	Provides a foundational waste-image dataset; does not cover all disposal scenarios.
Divakar [2]	Kaggle waste-classification dataset	Potential image source; source-wise counts and split details are not recorded in the supplied project report.
akshat103 [3]	Kaggle E-Waste Image Dataset	Relevant to e-waste extension; independent three-class evaluation is not supplied.
Dabhane [7]	Transfer learning for organic/recyclable waste	Related binary classification task; dataset and protocol differ.
Özyurt and Sevinç [8]	Deep-learning architectures for recyclable waste	Supports CNN-based waste classification; metrics are not directly comparable.
Adedeji and Wang [9]	CNN-based intelligent waste classification	Demonstrates deep-learning application; uses a different dataset and class setup.

3. RESEARCH GAP AND OBJECTIVES

Existing studies demonstrate that deep-learning models can classify waste images, but a prediction alone does not necessarily help a user decide what to do next. A practical application should present understandable disposal instructions and provide a simple interface for repeated use. It should also maintain a record of scans and support user engagement.

A further gap concerns the difference between the evaluated model and the latest application interface. The supplied experimental report evaluates two categories—organic and recyclable—while the current SortWise interface screenshot displays E-Waste, Non-Recyclable and Recyclable. A separate three-class test set and corresponding metrics were not supplied. This paper therefore distinguishes the measured binary experiment from the three-label prototype interface.

The objectives are to develop an image-based waste-classification workflow; prepare image data through resizing, normalization and augmentation; evaluate a transfer-learned MobileNetV2 model; integrate the model with a Flask web application; provide disposal guidance and scan history; and identify the validation required before the three-category interface can be treated as a quantitatively reliable classifier.

4. PROPOSED SYSTEM AND METHODOLOGY

SortWise is organised into five stages: image acquisition, preprocessing, model inference, result presentation and application-data management. A user selects an image through the Scan page. The backend preprocesses the image and passes it to the trained model. The model returns class probabilities, from which the predicted label and confidence are selected. The frontend displays the result with disposal guidance.

4.1 Dataset and image preparation

The project identifies public image sources including TrashNet and two Kaggle datasets [1]–[3]. The original experiment uses two target classes: organic (biodegradable) and recyclable. The supplied project record reports a test set of 4,512 images, comprising 2,513 organic images and 1,999 recyclable images. A complete source-wise count and a reproducible list of filenames for each partition were not included in the available material.

The documented preprocessing pipeline resizes images to 224 × 224 pixels, normalizes pixel values, applies denoising and converts the images into a consistent tensor representation. Rotation, horizontal flipping and zoom transformations are used as augmentation operations to increase variation in the training data. The project report also describes removing unnecessary images and balancing the classes. For a reproducible experiment, augmentation should be applied only to the training partition, while validation and test images should remain unchanged.

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4.2 Model architecture and training

The project considered a custom convolutional neural network and transfer-learning architectures including VGG16, ResNet50, MobileNet and EfficientNet. The selected deployment model is MobileNetV2. The original project record specifies TensorFlow/Keras for model development and the Adam optimizer with categorical cross-entropy loss. During training, the model performs a forward pass to generate predictions, calculates the loss against the true labels and updates trainable weights through backpropagation.

MobileNetV2 is designed for computational efficiency. Its inverted residual structure and linear bottlenecks reduce the number of operations compared with many conventional convolutional networks [5]. The available report does not contain complete numerical results for every candidate architecture; therefore, this paper reports the measured performance of the selected MobileNetV2 model only and does not claim a quantitative ranking of all considered models.

4.3 Prediction and disposal guidance

The application accepts an image and returns a predicted category with confidence information. It then displays short disposal instructions intended to help the user handle the item appropriately. The current interface includes three visible labels: E-Waste, Non-Recyclable and Recyclable. Since the measured model results in the original report are for two classes, the three-label display is treated as a prototype/interface capability and not as evidence of a validated three-class model.

