Journal of Communication Systems, Networks, and Security (JCSNS), Vol. 1, Issue 1
April 2026

Inorganic Trash Sorting Mobile Application using MobileNetV3 Method

Reivan Haidar Ghiffari, Afifah Dwi Ramadhani*, Aries Pratiarso
Politeknik Elektronika Negeri Surabaya, Indonesia
**Corresponding author: Afifah Dwi Ramadhani; email: afifah@pens.ac.id*

Manuscript received April 10, 2026, revised April 17, 2026, accepted April 21, 2026

Abstract – *This study aims to develop a mobile application for inorganic waste sorting that can detect seven object classes (plastic, Glass, metal, electronics, paper, fabric, and cardboard) using the MobileNetV3 Deep Learning architecture. Based on comparative testing results, the MobileNetV3 method proved more effective than EfficientDet-d0, achieving consistent loss reduction, better computational efficiency, and optimal generalization without overfitting. Dataset quality was found to be a fundamental factor in model performance, with the use of a standardized, noise-free dataset yielding superior results: detection accuracy reached 97.14%, and Overall mAP was 94.13%. In-depth analysis showed that while detection performance was very stable across the fabric and electronics categories, accuracy in the plastic, Glass, and metal categories tended to decrease when high Intersection over Union (IoU) precision was required. Operationally, the system achieved a 100% success rate within the distance range of 30 cm to 150 cm, with the best time efficiency observed between 60 cm and 90 cm. Furthermore, hardware testing showed that high specifications provided significant advantages only for long-distance detection (>150 cm). In contrast, for the ideal operational range, devices with standard specifications were sufficient and efficient for system implementation.*

Keywords: *MobileNetV3, Inorganic Waste Sorting, Object Detection, Dataset Quality, Operational Distance*

I. Introduction

In recent years, the trash problem has become a major challenge worldwide. The absence of an effective trash processing system leads to trash accumulating in landfills, resulting in environmental pollution, economic losses, and public health issues. Every program designed to process trash consistently fails or becomes ineffective because the majority of the public is still unfamiliar with the different types of trash and how to process them [1].

However, many people still do not know how to sort trash properly. Several factors, including a lack of education and information about trash sorting and limited access to trash-sorting infrastructure, contribute to this. Meanwhile, the number of smartphone users in Indonesia is increasing; therefore, education on trash through mobile applications can be a solution. By using a mobile application, the public can classify trash types and sort them before they are disposed of in landfills.

One image recognition method that can be used for trash-sorting mobile applications is MobileNetV3. MobileNetV3 is an efficient, lightweight machine learning model, making it suitable for mobile devices. MobileNetV3 has been proven to have high accuracy in recognizing various types of trash [2].

In the real of computer vision for mobile devices, MobileNet faces stiff competition from advanced architectures such as ShuffleNet, EfficientNet-Lite, and GhostNet, each offering unique innovations to reduce computational load. ShuffleNet, for instance, excels in low latency thanks to *channel shuffle* techniques that accelerate data flow; EfficientNet-Lite offers high accuracy through *compound scaling* methods; while GhostNet minimizes mathematical operations by creating "ghost features" from existing data. Although these alternative models are sometimes capable of outperforming MobileNet in one specific aspect—such as pure speed or a slight edge in accuracy—they all operate in the same arena of optimizing AI performance on constrained hardware.

However, MobileNet (especially V2 and V3) is considered superior overall due to the combination of the highly efficient *Depthwise Separable Convolution* architecture and Neural Architecture Search (NAS), which automatically discovers the optimal network structure. The deciding factor for its dominance is massive ecosystem support; as the "gold" standard from Google, MobileNet receives the highest optimization priority within the TensorFlow Lite framework and across various hardware accelerators (NPU/DSP) on Android. This makes MobileNet the most balanced, stable, and deployment-ready solution compared to competitors that might appear faster on paper but lack real-world compatibility.

Therefore, the author proposes a mobile application that supports effective trash management by integrating image recognition based on MobileNetV3. This application will be used to recognize types of inorganic trash. The obtained data will be processed to provide the public with information on how to sort trash correctly.

