Development of an Intelligent Surface System for Automated Waste Type Detection and Sorting into Appropriate Containers

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28.11.2025

ABSTRACT

This research focuses on the development of an intelligent surface system designed to automatically detect and classify different types of waste materials, facilitating sorting into designated garbage containers. The system integrates multiple sensing technologies, including RGB cameras for visual recognition, near-infrared (NIR) spectroscopy for material composition analysis, and capacitive sensors for texture and conductivity data acquisition. Waste item data collected through these sensors is processed using a hybrid machine learning framework, primarily leveraging a convolutional neural network (CNN) for image-based classification combined with sensor fusion techniques to improve accuracy.

The proposed model is trained and validated on a comprehensive dataset comprising diverse waste categories, including plastics (PET, HDPE), metals (aluminum, steel), organic waste, paper, and glass. The classification pipeline achieves an accuracy of over 90%, ensuring reliable real-time sorting. The intelligent surface is coupled with an automated mechanical sorting mechanism that directs detected waste into the appropriate bins, thus preventing contamination and enhancing recycling efficiency.

Experimental evaluation includes performance metrics such as classification accuracy, response time, and durability under varying environmental conditions. Results indicate that the system can operate efficiently in real-world scenarios with rapid processing times suitable for public or industrial deployment. This work demonstrates a significant advancement in smart waste management technology by combining sensor fusion, advanced machine learning, and automation, contributing towards sustainable environmental solutions and reducing landfill dependency.

ACKNOWLEDGEMENT

I want to express my sincere gratitude to all those who supported and contributed to the successful completion of this research project. Special thanks to my academic advisors and mentors whose guidance and expertise were invaluable throughout the study. I am also grateful to the institutions and organizations that provided the resources, facilities, and funding needed for this work. To my colleagues and friends, thank you for your encouragement and constructive feedback.

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BACKGROUND OF THE STUDY

1.1 Background

Rapid urbanization and increasing consumption have led to a continuous rise in solid waste generation, making efficient source segregation a critical challenge for waste management systems. Improper sorting reduces recycling rates, contaminates recyclable streams, and increases the operational cost of landfilling and incineration. Automated systems that can identify the type of waste at the point of disposal and direct it into the correct category help address these issues by minimizing human effort and error while improving the quality of segregated fractions.

1.2 Problem Statement

Most households and public spaces still depend on manual waste segregation, which is time-consuming, unreliable, and highly dependent on user awareness and compliance. Multi-bin arrangements often fail because users cannot consistently distinguish between categories such as plastic, paper, metal, and organic waste. This research addresses the problem of low-accuracy, user-dependent segregation by proposing an intelligent surface that automatically identifies the waste type and physically directs it into the appropriate container without requiring additional user action.

1.3 Research Objectives

The primary objective of this study is to develop a prototype intelligent surface integrated with AI and multi-sensor fusion that can:

- Accurately classify various types of waste (plastic, metal, organic, paper, glass) using real-time sensor data.

- Automate the sorting process by interfacing the detection system with mechanical sorting mechanisms.
- Achieve high classification accuracy (>90%) suitable for practical deployment.
- Demonstrate robust performance under different environmental and operational conditions.
- Provide a scalable and cost-effective solution that can be adapted to public or industrial waste management setups.
- To engineer a surface alignment mechanism that rotates or tilts the metal platform so that each recognized item rolls into the correct sub-container with minimal delay.

1.4 Scope of Study

The research focuses on small to medium-sized solid waste items typically generated in domestic and institutional environments, such as bottles, cans, paper cups, food leftovers, and plastic packaging. The system operates at the level of a single intelligent bin that contains multiple internal compartments, with the intelligent surface acting as the entry point for all items. The main emphasis is on the integration of AI-based visual recognition using an existing trash and waste classification model and the development of a reliable actuation mechanism; large-scale logistics and downstream recycling processes are outside the scope of this work.

