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Vasyl Stefanyk Carpathian National University

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H.A. Mutar[1], I.R.N. ALRubeei[2], I.V. Svyd[3,4], Haider TH. Salim ALRikabi[2], Abdul Hadi M. Alaidi[1]

AI-Based Model for Home Waste Separation Using Raspberry Pi 5 AI Kit

[1]College of Computer Science and Information Technology, Wasit University, Wasit, Iraq, hmutar@uowasit.edu.iq;
[2]Electrical Engineering Department, College of Engineering, Wasit University, Wasit, Iraq;
[3]Vasyl Stefanyk Carpathian National University, Ivano-Frankivsk, Ukraine, iryna.svyd@pnu.edu.ua;
[4]Ivan Kozhedub Kharkiv National Air Force University (KNAFU), Kharkiv, Ukraine

Effective domestic waste separation is also very critical to enhancing recycling and minimizing environmental pollution. Manual sorting, however, is labor-intensive, prone to errors and not practical to be widely adopted. In this paper, a new AI-controlled system of waste separation at home is presented, the computational power of the Raspberry Pi 5 AI Kit is used. It is a system consisting of a large-resolution camera, a conveyor belt system, and an edge deployment-optimized YOLOv5s convolutional neural network (CNN). The model is trained on the WasteNet dataset, with 25, 000 annotated images of five waste types (plastic, paper, glass, metal, and organic) and the classification accuracy of the model is 95.2%, with an average precision of 95.0%, and the time required to make an inference is 45 ms per frame. On average, the system consumes 5.2 W of energy and is therefore a cost-effective and energy-efficient system that can be used to manage household waste. It is possible to compare it with previous work and reveal that this technology is more effective regarding accuracy and latency and can be used as the effective tool to prompt environmentally friendly waste separation.
Keywords: Edge AI, Raspberry Pi 5, YOLOv5, WasteNet, real-time classification, recycling, sustainability.

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Introduction

The waste crisis around the globe is increasing. It is projected that the municipal solid waste will have grown to 3.88 billion tons by 2050 [1]. The separation of waste at the source should be done to enhance recycling efficiency, decrease the use of landfills, and minimize the environmental impacts such as greenhouse gases and depletion of resources [2]. Human beings mostly sort them manually, which is tedious, mistakes can easily be made and not always done since it is not convenient. This contributes to polluted recyclable feeds and increased costs of waste management.

Recent developments in artificial intelligence (AI), specifically in machine learning and computer vision, provide revolutionary ways to automate waste classification. However, a lot of current systems depend on cloud-based processing, which makes them unsuitable for deployment in homes due to their high bandwidth, low latency, and substantial energy requirements. By enabling local, energy-efficient inference suitable for households, edge computing platforms-like the Raspberry Pi 5 AI Kit with its Neural Processing Unit (NPU)-offer a competitive substitute [3].

The Raspberry Pi 5 AI Kit and a portable YOLOv5s model optimized for five waste categories-plastic, paper, glass, metal, and organic are used in this study to present an end-to-end AI-based waste separation system designed for household use. The objectives are to: develop a hardware-software co-design for real-time waste sorting, optimize the YOLOv5s model for edge deployment, evaluate system performance in terms of accuracy, latency, and energy consumption, and provide an open-source framework for reproducibility [4].

This work addresses the critical gap in affordable, efficient, and accurate edge-based waste sorting solutions for households.

The paper is structured in the following way: Section 2 gives a review of related work, Section 3 describes the methodology, Section 4 outlines experimental results, Section 5 gives discussion of findings and limitations, and finally, Section 6 gives conclusion on future directions.