The Mobile Application for Sorting Inorganic Waste Using the MobileNetV3 Method is highly relevant to efforts to enhance waste management efficiency. By leveraging MobileNetV3, this application enables users to accurately and efficiently identify types of inorganic waste using their mobile phone cameras. This not only supports more effective waste management and reduced environmental pollution but also has the potential to raise public awareness of the importance of sustainable waste management and recycling.

II. Related Work

Several studies have explored the application of deep learning for waste detection and classification. Twisha Kotecha developed a mobile-based waste classification system using deep learning models such as MobileNetV2, InceptionV3, and NASNetMobile [3]. Similarly, Stephenn L. Rabano et al. investigated the use of MobileNet for common garbage classification, achieving 87.2% accuracy after 500 training iterations and implementing a simple image-detection application [4]. These studies demonstrate the effectiveness of lightweight deep learning architectures in mobile-based waste classification tasks.

In addition, Teny Handhayani et al. introduced Leboh 2, an Android application designed for solid waste detection and management, aiming to improve efficiency and usability in handling waste through an accessible mobile platform [5]. António Francisco Serol Sequeira also developed a mobile application capable of identifying recyclable materials using image processing and artificial intelligence. The system recognizes materials such as plastic, paper, Glass, and metal. It includes user-friendly features, including recycling information and nearby recycling center locations, achieving high accuracy and positive user feedback [6].

Further research by R. D. Ramadhani et al. implemented a deep learning-based Android application for classifying organic and inorganic waste using a Convolutional Neural Network (CNN) model integrated with TensorFlow Lite. Their results indicate high accuracy and fast classification performance, contributing to improved public awareness and efficiency in waste sorting [7]. This highlights the growing trend of deploying optimized AI models on mobile devices for real-time environmental applications.

Beyond waste classification, Cheng and F. Zhang demonstrated the effectiveness of YOLOv4 for real-time object detection on mobile devices, achieving a balance between speed and accuracy through model optimization [8]. Meanwhile, M. Kalpana and J. Jayachitra proposed an intelligent bin management system integrating IoT and mobile applications to monitor waste levels and optimize collection routes, thereby increasing operational efficiency and reducing costs in smart city environments [9]. Together, these studies illustrate the integration of AI, mobile computing, and IoT in advancing smart waste management solutions.

III. Proposed System

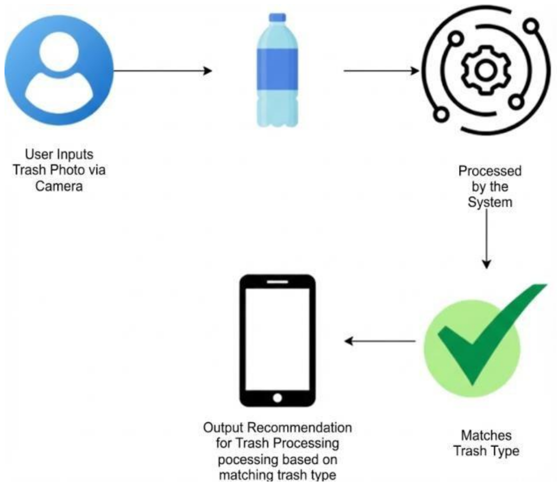


Fig.1. Proposed System

The working principle of this application is divided into three main parts: input, data processing, and output. The input is obtained from the user's device camera, followed by data processing using MobileNetV3 TFLite. This involves resizing the image to match the model's required input size and normalizing pixel values to a range of 0 to 1 or -1 to 1 before converting the image into a tensor, a multidimensional array understood by the ML model. The tensor is then fed into the model, where the interpreter runs inference to make predictions from the image. Finally, the output process consists of image classification into object labels and recommendations corresponding to the type of trash detected, with the application designed for inorganic trash across seven classes: plastic, Glass, metal, electronic, paper, fabric, and cardboard.

The system developed in this research has two main stages: the Training side and the Deployment side.

A. *Training*

In the Training planning, there are three main parts: dataset collection, labeling, and dataset training. Dataset collection is carried out by capturing images of inorganic trash using a device. Then, each of these trash images undergoes labeling, assigning labels or annotations to the data based on seven classes: plastic, Glass, metal, electronic, paper, fabric, and cardboard. The labeled dataset is then trained using the MobileNetV3 method on

Google Colab. More detailed information regarding each part of the training will be outlined in the following explanation.

