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INTELLIGENT PLASTIC BRAND AUDIT FOR EXTENDED PRODUCER RESPONSIBILITY INITIATIVES USING MACHINE LEARNING MODEL

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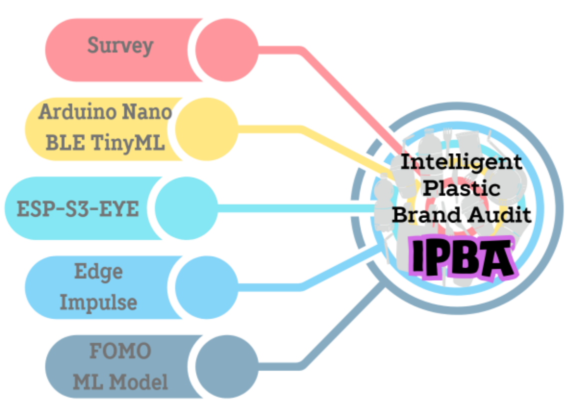
Graphical abstract



Abstract

The ever-growing volume of plastic waste poses a significant threat to global ecosystems. Existing waste management systems often struggle with the identification and sorting of plastic waste due to limitations in the scalability and cost-effectiveness of smart technologies. One key aspect of plastic waste mitigation is to enhance extended producer responsibility (EPR) capacity through plastic waste auditing. While computer vision techniques have been explored for general waste sorting, there is a lack of research focused on automated brand identification within plastic waste. This paper proposes a novel Intelligent Plastic Brand Audit (IPBA) system leveraging TinyML with machine learning capabilities for resource-constrained edge devices. The system utilizes a lightweight Faster Objects More Objects (FOMO) model trained on user-generated labelled photos and data. The performance evaluation of FOMO for IPBA was performed on two hardware platforms: Arduino Nano BLE and ESP32-EYE-CAM. Across both configurations and with five plastic brand classes, the system achieves high accuracy, with a minimum F1 score of 93.5%. These results indicate the potential of IPBA to improve existing manual sorting systems and support circular economy initiatives. By facilitating automated brand identification in plastic waste, IPBA can enhance EPR programs and hold brands accountable for their waste footprints.

Keywords: Waste brand audit, waste management, machine-learning, FOMO, faster objects more objects, TinyML

Abstrak

Jumlah sisa plastik yang semakin meningkat menimbulkan ancaman besar kepada ekosistem global. Sistem pengurusan sisa sedia ada sering bergelut dengan pengenalpastian dan pengasingan sisa plastik adalah terbatas kepada skalabiliti dan keberkesanan kos teknologi pintar. Satu aspek utama mitigasi sisa plastik adalah untuk meningkatkan kapasiti tanggungjawab pengeluar lanjutan (EPR) melalui pengauditan sisa plastik. Walaupun teknik penglihatan komputer telah diterokai untuk pengasingan sisa, terdapat kekurangan penyelidikan yang tertumpu pada pengenalan jenama automatik dalam sisa plastik. Manuskrip ini mencadangkan sistem Audit Jenama Plastik Pintar (IPBA) baharu yang menggunakan TinyML dengan keupayaan pembelajaran mesin untuk peranti pinggir dengan kekangan sumber. Sistem ini menggunakan model ringan Objek Lebih Pantas Lebih Banyak Objek (FOMO) yang dilatih pada foto dan data berlabel yang dijana pengguna. Penilaian prestasi FOMO untuk IPBA telah dilakukan pada dua platform perkakasan: Arduino Nano BLE dan ESP32-EYE-CAM. Merentasi kedua-dua konfigurasi dan dengan lima kelas jenama plastik, sistem ini mencapai ketepatan yang tinggi, dengan skor F1 minimum sebanyak 93.5%. Keputusan ini menunjukkan potensi IPBA untuk menambahbaik sistem pengisihan manual sedia ada dan menyokong inisiatif ekonomi kitaran. Dengan pengenalan jenama sisa plastik secara automatik, IPBA boleh meningkatkan program tanggungjawab pengeluar (EPR) dan memastikan jenama bertanggungjawab terhadap kesan sisa mereka.

Kata kunci: Audit jenama sisa, pengurusan sisa, pembelajaran mesin, FOMO, objek lebih pantas lebih banyak objek, TinyML

1.0 INTRODUCTION

Plastic waste is generating significantly faster than our dated systems can manage. The most significant impact of this situation is the alarming amount of plastic waste making its way into our landfills and later into our ecosystems. This is a multifaceted global issue with many key contributors [1].

Mitigation of plastic waste is a global priority for a whole range of organizations. These strategies usually involve efforts to improve recycling capacities, waste management systems and cleanup efforts. Organizations and volunteers who offer their services to help with these activities rely on manual effort in all stages of this mitigation strategy. For example, a relevant organization like Impaclution Sdn. Bhd. [2] based in Malaysia was observed to routinely arrange volunteers for cleanup activities followed by a visual plastic waste audit based on plastic type. It is also very common for businesses with extended producer responsibility (EPR) to routinely support these activities. This is one of the core reasons EPR was designed, to help businesses [3] become an instrument for solid waste management efforts globally. Although this serves some of the purposes of the EPR, it must be acknowledged that the EPR was mainly designed for businesses to identify and mitigate waste generated specifically by them [4]. With a generalized approach to help in mitigation efforts, the core responsibility of the producer is sidetracked, and their actual contribution cannot be quantified respective to their waste contribution.

One of the reasons that auditing mixed plastic waste for brands has been difficult is the complexity and size of the task. In developing countries where the amount of waste generated is unmanageable, the EPR tasks are often relayed to Producer Responsibility Organizations (PRO). One study of such an instance in India showed how relaying the task to a PRO who was driven by technology was able to significantly improve brand auditing and EPR capacities [5]. By using a multifaceted approach, the PRO company used a mobile application called 'Uzed App' for manual reporting of brands in plastic waste on an individual household level. This resulted in a drastic increase in plastic and electronic waste brand audits in their specific case, showcasing that such a solution could be an ideal way to look at EPR and waste management in developing countries. In our effort, the idealism is to replicate this model where individuals could participate in plastic brand audits alongside organizations so that the EPR could be realized more effectively.