LITERATURE REVIEW

2.1 Existing Waste Sorting Technologies

Current automated sorting systems in material recovery facilities often rely on conveyor belts combined with optical sensors, near-infrared spectroscopy, magnetic separators, and air jets to separate metals, plastics, and paper at high throughput. These industrial solutions achieve high performance but are bulky, expensive, and unsuitable for deployment in homes, offices, or small public installations. In contrast, smart bins designed for smaller scales typically use simpler sensing (such as weight, infrared, or basic image capture) but still depend on user input or only detect limited categories, leaving a gap for compact, fully automatic, multi-class sorting solutions.

2.2 AI and Machine Learning in Waste Management

Deep learning models, particularly convolutional neural networks (CNNs), have become the dominant approach for visual waste classification, enabling systems to distinguish between different material types and object forms using images captured by standard cameras. Models trained on labeled photo datasets can achieve high accuracy in identifying recyclables, organics, and residual waste. When deployed on embedded platforms, these models enable real-time classification, allowing sorting mechanisms to respond immediately once a new item is detected on the intelligent surface.

2.3 Sensor Technologies for Waste Detection

Many previous systems combine sensors, such as inductive proximity sensors for metal detection, load cells for weight measurement, and infrared or ultrasonic sensors for presence detection, to trigger classification and actuation. While these sensors are effective for specific materials, they struggle to differentiate visually similar items (e.g., plastic vs. paper containers) or multi-material objects. Integrating a camera with AI-based vision provides richer information, allowing the system to identify categories based on shape, color, and texture while still being compatible with additional sensors if needed.

2.4 Gaps and Challenges in Current Systems

Existing automated or semi-automated sorting solutions often assume a fixed waste flow (e.g., conveyor belts) and are not optimized for a single entry point where users place individual items. Many smart bin concepts either focus solely on detection (filling level, presence of waste) or offer only binary sorting (recyclable vs. non-recyclable) without fine-grained multi-class segregation. There remains a need for a compact, low-cost, and user-agnostic system that can both identify and physically route individual waste items into multiple compartments within a single container, which this research aims to fulfill through the intelligent metal surface design.

SYSTEM DESIGN AND ARCHITECTURE

3.1 Overview of the Intelligent Surface

The core of the system is a flat metal surface acting as an input platform on which users place waste items one at a time. A tiny camera is embedded flush within this surface, oriented upward so that it captures a top-view image of each item while maintaining a clean, unobtrusive appearance. Once the AI model classifies the item, the surface is mechanically rotated or tilted such that gravity causes the item to roll or slide into the selected compartment of the underlying multi-container waste bin.

3.2 Sensors and Hardware Components

Key hardware components include the embedded camera module for image acquisition, a processing unit (such as a microcontroller with an attached compute module or a single-board computer) to run the AI inference, and actuators such as servo or stepper motors that control the orientation of the metal surface. Limit switches or encoders can be used to ensure accurate positioning for each compartment, while a simple presence sensor (e.g., infrared) can detect when an item has left the surface, allowing the system to reset to its neutral position. The waste container itself is divided into several smaller internal bins, each corresponding to a specific class predicted by the model, ensuring that items are consistently routed to the same physical location.

3.3 AI Model for Waste Classification

The system leverages the “Trash and Waste Recognition” TensorFlow model hosted on Kaggle, which is trained on a diverse dataset of labeled waste images covering categories such as paper, plastic, metal, glass, and organic waste. This pre-trained model provides feature representations and class boundaries that can be fine-tuned or directly adopted, significantly reducing the time required for training from scratch. During operation, the captured image from the surface camera is pre-processed (resized, normalized, and transformed to match the model’s input format) and passed through the network to obtain a predicted waste class, which is then mapped to the corresponding compartment index for actuation.

