

Waste Opportunity Engine: Literature Survey and Proposed System

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Abstract: *Waste management guidance for ordinary people usually stops at two choices: throw it away or recycle it. This paper surveys the research that a system like the Waste Opportunity Engine builds on and then presents the proposed system. The survey covers four areas: (1) the scale of the global waste problem, (2) circular economy thinking, which ranks reuse, repair and upcycling above disposal, (3) deep-learning methods for recognising items and materials from images, and (4) text-based (NLP) analysis for matching descriptions to stored solutions. The studies are compared in a literature review and grouped by theme. The survey finds that existing work is strong at classifying waste but largely stops there: it does not recommend ranked reuse, repair, upcycle and business options for an individual item. To address this gap, the proposed system accepts an item photo, a short text description, or both. A convolutional neural network identifies the item, material and condition, an NLP module extracts keywords from the text, and a condition-aware decision engine queries an SQL database of curated solutions to return ranked options, step-by-step guidance and a business idea. Each analysis is stored so that the solution database can improve over time*

Keywords: Waste Classification; Circular Economy; Convolutional Neural Networks; Transfer Learning; Upcycling; Repair and Reuse; Recommendation; NLP; Decision-Support System

I. INTRODUCTION

The world generates billions of tonnes of municipal solid waste every year, and the amount is still rising. Much of what is thrown away still has value: furniture that needs a new joint, clothes that could be remade, or materials that could become a small product. Households rarely know these options, so useful items end up in landfill.

This paper answers one question: what has already been done on identifying waste and guiding people toward better use of it, and what is still missing? The review covers (a) waste-scale studies, (b) circular economy and upcycling literature, (c) image-based waste and object classification, and (d) text processing for keyword extraction. It focuses on foundational and widely cited work that supports the project's technology choices: a CNN for images, NLP for text, and an SQL database of solutions. Based on the gaps found, a proposed system is described in Section VI.

II. SURVEY METHOD

A. Search Strategy

Keywords were combined as topic + method + application, for example “waste classification” + “CNN”, “circular economy” + “upcycling”, and “TF-IDF” + “text retrieval”. Sources included Google Scholar, IEEE Xplore, ACM Digital Library, ScienceDirect, and publications from the World Bank and the Ellen MacArthur Foundation.

B. Selection Criteria

Papers were included if they were peer-reviewed or from a recognised institution, were widely cited or foundational, and were relevant to waste recognition, circular economy practice or text-based matching. Papers were excluded if they were off-topic or gave no usable method or result. Selected works were compared according to their key finding and limitation and grouped into six themes.



III. LITERATURE REVIEW BY THEME

A. The Scale of the Waste Problem

The World Bank's What a Waste 2.0 [4] estimates that the world generated about 2.01 billion tonnes of municipal solid waste in 2016. It projects growth to about 3.40 billion tonnes by 2050 if no action is taken, and notes that at least a third of this waste is not managed in an environmentally safe way. It shows why better item-level guidance matters, but it works at city and country level and does not help an individual decide what to do with one object.

B. Circular Economy, Reuse, Repair and Upcycling

The Ellen MacArthur Foundation [5] argues for designing out waste and keeping products and materials in use for as long as possible, instead of the linear take-make-dispose model. Stahel

[7] describes the circular economy as a way to keep goods in use through reuse, repair and remanufacturing. Geissdoerfer et al. [8] review the concept and its links to sustainability. Bocken et al. [9] describe business-model strategies, such as slowing and closing resource loops, that make these ideas commercially workable. Sung [10] reviews the upcycling literature and notes that research on practical, consumer-level upcycling guidance is still thin.

Together these works justify the order of preference the project uses (reuse and repair before recycling) and support the business-idea output. Most are conceptual or policy-oriented; none provides a software tool that applies the principles to a single item a user photographs.

C. Deep Learning for Image Recognition

Krizhevsky et al. [1] showed that a deep CNN trained on about 1.2 million ImageNet images across 1,000 classes could cut recognition error sharply compared with earlier methods, making CNNs the standard approach for image-based feature extraction. He et al. [2] introduced residual networks (ResNet), whose skip connections allow very deep models (up to 152 layers) to be trained effectively, and which won the ILSVRC 2015 classification task.

Training a large CNN from scratch needs a lot of labelled data. Pan and Yang [11] survey transfer learning, where a model trained on a large dataset is adapted to a smaller one; this is the practical route for a student project with limited waste images. Lightweight architectures such as MobileNets [12] allow image models to run on phones and modest servers, which supports the future scope of a mobile camera scan.