4.4 Web application and database layer

The backend is developed using Python and Flask. The frontend uses HTML, CSS and JavaScript. The supplied screenshots show MongoDB Atlas collections named users, scans, classifications and rewards. The application interface includes login and registration pages, a profile view, scan history, an eco-points system, a community leaderboard and the SortWise AI chatbot. The database screenshots indicate that scan records include classification information, confidence values, probabilities, timestamps and reward-related fields. Sensitive account identifiers and authentication-related values are intentionally not reproduced in this paper.

4.5 User workflow

The typical workflow is: (1) the user creates an account or logs in; (2) opens the Scan page; (3) selects a photograph of a waste item; (4) submits the image for classification; (5) reviews the category, confidence and disposal advice; and (6) checks the result in My History or views the community leaderboard. The chatbot provides an additional text-based channel for waste-disposal questions.

5. IMPLEMENTATION DETAILS

The project report specifies Python 3.10, TensorFlow/Keras, NumPy, Pandas, Matplotlib, OpenCV and Scikit-learn for model development, with Flask connecting the model to the web application. The frontend is implemented using HTML, CSS and JavaScript. The supplied database screenshots demonstrate the use of MongoDB Atlas for application records. The screenshots do not provide enough information to reproduce the full database schema, deployment configuration or security controls.

The interface demonstration uses a photograph of a battery. The result screen displays E-Waste with 87% confidence and shows probability values of 87% for E-Waste, 3% for Non-Recyclable and 10% for Recyclable. The same screen awards 15 eco-points and displays a first-scan badge. This is a single illustrative output from the interface; it is not a statistical evaluation of the three displayed classes.

The application also displays a leaderboard with example user point totals, a history entry for a previous E-Waste scan and a chatbot response about disposal. These screenshots demonstrate the presence of the respective interface components. They do not establish long-term user engagement, improved recycling behaviour, chatbot factual accuracy or performance under concurrent traffic.

6. EXPERIMENTAL RESULTS AND DISCUSSION

6.1 Test-set performance

The quantitative evaluation available for this paper concerns the binary MobileNetV2 experiment. The independent test set contains 4,512 images: 2,513 organic (biodegradable) images and 1,999 recyclable images. The confusion matrix is interpreted with actual classes as rows and predicted classes as columns. Of the 2,513 organic images, 2,245 were correctly classified as organic and 268 were predicted as recyclable. Of the 1,999 recyclable images, 1,908 were correctly classified as recyclable and 91 were predicted as organic.

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Table 2. Confusion matrix of the MobileNetV2 model on the test set.

Actual class	Predicted: Organic	Predicted: Recyclable	Total
Organic	2,245	268	2,513
Recyclable	91	1,908	1,999
Total	2,336	2,176	4,512

The model correctly classified 4,153 of 4,512 images, giving an accuracy of 92.04%. Table 3 presents the class-wise precision, recall and F1-score reported in the original project record.

Table 3. Class-wise precision, recall and F1-score on the test set.

Class / Metric	Precision	Recall	F1-score	Support
Organic / biodegradable	0.96	0.89	0.93	2,513
Recyclable	0.88	0.95	0.91	1,999
Macro average	0.92	0.92	0.92	4,512
Overall accuracy	—	—	92.04%	4,512

The results indicate higher recall for recyclable waste (0.95) than for organic waste (0.89). Recyclable precision is 0.88, indicating that some organic samples were incorrectly assigned to the recyclable category. In a practical sorting environment, this type of error may contaminate a recycling stream. The supplied evidence does not include a reviewed error-analysis set, so the visual causes of these misclassifications cannot be confirmed.

6.2 Interpretation of the application output

The E-Waste screenshot demonstrates that the current interface can display three class probabilities and present a disposal instruction for a battery image. Its 87% displayed confidence is an example prediction only. It must not be combined with the 92.04% binary test accuracy or interpreted as a measured three-class result. A separate e-waste test dataset, confusion matrix and per-class evaluation are needed.