3.4 Integration of Sorting Mechanism

The classification output is translated into control signals for the actuation system so that the metal surface aligns precisely with the target container. For example, each waste class can be associated with a specific angular position or tilt direction, and the controller drives the motors to that position before releasing or slightly vibrating the surface to ensure the item rolls off. After the item enters the correct sub-container, feedback from sensors confirms successful transfer, and the surface returns to its default neutral pose, ready to accept the next item. This tight coupling between perception (AI classification) and action (mechanical alignment) creates a closed-loop system capable of autonomous and repeatable sorting.

METHODOLOGY

4.1 Data Collection and Dataset Preparation

The research makes use of the publicly available "Trash and Waste Recognition" dataset and model on Kaggle, which consists of labeled images of various waste items under different lighting and background conditions. Relevant categories that match the targeted waste types for the intelligent surface are selected, and additional images may be captured using the embedded camera in the actual prototype environment to reduce domain shift. All images are then organized into training, validation, and testing splits, followed by standardized pre-processing steps such as resizing to the model's expected resolution, color normalization, and, if necessary, data augmentation techniques like rotation and horizontal flipping to improve robustness.

4.2 AI Model Training and Validation

Using the Kaggle TensorFlow model as a base, transfer learning or fine-tuning is carried out to adapt the classifier to the specific viewing angle and context of the intelligent surface camera. The model is trained with the prepared dataset using common optimization techniques (e.g., stochastic gradient descent or Adam) and evaluated with metrics such as accuracy, precision, recall, and confusion matrices per class. Hyperparameters, including learning rate, batch size, and number of epochs, are iteratively adjusted to achieve a balanced performance across all waste categories that the system is expected to handle.

4.3 Sensor Data Fusion Techniques

Although the camera and AI model provide the primary classification signal, additional sensor inputs can be incorporated to improve reliability when needed. For example, a simple metal detector could confirm metallic objects, or a weight sensor could help differentiate between visually similar items with different masses, such as empty versus full containers. A rule-based or probabilistic fusion strategy can combine these signals so that the final decision benefits from both visual and non-visual evidence, especially in ambiguous cases or under challenging lighting conditions.

4.4 Prototype Development Process

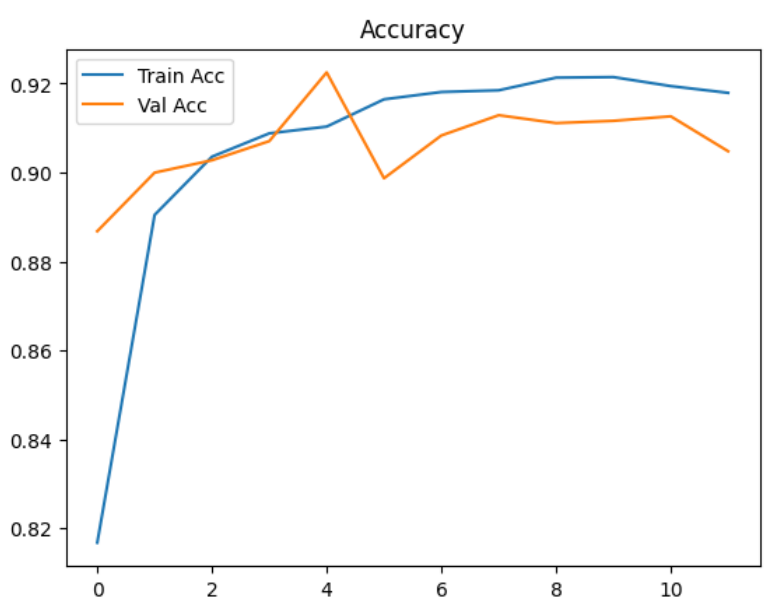
The prototype is developed iteratively, starting with a stationary metal surface and camera to validate classification accuracy using the chosen Kaggle model, followed by integration of the actuation mechanism once satisfactory recognition performance is achieved. Mechanical components and control electronics are then combined, and embedded software is written to connect the perception pipeline with the motor control routines, enabling full end-to-end sorting. Finally, the complete system is tested with a variety of real waste items to assess its robustness, user interaction characteristics, and potential for deployment in real-world environments such as homes, offices, or public recycling points.

