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Iot-Based Automated Waste Segregation System

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Abstract Waste segregation is an important step in recycling and responsible waste management. When different materials are mixed together, reusable items may become more difficult to recover and the quality of collected material can be reduced. Recent research has explored image-based waste classification using deep learning along with edge computing, sensors and mechanical sorting. This survey reviews ten recent research papers that address these areas. It organizes the literature by image classification, object detection, edge deployment, physical sorting, IoT monitoring, model efficiency and explainability. The studies use different datasets, waste categories and evaluation conditions. Their reported performance should therefore be understood in the context of each individual system. The review discusses shared challenges such as changing image conditions, differences in category definitions, limited training data and the gap between recognizing an item and sorting it correctly. It also outlines future research directions for more reliable and practical systems. The proposed project is presented only at a general level. Its hardware design, implementation status and test results are not assumed.

Keywords - Waste classification, automated segregation, deep learning, computer vision, edge computing, Internet of Things, smart waste management

1.INTRODUCTION

The volume and variety of solid waste create difficulties for households, institutions and municipal services. Different materials often enter the same waste stream even though they need different handling. Plastic, paper, metal, glass, food waste and electronic items have different recycling or disposal routes. If these materials are mixed together at the point of disposal, sorting becomes more difficult later in the process. Source segregation is therefore an important part of a broader waste-management system.

Manual sorting remains common in many settings. It can be slow when large numbers of items must be handled and the result may vary between workers or operating conditions. Some items are dirty, crumpled, partly hidden or made from more than one material. Such conditions make visual identification harder. The challenge is not only to distinguish one waste class from another. A working system must also respond safely and consistently after it has made a prediction.

Computer vision provides a way to analyze images of waste items. Earlier image-analysis approaches often used manually selected features such as colour, shape or texture. Deep learning methods instead learn useful visual patterns from labelled examples. When a camera and a suitable computing platform are available, these models can support classification close to the point where waste is placed. A motor or other mechanical arrangement can then act on the predicted class. Sensors and communication features may also provide bin-level information to operators.

Recent studies approach the problem from different directions. Some focus on classification accuracy and dataset construction [2], [5], [10]. Others connect a model to a physical sorting mechanism [1], [3], [4], [6]–[8]. Research on edge models considers the balance between prediction quality and computing resources [9]. Work on explainable AI examines whether a model relies on relevant parts of an image [10]. Together these studies show that automated waste segregation involves several connected tasks rather than a single classification model.

This paper surveys ten research studies published in 2026 that are relevant to AI-based waste classification and automated segregation. It groups them by method and system role. It compares their reported scope and identifies common limitations. The review is intended to support planning for a proposed waste-classification project. It does not claim that the project hardware has been built or that its performance has been measured. Project-specific design choices are kept general because the final categories, platform and mechanism have not been confirmed in the available material.

2. AI-Based Waste Classification and Segregation

An automated waste-segregation workflow generally includes image capture, item recognition, decision-making and physical handling. A camera provides an image, a model identifies a likely category and a control unit uses that prediction to select an action. The item may then be directed into a bin or handled by a robotic mechanism. Some systems add fill-level or environmental monitoring. The exact arrangement depends on whether the intended application is a small smart bin, a campus installation or a larger sorting line.

The reviewed papers do not all implement the same parts of this workflow. Several present classification models without a described physical sorting stage. Others report a complete

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prototype with sensors and motors. This difference matters when interpreting their results. A model score measures prediction on a specified dataset. A sorting score measures whether an item reached its intended destination. Both can be useful but they represent different outcomes.

2.1 Traditional Image Features

Before deep learning became common, image-classification systems often relied on hand-designed features. Colour can help distinguish certain materials when lighting and background are stable. Shape can support recognition of objects such as bottles or cans. Texture may provide information about the surface of paper, fabric or other materials. These features can be paired with conventional machine-learning classifiers.

Feature-based methods have practical advantages. They can be relatively small and may need less training data than a deep neural network. Their behavior can also be easier to inspect because the system relies on defined measurements. However waste items vary in appearance. A plastic package may be transparent, coloured, folded or covered by a label. Paper may be clean, printed, wet or torn. When lighting changes or objects overlap, a fixed feature set may not capture enough of the visual difference between classes.