In this stage, trash images are collected from each of the seven classes: plastic, Glass, metal, electronic, paper, fabric, and cardboard trash. The images collected for each class represent trash frequently encountered by the public in daily activities. Labeling or annotation is performed on the data used to train the dataset. These labels provide information about the target or expected result of the dataset.

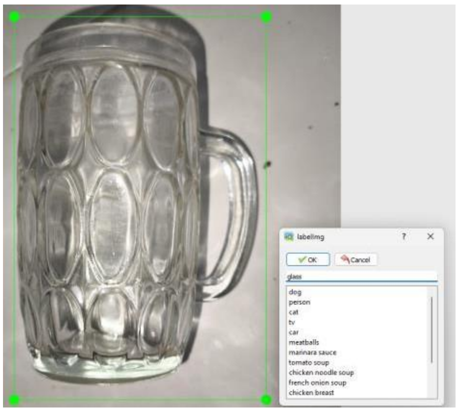


Fig. 2. Labeling

Next, the dataset is trained in Google Colab using the MobileNetV3 method. Configuration for selecting and using an object detection method with the TensorFlow Object Detection API. The chosen_model variable determines the method used, utilizing ssd-mobilenet-v3-fpnlite-320. The configuration for each method is stored in the MODELS_CONFIG dictionary, which includes the method name (model_name), the location of the pipeline configuration file (base_pipeline_file), and the pre-trained checkpoint (pretrained_checkpoint). Then, we configure the object detection method's training parameters using the TensorFlow Object Detection API. num_steps determines the number of training iterations, while batch_size is adjusted based on the chosen method, which is MobileNetV3 here. Training the object detection model using the TensorFlow Object Detection API. The model_main_tf2.py script reads the pipeline configuration file, which contains model settings, dataset, optimizer, and hyperparameters. The dataset is processed according to the pipeline for training and evaluation. The model is trained for 20,000 steps (num_train_steps), with the model weights saved to model_dir. Training logs are displayed on the screen and saved for analysis. Evaluation is performed periodically to measure model performance using the validation dataset. The final result is a trained model (checkpoint) and training logs in that directory, ready for use for inference or further evaluation.

TABLE I. DATASET TABLE

Dataset	**Number Of Images**	**Batch Size**	**Training Steps**
First	940	16	20000
Second	140	16	20000
Third	210	16	20000
Fourth	350	16	20000

B. Deploy

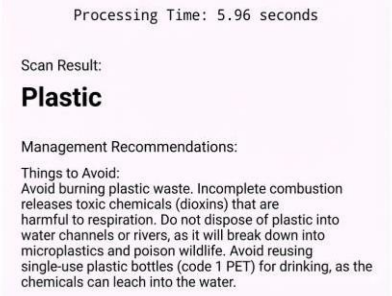
In the Deployment planning, there are two main parts: model integration and UI design. In the model integration stage, the MobileNetV3 TFLite model is exported to Android Studio and then integrated into the Android Studio project by placing it in the assets directory. The UI design stage involves designing the home page, camera page, recommendation page, and history page. More detailed information regarding each of these parts will be outlined in the following explanation.

This involves exporting the MobileNetV3 TFLite model trained on the dataset. The exported model is then integrated into the Android Studio project by placing it in the assets directory. Furthermore, the code uses libraries such as TensorFlow Lite or ML Kit to load and run the model on Android devices.

Next, in this stage, UI design is performed using XML. There are 4 pages in this application: the main page, camera page, recommendation page, and history page. The following are the designs of these pages.

On the main page, there are two buttons: Scan Trash and History. The scan trash button opens the camera page, where the user can scan trash using the MobileNetV3 model, while the history button opens the history page to view the trash scanning history. On the camera page, there is a scan button that captures photos from the user's camera; the MobileNetV3 model processes the captured images. On the recommendation page, the output of the above process is the name of the trash type detected by the model from the captured image and the Trash Processing Recommendation corresponding to the trash type; there is a "Done" button that will save the history data.