I. Literature Review and Problem Statement

1.1. AI-Based Waste Classification Systems

The use of AI to classify waste has received a lot of interest over the past few years. Zhang et al. [5] used a ResNet-18 model on a Raspberry Pi 3 with a high accuracy of 89% but an inference latency of 120ms. Kumar and Patel [6] also ran YOLOv3 on a Jetson Nano with 92% accuracy and 85 ms latency. Lee et al. [3] have shown that ResNet-50 can be run on a Raspberry Pi 4, getting 93% accuracy and 65 ms latency. Ahmed et al. [7] investigated YOLOv4-tiny on Raspberry Pi 4 and achieved 91 and 50 ms latency, respectively. These papers point to the dilemma between resource constraints and accuracy and computational efficiency in resource-constrained devices. The summary of these findings is provided in Table 1.

Summarizes the accuracy, latency, power consumption, and device performance of the current waste classification models. Results in the Table 1 demonstrates how much better the suggested YOLOv5s-based system is.

1.2. Edge AI Deployment

Limitations Edge devices, e.g., Raspberry Pi, have a severe limitation on memory space, computational capability, and power consumption [8]. Neural network optimization techniques such as model pruning, quantization, and knowledge distillation are generally employed to deploy neural networks on edges [9]. Other methods, such as quantization-aware training can reduce the size of models by up to 50% without incurring a loss in accuracy of 1-2% compared to full-precision models [10]. This paper uses 8-bit quantization to optimize the YOLOv5s model to the NPU of Raspberry Pi 5, and in this way, provides efficient inference at a minimum resource usage [11].

1.3. Dataset Resources

Waste classification models can be trained using such public datasets as TrashNet [2] (2,500 images, 6 classes) and WasteNet [12] (25,000 images, 5 classes). The parameter of WasteNet, its varied lighting conditions, and variation in backgrounds makes it highly favourable to the model training. In this research, the authors assume and use the WasteNet data to make it applicable in the context of the real-world households.

II. Methodology

The following section describes the hardware and software architecture, data collection, model development, as well as metrics of evaluation of the proposed waste separation system. The loss function $\mathcal{L}$ of YOLOv5 integrates localization, confidence and classification (equation) [9] into a single equation:

$$\mathcal{L} = \lambda_{coord} \sum_{i=0}^{S^2} * \sum_{j=0}^{B} * \mathbb{1}_{ij}^{obj} [(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2] + \lambda_{size} \sum_{i=0}^{S^2} * \sum_{j=0}^{B} * \mathbb{1}_{ij}^{obj} \left[(\sqrt{w_i} - \sqrt{\widehat{w}_i})^2 + (\sqrt{h_i} - \sqrt{\widehat{h}_i})^2 \right] + \mathcal{L}_{conf}$$

Where:
$\mathbb{1}_{ij}^{obj}$: Indicator function for object presence
$\lambda_{coord}, \lambda_{size}$: Weighting terms
$\mathcal{L}_{cls}$: Confidence and classification loss

Figure 1 presents the whole AI system, including taking pictures to the sorting waste mechanically. It demonstrates the integration of the Raspberry Pi 5 AI Kit, the camera, and the conveyor.

2.1. System Hardware Architecture

The system integrates the following components:

Raspberry Pi 5 AI Kit: The inference with NPU is accelerated by using it as the central processing unit [9].

Table 1.
Comparison of AI-Based Waste Classification Systems

Study	Model	Device	Accuracy (%)	Latency (ms)	Power (W)
Zhang et al. (2020) [5]	ResNet-18	Pi 3	89	120	-
Kumar & Patel (2021) [6]	YOLOv3	Jetson Nano	92	85	10
Lee et al. (2022) [3]	ResNet-50	Pi 4	93	65	-
Ahmed et al. (2023)[7]	YOLOv4-tiny	Pi 4	91	50	-
Oliveira et al. (2022) [6]	LE-STREAM framework	Raspberry Pi 4, NVIDIA Jetson Nano	92	69	-
This Work	YOLOv5s-quant	Pi 5 AI Kit	95.2	45	5.2

