

DESIGN AND VALIDATION OF A LOW-COST AI-BASED RECYCLABLE WASTE CLASSIFICATION SYSTEM

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Abstract

This paper presents the design and validation of a low-cost AI-based Smart Electronics Classification System for recyclable waste sorting. It was developed as a low-cost technical prototype that can be independently assembled using accessible components and manually collected training data, with future application as a STEM learning tool to be evaluated in subsequent work. The system uses a DC motor-driven rotating the three waste bins positioned at 120°, 240°, and 360°, controlled by Arduino Uno microcontroller combined with a result of an image-based classifier trained by PictoBlox. Images were classified into four classes: Class A (clear PET with label and cap), Class B (clear PET without label or cap), Class C (HDPE with label and cap), and Class D (empty tray). The 1,496 images dataset was manually collected, labelled and trained using PictoBlox's built-in image learning feature by achieving 100% accuracy on the images test set. Motor positioning validation was tested over 15 trials with result of a mean absolute error of 17.0°, while end-to-end system testing over 56 trials achieved an overall system accuracy of 96.4%. The validated prototype demonstrates technical feasibility and reliability, establishing a foundation for future STEM-based learning activities. It offers a practical platform for

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students to engage with machine learning, embedded systems, engineering design, and problem-solving through hands-on construction and testing.

Keywords: waste classification system, machine learning, recyclable waste sorting, environment technology, smart waste management

Introduction

Nowadays, global solid waste generation continues to grow at an alarming rate. The recycling management has been consider as a strategy for environmental sustainable. The process of recyclable waste sorting was widely used but still remain manually sorting by labour to classify the waste which cause the error prone (Zhang et al., 2022). STEM (Science, Technology, Engineering, and Mathematics) education frameworks, which promote active learning through project-based work, promote development in both environmental awareness and problem solving competencies (Alkair et al., 2023). The project-based STEM activities which integrating embedded machine learning and AI tools were enhance the learner motivation, deeply understanding the conceptual and develop the analytical thinking skills (Omeh & Ayanwale, 2025).

Artificial intelligence (AI) and machine learning (ML) are increasingly used in term of educational tools within STEM curricula. AI literacy is mostly important recognised as foundational competency for future citizens and engineers (Ng et al., 2021), (Casal-Otero et al., 2023). The ‘kids making AI’ starting to demonstrate strong learner engagement and integrating skill by practicing, hands-on AI learning experience including IoT STEM kits for educational setting (Kusmin et al., 2018), (Sakulkueakulsuk et al., 2018). AI education is broadly accessible to learners having no prior experience in programming to cross the barrier of AI learning platform, which can construct, train, and deploy functional classifiers within structured learning activities (Pope et al., 2024). AI education is demonstrates with evidence to launch with students from primary to university level (Kandlhofer et al., 2016). Physical computing and IoT-based ecosystems have been designed

to facilitate collaborative learning and motivate learners in educational contexts (Katterfeldt et al., 2018), (Benita et al., 2021).

The convolutional neural networks (CNNs) in waste classification management domain is demonstrated high accuracy across various type of recycling tasks (Shi et al., 2021). However, the AI-based waste sorting prototype was designed for STEM learning, validate the accuracy of system working before deploying to classroom. This study focus on a Smart Electronics Classification System integrated hardware design with AI-based learning to be presenting as a tool for the learner on main system knowledge. The principal contributions are: (i) low-cost system; (ii) the step-by-step investigation method of both mechanical and AI system; and (iii) validated evidence of the prototype's technical feasibility and reliability, establishing a foundation for future pedagogical implementation and evaluation within STEM education.

Materials and method

1. System Overview

The Smart Electronics Classification System consists of two subsystems: (1) a mechanical rotating platform driven by a DC motor, with three waste bins positioned at 120° angular separations; and (2) a software subsystem running on a laptop connected to a USB webcam, executing a PictoBlox program that classifies captured images using an ML model to control the motor angular positioning and gate opening state. This hardware-software subsystem is used to examine the intelligent system that collects image data as reported in the literature (Antora et al., 2022), (Sirawattananon et al., 2021). Fig. 1 shows the prototype system overview (a) photograph of the assembled prototype; (b) annotated diagram identifying key components, including the rotating tray assembly (three bins positioned at 120°, 240°, and 360°), the webcam, the servo motor controlling the chute gate, and the Arduino Uno, relay module, and DC motor housed beneath the turntable.