The reviewed 2026 papers mostly emphasize deep-learning approaches rather than traditional feature engineering. This reflects the current research direction in the selected literature. It does not mean that classical features have no role. They may still be useful in low-cost systems or as a comparison baseline. A careful evaluation should determine whether a more complex model offers enough practical value for the target device and setting.

2.2 Deep Learning for Waste Classification

Deep-learning classifiers learn visual patterns from labelled images. A model is trained using examples for each waste category and then predicts the category of new images. Convolutional neural networks have been widely used because they can learn patterns from image pixels. Transfer learning can reduce the amount of training needed by starting from a model that has already learned general visual features.

Rusdan and Kuswayati use EfficientNet-B0 transfer learning in an AIoT waste-sorting system [1]. Their model recognizes plastic, paper, metal, glass and organic waste. The study reports 92.3% classification accuracy during its campus evaluation. Zhalgas *et al.* compare YOLOv8, DenseNet169 and ResNet50v2 using a self-collected dataset of 2,790 images across six categories [2]. The paper reports 92% overall accuracy for DenseNet169. These results are useful within their own datasets and conditions. They do not establish that either model would reach the same performance on a different set of images.

Partosan *et al.* use YOLOv8n on Raspberry Pi 5 for campus-scale recognition of paper, plastic, metal, food waste and electronic waste [5]. Their paper reports mAP50 of 0.990 on the evaluation dataset. The study focuses on classification deployment. A high detection or classification metric does not by itself show how a mechanical sorter would perform. That distinction should be retained when summarizing model-only research.

2.3 Object Detection Approaches

Image classification assigns a label to an image or crop. Object detection also identifies where an object appears by drawing a bounding box around it. Detection can be useful when the image contains a scene with more than one item or when the system needs to locate an object for physical handling. The model must both identify the category and estimate the object position.

Several reviewed studies use versions of the YOLO family. Oreke and Al Seyab combine YOLOv5 detection with ResNet50 classification as part of a six-class system [3]. Siyad *et al.* deploy YOLOv11n on Raspberry Pi 5 and group 19 image classes into four major sorting categories [4]. Chiliquinga-Toapanta *et al.* report a YOLOv11s model running on Jetson Nano in a system connected to an ESP32 [8]. These examples show how object detection can be combined with a separate classifier or used as the principal recognition model.

Detection scores must be interpreted according to the metric. Mean average precision measures aspects of detection quality under a stated threshold and class setup. It is not the same as simple classification accuracy or end-to-end sorting success. Papers should state the metric, test set, class distribution and threshold clearly. Without those details a numerical result is difficult to interpret or reproduce.

2.4 Waste Classes and Dataset Preparation

The choice of waste categories affects the entire system. A model can only predict categories represented in its training labels. The papers reviewed here use different class lists. Some distinguish paper, plastic, metal and glass. Others add cardboard, organic waste, electronic waste or hazardous materials [1]–[8]. Some systems combine several image classes into broader output groups. As a result, a category called “biodegradable” in one study may not correspond exactly to the classes used in another.

Dataset quality is also important. Images should represent the materials and conditions expected during use. A dataset gathered against a plain background may not reflect a bin environment with shadows, clutter or partially hidden items. Repeated images of the same object can also make a test set appear easier if similar examples occur in both training and testing. A sound evaluation separates data before augmentation and reports how the images were collected and labelled.

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Zhalgas *et al.* describe a self-collected dataset containing 2,790 images in six categories [2]. Siyad *et al.* report a much larger collection of 55,134 images across 19 classes before grouping them into four main outputs [4]. Shetty and Attigeri use the RealWaste dataset and report results across five random seeds [10]. These studies offer different data scales and methods. Dataset size alone does not determine generalization; diversity, balance, label quality and separation of training and test examples also matter.

2.5 Edge Computing and Embedded Deployment

Edge computing places some image processing on a device near the camera or bin. This can reduce reliance on a continuous connection to a remote server and may help a system respond locally. The device still needs enough processing power, memory and storage to run the model and control attached hardware.

