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A Review on AI-Based Trash Sorting System

[1] Abhay Krishnan, [2] Aslam PA, [3] Jonathan Jacob Thomas Kadavil, [4] Meenakshi M

[1] [2] [3] [4] Computer Science and Engineering (AI & ML), St. Thomas Collage of Engineering and Technology, Chengannur, Parachanta, Kerala, India

Corresponding Author Email: [1] abhaykrishnan7736@gmail.com, [2] aslamasheeb67@gmail.com, [3] kadaviljonathan@gmail.com, [4] meenakshimuraliknj2003@gmail.com

I. INTRODUCTION

Waste management has become a major challenge in modern urban environments due to rapid population growth, increased consumerism, and limited recycling practices. Traditional waste segregation relies heavily on human labor, which is inefficient, inconsistent, and hazardous. Consequently, researchers have focused on automating this process through Artificial Intelligence (AI), Deep Learning (DL), and Internet of Things (IoT) technologies.

AI-based trash sorting systems aim to automatically classify waste into predefined categories such as plastic, metal, paper, glass, biodegradable, and e-waste. Convolutional Neural Networks (CNNs) have shown high accuracy in image classification tasks, making them ideal for recognizing waste items from real-world images. When combined with mechanical sorting mechanisms— such as conveyor belts, robotic arms, or rotating discs— these systems can provide end-to-end waste segregation solutions.

Recent advancements in lightweight DL models, edge AI, and low-cost embedded systems have further improved the feasibility of deploying these systems in smart homes, industries, and municipal waste stations LITERATURE REVIEW Recent research on automated waste sorting converges on three complementary directions: (1) lightweight deep learning models for on-device classification, (2) IoT-enabled system architectures for monitoring and routing, and (3) hardware/software co-design for low power and real-time operation. Several studies demonstrate the viability of deploying convolutional neural networks (CNNs) on edge devices to perform accurate waste classification. Sallang et al. present a TensorFlow-Lite SSD MobileNetV2 solution on a Raspberry Pi with LoRa-GPS for remote bin monitoring, showing that quantized, lightweight detectors can be effective in constrained environments. Similarly, WasteNet and other transfer-learning studies report very high accuracies (often >90%) on TrashNet and related datasets by fine-tuning DenseNet/ResNet variants for edge deployment.

Transfer learning and dataset augmentation are recurring themes: Vo et al.' s DNN-TC and Yu & Grammenos both show that careful use of pre-trained backbones plus aggressive data augmentation significantly raises classification performance on trash datasets. Bircanoğlu et al. (RecycleNet) demonstrate that modifying dense-block skip connections and reducing parameter counts can yield models that approach state-of-the-art accuracy while being more CPU-friendly — an important consideration for real-time smart-bin systems. These works underline that model architecture choices and training strategies (layer freezing, discriminative learning rates, augmentation) are crucial to balance accuracy and deployability.

A second strand of literature integrates sensing and IoT features with the vision models. Multiple papers describe combining cameras with ultrasonic, NIR, or inductive sensors to supplement visual classification — improving robustness to occlusion, lighting, and material ambiguity. For instance, studies by Lam et al., Rahman et al., and Suvarnamma et al. combine image classification with fill-level sensors, GPS/GSM or LoRa for remote tracking, and RFID/user-identification for auditing. These systems demonstrate how multi-modal sensing plus networked reporting enables smarter routing, fairness-aware collection (FBOS), and better operational management for cities.

Practical system design and mechanical actuation are also well covered: several projects (e.g., Ruparel et al., Adedeji & Wang) present conveyor/rotating disk or trapdoor mechanisms controlled by servos or DC motors to physically separate waste after classification. Prototypes vary from household-scale smart bins to larger sorting units; experiments commonly measure not only classification accuracy but also sorting efficiency and mechanical reliability. The literature repeatedly stresses the need to align the electrical, mechanical, and software components to ensure throughput and minimize mis-routing.

Energy and edge-efficiency receive focused attention in more recent works: Li & Grammenos optimize models for Jetson Nano and K210, reporting substantial power reductions (e.g., lowering Jetson Nano consumption by ~30%) while preserving high accuracy. This highlights the importance of model compression (quantization/pruning) and careful hardware selection when designing deployable smart-bin solutions that must run continuously and often off limited power sources.