D. Waste-Specific Classification and Datasets

Yang and Thung [3] built the TrashNet dataset, about 2,500 photos of single items in six categories (glass, paper, cardboard, plastic, metal and general trash). A support vector machine on hand-crafted features outperformed their CNN on this small dataset, showing how strongly deep models depend on data volume. Adedjei and Wang [13] combined a pre-trained ResNet-50 feature extractor with an SVM classifier for waste sorting, supporting the transfer-learning approach. Proença and Simões [14] released TACO, a dataset of waste photographed in real-world scenes with object-level annotations, addressing the limitation that TrashNet images are clean and uncluttered.

These works confirm that waste type can be recognised from photos. Their labels, however, are mainly material or recyclability classes. They do not record the condition of an item (working, repairable or badly damaged) or what the item is (chair, bottle, phone), and condition is what decides between repair, reuse and recycling.

E. Text Analysis for Descriptions

Salton and Buckley [15], the basis of TF-IDF, show how to identify the most informative words in a text and match them against stored documents. Toolkits such as NLTK [16] provide tokenisation, stop-word removal and stemming. Keyword extraction followed by matching against a database is a simple, explainable and low-cost design, and suits a system whose output must come from a curated set of solutions rather than free-form generation.

F. Challenges and Limitations in the Literature

- Data size and quality: small or clean datasets lead to weaker real-world accuracy [3], [14].
- Cluttered and mixed items are harder to classify [14].
- Missing condition information: datasets rarely label whether an item is repairable [3].
- Conceptual gap: circular economy work is mostly theoretical and policy-level [5], [7]–[10].
- No validation of business value: upcycling ideas are rarely tested against real markets [10].



IV. LITERATURE REVIEW

- [1] Krizhevsky et al. (2012): A deep CNN on ImageNet sharply cut recognition error and became the basis for image feature extraction. However, it needs large data and computing power.
- [2] He et al. (2016): Residual networks make it possible to train very deep models and provide a strong pre-trained backbone. However, they are heavy for small devices.
- [3] Yang and Thung (2016): TrashNet showed that waste type can be classified from photos. However, the dataset is small, has six classes and has no condition labels.
- [4] Kaza et al. (2018): The study shows waste rising toward about 3.4 billion tonnes a year by 2050. However, it works at national level, not item level.
- [5] Ellen MacArthur Foundation (2013): The report argues for keeping products and materials in use, which supports reuse, repair and upcycling. However, it is conceptual and gives no software tool.
- [7] Stahel (2016): Reuse, repair and remanufacture keep goods in use. However, the discussion is at policy level.
- [8] Geissdoerfer et al. (2017): The review covers the circular economy concept and its link to sustainability. However, it is a conceptual review.
- [9] Bocken et al. (2016): The study shows that resource loops can be made profitable through business strategies. However, the strategies are not tied to household items.
- [10] Sung (2015): The review finds that consumer upcycling guidance is under-studied. However, it is a review only and provides no tool.
- [11] Pan and Yang (2010): The survey shows that pre-trained models can be adapted to small datasets. However, this works best when source and target are similar.
- [12] Howard et al. (2017): MobileNets provide small, fast models for mobile use. However, there is some accuracy trade-off.
- [13] Adedeji and Wang (2019): ResNet-50 features with an SVM show that transfer learning works for waste. However, the work covers only broad waste categories.
- [14] Proença and Simões (2020): TACO provides real-scene waste data with annotations. However, it targets litter detection and gives no reuse guidance.
- [15] Salton and Buckley (1988): Term weighting (TF-IDF) finds informative words automatically. However, it ignores deeper sentence meaning.
- [16] Bird et al. (2009): NLTK offers tokenisation, stop-word removal and stemming. However, it is rule-based with no deep semantics.

V. RESEARCH GAP

Existing studies have shown that waste can be recognised from images [1]–[3], [13], [14], that waste volumes are a serious global problem [4], and that circular economy practice favours reuse, repair and upcycling over disposal [5], [7]–[10]. However, limited attention has been given to combining these strands into one practical tool.

- Classification stops at the label: recognition work outputs a category such as plastic or paper, not what to do with the item.
- No condition-aware decisions: models rarely capture whether an item is working, repairable or damaged.
- No ranked options: users get one answer, not several practical choices ordered by usefulness.
- No step-by-step guidance: repair and reuse methods are not linked to detected items.
- Business value is not explored: upcycling and small-business ideas are discussed conceptually but not generated for an individual item.
- No learning loop: few systems store each analysis so the solution database improves over time.