Rusdan and Kuswayati deploy EfficientNet-B0 on Raspberry Pi 4 [1]. Partosan *et al.* and Siyad *et al.* use Raspberry Pi 5 for YOLO-based recognition [4], [5]. Sabu *et al.* also describe a YOLOv8 smart dustbin running on Raspberry Pi 5 [6]. Chiliquinga-Toapanta *et al.* use Jetson Nano as the vision platform and connect it with an ESP32 for sensing and actuation [8]. These examples provide reference points for embedded system design but do not prove that one board will suit every project.

Deployment involves practical trade-offs. A larger model may be more accurate on a given dataset but may run more slowly or require more memory. A smaller model may respond faster but could miss difficult items. The camera, lighting and image resolution also affect processing needs. A platform should therefore be selected after measuring model performance on the intended device rather than from desktop results alone.

2.6 Mechanical Sorting Mechanisms

After recognition, an automated system needs a method to move an item into the selected container. Some prototypes use a rotating base or compartment selector. Others use flaps, gates or a robotic manipulator. The mechanism should accommodate the size, shape and weight of the intended items. It also needs a predictable way to respond when an image is unclear or the predicted class is outside the supported list.

Rusdan and Kuswayati describe servo-based sorting and report a 94.5% mechanical sorting success rate [1]. Oreke and Al Seyab integrate an Arduino-controlled sorting module with the recognition pipeline [3]. Siyad *et al.* introduce a dual-axis actuator and report a YOLOv11n model with mAP50 of 90.17% [4]. Sabu *et al.* describe a rotating bin and servo-operated flap in their smart dustbin system [6]. These systems show different mechanical approaches and should not be treated as interchangeable designs.

An integrated evaluation should separate recognition errors from actuation or placement errors. If the model predicts the wrong class, the item may be sent to the wrong bin even if the mechanism works as designed. If the class is correct but the object slips or jams, the final sorting result can still be incorrect. Reporting both stages can help explain where a system needs improvement.

2.7 Robotic Sorting Platforms

Robotic sorting uses a manipulator to pick up and place waste items. Compared with a fixed gate or rotating compartment, a robot can potentially reach objects at different positions. It also requires more control, coordination and mechanical setup. The item must be visible, reachable and stable enough to grasp.

Prakash *et al.* describe a vision-enabled robotic platform that combines a YOLOv8-based perception pipeline with a Raspberry Pi 5, Arduino Uno, sensors and a SCORBOT-ER 4U arm [7]. They report an overall sorting accuracy of approximately 81.8% across their test batches. The study is valuable for its integration of perception and handling. Its reported result should be read with the platform and test conditions in mind. The article also describes an educational-grade setup and notes limits for continuous industrial use.

Robotic systems illustrate why evaluation should include physical behavior. A model can detect a bottle correctly but the robot may fail to grasp it. Position estimation, object orientation, gripping force and timing can affect whether the item is placed correctly. These factors make robotics research relevant to automated segregation while also making direct metric comparisons with smart-bin studies difficult.

2.8 Internet of Things and Monitoring

The Internet of Things can connect sensors, controllers and dashboards so operators can view system status. In a waste-management application, sensors may measure fill level or environmental conditions. A communication service can send alerts when a bin needs attention. These functions support operations around the sorting process but do not replace accurate recognition or reliable handling.

Rusdan and Kuswayati combine ultrasonic fill-level sensing with WhatsApp notifications [1]. Oreke and Al Seyab include ultrasonic sensing, temperature and humidity monitoring, GPS and a cloud dashboard [3]. Chiliquinga-Toapanta *et al.* describe a local Flask interface for displaying bin information [8]. Their reported prototype does not implement cloud connectivity or remote alerts. The difference between local monitoring and cloud-based monitoring should be made explicit when comparing systems.

IoT integration also introduces requirements for power, connectivity and data handling. A sensor reading can be inaccurate if the bin shape or waste surface interferes with measurement. A notification is only useful if it reaches the intended operator in time. Authors should report the monitoring method and its evaluation separately from image classification.

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This helps readers understand which functions were tested and which remain conceptual.