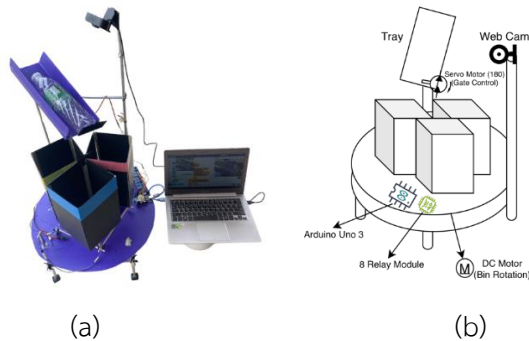


Fig. 1 Prototype system overview: (a) photograph of the assembled prototype; (b) annotated diagram identifying key components

The system communicates from hardware to software via Pictoblox system. PictoBlox controls both ML inference and transferring classified commands to Arduino Uno microcontroller system. Once the microcontroller receives a command, it translates software commands into physical action to control the DC motor and servo gate. Fig. 2 showing the electrical connections among the Arduino Uno, relay module (active LOW), DC motor, servo motor, 9V power adapter, and USB webcam. Two relay channels are used to reverse the polarity supplied to the DC motor, controlling its rotation direction; the servo motor's signal line is connected to a dedicated PWM-capable digital pin. The Arduino Uno communicates with the host computer running PictoBlox via a USB serial connection. This integration makes repeatable operation in the same result in each classification cycle run to reduce human intervention.

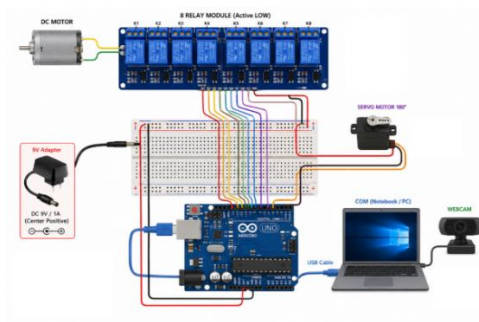


Fig. 2. Schematic of wiring diagrams

2. Bin Positions and Motor Control

Three bins are fixed to the turntable at 120° , 240° , and 360° , corresponding to Classes A, B, and C respectively. A DC motor powers the turntable. The system uses timing-based control: each target angle is reached by running the motor for a fixed duration. The motor was tested and verified to produce repeatable rotation for a pre-calibrated duration corresponding to each target angle. Open-loop control was chosen instead of encoder-based feedback to reduce build complexity. This follows design principles for introductory STEM courses, where simpler construction helps students focus on learning. Fig. 3 shows the rotation schematic.

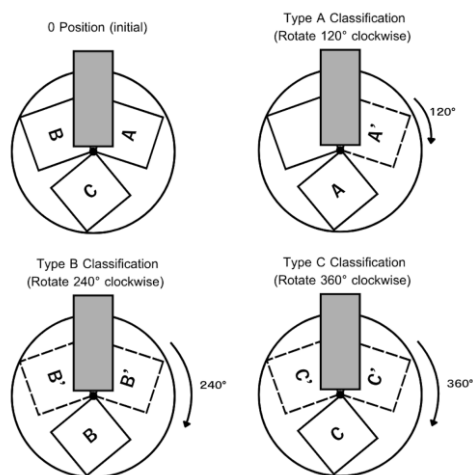


Fig. 3. Schematic of the three-bin turntable. Bins A, B, and C are at 120° , 240° and 360° . The motor (M) is at the base.

3. Waste Class Definitions

Four waste classes are defined based on visual appearance, PET and HDPE plastic bottles, the most commonly recyclable plastic types in consumer waste streams (Schade et al., 2024):

- Class A – Clear PET bottle with label and cap: fully intact, transparent PET beverage bottle.

- Class B – Clear PET bottle without label or cap: transparent PET bottle with exterior markings removed, representing a realistic post-consumer recycling scenario.
- Class C – HDPE bottle with label and cap: white/translucent high-density polyethylene (HDPE) bottle, distinguishable by opacity and surface texture.
- Class D – Empty tray: no waste item is placed on the tray; the motor remains stationary in this state.

4. Image Recognition Model: PictoBlox

The classification model is developed within PictoBlox using its built-in image learning feature, which applies transfer learning based on MobileNet architecture pre-trained on ImageNet, fine-tuned on a manually curated, domain-specific dataset. MobileNet is a lightweight convolutional neural network architecture designed for computationally constrained environments such as mobile devices and standard laptops without a dedicated GPU. It achieves this efficiency through depthwise separable convolutions, which factorize a standard convolution into a per-channel depthwise convolution followed by a 1×1 pointwise convolution, substantially reducing parameters and computation while retaining comparable feature-extraction capability. Since the model was pre-trained on the large-scale ImageNet dataset, transfer learning required fine-tuning only the final classification layers on the four-class waste dataset rather than training from scratch, enabling the model to be trained within PictoBlox on a standard laptop CPU in a short time, consistent with the system's low-cost, classroom-deployable design goal. Training images were collected and labelled by the researchers across four predefined classes: two variants of clear PET bottles (Class A and Class B), one HDPE bottle category, and an empty tray class. The empty tray class prevents the motor from running when no item is present. The dataset comprises 1,496 images in total, partitioned into training and test sets at an 75:25 ratio (1,122 training / 374 test images). Transfer learning

reduced the number of training images needed compared to training from scratch, and without requiring a GPU. This makes the approach suitable for school-based projects. Table 1 summarises the training configuration.