Unfortunately, within the scope of waste management, many of our technological advancements have fallen short of creating actual impact [6]. Despite international and organizational efforts, plastic waste monitoring and management systems still prefer lower-cost manual methods. The inertia to change from these manual methods featuring dated mechanisms such as visual surveys still supersede high-tech smart solutions.

Lately, a lot of effort has been made to make plastic waste segregation somewhat easier using computer vision with varying degrees of success [7-9]. From global waste datasets, it is evident that few consumer brands cater to significant portions of the waste generated [10]. However, even the most modern waste segregation and management techniques still sort waste based on only type of waste. In this process, critical insight into key polluters is lost. This data, if available, can directly feed EPR policies and help shape the responsibility, accountability, and future planning for these large consumer brands [11].

By examining the global initiatives around smart plastic waste segregation, it can be learned that any system must be made affordable and easy to integrate to become a part of plastic waste management [12]. Based on these values and insights, the approach to auditing brands in plastic waste has been proposed.

Recent approaches to auditing brands in plastic waste involve utilising technologies such as near-infrared spectroscopy and hyperspectral imaging for quality assessment and classification of plastics in recycling plants [13]. Various machine learning (ML) models have also been proposed to create inexpensive and automated waste detection, usually by type of waste material [14]. The use of ML detection showed significant improvement when shifted from manual methods in plastic management systems [15].

The ML models are usually compatible with microcomputing hardware like Raspberry Pi and NVidia Jetson. Nonetheless, the most common choices are microcontrollers like the Arduino [16] and Espressif (ESP) [17] platforms known for their inexpensive hardware that could be easily replicated and tested. The choice was made based on their availability of the lowest cost devices in the market which supported ML and inference from images. However, this created a new challenge where the existing lightweight ML models were throttled in the extremely resource-constrained hardware selection. Common models fail to deliver in these hardware constraints, especially during object detection.

However, Faster Objects More Objects (FOMO) provides a great alternative to these models because it is optimized to run on resource-constrained hardware performance [18]. FOMO is an optimized ML model built on MobileNet Single Shot Detector (SSD). Usually, SSDs are designed to be lighter models deployable for edge computing devices. However, during objection detection, these ML models can throttle resource-constrained devices due to the heavy workload. Unlike traditional ML models, FOMO provides a unique in-between solution by performing image classification during object detection [19]. It does so by splitting any input image into a grid and instead of looking for size, it identifies the location of objects and performs image classification on every box on that grid. This allows FOMO to perform with high degrees of accuracy under extreme resource constraints of flash memory and clock speed of the edge device. FOMO is also supported for convolutional image networks and transfer learning, which makes it an easy deployment model even for datasets trained on devices with higher computational power. Some adoptions of FOMO have already been explored such as its application in identifying dangerous mosquito species [20] with a significant degree of accuracy. Moreover, the Edge Impulse platform allows for FOMO to be simulated for different low-cost hardware configurations with a range of results to justify parametric choices of relevant hardware.

Additionally, making the device edge intelligent meant that users would interact more seamlessly and increase their participation in the process willingly. Previous work has indicated that a citizen science approach is the most optimized way to deal with plastic waste [21]. Organizations have used apps like 'Litter Club' developed by LIAA Environmental Empowerment Solutions Sdn. Bhd. [22] for reporting on plastic waste. Our concept was built upon the idea of automating user input by allowing photos taken by users to automatically detect and audit brands from plastic waste. Making the process inexpensive meant that businesses with EPR could support these initiatives at a low upfront cost while engaging a community to incite behaviour on the consumer level.

In this paper, we propose an intelligent plastic brand audit (IPBA) system using a ML model, especially for edge deployment. The scope of the IPBA was to be able to equip citizens and organizations with a mobile tool to help track and audit brands from within plastic waste. To make the IPBA system truly inclusive of citizen scientists around the globe, the focus is on exploring and choosing the most inexpensive hardware options for implementation. The IPBA system is not meant as a drop-in replacement for generic manual and intelligent waste segregation systems. It is rather proposed as a complementary system to the existing infrastructure. Our work has allowed further exploration of a FOMO ML model's viability in IPBA use cases which are cost-sensitive and require large-scale adoption for impact.

The contributions of this paper can be summarised as follows:

1. Design of an IPBA system based on efficient FOMO to be very lightweight and affordable for both businesses and consumers.
2. Performance evaluation of the IPBA system using two different low-cost hardware configurations: Arduino Nano BLE TinyML kit and ESP32-EYE-CAM modules respectively, to identify the best hardware recommendation for object detection.
3. Integration of an edge solution using Edge Impulse software, for the deployment of ML with citizen science inclusion.

The rest of the paper is structured as follows. Section 2 elaborates on the development of the IPBA system and its assessment, and Section 3 presents and discusses the results. Finally, Section 4 concludes the study.

2.0 METHODOLOGY

Figure 1 illustrates the methodology used in this study, which consists of four main phases described in the following subsections.