2.9 Lightweight Models and Resource Use

Model efficiency is important when waste recognition is performed on mobile or embedded hardware. Useful measures include parameter count, model size, memory use, inference latency and energy consumption. A system that produces a strong prediction but takes too long to respond may not fit a real-time task.

Kunwar compares EfficientNetV2, ResNet, MobileNet and YOLO variants for mobile and edge devices [9]. The paper reports a trade-off between classification performance and resource use. EfficientNetV2S reached about 96% accuracy in the reported evaluation but had higher latency and carbon emissions than some smaller detection models. Lightweight detection models achieved up to 80% mAP with inference near 0.03 seconds and model sizes below 7 MB. Quantization reduced model size and VRAM use by up to 75% in the described experiments.

These figures should be interpreted within Kunwar's own dataset and setup. They do not establish that the same model will be best for all waste categories or devices. A practical comparison should run candidate models on the target hardware and use the same test images. It should also report the trade-off between recognition performance and response time rather than selecting a model using one metric alone.

2.10 Explainability and Model Reliability

Deep-learning systems can be difficult to interpret because their predictions emerge from many learned parameters. A model may achieve a strong score while relying on background patterns that happen to correlate with a class in the training data. Such shortcuts can fail when the image background or lighting changes.

Shetty and Attigeri study EfficientNet-B0 on RealWaste and use LIME to examine image regions that influence the model's predictions [10]. Across five random seeds, they report a mean test accuracy of 91.30% with a standard deviation of 1.11%. Their work also identifies cases where a classifier may use spurious visual correlations. The authors note that the experiments are controlled and do not demonstrate large-scale deployment.

Explainability tools can help inspect model behavior but they are not a guarantee that every prediction is correct. They should be used alongside class-level metrics, confusion matrices and tests on varied images. For waste systems, it is useful to understand whether the model focuses on the material itself or on irrelevant background details. Reliability also includes how the system handles unknown items and low-confidence predictions.

2.11 Integrated Waste-Segregation Systems

End-to-end systems combine recognition with sensing or mechanical control. Oreke and Al Seyab report a six-class architecture that uses YOLOv5 and ResNet50, an Intel NUC, Arduino-controlled sorting, environmental sensors, GPS and a cloud dashboard [3]. They report an accuracy of 90.44% and an estimated fabrication cost of £1,231.17. Their choice of an Intel NUC distinguishes the system from projects focused on lower-cost Raspberry Pi deployment.

Sabu *et al.* describe a Raspberry Pi 5 smart dustbin that uses YOLOv8, an ultrasonic input trigger, a camera, a stepper motor and servo motors [6]. The five classes are paper, plastic, metal, biodegradable waste and glass. The reported classification evaluation used 100 samples and produced approximately 90% overall accuracy. The paper also describes an average inference time of about 0.7 to 1 second per image and a sorting cycle of roughly 3 to 4 seconds. These figures apply to the authors' prototype and their stated test conditions.

The integrated-system papers are especially relevant to projects that aim to join AI and automation. However, they differ in the number of classes, sensors, processors and mechanical designs. A reader should distinguish published system details from a proposed project's own choices. In particular, a design mentioned in a related paper should not be described as implemented in another project unless that implementation has actually taken place.

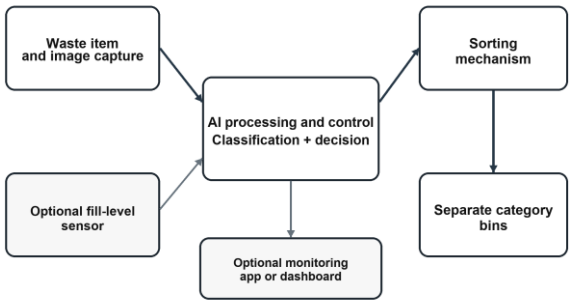


Fig. 1. Proposed high-level block diagram for waste classification and segregation.