6.3 Overall discussion

The binary experiment shows that the selected MobileNetV2 model can distinguish organic and recyclable images with 92.04% test accuracy on the reported dataset. The application adds practical features around the classifier, including disposal guidance, scan history and points-based engagement. However, public-dataset performance may not fully represent photographs captured in homes, streets or collection centres. Changes in lighting, camera angle, background, object damage and mixed materials may affect predictions. Real-world evaluation is therefore necessary before the system is used for operational waste decisions.

7. APPLICATION SCREEN ANALYSIS

Figures 1–7 analyse the supplied SortWise screenshots. They document application workflows and interface behaviour; they are not substitutes for model-performance measurements.

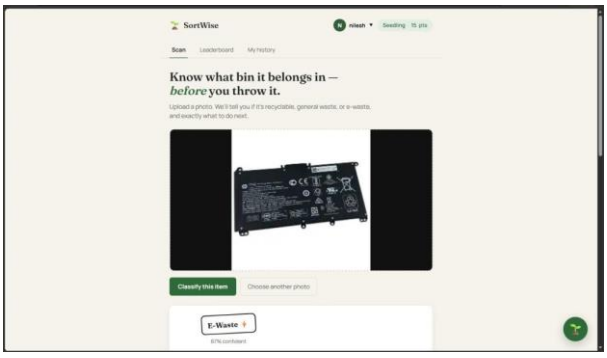


Fig. 1. SortWise Scan page showing image selection before classification.

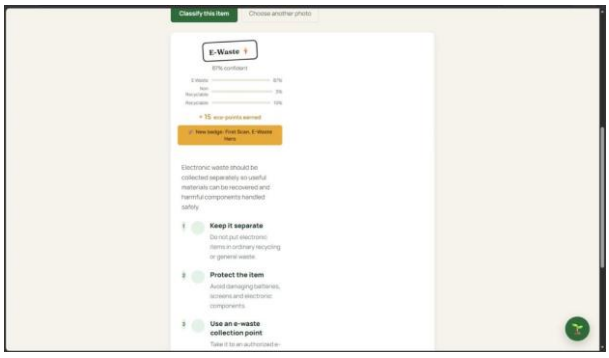


Fig. 2. Example E-Waste result with displayed confidence, class probabilities, eco-points and disposal guidance.

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8. LIMITATIONS AND FUTURE WORK

The study has several limitations. First, the reported quantitative evaluation covers two classes, whereas the latest interface displays three labels. Second, a complete dataset manifest, source-wise image counts and reproducible split information are not available in the supplied project record. Third, the test set is based on public image collections; performance on photographs captured in real disposal environments has not been established. Fourth, a single-image classifier does not demonstrate detection of multiple objects in one scene. Fifth, the displayed confidence value should not be treated as a guarantee of correctness. Finally, the screenshots do not establish the application's security, scalability or reliability under real multi-user load.

Future work should create and freeze a clearly documented three-class dataset with adequate e-waste, non-recyclable and recyclable examples. The three-class model should be evaluated on an independent test set using a confusion matrix, perclass precision, recall and F1-score, macro-F1 and confidence calibration. Testing should include images captured using different mobile devices and under varied lighting and backgrounds. Further improvements may include multi-object detection, more detailed material categories, uncertainty-based rejection, locally verified disposal guidance, stronger database access controls and performance testing under concurrent requests.

9. CONCLUSION

This paper presented SortWise, a web-based waste-classification application that connects image-based prediction with disposal guidance and user-engagement features. The available experimental record reports 92.04% accuracy and a macro F1-score of 0.92 for a MobileNetV2 model evaluated on 4,512 images in a binary organic/recyclable task. The supplied application screenshots additionally demonstrate a three-label result interface, account access, scan history, an eco-points leaderboard and a disposal assistant. The distinction between measured model performance and interface functionality is essential: the binary test metrics do not validate the three-category interface. The next research step is to train and independently evaluate a three-class model that includes e-waste, then test the complete application using real-world photographs and locally verified disposal instructions.

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