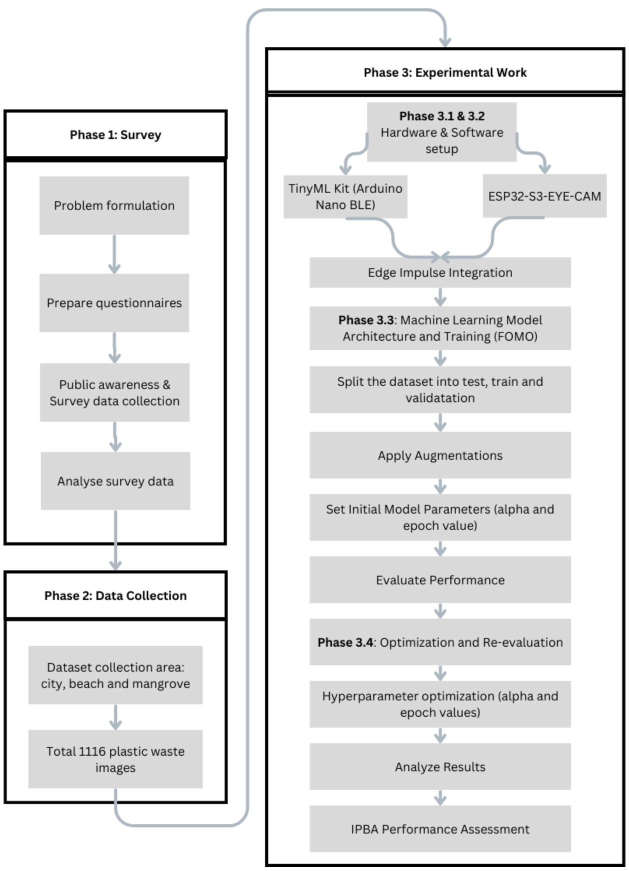


Figure 1 Flowchart of the methodology adopted for the IPBA study

2.1 Survey

The method of using a survey to analyse benchmark results and key parameters was used based on recent works in identifying awareness of solid waste management [23-26]. A survey carried out by students of Universiti Kebangsaan Malaysia (UKM) targeting a minimum of 100 respondents was used to understand and identify the most common plastic waste contributors in Malaysia categorized through brands. The survey was shared on social platforms such as WhatsApp, Telegram, Facebook and Instagram to collect responses. The survey was carried out for 2 weeks between the 11th of May 2022 to the 25th of May 2022. The survey and the public awareness on the topic of brand audit among these students were also studied. The survey consisted of 5 demographic questions (Age, Gender, Ethnicity, Occupation and State in Malaysia), 4 questions on the Plastic waste tendency and 3 questions on Brand Audit/Plastic recycling campaigns. One more question was added to know if any of the respondents were interested in becoming volunteers for the Plastic Brand Audit efforts with the team.

2.2 Data Collection

For training of our FOMO model, various user-generated images of plastic waste with visible branding were collected and sorted into categories of test, train and validation. The sources include direct data collection from waste around the campus and indirect images available on open-source databases. The images were augmented before training to introduce external factors such as noise to help create a more robust ML model. Figure 2 shows two sample images from the user-generated dataset.

Figure 2 Sample of a plastic waste dataset collected by the volunteers and the different quality of the image (Left) Coca-Cola bottle (Right) Sprite bottle

2.3 Experimental Method

The IPBA method introduced in this paper provides a novel approach to better prepare businesses for their EPRs while creating consumer awareness. Since this was a novel approach, two different hardware configurations were tested to validate the best optimization technique to conduct the IPBA. The experimental setup was designed to compare two competing inexpensive configurations using the same dataset and FOMO model.

2.3.1 Hardware Setup

The experimental setup featured two microcontroller boards, the Arduino Nano BLE and ESP-S3-EYE. These boards were chosen mainly due to 3 factors:

1. Cost
2. Machine Learning Capacity
3. Market Availability

The first setup included an Arduino Nano BLE-based Tiny ML Kit (TinyML Kit) built on the tiny ML shield paired with an OV7675 camera module. The Arduino board is built using a 32-bit Atmel chip with an ARM architecture powered by an NRF semiconductor chip for Bluetooth connectivity. The ARM Cortex-M4 contains 1MB of flash, 256 kB of Random Access Memory (RAM) and relies on a floating-point unit (FPU) working on a 32-bit instruction set to maximize code density and performance. It also implements features to enable energy-efficiency arithmetic and high-performance signal processing. The OV7675 camera mounted through the TinyML shield is a standard VGA camera that can work with a host of development boards for computer vision experiments featuring a VGA (640x480) sensor.

The second setup included an ESP32-S3-EYE built using the Espressif 32-S3 AI-powered chip featuring an onboard OV2640 camera, TFT display and memory card slot. The ESP32-S3 is a dual-core Microcontroller Unit (MCU) with a capacity to run at 240MHz, with 512 KB of internal (SRAM). OV2640 camera features a 2-megapixel (1600x1200) sensor. The OV2640 offers higher resolution than the OV7675 has an on-chip JPEG encoder to offload the processing power from low-end MCUs and takes much less memory footprint on limited MCU internal RAM. This development board also features a higher flash memory of 8 MB among improvements in other features, on which different implications are discussed in the results section of this paper. Figure 3 shows the two development boards.

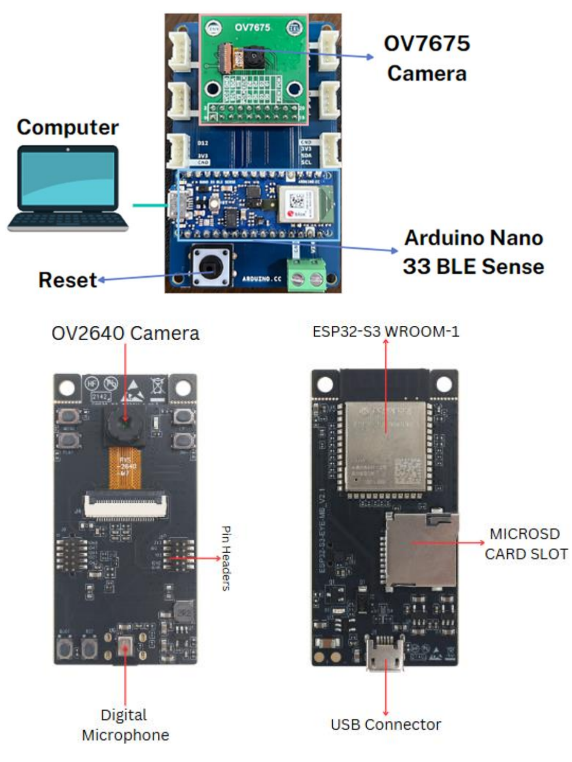


Figure 3 (Top) Arduino Nano BLE TinyML development kit, and (Bottom) ESP-EYE-CAM S3 board (front and back)

2.3.2 Software Configuration

The Edge Impulse [18] platform was used to deploy the FOMO model on our microcontroller configurations. This platform was used because it already had sufficient documentation and support for our microcontroller configurations. This reduced redundancies in our testing procedure by having a standardized platform to create and deploy identical models on both of our setups.