Fig. 7. Main Page



Processing Time: 5.96 seconds

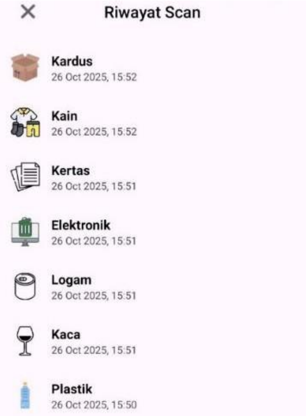
Scan Result:

Plastic

Management Recommendations:

Things to Avoid:
Avoid burning plastic waste. Incomplete combustion releases toxic chemicals (dioxins) that are harmful to respiration. Do not dispose of plastic into water channels or rivers, as it will break down into microplastics and poison wildlife. Avoid reusing single-use plastic bottles (code 1 PET) for drinking, as the chemicals can leach into the water.

Fig. 8. Recommendation Page



Riwayat Scan

Kardus
26 Oct 2025, 15:52

Kain
26 Oct 2025, 15:52

Kertas
26 Oct 2025, 15:51

Elektronik
26 Oct 2025, 15:51

Logam
26 Oct 2025, 15:51

Kaca
26 Oct 2025, 15:51

Plastik
26 Oct 2025, 15:50

Fig. 9. History Page

The following are the recommendations for each type of waste:

Plastic: Avoid burning plastic waste because incomplete combustion releases toxic chemicals (dioxins) that are hazardous to health [10]. Do not dispose of plastic into waterways, as it will fragment into microplastics that contaminate the ecosystem [11]. The crucial step is separating plastic from other waste while it is clean and dry. Independently, soft plastics can be upcycled into Eco-bricks, while large bottles can be repurposed into pots. At recycling facilities, plastic is shredded and melted into plastic pellets or textile fibers.

Glass: Do not dispose of Glass (especially broken shards) in the regular trash, as it endangers waste management workers. Separate Glass from other waste; if broken, wrap it tightly in thick cardboard. The best method is to reuse jars or bottles. Glass is 100% recyclable indefinitely, with no loss of quality [12]. The glass recycling process (using cullet) is also proven to significantly save energy compared to manufacturing new Glass from silica sand [13].

Metal: Do not dispose of pressurized aerosol cans due to the risk of explosion. Separate metals using a magnet: steel cans (ferrous) will stick to the magnet, while aluminum (non-ferrous) will not [14]. To save space, crush aluminum cans. Metal is a high-value material; recycling aluminum saves up to 95% of the energy required for new production from bauxite ore, and it is remolded into new products or automotive parts.

Electronic: Do not dispose of this in regular trash because it contains hazardous and toxic substances (B3) (such as 8/mercury and lead) that are strictly regulated by law [1916]. Do not disassemble it yourself. Collect it separately in a safe place and wipe personal data (perform a factory reset) before handing it over. Processing must be performed by licensed facilities to extract precious metals in accordance with international safety standards.

Paper: Paper contaminated with oil, food, or moisture cannot be recycled [15]. Ensure the paper is dry and clean; separate office paper (HVS) from cardboard/newspapers. Maximize the use of the blank sides of the paper (reuse). At recycling facilities, paper will be shredded and processed into pulp. Contamination in paper can degrade pulp quality and result in rejection at recycling facilities [16].

Fabric: Do not dispose of clothing in regular trash because it is difficult to decompose and contributes to global waste piles [17]. Sort into categories: Wearable (donate) and Damaged (upcycle). Damaged fabric can be turned into cleaning rags or doormats. At recycling factories, fabric will be shredded into fibers for insulation material or mattress filling, in accordance with the textile waste management hierarchy [18].

Cardboard: Grease-stained cardboard (such as pizza boxes) must have the soiled parts discarded as a residue, as oil interferes with fiber bonding [19]. Ensure the cardboard is dry, clean, and free of tape. Always flatten cardboard for space efficiency. Cardboard has a high recycling rate and is reprocessed into corrugated medium [20].

Unidentified Waste: If in doubt, treat unidentified waste as residual waste in accordance with national waste management regulations. Do not burn it or dispose of it in rivers. Collect it in a separate bag for transport to the Landfill (TPA). The accumulation of organic and inorganic residue in landfills without sorting contributes significantly to methane gas emissions [21].

The history page lists trash items previously detected by the application, along with their dates and times, as shown in Fig. 9.