To the best of this survey, no widely known work addresses all of these together. The proposed Waste Opportunity Engine addresses these gaps by combining image and text input with a condition-aware decision engine and a curated solutions database.



VI. PROPOSED SYSTEM

A. Overview

The Waste Opportunity Engine is a web-based decision-support system. A user uploads a photo of a waste item, types a short description, or does both. The system identifies what the item is, what it is made of and what condition it is in, and then returns ranked options: reuse or repair first, then upcycling, then recycling, together with a small-business idea and step-by-step instructions. All results come from a curated solutions database, so the output is explainable and controlled.

B. System Architecture

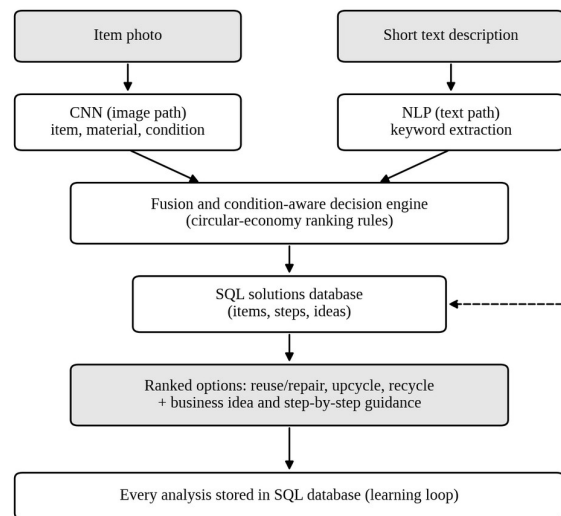


Fig. 1. Architecture of the Proposed Waste Opportunity Engine.

C. Modules

- Input Module: A Python Flask [6] web interface accepts an image, text, or both.
- Image Path (CNN): A pre-trained CNN (ResNet or MobileNet [2], [12]) is fine-tuned on waste images using transfer learning [11] to predict the item type, material and condition (working, repairable, damaged).

Input processing and output Decision core Inputs and storage

- Text Path (NLP): The description is tokenised, cleaned of stop-words and stemmed [16], and TF-IDF-style weighting [15] extracts the keywords used to look up matching items and materials.
- Fusion: When both inputs are given, the text confirms or corrects the image prediction; when only one is given, that path is used alone.
- Decision Engine: Rules based on the circular-economy hierarchy [5], [7] map item, material and condition to ranked options. A working item leads to reuse, a repairable one to repair, an unusable item with valuable material to upcycling, and the rest to recycling.
- Solutions Database (SQL): Tables hold items, materials, conditions, repair and reuse steps, upcycling ideas, business ideas and past analyses.
- Output Module: Displays ranked options, step-by-step guidance and a business idea for the item.
- Learning Loop: Every analysis is stored, so frequent items and weak matches can be reviewed and the solution database extended.



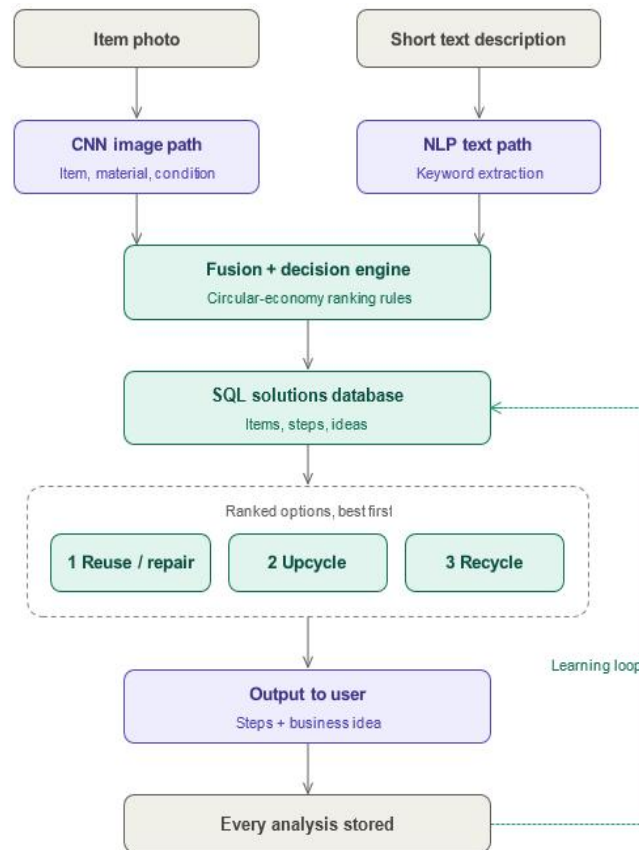


Fig. 1(b). Detailed Architecture Diagram of the Proposed Waste Opportunity Engine.