The plastic bottle images were labelled manually in the "Labelling queue" for a total of 1166 images, of which 80% of the data was dedicated for training and 20% data was allocated for testing. The model is trained so that it can detect different classes of objects in the dataset. The classes of data included plastic bottles from beverage brands, which are Coca-Cola, Sprite, F&N and Sarsi and included the international food brand 'Maggi' for their instant cup noodles. To reduce background effects, which could skew the training, only the labels of the brands on the plastic waste images were bound during manual labelling.

In creating impulse, the Objection Detection block was chosen, instead of the Transfer Learning block in Image Classification. This training model applied FOMO MobileNetV2 0.35. It is an object detection model based on MobileNetV2 (alpha 0.35) designed to coarsely segment an image into a grid of background vs. objects of interest. These models are designed to be less than 100KB in size and support a grayscale input at any resolution. The ML model was initially deployed on the Arduino-based TinyML kit and later deployed on the ESP-EYE-CAM. The same dataset was used to verify differences in key parameters of performance on both these configurations. However, due to restrictions in GPU time usage on Edge Impulse, for the ESP-EYE-CAM instead of training for 140 epochs training was carried out for 60 epochs model.

2.3.3 Machine Learning Model Architecture and Training

The ML model chosen for our study was FOMO. FOMO is a deep learning object detection model that weighs less than 200 kilobytes. The algorithm runs real-time object detection on devices with very small computation and memory capacity. The model is highly efficient, up to 30 times faster than traditional MobileNet SSD models which are usually used for these types of low-cost hardware configurations [27].

FOMO applies a major structural change to traditional deep learning architectures. FOMO provides an object detection solution but uses image classification techniques. It provides an in-between but lightweight solution which is highly optimized for low-cost configurations. At first, the image is broken down into a grid. The center of relevant objects in our classes is identified in the grid and a heat map is created reflecting their relative positions. The relative location of the object is rather used instead of the traditional object detection method of also computing object size. Using the relative locations, an image classification model is applied to those objects. This allows for fast but effective object detection. Bounding boxes can later also be applied to the detected objects from the approximate location of the objects in the frame.

2.3.4 Training and Evaluation

Performance comparison metrics from the training and testing were based on generated outputs of the Edge Impulse platform using the FOMO model. These performance metrics included the following:

1. **Accuracy**: Proportion of correct predictions by the model to the total number of predictions.
2. **Peak RAM Usage**: The peak RAM usage indicates the maximum amount of memory that the model and associated processes required to perform inference or training tasks.
3. **Memory Usage**: Amount of storage required to store the model.
4. **Inference Time**: Time taken for the model to make predictions on new data.
5. **F1 Score**: harmonic mean of precision and recall (Precision measures the accuracy of positive predictions, while recall measures the ability to identify all positive instances; precision is True Positive divided by True Positive + False Positive, and recall is True Positive divided by True Positive + False Negative).

2.3.4 Optimization and Re-evaluation

Based on preliminary testing data, the FOMO model was optimized by adjusting the input parameters for the following three variables to check for performance improvements and re-evaluation based on the performance metrics.

1. **Learning Rate**: the step size for adjusting model parameters during training.
2. **Epochs**: number of times the dataset is passed through the learning algorithm during training.
3. **Weights**: representation of the parameters associated with the connections between neurons in a neural network, determining the strength and impact of each input on the network's output.

3.0 RESULTS AND DISCUSSION

3.1 Plastic Waste Brand Audit Survey

The initial survey conducted at the beginning of this study helped to provide valuable insight to guide the study. The survey featured questions on awareness of plastic waste, usability of recycled plastic bottles and awareness about brand auditing. The key demographic data of the survey is shown in Table 1. The survey has a total of 135 respondents with students contributing 89.5%, lecturers 5.3% and others 5.2%. In terms of gender, 63% of the respondents are male and only 37% are female.

Table 1 Demographic and user information from the brand audit survey

Type	Survey items	Results
	Total Respondents	135
Occupation	Students	89.5%
	Lecturers	5.3%
	Others	5.2
Age	18-24 years old	86.7%
	above 25 years old	13.3%
Gender	Male	63%
	Female	37%

Using this survey, the main sources of plastic waste in Malaysia were identified. Furthermore, consumer awareness regarding plastic waste and people's intention to contribute positively to reducing plastic waste, such as by using recyclable bottles were examined and assessed. According to the survey, the top five beverage brands commonly consumed were Nestle (84 respondents, 20.7%), Coca-Cola (80, 19.7%), F&N (60, 14.8%), Spritzer (47, 11.6%), and Sprite and Pepsi (45, 11.1%). These same five beverage brands were also the most frequently encountered plastic bottle brands, with Coca-Cola being the most prevalent at 23.5%, followed by Nestle at 9.9%. These findings are depicted in Figure 4.