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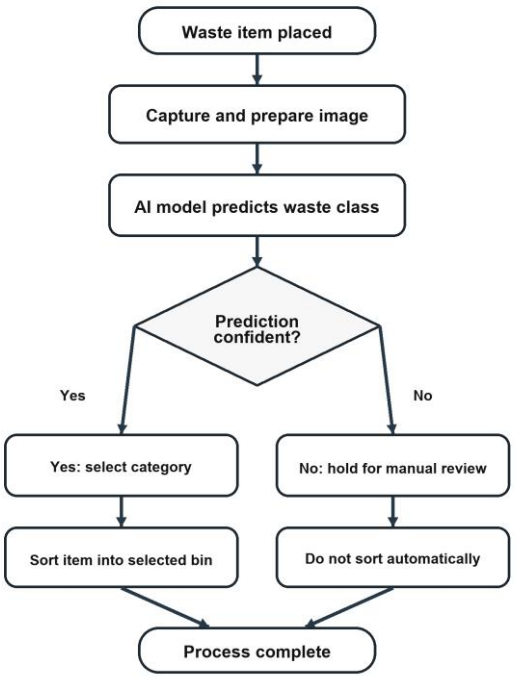


Fig. 2. Proposed flowchart for processing and sorting a waste item.

3. COMPARISON OF EXISTING METHODS

The ten reviewed papers can be grouped by the problem they address. Classification-focused studies examine the model and dataset used to assign waste categories [2], [5], [10]. Edge-device studies consider how recognition can run on a small computer or mobile device [1], [4]–[6], [8], [9]. Integrated sorting studies connect predictions to actuators or robotic mechanisms [1], [3], [4], [6]–[8]. IoT-focused studies add monitoring or notifications around the bin [1], [3], [8]. These groups overlap because some papers address several parts of a system.

The studies also use different category sets. Rusdan and Kuswayati use five categories and include glass and organics [1]. Zhalgas *et al.* use six categories including cardboard [2]. Oreke and Al Seyab report six categories with cardboard and organics [3]. Siyad *et al.* group 19 object classes into biodegradable, plastic, metal and hazardous waste [4]. Partosan *et al.* include paper, plastic, metal, food waste and electronic waste [5]. Sabu *et al.* use paper, plastic, metal, biodegradable waste and glass [6]. Prakash *et al.* focus their described sorter on bottles, cans, paper and miscellaneous items [7]. Chiliquinga-Toapanta *et al.* use plastic bottles, paper, organic waste and electronic waste [8].

These differences limit direct comparison. An accuracy score based on five classes is not directly comparable with a detection metric from a four-bin system or a sorting score from a robot. Data collection and test conditions also differ. Some papers report image-level model performance while others report the success of an integrated process. A balanced comparison should therefore describe the categories, model, computing platform, physical mechanism and evaluation measure together.

The literature suggests several complementary design lessons. First, the category list should be defined before data collection. Second, model evaluation should include more than a single overall score. Third, the computing platform should be selected with latency and memory requirements in mind [9]. Fourth, a physical sorter should be evaluated separately from the vision model [1], [7]. Finally, monitoring and interpretability can provide useful information but should be described as distinct system functions [1], [3], [8], [10].

4. MAJOR CHALLENGES

4.1. Variation in Waste Appearance

Waste items within a single category can look very different. Plastic may be clear or opaque, rigid or flexible and clean or stained. Paper may be folded, printed or wet. Metal objects can have shiny or dull surfaces. A model trained on a narrow group of examples may not recognize the full range of materials encountered in practice. Diverse training images and transparent reporting of data sources can help explain how broad the evaluation is [2], [4].

4.2. Lighting and Image Quality

Image quality can change with shadows, glare, distance and camera angle. Reflective surfaces can create highlights that hide material features. A camera positioned inside a bin may also capture dark or partly blocked views. Studies should explain their image-capture conditions and test whether performance changes when lighting or object position varies. A model's published result cannot be assumed to hold under conditions that were not evaluated.

4.3. Similar or Composite Materials

Some items are made from more than one material. Food packaging may combine plastic, paper and metal layers. A classifier that assigns one label may not capture the complexity of a composite object. Items from different categories may also share colour or shape. The selected output categories should reflect the purpose of the system and include an appropriate response for objects that do not fit a class.

4.4. Class Imbalance

Training data may contain many examples of one category and relatively few of another. This can lead a model to perform well overall while missing less common classes. Researchers should report the number of samples in each class and provide class-level precision and recall where possible. A balanced overall score can hide performance gaps that matter to a sorter, especially if a low-frequency class is hazardous or difficult to recycle.