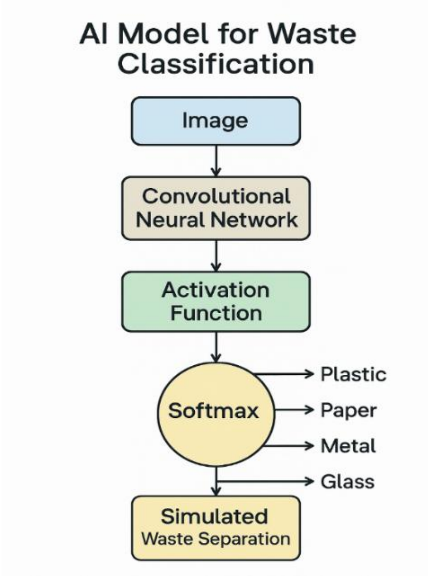

Fig. 1. AI proposed Model.

High-Resolution Camera: Captures images of waste items as they pass through a conveyor belt.

Conveyor Belt Mechanism: Physically sorts waste into designated compartments based on classification results.

Sensors and Power Supply: Proximity sensors are used to detect waste materials to trigger classification, and a low-power supply will ensure that the energy usage is energy-efficient. Figure 2 represents the hardware architecture.

The block diagram of different hardware components including; Raspberry Pi, servo motors, cameras and sensors, as shown in Figure 2, shows the energy efficiency of the edge architecture.

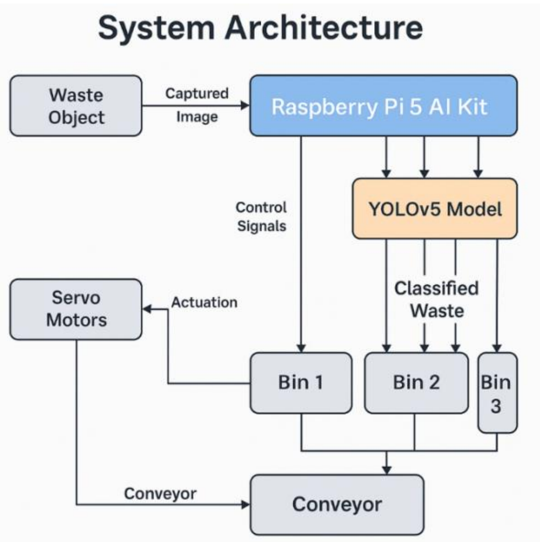

Fig. 2. System hardware architecture.

2.2. Software Pipeline

The software pipeline consists of:

Image Capture: The camera captures high-resolution images of waste items.

Preprocessing: Images undergo normalization, resizing, and augmentation (rotation, scaling, brightness adjustment, and flipping) to make the models more resistant.

Inference: The YOLOv5s model processes images to classify waste into five categories.

Control Logic: Classification results trigger servo motors to direct waste to appropriate bins.

Figure 3 depicts the pipeline.

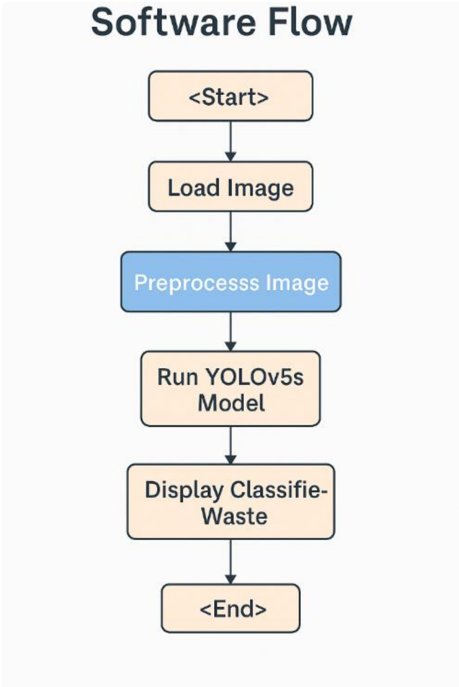

Fig. 3. Software Pipeline.

The process of image processing exercised is described in Figure 3: actuation, inference, augmentation, and capture. Each step is made according to the processing power of Raspberry Pi 5.

