

Plastic Subtype Recognition System Using a TinyML Based Lightweight CNN on ESP32 Smart Bin

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Abstract - Plastic waste segregation is important for optimizing the recycling process and minimizing the negative effects associated with improper disposal of plastic waste. Nonetheless, most of the smart waste management systems are designed mainly for general waste classification, fill level determination, or cloud computing, neglecting real time identification of different types of plastics at the disposal site. In this research, a plastic type recognition model based on edges is developed, embedded in a smart bin using the Light Weight Convolutional Neural Network and Tiny ML. The developed recognition model is able to classify plastic waste into five different types, namely PET, HDPE, LDPE, PP, and others/mixed. Hence, this result can be used to automatically sort the plastic waste to its correct compartment. The model was evaluated using a custom dataset created by combining images from multiple publicly available plastic waste image datasets. The lightweight MobileNetV2 architecture based CNN was trained with images of size 160 x 160 pixels (RGB format) and tested against the validation set. The trained model was then quantized to produce an INT8 TensorFlow Lite model to guarantee a smaller computation footprint for deploying the model in ESP32 hardware. While the trained Keras model gave an accuracy score of 92.08% on the validation data set, the quantized INT8 model produced an accuracy of 90.68% which translates to an approximate drop in accuracy of about 1.40 percent point. The implication is that with the help of lightweight deep learning models and INT8 quantization, one can still achieve an accurate classification of plastic subtypes. The conclusions drawn from this study is that TinyML based edge inference can be a practical way for plastic subtype classification in order to automate the process of smart waste segregation via classification without relying on cloud based classification continuously.

Keywords - Plastic subtype classification, lightweight CNN, TinyML, image processing, ESP32, edge computing, smart bin

I. INTRODUCTION

Plastic waste segregation has become an important requirement for improving recycling efficiency and reducing environmental damage, especially because different plastics need different recovery processes at recycling facilities [2], [24]. In practice, plastics are commonly categorized into seven resin types, namely PET, HDPE, PVC, LDPE, PP, PS, and Other. However, most recycling centers are more capable of handling widely recyclable groups such as PET, HDPE, LDPE, and PP, while less recyclable or mixed materials are often processed separately or grouped together [1], [7]. For this reason, the proposed smart bin focuses on PET, HDPE, LDPE, PP, and “Other & Mixed”, where the final class

represents remaining plastics such as PVC, PS, ABS, nylon, and mixed plastic items that are less consistent for direct recycling [8], [11]. Existing smart waste systems often focus on broad waste categorization, fill monitoring, or cloud based tracking, but subtype level plastic recognition is still limited, particularly on low cost embedded hardware [4], [20], [21]. Therefore, this work proposes a TinyML based lightweight CNN on ESP32 CAM to classify plastic subtypes directly at the point of disposal and support more practical smart bin segregation [4], [6].

II. PLASTIC SUBTYPE RECOGNITION APPROACH

Plastic subtype recognition is a fine grained image classification task because many plastic objects appear visually similar even when their resin types are different [7], [9]. PET bottles, HDPE containers, LDPE films, and PP cups may differ in texture, opacity, gloss, and shape, but these differences are often affected by lighting, labels, background clutter, and object deformation during disposal [10], [13]. A CNN based approach is suitable for this problem because it can learn hierarchical visual features directly from RGB images instead of depending only on manual feature engineering [9], [10]. In the proposed system, the captured image is classified into PET, HDPE, LDPE, PP, or “Other & Mixed”, and the predicted class is then used to guide the smart bin response for segregation [20], [23]. The plastic categories considered in this study are illustrated in Fig. 1.



Figure 1. Sample images illustrating different types of plastic

A. Research Gap and Motivation

Although prior research has shown that image based waste classification is useful, many systems still stop at broad categories such as plastic, paper, metal, and glass rather than identifying individual plastic subtypes [4], [5]. In addition, many vision based segregation systems rely on larger models or external computing resources, which are less practical for a compact smart bin intended for low cost local deployment [21], [22]. The research gap therefore lies in building a lightweight embedded model that can perform subtype oriented plastic recognition directly on edge hardware while remaining simple enough for real time smart bin use [6], [20]. This motivates the use of a TinyML based CNN on ESP32, where the main contribution is the embedded plastic classifier rather than the monitoring infrastructure [4], [6].