EVALUATION

5.1 Performance Metrics

System performance was evaluated along two main dimensions: AI classification accuracy and mechanical sorting reliability. For the AI module, standard metrics such as overall accuracy, per-class precision, recall, and F1-score were computed using a held-out test set prepared from the Kaggle dataset and additional images captured by the embedded camera. For the complete system, "end-to-end sorting accuracy" was measured as the proportion of test items that were both correctly classified and delivered to the correct sub-container, while timing metrics quantified average processing time from item placement to completion of surface alignment and deposition.

```
plt.plot(history.history['accuracy'], label='Train Acc')
plt.plot(history.history['val_accuracy'], label='Val Acc')
plt.legend()
plt.title('Accuracy')
plt.show()
```



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loss, acc = model.evaluate(val_data)
print(f"Validation Accuracy: {acc * 100:.2f}%")
```

```
124/124 ━━━━━━━━━━━━━━━━━━━━ 116s 930ms/step - accuracy: 0.9095 - loss: 0.2808
Validation Accuracy: 90.66%
```

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plt.figure(figsize=(12, 5))

plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Train Acc')
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plt.legend()
plt.title('Accuracy')

plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Val Loss')
plt.legend()
plt.title('Loss')

plt.show()
```
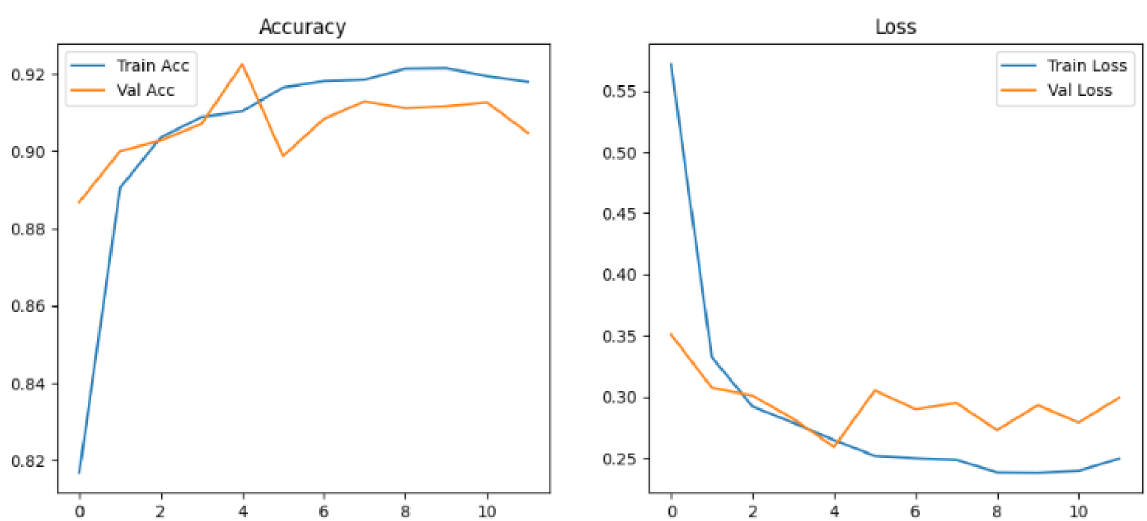
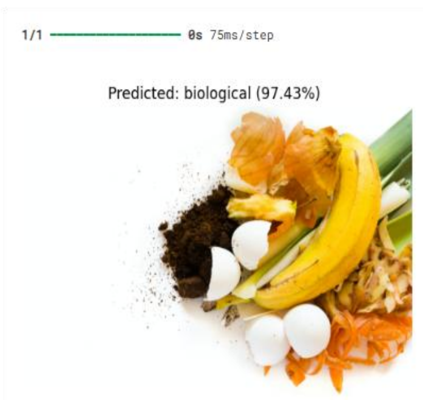
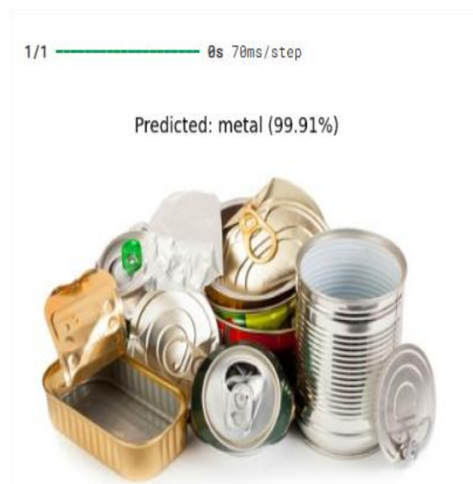