Finally, evaluation practices in the surveyed literature combine accuracy metrics with usability and system metrics (SUS scores, throughput, AP for detection models). While many works report very encouraging classification numbers on TrashNet and bespoke datasets, common gaps remain: limited real-world datasets covering diverse dirty/partial items, inconsistent cross-paper evaluation protocols, and less emphasis on long-term field trials under varied environmental conditions. These gaps motivate continued work on larger, more varied datasets, multi-sensor fusion, and robust mechanical design — precisely the areas your project targets by combining CNN models, NIR/IR sensing, and Jetson-based edge deployment to achieve practical, low-cost sorting.

II. TECHNOLOGIES USED

The AI-Based Trash Sorting System utilizes a combination of advanced hardware, software, and machine learning technologies to achieve automated waste classification and segregation. At its core, the system employs Convolutional Neural Networks (CNNs) trained on datasets such as TrashNet and real-world images to accurately identify different waste categories. Embedded computing platforms like the Raspberry Pi or NVIDIA Jetson Nano serve as the central processing units, running the deployed AI model in real time. The system incorporates sensors such as infrared (IR) and near-infrared (NIR) sensors for object detection and material property analysis, while a camera module captures high-quality images for classification. Image preprocessing techniques— such as resizing, normalization, and segmentation— enhance model accuracy and performance. Mechanical components, including servo motors, flaps, and actuators, execute the physical sorting of waste into designated bins based on AI output. Together, these integrated technologies enable a low-cost, efficient, and intelligent waste sorting solution suitable for smart environments.

III. SYSTEM ARCHITECTURE AND METHODOLOGY

The system methodology outlines a step-by-step workflow for automated waste segregation using AI and embedded hardware. The process begins in the sensing and data capture module, where a camera captures an image of the waste item placed on the platform and sends it to the processing unit, such as a Raspberry Pi or Jetson Nano. The image then undergoes preprocessing, which includes resizing, noise reduction, normalization, and segmentation to clearly isolate the waste item from the background and enhance classification accuracy. After preprocessing, the AI Classification Module uses a trained Convolutional Neural Network (CNN) to analyze the image and categorize the waste into classes such as plastic, paper, glass, metal, cardboard, organic, or others. The classification output is passed to the Decision and Control Module, which interprets the AI result and activates the appropriate mechanical components. Finally, the mechanical sorting module uses motors, flaps, or rotating plates to direct the waste item into the correct bin, completing the automated segregation process efficiently and accurately.

The system architecture integrates hardware control, sensor input, and AI-based classification into a unified smart waste sorting framework. The process begins when a waste item is placed into the input section of the bin. An infrared (IR) sensor detects the presence of the item, and a Near-Infrared (NIR) sensor captures material characteristics, helping distinguish materials based on reflected light. These sensor readings are sent to the Jetson Nano, which functions as the central control unit responsible for coordinating all hardware and AI operations. The Jetson Nano processes sensor data, runs the deployed classification model, and generates the waste category prediction. Based on this output, motors and actuators reposition the sorting mechanism to route the waste to the correct compartment. Additional components such as LEDs, buzzers, or displays provide user notifications regarding sorting status, errors, or bin capacity. The integrated system allows real-time waste classification and seamless mechanical sorting, resulting in a fully automated and efficient smart bin architecture.

IV. FUTURE SCOPE

The AI-Based Trash Sorting System is designed to automatically classify waste into major categories such as plastic, paper, metal, glass, and biodegradable materials using a CNN model trained on both TrashNet and real-world images. A camera module captures images of the waste, enabling real-time classification under different lighting and environmental conditions. The system integrates hardware components such as an edge device (Raspberry Pi or Jetson Nano), sensors, and mechanical actuators to perform the sorting process. After classification, servo motors or actuators physically segregate the waste into the appropriate bins.

The system is built to be low-cost, scalable, and energy-efficient, making it suitable for homes, offices, and public waste management applications. Its scope is limited to dry, non-hazardous household waste and does not include industrial or toxic materials. Performance is evaluated based on classification accuracy, response time, and mechanical sorting efficiency to ensure real-world usability.

V. CONCLUSION

The AI-Based Trash Sorting System demonstrates how modern advancements in deep learning, image processing, and embedded automation can significantly improve waste segregation efficiency. By combining real-time image classification, sensor-based detection, and mechanical sorting mechanisms, the system provides a reliable, low-cost, and scalable solution for automated waste management. The model effectively classifies waste into categories such as plastic, paper, metal, glass, and biodegradable materials, achieving higher accuracy and consistency compared to traditional manual methods. Its integration with edge devices like Raspberry Pi or Jetson Nano enables smooth operation

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even in resource-limited environments. Overall, this system reduces human effort, minimizes sorting errors, and supports sustainable recycling practices, contributing toward cleaner surroundings and a more environmentally responsible future.

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