Table 1 Model training configuration

Hyperparameter	Value
Model Architecture	MobileNet (Transfer Learning)
Pre-trained Weights	ImageNet
Number of Classes (K)	4 (Class A, B, C, D)
Total Training / Test Samples	1,122 / 374 images (75:25 split)
Training Epochs	10
Batch Size (N)	16
Learning Rate (η)	0.0001
Output Activation	Softmax
Loss Function	Categorical Cross-Entropy

5. Dataset Collection and Composition

A total of 1,496 images were captured under controlled indoor lighting using the external USB webcam. The dataset follows a 75:25 train-test partition (1,122 training / 374 testing). Four waste classes were used. The dataset exhibits an Imbalance Ratio ($IR = N_{\max}/N_{\min} = 462/159 \approx 2.91$), calculated following the maximum between-class ratio formula used to quantify imbalance severity in CNN classification studies (Johnson & Khoshgoftaar, 2019). Table 2 presents the per-class distribution.

Table 2 Dataset distribution across waste classes.

Class	Description	Train (n)	Train (%)	Test (n)	Test (%)	Ratio
A	Clear PET with label and cap	462	41.2%	154	41.2%	75:25
B	Clear PET without label or cap	235	20.9%	75	20.1%	75.8:24.2
C	HDPE with label and cap	266	23.7%	96	25.7%	73.5:26.5
D	Empty tray	159	14.2%	49	13.1%	76.4:23.6
Total		1,122	100%	374	100%	75:25

6. Three-Step System Workflow

In each operating cycle, the system follows three steps, consistent with the pipeline architecture of image-guided automated sorting systems as show software control workflow in Fig.4 :

1) Image capture and ML classification: The webcam captures the presented waste item; PictoBlox assigns it to one of four classes (A–D) and reports a confidence percentage. If Class D (empty tray) is detected, no control signal is transmitted and the motor does not activate, preventing incorrect bin rotation.

2) Motor rotation: For Classes A–C, PictoBlox transmits a control signal via serial communication to the Arduino Uno, which drives the DC motor to rotate the turntable to the angular position corresponding to the predicted class (120° , 240° , or 360°), aligning the correct bin under the chute opening.

3) Gate release and reset: The Arduino Uno actuates the servo-driven gate to open, dropping the item into the correct bin. The gate then closes, resetting the system. The system is then ready for the next cycle.

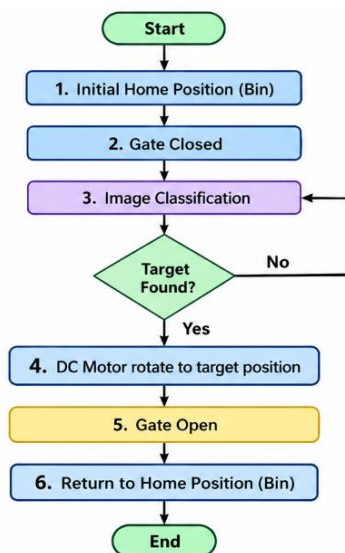


Fig. 4. Software control workflow

7. Cost Analysis

Table 3 presents the bill of materials for the prototype, with a total material cost of approximately 1,270 THB ($\approx$ USD 38.5). All electronic components (Arduino Uno, relay module, servo motor, DC motor, webcam, adapter, and jumper wires) are reusable across multiple builds, as is the foam-board and aluminum structural frame; only the hot glue is a single-use consumable. This cost is consistent with figures reported in the literature for comparable low-cost, AI or sensor-based waste-sorting and classification systems. A Raspberry Pi-based embedded computer-vision system for classifying recyclable materials was reported to cost £67.81 ($\approx$ USD 85) in total hardware (Myers & Secco, 2021), while a multi-spectral near-infrared plastic-recognition sensor priced at approximately £56 ($\approx$ USD 70) substantially cheaper than conventional spectroscopy-based sensors, which typically range from £6,000 to £50,000 (Martinez-Hernandez et al., 2024). Similarly, a per-unit hardware cost of USD 35–45 (excluding infrastructure and maintenance) for an IoT-based smart waste-bin monitoring system built from comparable microcontroller and sensor components (Alnanih et al., 2025). At a larger deployment scale, machine-learning-based automated sorting achieved a cumulative seven-year cost of €12.76 million, compared to €21.47 million for conventional sorting methods, underscoring the broader cost advantages of AI-driven approaches to waste management (Farshadfar et al., 2025). These studies indicate that AI- and embedded-system-based waste classification prototypes typically range from approximately USD 35 to USD 85 at the hardware level, situating the present system's cost of approximately USD 38.5 well within, and toward the lower end of, this established range.