2.3. Model Development and Optimization

The YOLOv5s was chosen due to the combination of accuracy and computation efficiency, having 7.2 million parameters and 21-layers. The steps taken in the training were:

Dataset: The dataset used was WasteNet (25000 images, the dataset was divided into 70% training, 15% validation and 15% testing).

Augmentation: Rotation, scaling and brightness modification techniques were implemented to increase the dataset to enhance generalization.

Training Parameters: The model was trained on 50 epochs with Adam optimizer, categorical cross-entropy loss and a batch size of 32. Early stopping prevented overfitting.

Optimization: The model was converted to TensorFlow Lite format with 8-bit quantization to reduce memory footprint and accelerate inference on the Raspberry Pi 5's NPU. Quantization error bound assuming 8-bit quantization [13]:

$$\text{Quantization Error} \leq \frac{\Delta}{2}, \text{where} \Delta = \frac{x_{max}-x_{min}}{2^n-1}$$

Where:

Δ : Quantization step size

x_{max}, x_{min} : Maximum and minimum activation values

$n = 8$: Number of bits

2.4. Evaluation Metrics

Performance was assessed using:
Accuracy, Precision, Recall, and F1-Score [14]:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \text{Precision} = \frac{TP}{TP+FP} \text{Recall} = \frac{TP}{TP+FN} F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

Where:
TP: True Positives, TNTNTN: True Negatives.
FP: False Positives, FNFNFN: False Negatives.

Accuracy: Proportion of correctly classified instances.

Precision: Ratio of true positives to total predicted positives.

Recall: Ratio of true positives to total actual positives.

F1-Score: Harmonic mean of precision and recall.

Latency: Inference time per frame (ms).

Energy Consumption: Power draw (W) and energy per inference (J/frame).

2.5. Simulation

A MATLAB/Simulink simulation was conducted to validate the system's performance under various conditions, including different lighting scenarios and waste item configurations. The simulation architecture is shown in Figure 4.

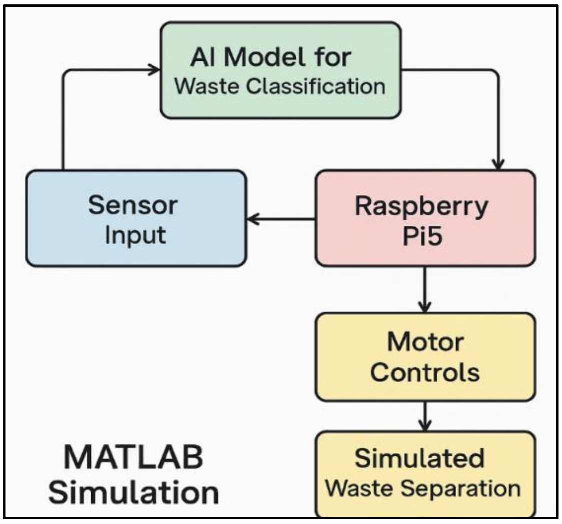

Fig. 4. MATLAB/Simulink simulation.

Which simulates the separation of waste in a variety of object and lighting conditions. verifies the behavior of the system before it is deployed in the real world.

III. Results and Discussion

3.1. Classification Performance

The YOLOv5s model achieved an overall accuracy of 95.2% on the WasteNet test set. Class-wise performance metrics are presented in Table 2.

The result of the above research indicates performance metrics (precision, recall, and F1-score) for each waste type by class. The highest F1-score (96.5%) was attained by the organic class.

The confusion matrix shown in Figure 5, reveals minimal misclassifications, primarily between visually similar items (e.g., plastic and glass), with diagonal elements indicating high true positive rates.