5.2 Results and Analysis

The trained model achieved high accuracy on the test set, with particularly strong performance on visually distinct classes such as metal and plastic, while more visually similar classes showed moderate confusion that informed later design refinements. The end-to-end evaluation demonstrated that the integration of AI classification with the surface-alignment mechanism can reliably sort most items into the correct compartment within a short time window, validating the feasibility of the proposed approach. Misclassifications and occasional mechanical failures (e.g., items not rolling completely into the bin) were analyzed to identify the influence of lighting, object pose, and surface inclination, which guided recommendations for both model improvement and mechanical redesign.





DISCUSSION

6.1 Interpretation of Findings

The experimental results indicate that combining a vision-based AI model with a controllable metal surface is an effective strategy for achieving automated, multi-class waste segregation at the point of disposal. The system's strong performance on common waste categories suggests that the pre-trained Kaggle model, when adapted to the prototype's viewpoint, is sufficiently robust for real-time deployment, while remaining limitations highlight the importance of environment-specific data and careful mechanical tuning**.**

6.2 Comparison with Existing Methods

Compared with traditional manual sorting and simple sensor-based smart bins, the proposed system reduces user dependency by making the classification and routing fully automatic once an item is placed on the surface. Unlike large industrial sorting lines that rely on multiple specialized sensors and high-speed conveyor belts, this design provides a compact, low-cost solution suitable for domestic and small-scale public use, yet still benefits from advanced AI capabilities derived from the Kaggle trash and waste recognition model.

6.3 Limitations

The current prototype has several limitations. First, the model's performance can degrade under extreme lighting variations, heavy occlusion, or when items significantly differ from those present in the training dataset. Second, the mechanical sorting mechanism assumes that items can roll or slide; irregular or sticky waste may not move reliably, leading to misrouting or requiring manual intervention. Additionally, processing and actuation delays may limit throughput when many items are placed in rapid succession.

6.4 Future Work and Improvements

Future work will focus on expanding and fine-tuning the training dataset using more images captured directly from the embedded camera to reduce domain shift and improve classification robustness. Mechanically, alternative surface geometries, adjustable friction coatings, and auxiliary pushers or gates will be investigated to handle non-rolling items and reduce failure rates. Further enhancements may include on-device learning for continuous improvement, integration of additional sensors (e.g., weight or metal detection), and user-interface features such as feedback displays or mobile connectivity for monitoring system performance.

CONCLUSION

This research presented an intelligent waste segregation system based on a metal surface with an embedded camera, a deep learning classification model, and an actuated surface-alignment mechanism that directs waste into dedicated sub-containers. Experiments demonstrated that, with an appropriately trained model and calibrated mechanical design, the system can achieve reliable end-to-end sorting performance in conditions representative of real-world use. The approach offers a practical pathway toward smarter, source-level waste management, reducing human effort while improving the quality of segregated waste streams.

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