III. RELATED WORKS

A. Image Based Waste Classification

Image based waste classification has been widely explored using deep learning, and CNNs have become one of the most effective methods for recognizing waste items under varying visual conditions [4], [5]. Previous studies show that CNN models can classify packaging waste, recyclable waste, and mixed solid waste with improved robustness compared with traditional image processing pipelines [16], [20], [21]. These works confirm that visual recognition is suitable for smart waste management, but many of them still focus on general waste classes rather than plastic subtype classification [22], [23].

B. Plastic Type and Material Level Classification

Recent studies on plastic specific recognition show that resin level classification is feasible using CNN based architectures and RGB image data [7], [8], [17]. Work on PET bottle identification, plastic material categorization, and plastic waste classification demonstrates that subtype level separation is technically meaningful because polymer groups differ in recycling value and downstream treatment [3], [10]. These studies also show that classification accuracy depends strongly on visual quality, background consistency, and class diversity, which makes compact but effective feature learning especially important [9], [11].

C. Embedded AI and TinyML

TinyML and edge oriented inference have made it increasingly practical to deploy lightweight neural networks on constrained devices for real time applications [4], [6]. In smart waste systems, lightweight models, TensorFlow Lite based deployment, and compact image classifiers have been adopted to reduce latency, model size, and hardware cost [20], [23]. This is important for a smart bin because embedded inference avoids constant cloud dependence and makes local decision making possible even in low resource environments [24], [25].

D. Smart Bin Systems

Smart bin research has largely focused on fill level monitoring, connectivity, alerts, and operational analytics through IoT platforms and sensors [25], [26], [30]. GPS based location tracking, cloud connectivity, mobile applications, and municipal monitoring features are already being integrated into modern waste management systems to improve collection

efficiency [31], [32]. However, these systems usually emphasize monitoring and logistics rather than fine grained plastic subtype classification, which leaves room for a classification centered smart bin approach [19], [27], [33].

E. Challenges and Limitations

Real world plastic classification remains difficult because waste objects may be reflective, crumpled, partially occluded, or visually contaminated by labels and mixed materials [12], [13]. Fine grained subtype recognition is even more sensitive to such variation because some classes share similar appearance across disposal conditions [14], [15]. As a result, an effective embedded model must balance compactness, classification power, and dataset diversity so that it remains practical for smart bin deployment while still producing meaningful subtype predictions [6], [18].

IV. PROPOSED METHODOLOGY

The proposed system is designed as an embedded image classification pipeline for real time plastic subtype recognition. First, the ESP32 CAM captures an image of the disposed plastic item. The image is then resized, normalized, and passed into a TinyML based lightweight CNN, which predicts one of five output classes: PET, HDPE, LDPE, PP, or "Other & Mixed". The predicted label is used to control the smart bin response, while the main research contribution remains the classification model itself rather than the monitoring layer.

A. System Overview

The overall workflow of the proposed system is shown in Fig. 2 and begins with image acquisition at the disposal point and continues through preprocessing, CNN based feature extraction, classification, and bin response. The ESP32 CAM captures the image, the lightweight CNN extracts material related visual features, and the predicted subtype is sent to the control layer so that the correct compartment or indication can be activated [20], [23]. This design keeps the model focused on subtype recognition while using the smart bin only as the execution environment [26], [28].

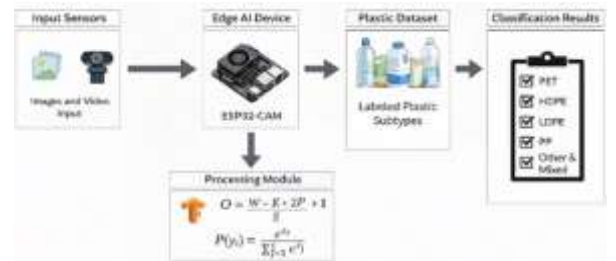


Figure 2. System overview of the proposed plastic subtype recognition system

B. Plastic Subtype Classification Using a TinyML-Based Lightweight CNN

The central model is a compact CNN built for embedded deployment. It uses lightweight convolution, pooling, and dense layers to learn texture, transparency, contour, and shape cues from plastic images [9], [10]. The convolution layers extract local features, pooling reduces spatial redundancy, and the final dense stage maps the learned representation into the five output classes [7], [8]. The final decision is produced

using a softmax layer so that the class with the highest probability can be selected for bin actuation [11], [13].