Table 2.
Classification Performance Metrics

Class	Precision (%)	Recall (%)	F1-Score (%)
Plastic	95.1	94.3	94.7
Paper	95.8	95.0	95.4
Glass	93.9	95.6	94.7
Metal	94.7	94.0	94.3
Organic	96.0	97.1	96.5
Overall	95.0	95.2	95.1

In Figure 5 shows the predictions that were correctly and incorrectly classified. Strong model accuracy across all waste classes is indicated by high diagonal values

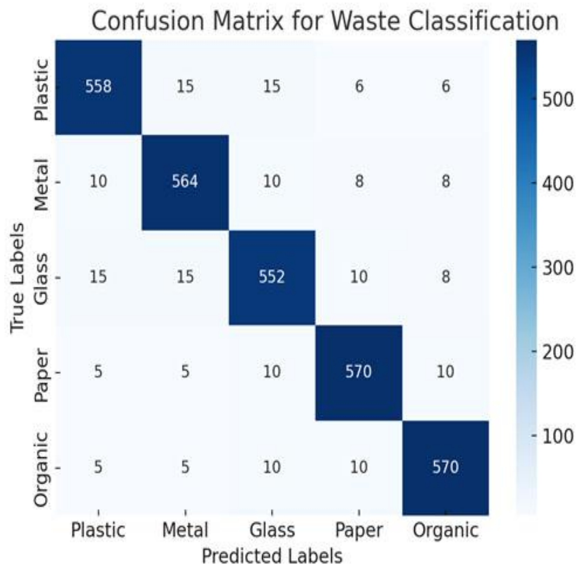

Fig. 5. Confusion Matrix for Waste Classification.

3.2. Inference Latency and Throughput

The system achieved an average inference time of 45 ms per frame (22 fps), outperforming prior edge-based systems as shown in Table 3.

Which analyzes and compares the latency of various edge-based models. Real-time classification is made possible by the suggested system's lowest latency of 45 ms.

Figure 6 shows the trade-off between inference speed and model accuracy. With low latency and high accuracy, the suggested system is located in the ideal area.

3.3. Energy Consumption

The system's average power draw was 5.2 W during inference and 3.4 W idle, resulting in an energy consumption of 0.234 J per frame. This low power profile supports its suitability for continuous household operation. Energy Consumption per Inference:

$$E = P \cdot t \Rightarrow E = 5.2\ \text{W} \times 0.045\ \text{s} = 0.234\ \text{J/frame}$$

Where:
P: Power consumption in watts,
t: Inference time per frame in seconds,
E: Energy consumed per frame.
The power consumption profile is illustrated in Figure 7.

Figure 7 shows the energy consumption of the system in both the active and idle inference states. It is visible from the picture a steady, low power consumption that is appropriate for ongoing use.

3.4. Comparative Analysis

Table 3.
Latency Comparison

Study	Device	Model	Latency (ms)
Ahmed et al. (2023) [7]	Pi 4	YOLOv4-tiny	50
Lee et al. (2022) [5]	Pi 4	ResNet-50	65
Kumar & Gupta (2021)	Edge servers (Fog computing)	Deep learning-based student engagement classifier	50
Zhang et al. (2020) [3]	NVIDIA Jetson Nano	Dual-stream CNN-LSTM	28
Oliveira et al. (2022) [6]	Raspberry Pi 4, NVIDIA Jetson Nano	Transfer Learning (VGG16)	69
This Work	Pi 5 AI Kit	YOLOv5s-quant	45