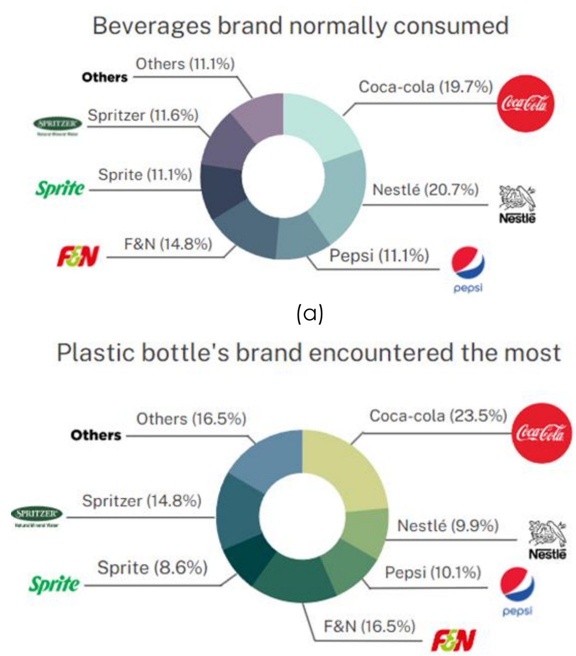


Figure 4 (a) Beverage brands normally consumed, and (b) Plastic bottle brands encountered the most based on the survey in Malaysia

Furthermore, the survey revealed that 63.7% of respondents disposed of between 1 to 5 bottles on average per week, contributing to the overall plastic waste issue. While 51% of respondents were aware of the United Nations' Sustainable Development Goals (SDGs), 37.8% were unaware of local government policies aimed at reducing plastic waste. Over half (63.7%) of the respondents expressed a willingness to pay extra for recycled bottles, even though the majority (95.6%) had no prior exposure to plastic brand audits. Another significant finding from the survey was that 65.9% of respondents were eager to actively volunteer for plastic waste sorting initiatives. The survey results were instrumental in developing the initial model for plastic brand audits, as they helped identify key consumer brands and critical gaps within the existing system. Based on the survey response, it was further possible to justify how a successful integrated plastic brand audit system could drastically improve plastic waste management initiatives and outcomes.

3.2 Performance Assessment of IPBA

The IPBA was tested on two different configurations. Both the low-cost hardware configurations were able to show promising detection results with a high degree of accuracy and a high F1 score. Results from the brand classification using both settings (Arduino Nano BLE and ESP32-EYE are presented in Figure 5 followed by their con-fusion matrices.

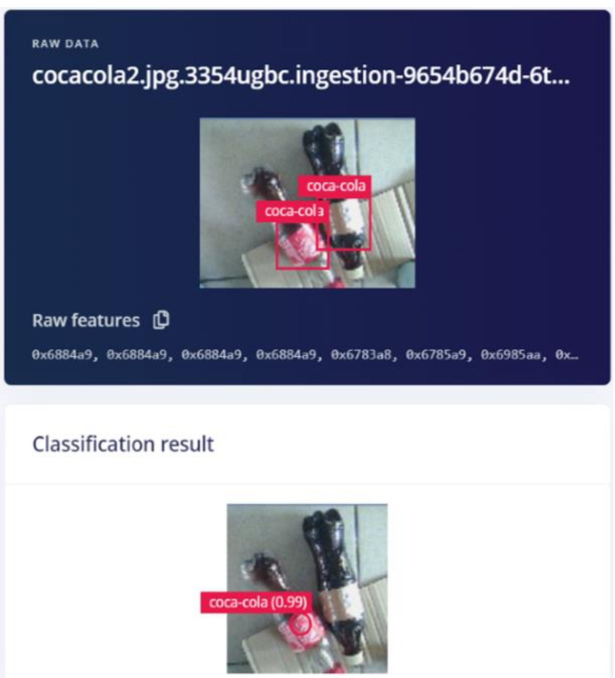


Figure 5 An example of results from the classification process. In this example, two Coca-Cola bottles were put side by side but only one can be detected, but with a 99% confidence rate

This specific type of confusion matrix is a representation of inference based on predicted (column) results vs actual (rows) data. For example, it can be observed in Table 2 second row and first column, 6.3% of F&N images were predicted as background images. These represent false positives in the assessment which impact the expected results.

The confusion matrix compares predicted results indicated in rows with actual results indicated in the columns of the matrix for each class. Using this matrix the true positive (TP), true negative (TN), false positive (FP), and false negative (FN) classifications are identified respectively. Using this data the following calculations are made to calculate the F1 score:

$$Precision = \frac{TP}{TP + FP} \quad (1)$$

$$Recall = \frac{TP}{TP + FN} \quad (2)$$

$$F1\ score = \frac{2(Precision \times Recall)}{(Precision + Recall)} \quad (3)$$

Table 2 Confusion matrix and F1 score for Arduino Nano BLE TinyML kit, alpha value = 0.35, 60 epochs

	Others	**F&N**	**Coca-Cola**	**Maggi (Nestle)**	**Sarsi**	**Sprite**
Others	99.9%	0.0%	0.0%	0.0%	0.0%	0.0%
F&N	6.3%	93.8%	0.0%	0.0%	0.0%	0.0%
Coca-Cola	18.0%	0.0%	82.0%	0.0%	0.0%	0.0%
Maggi (Nestle)	2.1%	0.0%	0.0%	97.9%	0.0%	0.0%
Sarsi	12.8%	0.0%	0.0%	0.0%	87.2%	0.0%
Sprite	0.0%	0.0%	0.0%	0.0%	0.0%	100%
			F1 score			
Per-Class	1.00	0.90	0.89	0.94	0.88	1.00
Average			0.9350			

The first confusion matrix has non-zero values in the off-diagonal elements inferring misclassifications. From the first column in Table 2, the Arduino Nano BLE with 60 epochs training configuration data shows some discrepancies in detection. Notable differences can be observed, especially for Coca-Cola and Sarsi where the difference in false positives between the two configurations is over 10%. The accuracy with which the labels are detected can be cross-referenced to the inference time where the inference time of the ESP-EYE-CAM with 60 epochs configuration is 340 ms or 30% more than that of the Arduino Nano BLE configuration. Overall, the second confusion matrix from Table 3 appears to have better performance and accuracy for most classes compared to the first confusion matrix, including a higher average F1 score. The Sprite label appears to be the best-performing class with no misrepresentations across either of the configurations.

Through an iterative method, the average F1 score of the model was successfully tuned to a maximum of 97.5% for the Arduino-based TinyML kit for 140 epochs as shown in Table 4.

The parameters which were kept constant during the process are: learning rate = 0.0005, alpha = 0.35, object weight = 100. Figure 6 shows the accuracy and feature map of the FOMO model on the Arduino Nano BLE corresponding to the 140 epochs optimisation.