$$O = \left(\frac{W - K + 2P}{S} \right) + 1 \quad (1)$$

From Equation 1, O represents the output feature map size, W represents the input size, K represents the kernel size, P represents the padding, and S represents the stride. This equation shows how the convolution layer transforms the input image into feature maps while preserving the important spatial characteristics needed for plastic subtype recognition.

$$P(y_i) = \left(\frac{e^{z_i}}{\sum_{j=1}^C e^{z_j}} \right) \quad (2)$$

From Equation 2, $P(y_i)$ is the predicted probability of class i , z_i is the score of class i , and C is the total number of classes. This equation shows how the softmax function converts the network output scores into probabilities for PET, HDPE, LDPE, PP, and “Other & Mixed”.

C. Model Optimization for Embedded Deployment

To support deployment on constrained hardware, the model is optimized using parameter reduction and low precision representation. Pruning helps remove unnecessary parameters from the original model so that memory and computation can be reduced, while quantization converts floating point values into more compact integer form for faster inference [4], [6]. These steps are important because the proposed classifier is intended for edge execution on a smart bin rather than on a high performance computing system [20], [24].

$$\text{Pruning Ratio} = \left(\frac{P_{\text{original}} - P_{\text{pruned}}}{P_{\text{original}}} \right) \times 100\% \quad (3)$$

From Equation 3, the Pruning Ratio is the percentage of parameters removed from the original model, P_{original} is the total number of parameters before pruning, and P_{pruned} is the number of parameters remaining after pruning. This equation explains how model pruning reduces complexity and makes the CNN more suitable for embedded deployment.

D. Smart Bin Integration

Once the classifier predicts the plastic subtype, the smart bin control layer can use that output to activate the relevant compartment, display the recognized subtype, and update system status. This keeps the visual classifier as the main intelligence component while the hardware side acts as the response mechanism [28], [29]. The integration also supports practical segregation at the source, which is more useful for recycling than classifying waste after it has already been mixed [1], [20].

E. Deployment Perspective

The proposed system is intended for deployment in places such as campuses, offices, and public recycling areas where local classification is more practical than depending entirely on remote processing. By keeping image inference at the edge, the model can make immediate subtype decisions while still allowing selected operational data to be transmitted to the monitoring layer for management and analytics [25], [31].

V. EXPERIMENTAL SETUP

The experimental setup was designed to evaluate plastic subtype classification using a TinyML based lightweight CNN trained on labeled RGB images of PET, HDPE, LDPE, PP, and “Other & Mixed”. Images were collected with variations in angle, background, lighting, object orientation, crumpled plastics, mixed materials, labels and partial occlusion to better reflect realistic smart bin conditions [9], [12]. Each image was resized and normalized before training, and the dataset of 19,564 images was split into 14,085 training (72%), 1,566 validation (8%), and 3,913 testing (20%) images. The CNN was trained using supervised learning with categorical cross entropy loss and softmax output probabilities, while evaluation focused on accuracy, precision, recall, F1 score, latency, and embedded suitability [10], [13]. The dataset split proportions and cloud based analytics dashboard are shown in Fig. 3 and Fig. 4, respectively.



Figure 3. Dataset split proportions for plastic subtypes

The smart bin itself includes practical sensing and interface components, but these are treated only as supporting elements in this study. Ultrasonic or fill level sensing can be used to monitor compartment levels, telemetry can be transmitted to the cloud, GPS can provide geo location, and a small display or LED indication can show the recognized class to the user [25], [26]. Through the connected analytics dashboard, municipal councils can monitor smart bins in different locations, observe fill levels, view the percentages of plastic types collected, and receive notifications when bins require collection or servicing [31], [32].



Figure 4. Analytics dashboard for remote monitoring of smart bins

VI. RESULTS AND DISCUSSION

The training and validation curves of the proposed TinyML based lightweight CNN as shown in Fig. 5, indicate that the

model learned steadily, with accuracy increasing across epochs and loss decreasing consistently. The close behavior of the training and validation curves indicates that the model generalized reasonably well without severe overfitting.