IV. Experimental Result and Discussion

A. Testing With Mean Average Precision

mAP (mean Average Precision) is a metric used to evaluate model performance, especially in tasks such as *object detection* and *information retrieval*. This metric measures how well the model detects and classifies objects by calculating the average precision across various recall levels for all classes. In *object detection*, mAP considers factors such as object location accuracy and IoU (*Intersection over Union*) to determine whether a prediction is valid. A high mAP value indicates an accurate model, while a low value suggests that the model requires improvement. This metric will be tested on each of the datasets used in the previous testing with different datasets.

TABLE II. TESTING WITH THE MAP RESULT

Class	Dataset 1 (%)	Dataset 2 (%)	Dataset 3 (%)	Dataset 4 (%)
Platic	22.15	80.11	85.15	90.50
Glass	30.80	85.30	90.00	95.10
Metal	25.01	82.90	88.40	93.00
Electronic	18.90	79.55	82.10	91.15
Paper	31.12	88.00	92.50	98.22
Fabric	34.10	81.10	91.00	96.81
Carboard	30.07	89.01	90.50	94.13
Overall	27.45	83.71	88.52	94.13

The analysis of mAP (mean Average Precision) results across the four datasets reveals significant performance disparities and provides critical insights into the quality of the datasets used to train the model. These results quantitatively validate the findings from the previous accuracy testing, where the Fourth Dataset once again proved to be the most superior.

With an Overall mAP of 94.13%, the Fourth Dataset not only achieved the highest average score but also demonstrated extraordinary performance consistency across all 7 classes. Almost all waste categories were successfully detected with an mAP above 90%. Specifically, the 'paper' (98.22%) and 'fabric' (96.81%) classes showed near-perfect performance. Even the lowest-scoring class in this dataset, 'plastic' (90.50%), still recorded a very high value. This indicates that the dataset is balanced, exhibits rich variation, and enables the model to recognize each category with very high confidence.

The Third Dataset (Overall 88.52%) and the Second Dataset (Overall 83.71%) serve as competent alternatives. Both show strong performance, with the Third Dataset consistently slightly outperforming the Second Dataset across almost every class. These datasets are clearly capable of producing functional and reliable models for most use cases. However, they do not reach the high level of precision found in the Fourth Dataset. For example, the 'electronic' class in the Second Dataset only reached 79.55%, indicating a weakness in recognizing that category compared to the better datasets.

The performance of the First Dataset stands in sharp contrast, highlighting fundamental quality issues. With an Overall mAP of only 27.45%, this dataset completely failed to train a functional model. Not a single class achieved an acceptable mAP; the best performance was 'fabric' (34.10%), while 'electronic' (18.90%) was almost unrecognizable. These results clearly demonstrate that the dataset (which, according to the initial description, contained mixed and unbalanced images) is inadequate and yields an inaccurate model.

Overall, the conclusion is unequivocal: dataset quality and composition are the most critical determining factors for model success. The Fourth Dataset proved to be the definitive dataset, producing a state-of-the-art model that is highly accurate and consistent across all categories. The Second and Third Datasets are viable secondary choices, while the First Dataset proved ineffective and should not be used for implementation.

B. Testing With Different Datasets

Testing was conducted to evaluate and compare system performance in terms of detection accuracy and processing time using four different datasets. The variation between datasets lies in their content composition rather than the detection method itself. The first dataset consists of a combination of self-collected and online images, with an unbalanced number of samples per class. In contrast, the other three datasets use only self-collected images with balanced class distributions but different total quantities.

All experiments were performed at a fixed distance of 90 cm, with 10 scans per waste category, for a total of 70 scans per dataset. Accuracy was calculated as the percentage of correctly detected images, and the average processing time was the mean time across all scans in each dataset.

The results show significant differences in performance across the datasets. The Fourth Dataset achieved the highest accuracy of 97.14%, making it the most reliable for correct detection. However, it also recorded the longest average processing time of 5.16 seconds, indicating a trade-off between accuracy and speed. Despite this, the increased processing time is considered acceptable given its superior detection performance.

In comparison, the Second and Third Datasets demonstrated moderate but stable performance, with accuracies of 84.29% and 87.14%, respectively, and faster processing times of 4.48 seconds and 4.41 seconds, respectively. Meanwhile, the First Dataset performed poorly, with only 12.86% accuracy, despite a relatively fast processing time of 4.40 seconds. Overall, the Fourth Dataset is the most suitable for implementation due to its highest accuracy. At the same time, the Second and Third datasets are acceptable alternatives, while the First Dataset is unsuitable for use.