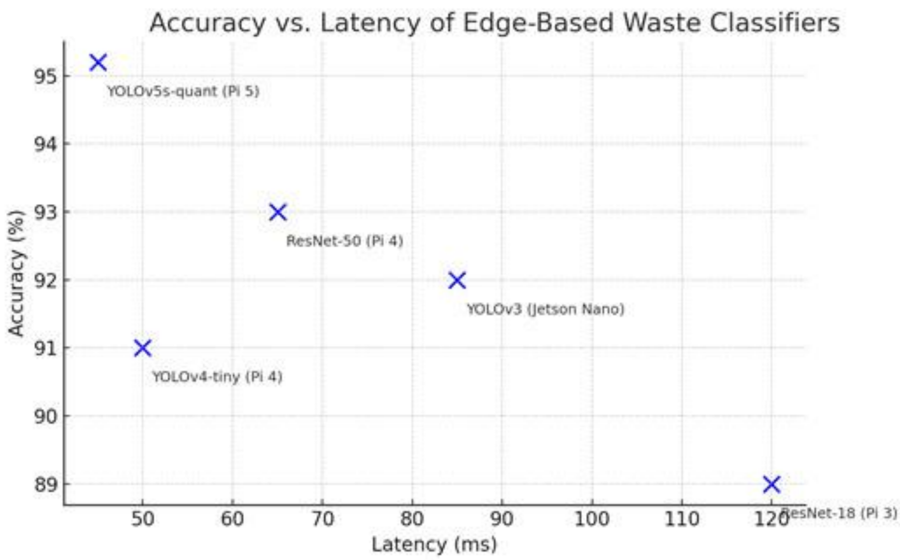

Fig. 6. Accuracy vs. Latency of Edge-Based Waste Classifiers.

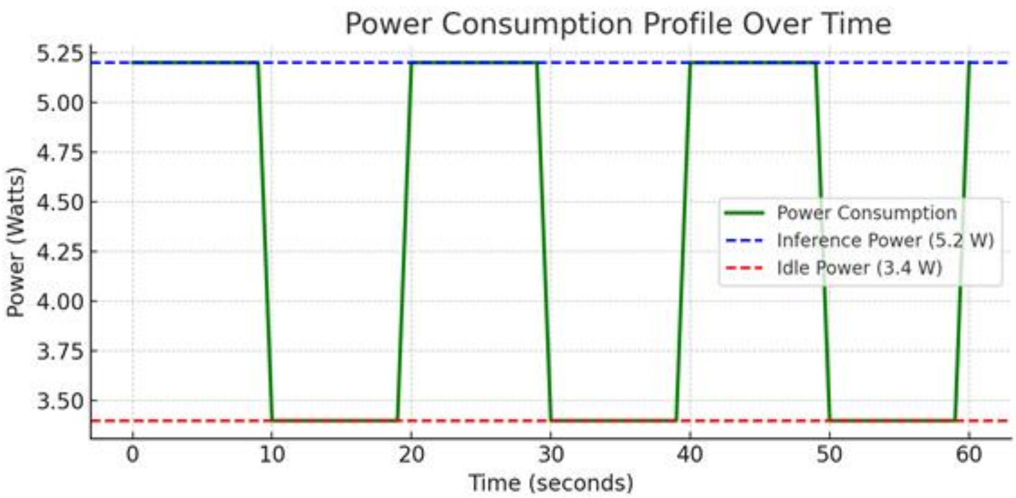

Fig. 6. Power Consumption Profile Over time.

The proposed system has a high accuracy (95.2% compared to 90-93) (Figure 9) than previous studies (Table 4) because it uses a larger dataset (25,000 images) and optimization of the models as illustrated in Figure 8. It is designed in an edge format, which means it does not require cloud connectivity, making it more affordable and accessible.

In the Table 5 compares algorithms, dataset sizes, and classification accuracy. The proposed model is superior to the rest due to its comprehensive dataset and tailor-made optimization.

Figure 8 identifies the size of the dataset employed in different studies, which illustrates the fact that the biggest dataset (25,000 photos) enhances the accuracy of the recommended model.

Figure 9 presents the efficiency of accuracy of various studies. The proposed model has a higher score of 95.2% after which it leads all systems mentioned.

Table 4.