Figure 6 Accuracy and feature map of the FOMO model on the Arduino Nano BLE TinyML Kit, alpha value = 0.35, 140 epochs

In comparison to Table 2, lower non-zero values can be observed in Table 4, beyond the off diagonal suggesting better performance for the same hardware configuration (with only a change in the number of epochs). Table 4 shows enhanced accuracy for Coca-Cola and Maggie Cup labels and no misclassification for Sprite. This implies that with a higher number of epochs the test results can be further tuned and optimized.

Table 3 Confusion matrix and F1 score for ESP32-EYE-CAM, alpha value = 0.35, 60 epochs

	Others	F&N	Coca-Cola	Maggi (Nestle)	Sarsi	Sprite
Others	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%
F&N	0.0%	100.0%	0.0%	0.0%	0.0%	0.0%
Coca-Cola	2.4%	0.0%	97.6%	0.0%	0.0%	0.0%
Maggi (Nestle)	5.3%	0.0%	0.0%	94.7%	0.0%	0.0%
Sarsi	0.0%	0.0%	0.0%	0.0%	100.0%	0.0%
Sprite	0.0%	0.0%	0.0%	0.0%	0.0%	100%
			F1 score			
Per-Class	1.00	1.00	0.98	0.96	0.99	1.00
Average			0.9833			

Table 4 Confusion matrix and F1 score for Arduino Nano BLE TinyML kit, alpha value = 0.35, 140 epochs

	Others	F&N	Coca-Cola	Maggi (Nestle)	Sarsi	Sprite
Others	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%
F&N	3.0%	97.0%	0.0%	0.0%	0.0%	0.0%
Coca-Cola	6.1%	0.0%	93.9%	0.0%	0.0%	0.0%
Maggi (Nestle)	2.6%	0.0%	0.0%	97.4%	0.0%	0.0%
Sarsi	5.4%	0.0%	0.0%	0.0%	94.6%	0.0%
Sprite	0.0%	0.0%	0.0%	0.0%	0.0%	100%
			F1 score			
Per-Class	1.00	0.96	0.97	0.96	0.96	1.00
Average			0.9750			

Because of limitations on the Edge Impulse platform on the usage of GPU time, the ESP-EYE-CAM could not be trained over 60 epochs. This impacted the accuracy of results, which is greatly dependent on the number of training cycles. Hence the improved accuracy for a greater number of epochs on the ESP platform is yet to be explored. For the Arduino-based TinyML kit, a result with 92.54% accuracy was produced using an iterative approach, as shown in Figure 4. With the same number of epochs, it can be inferred that the accuracy will remain comparable between the two configurations. At 60 epochs both the configurations had similar output results. The key difference was in the inference time and the F1 score. The inference time for the Arduino configuration was lower but the F1 score on the ESP configuration was 8.1% higher, which is a significantly better score.

Table 5 compares the performance metrics of the two configurations, and Table 6 records a comparison between the two microcontroller configurations with changes only in epochs from the optimization process.

Table 5 Comparison of performance metrics between 2 microcontrollers

Metrics	**Arduino Nano 33 BLE**	**ESP32-EYE CAM**
Accuracy	72.6%	72.6%
Peak RAM Usage	239.2K	239.2K
Memory Usage	72.9K	72.9K
Inference Time	1097 ms	1437 ms
F1 Score	90.3%	98.2%

Table 6 Comparison of learning configurations for optimization process between 2 microcontrollers

Metrics	**Arduino Nano 33 BLE**	**ESP32-EYE CAM**
60 epochs	93.5%	98.3%
140 epochs	97.5%	Unable to Verify

3.3 Discussion

From the initial brand audit survey, it is evident that consumers want to contribute positively towards the environment and are likely to support consumer brands that have a strong brand audit. During the trial with the two different hardware configurations, some key differences in the performance parameters were identified. The ESP-based system performed significantly well in comparison to the Arduino-based TinyML kit. The main reason can be attributed to the difference in hardware and processing capacity of the two devices as compared in Table 7.

From the results, the better performance shown by the ESP32 microcontroller can be easily identified due to the big difference in its specification. The higher processing power meant that the ESP32 EYE CAM was better at running the computations at a faster speed.

Table 7 Comparison of key specifications between Arduino Nano 33 BLE and ESP32 EYE CAM

Technical Specifications	Arduino Nano 33 BLE	ESP32-EYE CAM
Processor	nRF52840	ESP32-DOW DQ6
Architecture	ARM Cortex M4	Xtensa L6
RAM	256 KB	520 KB
Processor Speed	64 MHz	240 MHz (Max)
Flash Memory	1 MB	16 MB
Approx. Cost in USD	53	50

The larger RAM and Flash Memory allowed for the ESP to load and process the object classification model better allowing for a more complex and accurate model deployment. With increased storage space, it is possible to store larger and more accurate FOMO models, calibrated on bigger datasets allowing for future improvements. Memory also helps in resource management when the model must be loaded for computation and inference. A bigger model would work better with the ESP configuration due to its memory capacity. The conclusion can be definitively drawn from this result that, for the future development and deployment of edge computing, RAM and Flash memory will be identified as key contributors to micro-controller configuration choice.

Table 3 clearly shows how the F1 score of the model can be impacted without changing the dataset. This also implies that for such hardware configurations, it is important to fine-tune the input parameters to get optimal results and results are not always completely dependent on just the quality of input data alone. This model can be improved by collecting and reviewing a larger dataset that is less controlled and has a more diverse background. However, provided the amount of storage required this may only be possible on the ESP32-EYE-CAM configuration.