4.5. Differences Between Datasets

The reviewed papers use self-collected datasets, campus images, public repositories and the RealWaste dataset [2], [5], [8], [10]. Images gathered in one location may differ from those collected elsewhere. Backgrounds, camera types and material condition can influence results. Testing on data that is separate from the training collection gives a stronger indication of model behavior. Cross-dataset evaluation can further show whether a model depends too heavily on one collection environment.

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4.6. Edge-Device Limits

Small devices have finite computing power, memory and energy. A model that is practical on a desktop computer may be too slow on an embedded board. Latency can affect how quickly the system responds to each item and how many items can be processed in a given period. Resource-aware model selection and testing on the actual target device are important [9].

4.7. Recognition Versus Successful Sorting

A correct prediction is only one step in the process. The mechanism must also move the item to the right place. A jam, alignment error, missed grip or delayed motor response can produce a sorting failure even when the model predicted correctly. Studies that report only classification accuracy provide limited evidence about the full system. End-to-end trials should count correctly sorted items and explain where errors occurred [1], [7].

4.8. Unknown and Low-Confidence Items

A real waste stream can include items outside the model's training categories. If the system is required to always choose one known class, an unfamiliar item may be placed incorrectly. A reject or review option can reduce this risk. Researchers should state the confidence threshold, how unknown items are handled and whether the response was tested. These details are especially important when categories are grouped into a smaller number of bins [4], [8].

4.9. Sensor and Connectivity Reliability

Fill-level and environmental sensors can support bin monitoring, but their readings may be affected by placement, obstacles or changes in the contents. Notifications depend on working network connections and a clear action for the recipient. Local monitoring and remote cloud services also have different requirements. A paper should distinguish which features were implemented and evaluated from those proposed as future work [1], [3], [8].

4.10. Evaluation and Reproducibility

Performance results are meaningful only when test methods are clear. Papers should identify dataset splits, class balance, number of trials, device details and evaluation metrics. Repeated random seeds can reveal variation in model results [10]. Mechanical trials should describe the item types and operating conditions. Without these details, readers may find it difficult to reproduce a result or compare it fairly with another study.

5. RECENT DEVELOPMENTS

The reviewed studies show continued use of deep learning for waste recognition. CNN-based classifiers remain relevant for assigning a material category to an image [1], [2], [10]. YOLO models are used for detection tasks and for systems that need to locate an object before handling it [3]–[8]. The model choice often reflects the study's goal, such as comparing architectures, detecting multiple items or deploying on an embedded platform.

Another development is the growing connection between visual recognition and physical sorting. Research now describes systems that link a prediction to servos, stepper motors, rotating compartments or robotic arms [1], [3], [4], [6], [7]. This shifts attention from image scores alone toward practical system outcomes. The reported results also show why the classifier and mechanical stage should be measured separately.

Edge deployment is another recurring direction. Raspberry Pi and Jetson platforms are used to run models close to the camera [1], [3]–[8]. These systems indicate interest in compact deployments, while model-efficiency research examines the cost of running different architectures on limited hardware [9]. Quantization and smaller networks are among the approaches examined for reducing resource demands.

IoT features appear in studies that add fill monitoring, environmental sensing or dashboards [1], [3], [8]. Their implementation ranges from messaging alerts to a local interface or a cloud dashboard. This shows that monitoring is a flexible addition rather than a single standard design. The value of a monitoring feature depends on the intended users and how the information will support a decision.

Finally, recent work considers model reliability through explainability and repeated evaluation [10]. This is a useful development because a strong score does not reveal which image features influenced the result. Evaluation across multiple seeds and inspection of explanations can reveal instability or reliance on irrelevant visual patterns. These approaches complement the usual classification metrics.

6. FUTURE RESEARCH DIRECTIONS

Future studies can improve dataset diversity by collecting images under a wider range of backgrounds, lighting conditions, object positions and material states. Data collection should include items that are dirty, damaged, folded or partly hidden when such conditions are expected in the target environment. Clear documentation of class definitions would also make results easier to compare. Public datasets and shared evaluation procedures can support repeatable study, but project-specific testing remains necessary.