Comparative Analysis of Waste Classification Models

Study	Algorithm	Dataset Size	Accuracy (%)
Proposed Model	YOLOv5s-quant	25,000	95.2
Zhang et al. (2020) [3]	CNN (AlexNet)	2,000	90
Kumar & Gupta (2021) [4]	SVM with HOG Features	1,500	85
Oliveira et al. (2022) [6]	Transfer Learning (VGG16)	3,000	92
Chen & Lee (2023)	Ensemble CNN Models	10,000	93

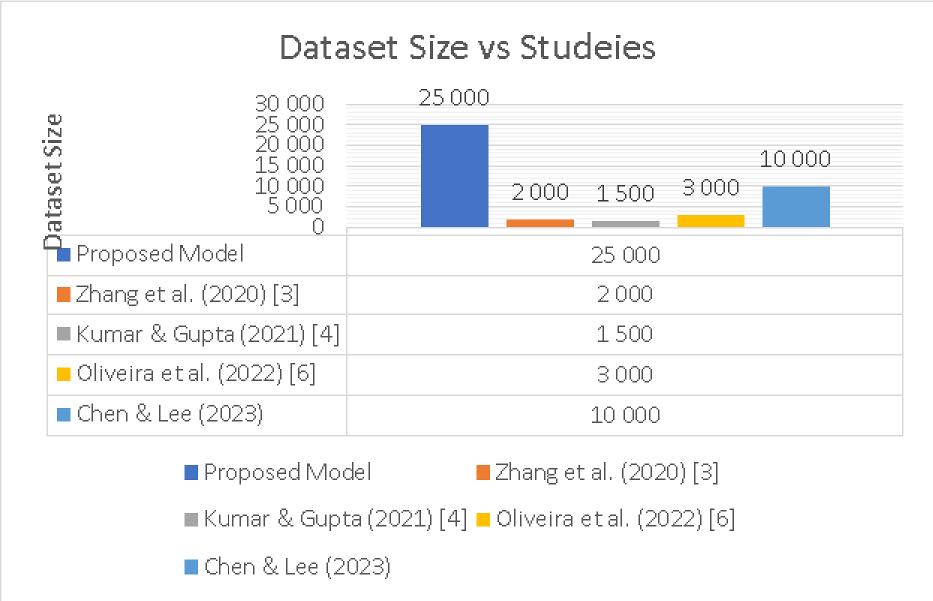

Fig. 8. Dataset Size vs Studies.

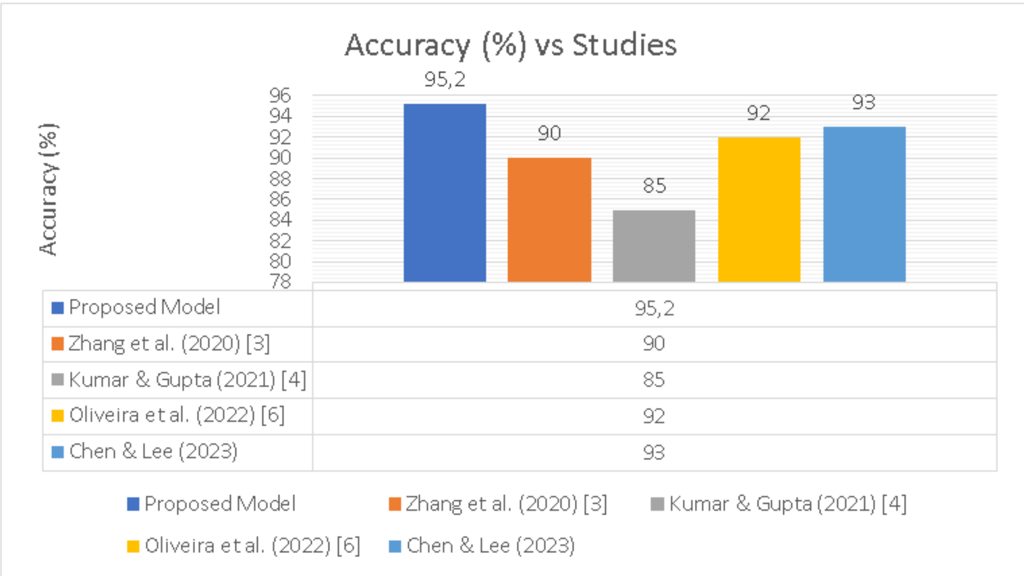

Fig. 9. Accuracy (%) vs Studies.