TABLE III. TESTING WITH DIFFERENT DATASETS RESULT

Dataset	Detected Correctly	Total Scan	Accuracy (%)	Average Processing Time (s)
First	9	70	12.86	4.4
Second	59	70	84.29	4.48
Third	61	70	87.13	4.41
Fourth	68	70	97.14	5.16

C. Testing With Different Distances

The testing phase utilized the Fourth Dataset, which had previously demonstrated the highest accuracy among all evaluated datasets. Experiments were conducted at six different distances—30 cm, 60 cm, 90 cm, 150 cm, 210 cm, and 300 cm—with two scans performed for each type of waste. The results indicate that distance plays a critical role in determining the overall performance of the detection system.

The analysis identifies a clear "perfect operational range" between 30 cm and 150 cm, within which the system consistently achieved 100% accuracy. This demonstrates that the model is highly reliable and maintains stable performance across moderate variations in distance. Within this range, the system shows strong robustness in detecting objects, with no classification errors.

Furthermore, optimal operational points were observed at 60 cm and 90 cm, where the system achieved the fastest processing times of 4.25 seconds and 4.17 seconds, respectively. These distances represent the most efficient working conditions, balancing both speed and accuracy. Slight increases in processing time were noted at 30 cm and 150 cm, suggesting minor delays when objects are either too close or near the upper limit of the effective detection range.

However, performance declines significantly beyond 150 cm. At 210 cm, accuracy dropped to 78.57%, and at 300 cm, it further decreased to 28.57%, indicating a substantial loss in detection capability. This degradation is accompanied by increased processing time, suggesting that the system requires more effort to interpret unclear inputs. Overall, the most effective operational range is between 60 cm and 90 cm, while distances beyond 150 cm should be avoided due to rapid performance deterioration.

TABLE IV. TESTING WITH DIFFERENT DISTANCES RESULT

Distance (cm)	Detected Correctly	Total Scan	Accuracy (%)	Average Processing Time (s)
30	14	14	100%	4.66
60	14	14	100%	4.25
90	14	14	100%	4.17
150	14	14	100%	4.86
210	11	14	78.57%	5.42
300	4	14	28.57%	5.83

D. Testing With OrganicTrash

Testing was conducted to evaluate and compare system performance in terms of detection accuracy and processing time using four different datasets. The variation between datasets lies in their content composition rather than the detection method itself. The first dataset combines self-collected images and images from an online dataset, with an unbalanced number of samples per class. In contrast, the other three datasets use only self-collected images with balanced class distributions but different total counts.

All experiments were performed at a fixed distance of 90 cm, with 10 scans per waste category, for a total of 70 scans per dataset. Accuracy was calculated as the percentage of correctly detected images, and the average processing time was the mean time across all scans in each dataset.

The results show significant differences in performance across the datasets. The Fourth Dataset achieved the highest accuracy of 97.14%, making it the most reliable for correct detection. However, it also recorded the longest average processing time of 5.16 seconds, indicating a trade-off between accuracy and speed. Despite this, the increased processing time is considered acceptable given its superior detection performance.

In comparison, the Second and Third Datasets demonstrated moderate but stable performance, with accuracies of 84.29% and 87.14%, respectively, and faster processing times of 4.48 seconds and 4.41 seconds, respectively. Meanwhile, the First Dataset performed poorly, with only 12.86% accuracy, despite a relatively fast processing time of 4.40 seconds. Overall, the Fourth Dataset is the most suitable for implementation due to its highest accuracy. At the same time, the Second and Third datasets are acceptable alternatives, while the First Dataset is unsuitable for use.