To enhance the capabilities of the IPBA system and better serve the project's objectives, the integration of Long Range (LoRa) communication into the Arduino Nano BLE and ESP32-EYE-CAM modules is advantageous. The integration is feasible due to their compatibility with LoRa modules, which can be easily connected to their general-purpose input/output (GPIO) pins. The LoRa technology's ability to transmit data over extended distances in various environmental conditions is crucial for remote or widespread deployment scenarios. By incorporating LoRa into the hardware configurations, the IPBA system can efficiently transmit critical data to a centralized cloud or database, enabling real-time monitoring and analysis of plastic waste brand auditing. This integration facilitates data-driven decision-making and helps enforce EPR policies by providing timely insights and accountability for consumer brands. There are multiple use cases where LoRa has been paired with similar hardware configurations to create decentralized data streams [28-30]. The addition of LoRa does not reduce the portability of the IPBA devices. However, there is scope to improve and optimize the energy usage of the system by implementing advanced battery control for the portable lithium-ion batteries and optimising the main code base to take advantage of standby or sleep times in between detections and transmission [30].

4.0 CONCLUSION

EPR is one of the most important instruments currently designed to help manage plastic waste globally. With proper implementation, it has shown a significant impact on the way consumers and businesses curate their services for a better future. However, EPR remains an especially difficult task in countries where basic waste management systems are already having to play catch up to the large amount of waste generated. Usually, these are developing countries with some of the highest plastic waste footprints. The IPBA can work as an initial support model for EPR, especially in these difficult situations. With highly accurate inexpensive hardware built for the masses, concerned consumers can actively participate in better brand audits. From the provided survey it is evident that consumers do want to generally contribute to such waste management activities and can make such hardware development and configurations popular. Technically, it performed significantly well compared to its price tag and more expensive alternatives. The better choice for hardware for the IPBA system is the ESP-S3-CAM module due to its robust performance and future scope of expansion. Using the FOMO model and the Edge Impulse platform, F1 and accuracy scores of over 90% were achieved which significantly validated the efficacy of the system. The GPU time usage limitation is one of the main limitations for improving the model. This can be mitigated either through paid subscriptions of the Edge Impulse platform or building and training the model using cloud computing services like Google Colab.

Future work with a wider range of integrations can be studied for real-time application of the suitable hardware configuration. Modules such as LoRa can be added to the ESP32-EYE-CAM configuration to allow for low-cost and low-energy data transmission.

As technology improves, it is important to find ways to integrate them into global problems like plastic waste management. This method can be scaled in the future to adapt to all nodes in the plastic waste management cycle, from recycling centres to disposal services and personal trash cans; and lead the way for consumers and producers to harmonize their waste reduction efforts.

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Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper.

References

[1] Kumar, R., Verma, A., Shome, A., Sinha, R., Sinha, S., Jha, P.K., Kumar, R., Kumar, P., Shubham, Das, S. and Sharma, P. 2021. Impacts of Plastic Pollution on Ecosystem Services, Sustainable Development Goals, and Need to Focus on Circular Economy and Policy Interventions. *Sustainability*. 13(17): 9963. Doi: http://dx.doi.org/10.3390/su13179963.

[2] Glass Upcycling Programme Gives a Ray of Hope to Underprivileged Women https://www.thestar.com.my/lifestyle/people/2023/07/24/how-a-glass-upcycling-programme-is-empowering-underprivileged-women). [Accessed on 2nd of September 2022].

[3] Filho, W., Saari, U., Fedoruk, M., Iital, A., Moora, H., Klöga, M., Voronova, V. 2019. An Overview of the Problems Posed by Plastic Products and the Role of Extended Producer Responsibility in Europe. *Journal of Cleaner Production*. 214: 550–558. Doi: http://dx.doi.org /10.1016/j.jclepro.2018.12.256.

[4] Joltreau, E. 2022. Extended Producer Responsibility, Packaging Waste Reduction and Eco-design. *Environmental and Resource Economics*. 83(3): 527–578. Doi: http://dx.doi.org /10.1007/s10640-022-00696-9.

[5] Bhadra, U., Mishra, P. 2021. Extended Producer Responsibility in India: Evidence from Recykal, Hyderabad. *Journal of Urban Management*. 10(4): 430–439. https://doi.org/10.1016/j.jum.2021.07.003.

[6] Li, C., Wang, L., Zhao, J., Deng, L., Yu, S., Shi, Z. and Wang, Z., 2021. The Collapse of Global Plastic Waste Trade: Structural Change, Cascading Failure Process and Potential Solutions. *Journal of Cleaner Production*. 314: 127935. Doi: http://dx.doi.org/10.1016/j.jclepro.2021.127935.

[7] Agarwal, S., Gudi, R. and Saxena, P. 2022. Image Classification Approaches for Segregation of Plastic Waste based on Resin Identification Code. *Transactions of the Indian National Academy of Engineering*. 7(3): 739–751. Doi: http://dx.doi.org/ 10.1007/s41403-022-00324-4.

[8] Bobulski, J. and Kubanek, M. 2019. Waste Classification System using Image Processing and Convolutional Neural Networks. *Advances in Computational Intelligence: 15th International Work-Conference on Artificial Neural Networks (IWANN 2019) Proceedings, Part II*. 15: 350–361. Springer International Publishing. Doi: http://dx.doi.org/ 10.1007/978-3-030-20518-8_30.

[9] Kroell, N., Chen, X., Maghmoumi, A., Lorenzo, J., Schlaak, M., Nordmann, C., Küppers, B., Thor, E. and Greiff, K. 2023. NIR-MFCO Dataset: Near-infrared-based False-color Images of Post-consumer Plastics at Different Material Flow Compositions and Material Flow Presentations. *Data in Brief*. 48: 109054. Doi: http://dx.doi.org/ 10.1016/j.dib.2023.109054.

[10] Plastic Waste Makers Index - Minderoo Foundation. https://www.minderoo.org/plastic-waste-makers-index [Accessed on 29th April 2024].

[11] Gupt, Y. and Sahay, S. 2015. Review of Extended Producer Responsibility: A Case Study Approach. *Waste Management & Research*. 33(7): 595–611. Doi: http://dx.doi.org/ 10.1177/0734242X15592275.