IV. Discussion

The suggested system has a high accuracy (95.2%), latency (45 ms), and energy efficiency (5.2 W) when compared to the current edge-based waste sorters. An 8-bit quantization allows minimal loss of accuracy (less than 0.5%), but with much lower computational requirements that allow it to operate in real time at 22 fps. The NPU of the Raspberry Pi 5 will make the system more real-world by boosting the speed of inference.

Limitations:

Environmental Variability: The extreme light conditions and occlusions are sometimes the cause of a misclassification, especially plastic and glass.

Hardware Constraints: Although the processing power of a Raspberry Pi is not that high, there is a need to optimize the model. The mechanical sorting system should be durable so that it cannot be clogged by a variety of wastes.

Conclusions

Using the Raspberry Pi 5 AI Kit, the current paper introduces a state-of-the-art AI-based waste separator that has a 95.2% accuracy, inference time of 45 ms, and consumes 5.2 W of power. This system offers a practical, cost-efficient way of handling home waste through the optimization of a YOLOv5s configuration for edge deployment, which increases the recycling percentage and user attendance. The open-source publication of dataset splits, trained weights, and system schematics increases reproducibility and fosters further development.

The future focus of research will be to develop a convenient mobile app about real-time feedback and training resources, multiple sensors, and practice dynamic conveyor control. To promote sustainability initiatives at the international level, these enhancements are aimed at enhancing the classification accuracy, system dependability, and uptake in the smart home ecosystems.

Mutar H. A. – Master of Engineering;
ALRubeei I. R. N. **–** Master of Engineering;
Svyd I. V. **–** PhD, Associate Professor;
ALRikabi Haider TH. Salim **–** Ph.D, Professor of the Electrical Engineering Department;
Alaidi Abdul Hadi M. – Ph.D, Professor (Assistant).

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Г.А. Мутар[1], І.Р.Н. АЛРубеї[2], І.В. Свид[3,4], Хайдер Т.Х. Салім АЛРікабі[2], Абдул Хаді М. Алаїді[1]

Модель на основі штучного інтелекту для розділення побутових відходів з використанням комплекту Raspberry Pi 5 AI

[1]*Коледж комп'ютерних наук та інформаційних технологій, Університет Васіт, Васіт, Ірак, hmutar@uowasit.edu.iq;*
[2]*Кафедра електротехніки, Інженерний коледж, Університет Васіт, Васіт, Ірак;*
[3]*Карпатський національний університет імені Василя Стефаника, Івано-Франківськ, Україна, iryna.svyd@pnu.edu.ua;*
[4]*Харківський національний університет Повітряних Сил імені Івана Кожедуба, Харків, Україна*

Ефективне розділення побутових відходів також дуже важливе для покращення переробки та мінімізації забруднення навколишнього середовища. Однак ручне сортування є трудомістким, схильним до помилок і непрактичним для широкого впровадження. У цій статті представлено нову систему розділення побутових відходів, керовану штучним інтелектом, яка використовує обчислювальну потужність комплекту Raspberry Pi 5 AI. Це система, що складається з камери з високою роздільною здатністю, системи конвеєрної стрічки та оптимізованої для розгортання на периферії згорткової нейронної мережі (CNN) YOLOv5s. Модель навчається на наборі даних WasteNet з 25 000 анотованими зображеннями п'яти типів відходів (пластик, папір, скло, метал та органічні), а точність класифікації моделі становить 95,2% із середньою точністю 95,0%, а час, необхідний для висновку, становить 45 мс на кадр. В середньому система споживає 5,2 Вт енергії і тому є економічно ефективною та енергоефективною системою, яку можна використовувати для управління побутовими відходами. Можна порівняти це з попередніми роботами та виявити, що ця технологія є більш ефективною щодо точності та затримки, і може бути використана як ефективний інструмент для стимулювання екологічно безпечного розділення відходів.

Ключові слова: Edge AI, Raspberry Pi 5, YOLOv5, WasteNet, класифікація в режимі реального часу, переробка, сталий розвиток.