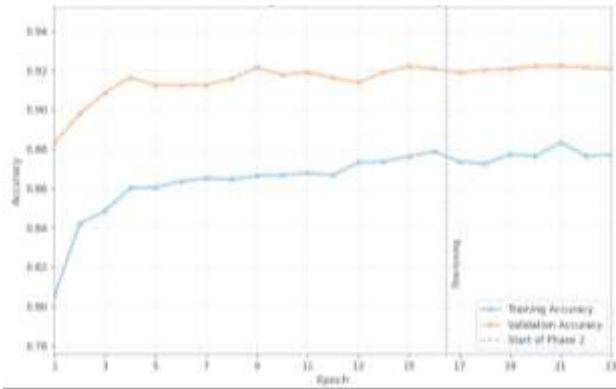


Figure 5. Training and validation accuracy of the proposed lightweight CNN model across 30 epochs

The final Keras model achieved a verified validation accuracy of 92.08% on the fixed set of 1,566 validation images. The selected model was subsequently converted into a full integer INT8 TensorFlow Lite model using all 14,085 training images as representative calibration data. The resulting int8.tflite model achieved 90.68% validation accuracy on the same validation set as shown in Fig.6. The reduction was therefore approximately 1.40 percentage points. At the same time, the model size was reduced from approximately 2.2 MB to approximately 611 KB, providing a substantially more suitable representation for embedded deployment as shown in Fig.7.

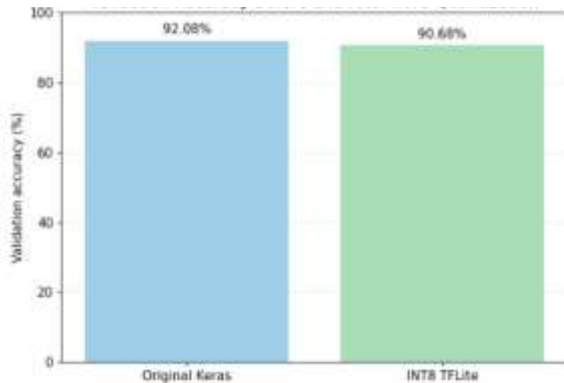


Figure 6. Validation accuracy before and after INT8 Quantization

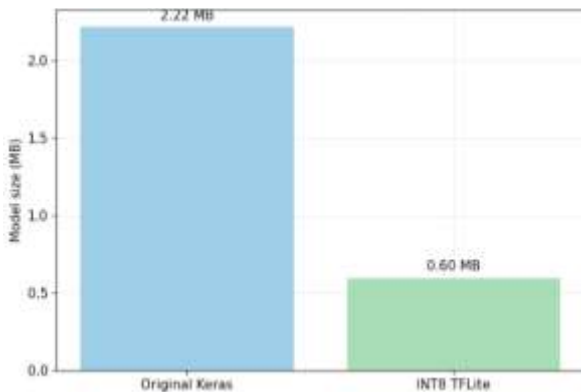


Figure 7. Model size before and after INT8 Quantization

The test set confusion matrix and per class metrics, shown in Fig.8 and Fig.9, demonstrate strong classification performance across all five classes. LDPE achieved the strongest recognition, while PP and Other showed comparatively higher confusion, particularly between each other, indicating the challenge of distinguishing visually similar plastic materials.