Table 3 Bill of materials and estimated cost of the prototype

No.	Component	Qty	Unit Price (THB)	Total (THB)
1	Corrugated plastic board (1x1 m)	2	100	200
2	Hollow aluminum rod ($\varnothing 1 \times 1$ cm)	4	20	80
3	DC motor	1	100	100
4	Arduino Uno	1	250	250
5	Relay module (active LOW)	1	60	60
6	Servo motor (180°)	1	70	70
7	9V power adapter	1	100	100
8	Jumper wires	4	40	160
9	USB webcam	1	150	150
10	Rubber feet for aluminum posts (2x2 cm)	4	15	60
11	Hot glue sticks	10	4	40
Total				1,270

Total: 1,270 THB ($\approx$ USD 38.5, at an exchange rate of THB 33 = USD 1)

Results and discussion

1. Degree Validation

Before full system integration, the motor positioning subsystem was validated independently. The turntable was commanded to each of the three target angles (120°, 240°, and 360°) and the actual resulting position was measured manually over 15 trials. This approach follows standard practice in automated sorting system development (Sallang et al., 2021), (Sheng et al., 2020). Table 4 presents the results, and Fig. 5 plots the target versus measured angle across all trials.

Table 4 Degree validation results.

Trial	Target Angle (°)	Estimated Angle (°)	Error (°)
1	120	75	45
2	120	110	10
3	120	90	30
4	120	120	0
5	120	110	10

Trial	Target Angle (°)	Estimated Angle (°)	Error (°)
6	240	240	0
7	240	210	30
8	240	255	-15
9	240	220	20
10	240	255	-15
11	360	330	30
12	360	350	10
13	360	340	20
14	360	355	5
15	360	345	15

As shown in Fig. 5, positioning error is more variable at the 120° target (Trials 1–5, errors: 0°–45°) than at the 240° and 360° targets (Trials 6–10 and 11–15, errors: 0°–30° and 5°–30°, respectively). Table 4 presents the degree validation results across all three target positions (120°, 240°, and 360°), each evaluated over five trials. The mean absolute positioning error (MAE) was 19.0° at 120°, 16.0° at 240°, and 16.0° at 360°, yielding an overall MAE of 17.0° across all 15 trials. At the 360° position, the estimated angle was consistently below the target across all five trials, indicating a small systematic under-rotation bias rather than random variation – likely reflecting mechanical slack or accumulated timing drift over the longest angular displacement among the three positions.

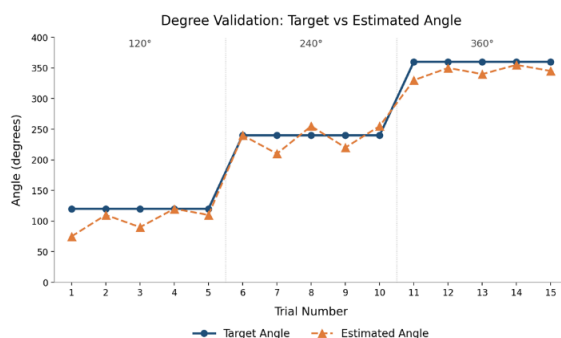


Fig. 5 Degree validation: target versus estimated motor angle across 15 trials
(Trials 1–5: 120°; Trials 6–10: 240°; Trials 11–15: 360°)

2. Testing

2.1 Testing on Degree Rotation

System-level motor rotation testing evaluates functional accuracy (whether the waste item lands in the correct bin) rather than exact angular precision. If the error stays within the bin's angular span, the item still lands correctly, otherwise the item lands in the wrong bin. System-level motor rotation was evaluated over 18 trials covering all three bin positions, starting from a defined home position at the start of each trial. Table 5 presents the results.

Table 5 Motor rotation testing results (18 trials).