D. Workflow

The user submits a photo and/or description. The CNN and NLP paths run on their inputs, and the results are fused into one item, material and condition record. The decision engine queries the solutions database and the options are ranked by the circular-economy order. The user sees the steps and a business idea, and the analysis is saved for future improvement.

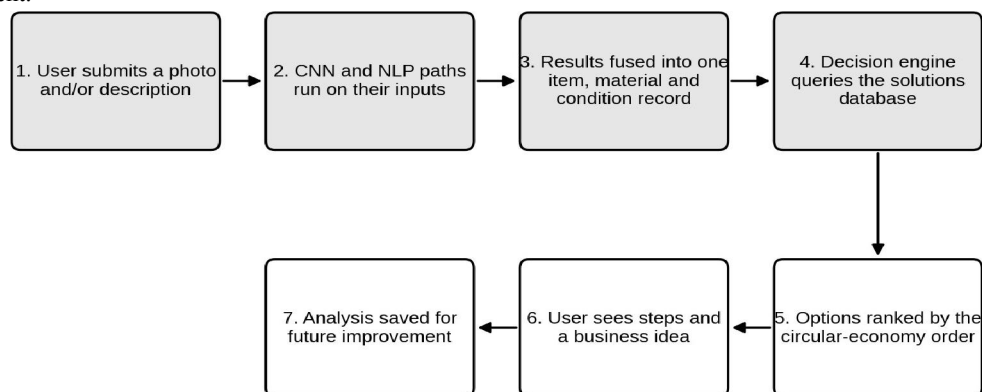


Fig. 2. Complete System Workflow of the Proposed System.



E. How the Proposed System Responds to the Literature

Literature Finding	Proposed System Response
CNNs and ResNet recognise images well [1], [2]	CNN image path identifies item, material and condition.
Transfer learning suits small datasets [11]	Start from a pre-trained model and fine-tune on waste images.
Waste datasets lack condition and context [3], [14]	Detect condition explicitly; test on varied real photos.
TF-IDF keyword extraction is simple and effective [15]	NLP text path with keyword extraction.
Circular economy ranks reuse and repair above disposal [5], [7]	Rank: reuse/repair, then upcycle, then recycle.
Business models can close resource loops [9]	Business-idea output for each item.
Systems should improve over time	Store every analysis in the SQL database.

F. Planned Evaluation

The image path will be evaluated with accuracy, precision, recall and F1-score for item, material and condition labels on a held-out set of varied real photographs. The text path will be checked for keyword-to-item matching accuracy. Usefulness of the ranked options will be judged through feedback from sample users on whether the top-ranked option was practical.

VII. EXPECTED OUTCOME

- Identify the item, material and condition from a photo, a text description, or both.
- Rank options as reuse or repair, then upcycling, then recycling, using circular-economy rules.
- Provide step-by-step guidance for the top-ranked option.
- Suggest a small-business idea for the item.
- Store every analysis so the solution database can be reviewed and extended.
- Provide a practical web-based decision-support tool for individual waste items.

VIII. DISCUSSION

The proposed system combines image recognition, text analysis and a curated solutions database in a single decision-support tool. The use of both a photo and a text description can provide complementary information, because the text can confirm or correct the image prediction.

Condition detection is important because it decides between repair, reuse and recycling, but existing datasets rarely label condition [3]. Because all output comes from a curated database, it is explainable and controlled, but its coverage depends on the items and solutions stored.

Therefore, dataset quality, cluttered images, solution coverage and validation of business ideas against real markets are important considerations.

IX. CONCLUSION AND FUTURE SCOPE

This survey shows a strong base of research on waste scale, circular economy principles, image recognition and text matching, but little work that joins them into a decision tool for individual items. Image classification is mature enough to build on, circular economy research gives a clear ranking of preferred options, and business-model research supports a commercial angle. What is missing is the layer that converts a detected item and its condition into ranked, practical, step-by-step options. The proposed Waste Opportunity Engine is designed to supply that layer.



Future scope includes a mobile camera scan, a marketplace for upcycled products, a finder for nearby repair shops and recyclers, and validation of business ideas against local market data.

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