[12] Wolf, M., Van Den Berg, K., Garaba, S. P., Gnann, N., Sattler, K., Stahl, F., Zielinski, O. 2020. Machine Learning for Aquatic Plastic Litter Detection, Classification and Quantification (APLASTIC-Q). *Environmental Research Letters*. 15(11): 114042. Doi: https://doi.org/10.1088/1748-9326/abbd01.

[13] Pelonero, L., Fornaia, A. and Tramontana, E. 2020. From Smart City to Smart Citizen: Rewarding Waste Recycle by Designing a Data-centric IoT based Garbage Collection Service. *2020 IEEE International Conference on Smart Computing (SMARTCOMP)*. 380–385. Doi: http://dx.doi.org/ 10.1109/ SMARTCOMP50058. 2020. 00081.

[14] Stiebel, T., Bosling, M., Steffens, A., Pretz, T. and Merhof, D., 2018. An Inspection System for Multi-label Polymer Classification. *2018 IEEE 23rd International Conference on Emerging Technologies and Factory Automation (ETFA)*. 623–630. Doi: http://dx.doi.org/10.1109/ETFA.2018.8502474.

[15] Tamin, O., Moung, E.G., Dargham, J.A., Yahya, F., Omatu, S. and Angeline, L. 2022. Machine Learning for Plastic Waste Detection: State-of-the-art, Challenges, and Solutions. *2022 International Conference on Communications, Information, Electronic and Energy Systems (CIEES)*. 1–6. Doi: http://dx.doi.org/10.1109/CIEES55704.2022.9990703.

[16] Barrett, S. F. 2023. Arduino Nano 33 BLE Sense. In *Synthesis Lectures on Digital Circuits and Systems*. 17–65. Springer Nature. Doi: http://dx.doi.org/10.1007/978-3-031-21877-4_2.

[17] Dokic, K. 2020. Microcontrollers on the Edge – is ESP32 with Camera Ready for Machine Learning? In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*. 12119: 213–220. Doi: http://dx.doi.org/10.1007/978-3-030-51935-3_23.

[18] Edge Impulse. Getting started. 2022. https://docs.edgeimpulse.com/docs [Accessed on 30th April 2024].

[19] Announcing FOMO (Faster Objects, More Objects). https://edgeimpulse.com/blog/announcing-fomo-faster-objects-more-objects [Accessed on 24th of April 2024].

[20] Aira, J., Teresa, O., Delicado, F. M., Darío, V. 2023. MosquIoT: A System Based on IoT and Machine Learning for the Monitoring of Aedes aegypti (Diptera: Culicidae). *IEEE Transactions on Instrumentation and Measurement*. 72: 2509613.

Doi: http://dx.doi.org/ 10.1109/TIM.2023.3265119.

[21] Ammendolia, J., Walker, Tony R. 2022. Citizen Science: A Way Forward in Tackling the Plastic Pollution Crisis during and Beyond the COVID-19 Pandemic. *Science of the Total Environment*. 805: 149957.
Doi: http://dx.doi.org/10.1016/j.scitotenv.2021.149957.

[22] Tan, T. 2021. Encouraging Malaysians to Pick up Litter to Save the Ocean. *Citizens Journal - Community, Food and Lifestyle*.
Doi: https://cj.my/120236/encouraging-malaysians-to-pick-up-litter-to-save-the-ocean/ [Accessed on 30th April 2024].

[23] Zulkipli, F., Nopiah, Z. M., Jamian, N. H., Basri, N. E. A., Kie, C. J. 2022. Sustainable Public Awareness on Solid Waste Management and Environmental Care Using Logistics Regression. *Jurnal Kejuruteraan, Special Issue*. 5(2): 139–148.
Doi: http://dx.doi.org/ jkukm-2022-si5(2)-15.

[24] Mohamad, N., Affandi, H. M., Matore, M. E. 2022. Kesedaran Pengurusan Sisa Botol Plastik di Kalangan Pelajar Kolej Vokasional Di Malaysia. *Jurnal Kejuruteraan, Special Issue*. 5(2): 57–62.
Doi: http://dx.doi.org/10.17576/jkukm-2022-si5(2)-06.

[25] Merenda, M., Porcaro, C., Iero, D. 2020. Edge Machine Learning for AI-Enabled IOT Devices: A Review. *Sensors*. 20(9): 2533.
Doi: http://dx.doi.org/10.3390/s20092533.

[26] Merican, F. M., Osman, S., Zainudin, N., Jusoh, Z. M., Puteh, F. 2022. Exploring Consumer Single-Use Plastic Reduction Behaviour: A Conceptual Framework. *Geografia*. 18(1): 32–45.
Doi: http://dx.doi.org/10.17576/geo-2022-1801-03.

[27] GeeksforGeeks. F1 Score in Machine Learning. https://www.geeksforgeeks.org/f1-score-in-machine-learning/ [Accessed on 4th July 2024].

[28] Apriani, Y., Oktaviani, W. A., Sofian, I. M. 2022. Design and Implementation of LORA-Based Forest Fire Monitoring System. *Journal of Robotics and Control (JRC)*. 3: 236–243.
Doi: http://dx.doi.org/10.18196/jrc.v3i3.14128.

[29] Toschke, Y., Lusmoeller, J., Otte, L., Schmidt, J., Meyer, S., Tessmer, A., Brockmann, C., Ahuis, M., Hüer, E., Kirberger, C. and Berben, D. 2022. Distributed LoRa based CO_2 Monitoring Network–A Standalone Open Source System for Contagion Prevention by Controlled Ventilation. *HardwareX*. 11: p.e00261.
Doi: http://dx.doi.org/ 10.1016/j.ohx.2022.e00261.

[30] Yazid, M. A. M., Ahmad, J., Rodzi, M. Z. M., Husman, M. A., Afif, A. R. 2022. A Method for Preserving Battery Life in Wireless Sensor Nodes for LORA based IOT Flood Monitoring. *Journal of Communications*. 230–238.
Doi: http://dx.doi.org/10.12720/jcm.17.4.230-23.