Trial	Target	Time (s)	Angle (°)	Result	Correct	Remarks
1	A	0.46	120	A	1	Correct
2	A	0.29	120	A	1	Correct
3	A	0.45	120	A	1	Correct
4	A	0.41	120	A	1	Correct
5	A	0.56	120	A	1	Correct
6	A	0.41	120	A	1	Correct
7	B	0.76	240	B	1	Correct
8	B	0.56	240	A	0	Wrong → A
9	B	1.31	240	B	1	Correct
10	B	1.16	240	B	1	Correct
11	B	1.18	240	A	0	Wrong → A
12	B	1.55	240	B	1	Correct
13	C	1.88	360	A	0	Wrong → A
14	C	2.18	360	C	1	Correct
15	C	1.98	360	C	1	Correct
16	C	1.79	360	C	1	Correct
17	C	1.88	360	C	1	Correct
18	C	1.9	360	C	1	Correct

Position A (120°) achieved $6/6 = 100\%$. Position B (240°) achieved $4/6 = 66.7\%$, failing at Trials 8 and 11. Position C (360°) achieved $5/6 = 83.3\%$, failing at Trial 13. Overall motor positioning accuracy was $15/18 = 83.3\%$. This reflects cumulative timing error over longer travel arcs, a known issue with open-loop motor control in low-cost embedded systems.

2.2 Classification by Machine Learning

Fifty-six previously unseen objects spanning all four classes were presented to the trained PictoBlox ML model, as shown in Fig. 6. Table 6 presents the classification results and confidence scores. Of 56 samples, 54 were correctly classified, yielding an overall accuracy of 96.4%. The transfer learning framework implemented via PictoBlox has achieved high classification effectiveness in prior waste classification studies (Rabano et al., 2018), and the present results are consistent with these findings.

Both misclassifications (samples 10 and 14) involved Class B items predicted as Class A – a pattern attributable to the high visual similarity between the two categories, as both are transparent PET bottles differing only by the presence or absence of a label and cap. As illustrated in Fig. 8, all misclassifications occurred in Class B, while Classes A, C, and D achieved zero classification errors, likely because removing the label and cap makes Class B harder to distinguish from Class A. Similar confusion between visually similar classes and class imbalance effects has been reported in broader recyclable plastic classification systems (Wu et al., 2023).

As shown in Fig. 8, the confidence scores of misclassified samples (58%–72%) were substantially lower than the mean confidence of correct predictions (92.1%). Every correctly classified sample retained a confidence of at least 77%, indicating a clear separation between correct and incorrect predictions at this operating point. Fig.7 presents the accuracy and loss curves over 10 training epochs.

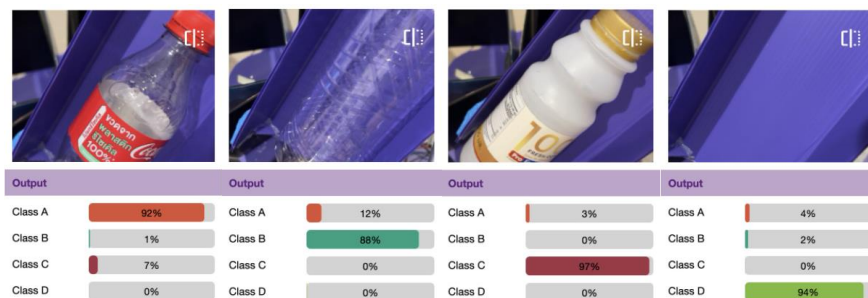


Fig. 6 PictoBlox classification output examples for each waste class: Class A (clear PET with label and cap), Class B (clear PET without label or cap), Class C (HDPE with label and cap), and Class D (empty tray)

Table 6 Machine learning classification results (56 trials).

Sample	True	Predicted	Correct	Conf.(%)	Remarks
1	A	A	1	91%	Correct
2	B	B	1	92%	Correct
3	C	C	1	99%	Correct
4	D	D	1	82%	Correct
5	A	A	1	92%	Correct
6	B	B	1	89%	Correct
7	C	C	1	97%	Correct
8	D	D	1	84%	Correct
9	A	A	1	85%	Correct
10	B	A	0	72%	Misclassified → A
11	C	C	1	98%	Correct
12	D	D	1	77%	Correct
13	A	A	1	78%	Correct
14	B	A	0	58%	Misclassified → A
15	C	C	1	98%	Correct
16	D	D	1	80%	Correct
17	A	A	1	99%	Correct
18	B	B	1	90%	Correct
19	C	C	1	98%	Correct
20	D	D	1	96%	Correct
21	A	A	1	98%	Correct
22	B	B	1	95%	Correct
23	C	C	1	95%	Correct
24	D	D	1	94%	Correct
25	A	A	1	89%	Correct
26	B	B	1	99%	Correct
27	C	C	1	93%	Correct
28	D	D	1	95%	Correct
29	A	A	1	98%	Correct
30	B	B	1	98%	Correct
31	C	C	1	94%	Correct
32	D	D	1	96%	Correct
33	A	A	1	94%	Correct
34	B	B	1	100%	Correct
35	C	C	1	97%	Correct
36	D	D	1	94%	Correct
37	A	A	1	94%	Correct