TABLE V. TEST RESULT

Organic Trash	Application Detection Result
Banana Peel	Detected (Fabric)
Dry Leaf	Detected (Cardboard)
Red Apple	Detected (Fabric)
Twig	Detected (Cardboard)
Rice	Detected (Paper)
Raw Fish	Detected (Glass)
Orange Peel	Detected (Plastic)

V. CONCLUSION

Dataset quality proved to be the most crucial factor for the system's success, with the noise-free Fourth Dataset performing superiorly, achieving a detection accuracy of 97.14%. Operational distance testing mapped a perfect performance range, where the system consistently achieved 100% accuracy at distances from 30 cm to 150 cm, with the most efficient and fastest point located in the 60 cm to 90 cm range. A distance of 150 cm is the reliable maximum limit, as testing beyond this distance showed a drastic decline in accuracy and an increase in processing time, as the system struggled to detect objects. The application has a validation weakness, with a 100% False Positive rate, stemming from the algorithm's reliance solely on color and shape features without understanding the material context. The forced classification mechanism occurred because the dataset lacked negative data, leading the system to assign every organic object to the nearest inorganic category.

References

[1] Haris, Alfian Ma'arif, and L.-Y. Chin, "The Development of Real-Time Mobile Garbage Detection Using Deep Learning," vol. 7, no. 3, pp. 472–472, Jan. 2022.

[2] A. Howard et al., "Searching for MobileNetV3," arXiv, 2019.

[3] T. Kotecha, "Waste Material Detection," ERA, Jan. 01, 2022.

[4] S. L. Rabano, M. K. Cabatuan, E. Sybingco, E. P. Dadios, and E. J. Calilung, "Common Garbage Classification Using MobileNet," 2018 IEEE 10th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management (HNICEM), Nov. 2018.

[5] T. Handhayani, A. H. Pawening, and J. Hendryli, "Leboh 2: An Android Application for Solid Waste Detection," IAENG International Journal of Computer Science, vol. 50, no. 4, pp. 1479-1487, 2023.

[6] A. Francisco, S. Sequeira, M. Ana, Carvalho De Almeida, M. Luís, and Nunes, "Mobile Application to Identify Recyclable Materials," iscte, 2020.

[7] R. D. Ramadhani, A. N. A. Thohari, C. Kartiko, A. Junaidi, and T. G. Laksana, "Implementation of Deep Learning for Organic and Anorganic Waste Classification on Android Mobile" Atlantis Press, Nov. 30, 2021.

[8] Z. Cheng and F. Zhang, "Flower End-to-End Detection Based on YOLOv4 Using a Mobile Device," Wireless Communications and Mobile Computing, vol. 2020, pp. 1–9, Sep. 2020.

[9] M. Kalpana and J. Jayachitra, "Intelligent Bin Management System for Smart City using Mobile Application," Asian Journal of Applied Science and Technology (AJAST), vol. 1, no. 5, pp. 172–175, 2017.

[10] World Health Organization, "Dioxins and their effects on human health," WHO, Geneva, Switzerland, 2016.

[11] United Nations Environment Program, "Legal Limits on Single-Use Plastics and Microplastics: A Global Review of National Laws and Regulations," UNEP, Nairobi, Kenya, 2018.

[12] Glass Packaging Institute, "Glass Recycling Facts," GPI, Arlington, VA, USA, 2023.

[13] U.S. Environmental Protection Agency, "Advancing Sustainable Materials Management: Facts and Figures Report," EPA, Washington, D.C., USA, 2020.

[14] The Aluminum Association, "The Environmental Good of Aluminum," Arlington, VA, USA, 2021. [24] Institute of Scrap Recycling Industries (ISRI), "Scrap Specifications Circular," ISRI, Washington, D.C., USA, 2022.

[15] Confederation of European Paper Industries (CEPI), "Paper Recycling Guidelines for Households," CEPI, Brussels, Belgium, 2021.

[16] U.S. Environmental Protection Agency, "Paper and Paperboard: Material-Specific Data," EPA, Washington, D.C., USA, 2023.

[17] Ellen MacArthur Foundation, "A New Textiles Economy: Redesigning fashion's future," EMF, Cowes, UK, 2017.

[18] WRAP UK, "Textiles Market Situation Report," Waste and Resources Action Programme, Banbury, UK, 2019.

[19] Corrugated Packaging Alliance, "Corrugated Recycles: Technical Fact Sheet," CPA, Itasca, IL, USA, 2020.

[20] Earth911, "How to Recycle Pizza Boxes," Earth911 Inc., Plano, TX, USA, 2022.

[21] Intergovernmental Panel on Climate Change (IPCC), "Climate Change 2013: The Physical Science Basis," Cambridge University Press, Cambridge, UK, 2013, ch. 6.