Cross-environment testing is another useful direction. A model trained on one campus or waste facility may behave differently in a home, office or public space. Researchers could test a model on images collected from locations not represented in training. Such evaluation would help show whether the system learned material features or location-specific background patterns. Model updates should also be assessed for their effect on older categories and devices.

Edge models could be studied through a common set of measures that includes accuracy, class-level performance, inference time, memory use and energy consumption.

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Quantization and compact architectures may reduce computing demands, but any efficiency gain should be reported alongside changes in prediction quality [9]. Testing should use the intended camera and device because image resolution and hardware can influence both response time and recognition.

Mechanical research could focus on reliable handling across different item sizes and shapes. Sorting trials should include repeated cycles and report jams, placement errors and the time required for a full operation. Systems should have a defined response for uncertain predictions or unsupported items. These features can be examined without assuming that one mechanical arrangement suits all waste categories.

Monitoring systems could be evaluated in terms of sensor accuracy, notification delivery and the usefulness of information to operators. Local and cloud-based options have different requirements for connectivity and maintenance. Researchers should state clearly whether a dashboard or alert system was implemented and how it was tested. Monitoring results should remain separate from classification results so readers can distinguish the function of each subsystem.

Explainability and robustness deserve continued study. Tools such as LIME can help inspect image regions that influence a prediction [10]. Their outputs should be reviewed with examples of correct and incorrect classifications. Additional tests can measure how predictions change when lighting, background or image quality changes. Such work may help identify failure conditions before a system is used outside a controlled setting.

Finally, more complete end-to-end evaluations are needed. A useful study can report model performance, mechanical sorting success, system latency and sensor behavior in the same experimental setup. Repeated trials and clearly described test items would make the results more informative. These studies can support careful design decisions without overstating the maturity of a prototype.

7. DISCUSSION

The reviewed papers show that AI-based waste segregation is a collection of related tasks. A vision model may classify an image, a detection model may locate one or more objects and a control system may direct a mechanism. Sensors can add information about the bin while edge computing can make local inference possible. These functions can be combined, but each one needs its own evaluation.

The diversity of waste categories is one of the main issues in comparing papers. A model that recognizes six detailed categories is not directly comparable with one that groups many items into four output bins. The relationship between model labels and physical compartments should therefore be stated. The same issue applies to performance measures: image classification, object detection and sorting success describe different parts of the system.

The hardware platform influences what can be deployed. Studies use Raspberry Pi, Jetson Nano, Intel NUC and robotic systems with additional controllers [1], [3]–[8]. The platform should fit the required response time and model size. It is not enough to select hardware because it appears in a related paper. The full camera-to-actuator workflow must be considered.

Accuracy remains useful, but it should not be treated as the only sign of reliability. Class-level errors, confidence handling, varied test images and mechanical outcomes provide additional information. Explainability and multi-seed evaluation can also expose limitations that a single score may not show [10]. Resource measures such as latency and model size matter when the system is expected to run on a small device [9].

For the proposed project, the reviewed work provides a basis for selecting and evaluating methods. It does not determine the project's final categories, hardware or mechanical design. Those decisions should be based on project requirements and actual testing. Keeping the project description high-level at this stage avoids confusing published results with proposed work.

8. CONCLUSION

This survey reviewed ten recent studies on AI-based waste classification and automated segregation. The literature covers image classifiers, object detectors, edge-device deployment, physical sorting, robotic platforms, IoT monitoring, efficient models and explainable AI [1]–[10]. It shows that recent systems combine these components in different ways and use different categories and test methods.

The studies suggest that a practical system should be evaluated as more than an image classifier. Data quality, category definition, edge performance and mechanical handling all affect the final outcome. Classification results and sorting success should be reported separately. Monitoring and explainability can add value when their function is clearly defined and tested.

The proposed project is intended to address waste classification and automated segregation. Its detailed design and performance remain to be established. Future work should define the target categories, select a suitable platform and evaluate the complete workflow under stated conditions. The survey provides a research basis for that work without claiming that implementation is complete.

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