Sample	True	Predicted	Correct	Conf.(%)	Remarks
38	B	B	1	79%	Correct
39	C	C	1	91%	Correct
40	D	D	1	95%	Correct
41	A	A	1	85%	Correct
42	B	B	1	81%	Correct
43	C	C	1	92%	Correct
44	D	D	1	86%	Correct
45	A	A	1	98%	Correct
46	B	B	1	98%	Correct
47	C	C	1	92%	Correct
48	D	D	1	93%	Correct
49	A	A	1	91%	Correct
50	B	B	1	88%	Correct
51	C	C	1	86%	Correct
52	D	D	1	98%	Correct
53	A	A	1	86%	Correct
54	B	B	1	93%	Correct
55	C	C	1	94%	Correct
56	D	D	1	97%	Correct

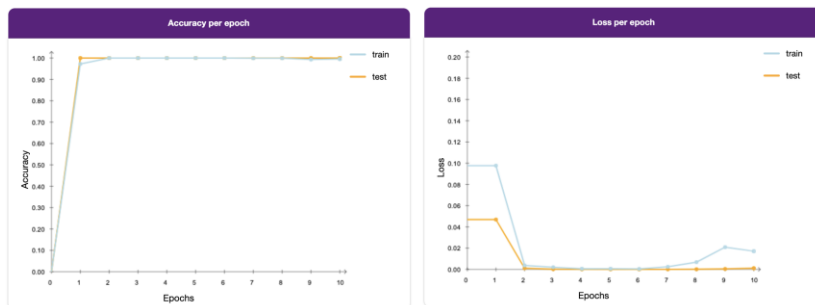


Fig. 7 Training and test accuracy (left) and cross-entropy loss (right) across 10 epochs. Both metrics converge by epoch 2, indicating rapid Transfer Learning convergence without overfitting.

As shown in Fig. 7, rapid convergence within two epochs reflects the efficiency of transfer learning: pre-learned features from MobileNet required minimal adaptation for the plastic bottle classification task. The 100% test accuracy

matches results reported in transfer learning-based waste classifiers under similar laboratory conditions. The gap between test accuracy (100%) and real-world accuracy (96.4%) is common in applied deep learning, where controlled test conditions rarely reflect real-world variation.

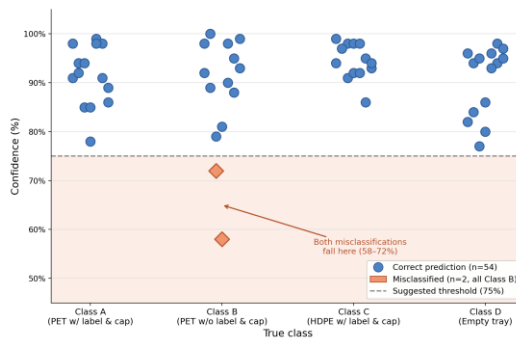


Fig. 8 Classification confidence score grouped by true class (n = 56 trials). Blue circles = correct predictions; orange diamonds = misclassified samples (Samples 10, 14).

2.3 Generalization test

Data test images were captured under two lighting conditions (standard room lighting; white LED lighting with room lights off), four viewing angles (10–20°, 45°, 45–50°, and 50–60° tilt), and three background conditions (the original background, a cluttered background, and a tile-floor background).

The model achieved an overall accuracy of 96.4% (54/56) on this generalization test. Table 7 reports per-class accuracy, precision, recall, and F1-score, and Table 8 presents the corresponding confusion matrix. Classes A, C, and D achieved 100% accuracy, while Class B achieved 85.7%, with two images misclassified as Class A. Both misclassifications occurred at a shallow viewing angle (10–20°) against a cluttered background, with comparatively low prediction confidence (72% and 58%, versus a mean above 90% for correct predictions).

Table 7 Per-class accuracy, precision, recall, and F1-score (n = 56):

Class	n tested	n correct	Accuracy (%)	Precision	Recall	F1-score
A	14	14	100.0	0.875	1.000	0.933
B	14	12	85.7	1.000	0.857	0.923
C	14	14	100.0	1.000	1.000	1.000
D	14	14	100.0	1.000	1.000	1.000
Macro avg.	56	54	96.4	0.969	0.964	0.964

Table 8 Confusion matrix (n = 56):

True \ Predicted	A	B	C	D
A	14	0	0	0
B	2	12	0	0
C	0	0	14	0
D	0	0	0	14

2.4 Three-Step System Integration Performance

The end-to-end three-step cycle was evaluated across all 56 trials. Steps 2 and 3 (motor rotation and gate control) executed correctly in every trial where Step 1 produced a valid prediction. Both failures came from Step 1 misclassification.