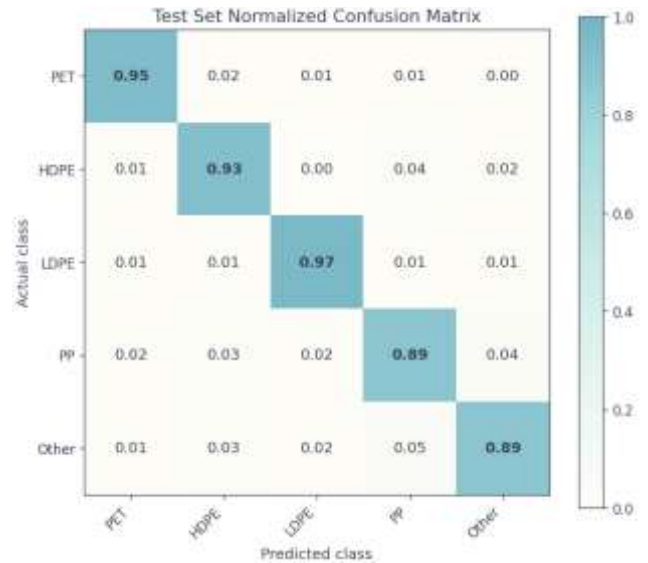


Figure 8. Normalized confusion matrix of the proposed model

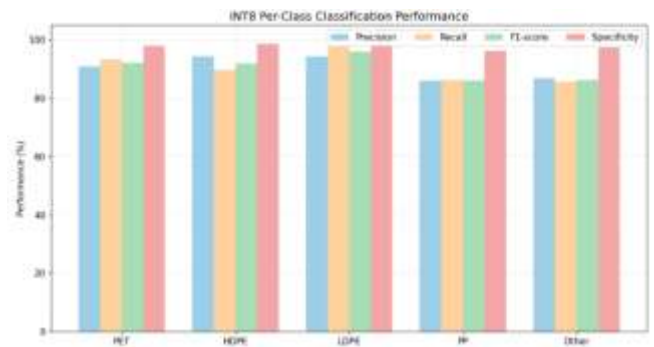


Figure 9. Per class precision, recall, F1-score, and specificity of the proposed model on the test set

The representative test predictions as shown in Fig.10 further confirm the effectiveness of the model. Samples from all five classes were correctly classified with very high confidence, including 100.0% for LDPE, 100.0% for HDPE, 98.5% for “Other & Mixed”, 100.0% for PET, and 99.9% for PP. Overall, the results demonstrate that the proposed lightweight CNN provides a good balance between classification performance and embedded deployment feasibility for smart plastic waste segregation.



Figure 10. Representative test predictions showing actual label, predicted label and confidence score for each plastic subtype

A comparison of the proposed system with existing waste and plastic classification approaches is presented in Table I.

TABLE I. COMPARISON WITH EXISTING WASTE AND PLASTIC CLASSIFICATION APPROACHES

Study	Classification Focus	Edge Deployment	Smart Bin Integration	Key Difference from Proposed Work
Sallang et al. [4]	General waste classification	Yes	Yes	Focuses on broad waste categories rather than plastic subtypes
Qibthiyah & Dhelika [7]	Resin based plastic bottle classification	No	No	Focuses on resin classification using CNN architectures rather than constrained smart bin edge deployment
Raviprabhakaran [10]	Plastic material identification	No	No	Focuses on CNN based material identification rather than an integrated TinyML smart bin implementation
Proposed Work	PET, HDPE, LDPE, PP, Other & Mixed	Yes INT8 TinyML	Yes	Five class subtype recognition, local inference, automated smart bin segregation on resource constrained hardware

VII. CONCLUSION

This paper presents an edge based plastic subtype recognition system using a TinyML based lightweight CNN for smart bin applications. The main contribution of this work is the integration of five class plastic subtype recognition (PET, HDPE, LDPE, PP, and Other & Mixed) with a compact INT8 model suitable for local inference on resource constrained ESP32 class hardware and automated smart bin segregation. The final INT8 model achieved 90.68% validation accuracy with a model size of approximately 611 KB, demonstrating a practical balance between classification performance and embedded efficiency. The system can support source level plastic segregation in locations such as campuses, offices, and public recycling areas by enabling immediate local classification without continuous dependence on cloud processing. However, the current dataset has limited representation of challenging real world conditions, including severe occlusion, deformation, low lighting, label contamination, and complex mixed material objects, which may affect classification robustness.

VIII. FUTURE WORK

Future research can extend this work by increasing dataset diversity to improve performance under more challenging real world conditions. The system can also be expanded to support additional plastic categories or finer subtype distinctions where recycling workflows require more detailed separation. In addition, future work can focus on improving model robustness under difficult disposal scenarios such as occlusion, deformation, low lighting, and contamination by

labels or mixed materials. Further improvements may also explore stronger lightweight architectures, better augmentation strategies, and more advanced optimization techniques to improve both classification accuracy and embedded efficiency. Real world pilot deployment across multiple locations can also be carried out to evaluate long term performance, reliability, and scalability in practical municipal waste management environments.

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