Compared with CNN-based waste classification systems that typically achieve 87.20%–96.31% accuracy on the TrashNet benchmark (Tian et al., 2024), the 96.4% accuracy of this educational prototype is appropriately modest given its open-loop control and controlled-environment dataset.

Conclusion

This study presents a low-cost AI-based recyclable waste classification system for future STEM education, integrating a DC motor-driven three-bin rotating turntable with a transfer learning classifier implemented via PictoBlox to distinguish four plastic bottle categories (Classes A–D).

Three key performance metrics were obtained. First, the image classification model achieved 96.4% accuracy on an independent generalization test using 56 unseen objects, showing that transfer learning via PictoBlox generalizes well beyond the training dataset of 1,496 images. Second, degree validation revealed a mean absolute error of 17.0° over 15 positioning trials, quantifying the limitations of open-loop timing-based motor control. Third, end-to-end integration testing across 56 trials yielded 96.4% overall accuracy. Both failures were attributable to visual similarity between Class A (labelled PET) and Class B (unlabelled PET), with misclassified samples returning lower confidence scores (mean 65%) compared with correct predictions (mean 92.1%).

The system demonstrates potential to support hands-on, inquiry-based learning through apparatus construction, controller programming, and independent analysis. Students can develop critical thinking, interdisciplinary thinking, and problem-solving skills across future STEM subjects in secondary students as a field of energy and environment topics. It will be integrated with foundational instruction in programming (C language) and artificial intelligence to support project-based learning on waste management and environmental sustainability.

While data augmentation techniques such as random rotation, zoom, and brightness adjustment were not applied during training-set preparation, the model's robustness to precisely these variations was empirically demonstrated through the generalization test (Section 2.3), which evaluated performance across varied lighting, viewing-angle, and background conditions and achieved 96.4% accuracy. Building on this demonstrated robustness, incorporating data augmentation into future training cycles represents a natural next step to further strengthen model generalization ahead of deployment in diverse real-world classroom settings.

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References

- Alkair, S., Ali, R., Abouhashem, A., Aledamat, R., Bhadra, J., Ahmad, Z., Sellami, A., & Al-Thani, N. J. (2023). A STEM model for engaging students in environmental sustainability programs through a problem-solving approach. *Applied Environmental Education & Communication*, 22(1), 13–26.
- Alnanih, R., Elrefaei, L., & Al-Ahwal, A. (2025). Advancing sustainability through an IoT-driven smart waste management system with software engineering integration. *Sustainability*, 17(21), 9803.
- Antora, N. A., Rahman, M. A., Al Mosharraf, A., Ehsan, M. I., Alve, M., & Elahi, M. M. (2022). *Design and implementation of a smart bin using IoT for an efficient waste management system*. In: Proceeding of 25th International Conference on Computer and Information Technology (ICCIT), 17-19 December, 2022, Bangladesh. Doi 10.1109/ICCIT57492.2022.10055998.
- Benita, F., Virupaksha, D., Wilhelm, E., & Tunçer, B. (2021). A smart learning ecosystem design for delivering data-driven thinking in STEM education. *Smart Learning Environments*, 8, 11.
- Casal-Otero, L., Catala, A., Fernández-Morante, C., Taboada, M., Cebreiro, B., & Barro, S. (2023). AI literacy in K-12: A systematic literature review. *International Journal of STEM Education*, 10, 29.

- Farshadfar, Z., Khajavi, S. H., Mucha, T., & Tanskanen, K. (2025). Machine learning-based automated waste sorting in the construction industry: A comparative competitiveness case study. *Waste Management*, 194, 77–87.
- Johnson, J. M., & Khoshgoftaar, T. M. (2019). Survey on deep learning with class imbalance. *Journal of Big Data*, 6, 27.
- Kandlhofer, M., Steinbauer, G., Hirschmugl-Gaisch, S., & Huber, P. (2016). *Artificial intelligence and computer science in education: From kindergarten to university*. In: Proceeding of 2016 IEEE Frontiers in Education Conference (FIE), 12-15 October, 2016, Pennsylvania, USA. Doi 10.1109/FIE.2016.7757570.
- Katterfeldt, E. S., Cukurova, M., Spikol, D., & Cuartielles, D. (2018). Physical computing with plug-and-play toolkits: Key recommendations for collaborative learning implementations. *International Journal of Child-Computer Interaction*, 17, 72–82.
- Kusmin, M., Saar, M., & Laanpere, M. (2018). *Smart schoolhouse - Designing IoT study kits for project-based learning in STEM subjects*. In: Proceeding of 2018 IEEE Global Engineering Education Conference (EDUCON), 17-20 April, 2018, Canary Islands, Spain. Doi 10.1109/EDUCON.2018.8363412.
- Martinez-Hernandez, U., West, G., & Assaf, T. (2024). Low-cost recognition of plastic waste using deep learning and a multi-spectral near-infrared sensor. *Sensors*, 24(9), 2821.
- Myers, K., & Secco, E. L. (2021). A low-cost embedded computer vision system for the classification of recyclable objects. *Congress on Intelligent Systems (CIS 2020): Lecture notes on data engineering and communications technologies*, 61, 11–30.
- Ng, D. T. K., Leung, J. K. L., Chu, S. K. W., & Qiao, M. S. (2021). Conceptualizing AI literacy: An exploratory review. *Computers and Education: Artificial Intelligence*, 2, 100041.

- Omeh, C. B., & Ayanwale, M. A. (2025). Artificial intelligence meets PBL: transforming computer-robotics programming motivation and engagement. *Frontiers in Education*, 10, 1674320.
- Pope, N., Vartiainen, H., Kahila, J., Laru, J., & Tedre, M. (2024). *A no-code AI education tool for learning AI in K-12 by making machine learning-driven apps*. In: Proceeding of 2024 IEEE International Conference on Advanced Learning Technologies (ICALT), 1-4 July, 2024, North Cyprus, Cyprus. Doi 10.1109/ICALT61570.2024.00037.
- Rabano, S. L., Cabatuan, M. K., Sybingco, E., Dadios, E. P., & Calilung, E. J. (2018). *Common garbage classification using MobileNet*. In: Proceeding of 2018 IEEE 10th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management (HNICEM), 29 November – 2 December, 2018, Baguio City, Philippines. Doi 10.1109/HNICEM.2018.8666300.
- Sakulkueakulsuk, B., Pataranutaporn, P., Witoon, S., Surareungchai, W., Subsoontorn, P., Ngarmkajornwiwat, P., & Pataranutaporn, P. (2018). *Kids making AI: Integrating machine learning, gamification, and social context in STEM education*. In: Proceeding of 2018 IEEE International Conference on Teaching, Assessment, and Learning for Engineering (TALE), 4-7 December, 2018, NSW, Australia. Doi 10.1109/TALE.2018. 8615249
- Sallang, N. C. A., Islam, M. T., Islam, M. S., & Arshad, H. (2021). A CNN-based smart waste management system using TensorFlow Lite and LoRa-GPS shield in Internet of Things environment. *IEEE Access*, 9, 153560–153574.
- Schade, A., Melzer, M., Zimmermann, S., Schwarz, T., Stoewe, K., & Kuhn, H. (2024). Plastic waste recycling - A chemical recycling perspective. *ACS Sustainable Chemistry & Engineering*, 12(33), 12270–12288.
- Sheng, T. J., Islam, M. S., Misran, N., Baharuddin, M. H., Arshad, H., Islam, M. R., Chowdhury, M. E. H., Rmili, H., & Islam, M. T. (2020). An Internet of Things based smart waste management system using LoRa and TensorFlow deep learning model. *IEEE Access*, 8, 148793–148811.

- Shi, C., Tan, C., Wang, T., & Wang, L. (2021). A waste classification method based on a multilayer hybrid convolution neural network. *Applied Sciences*, 11(18), 8572.
- Sirawattananon, C., Muangnak, N., & Pukdee, W. (2021). *Designing of IoT-based smart waste sorting system with image-based deep learning applications*. In: Proceeding of 2021 ¹⁸th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON), 19-22 May, 2021, Chiang Mai, Thailand. Doi 10.1109/ECTI-CON51831.2021.9454826.
- Tian, X., Shi, L., Luo, Y., & Zhang, X. (2024). Garbage classification algorithm based on improved MobileNetV3. *IEEE Access*, 12, 44799–44807.
- Wu, T. W., Zhang, H., Peng, W., Lü, F., & He, P. J. (2023). Applications of convolutional neural networks for intelligent waste identification and recycling: A review. *Resources Conservation and Recycling*, 190, 106813.
- Zhang, X., Liu, C., Chen, Y., Zheng, G., & Chen, Y. (2022). Source separation, transportation, pretreatment, and valorization of municipal solid waste: A critical review. *Environment, Development and Sustainability*, 24, 11471–11513.