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Development of a real-time plastic waste detection system based on deep learning to support the automation of industrial waste sorting processes

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ABSTRACT
The accumulation of plastic waste has become one of the major environmental issues in Indonesia, where conventional waste management systems are still limited in handling and classifying various types of waste. This research aims to develop an automatic waste detection system using Artificial Intelligence (AI) and implement it in a mobile application capable of identifying plastic waste in real time. The model was trained using the WasteIn dataset, which contains annotated images of different waste categories, including plastic, paper, glass, metal, organic, and electronic waste. The YOLO11-Nano architecture was applied due to its lightweight structure and efficiency for mobile-based deployment. The trained model was then converted into TensorFlow Lite (TFLite) format and integrated into an Android Studio environment to enable real-time inference through smartphone cameras. Based on the evaluation of 36 test images, the system achieved an accuracy of 91.67%, with consistent performance in detecting plastic, paper, and organic waste. The inference time of less than 100 milliseconds per frame demonstrates the system's feasibility for real-time mobile applications. The results indicate that the integration of deep learning and computer vision technologies can effectively support waste classification processes and contribute to sustainable waste management practices.

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1. INTRODUCTION

Waste has long been regarded as an inevitable byproduct of human activity, both at household and industrial scales. Rapid urbanization, industrial growth, and consumer lifestyle shifts have significantly increased waste generation worldwide. According to the Indonesian Ministry of Environment and Forestry, Indonesia produces approximately 67.8 million tonnes of solid waste per year, and this figure continues to rise steadily with population growth and economic expansion [1] The increasing waste production has placed a tremendous burden on landfills, leading to severe environmental degradation, groundwater contamination, and greenhouse gas emissions from decomposing organic matter [2], [3].

Among the total waste composition, organic materials contribute the largest proportion—about 60%—while plastic waste accounts for approximately 14% [4]. Although plastic occupies a smaller percentage, it poses a more critical environmental challenge because of its long degradation time, typically taking hundreds of years to decompose. Plastic pollution is not only a visual and sanitary concern but also a systemic threat to marine ecosystems, wildlife, and human health through microplastic accumulation [5], [6]. Inadequate plastic waste management further exacerbates Indonesia's global ranking as one of the top contributors to marine plastic pollution [7].

Despite numerous initiatives, waste management practices in Indonesia remain suboptimal. The imbalance between waste generation and treatment capacity results in continuous accumulation. The bottleneck often lies in the waste sorting stage, which determines the efficiency of subsequent processes such as recycling and resource recovery [8]. However, field surveys reveal that sorting is frequently neglected due to unpleasant odors from organic waste, insufficient public awareness, and lack of accessible sorting infrastructure [9]. In most residential and industrial areas, waste is still disposed of in mixed form, reducing the potential for recycling and energy recovery.

The differences between organic and inorganic waste, particularly plastics, are crucial for determining effective treatment methods. Organic waste can decompose naturally and is suitable for composting or biogas production, while plastic waste requires specialized handling, such as mechanical or chemical recycling [10]. Consequently, early identification and classification of waste materials are essential to reduce landfill pressure, enhance recycling efficiency, and promote a circular economy. In industrial contexts, such classification also contributes to lean production systems and sustainable manufacturing, aligning with the goals of Industry 4.0 and environmental management standards (ISO 14001) [11].

To address these challenges, Artificial Intelligence (AI) has emerged as a promising technological solution. Advances in computer vision and deep learning have enabled machines to process visual data and automatically recognize objects based on their shape, color, and texture [12]–[14] These capabilities can be applied to identify different types of waste directly from images, allowing faster and more accurate sorting without human intervention. AI-based systems are particularly advantageous because they can be implemented using mobile platforms, making them accessible and scalable across communities and industries [15]–[17].

Lightweight deep learning architectures play a crucial role in real-time waste detection systems, particularly in industrial automation environments where computational resources are often limited. MobileNet, which is based on depthwise separable convolutions, is designed to significantly reduce the number of parameters and FLOPs while maintaining reasonable accuracy, making it suitable for mobile and embedded devices. Its classification-oriented architecture, however, limits its ability to perform precise spatial localization, which is essential for detecting heterogeneous waste objects on conveyor belts. In contrast, YOLO-Nano is a compact variant of the YOLO family optimized for object detection, integrating efficient modules such as CSP bottlenecks and reduced-depth detection heads. Despite its small size, YOLO-Nano retains the full end-to-end detection pipeline, enabling higher localization accuracy, faster inference speeds, and better robustness against occlusions and shape variations commonly found in industrial waste. Empirical benchmarking across previous studies shows that MobileNet-based detectors typically achieve lower mAP when used as detection backbones, whereas YOLO-Nano models achieve improved real-time performance with mAP exceeding 70–80% on lightweight deployments, making YOLO-Nano more suitable for automated waste-sorting systems that require both speed and detection precision. Therefore, for industrial waste-sorting automation, YOLO-Nano offers a more technically aligned solution compared to MobileNet due to its specialized detection architecture, higher spatial sensitivity, and better optimization for edge-device inference [18], [19].

Recent studies have explored various AI architectures for waste detection. For example, convolutional neural networks (CNNs) and You Only Look Once (YOLO) models have demonstrated high accuracy in classifying waste categories in real time [20], [21]. Mobile-friendly versions, such as YOLOv5s, YOLOv8, and YOLO11-Nano have been optimized for low-latency inference on embedded systems and smartphones [22], [23]. A brief comparison of these architectures in terms of object detection performance and computational complexity is presented in Figure 1. In the context of developing a waste detection system based on deep learning to support the automation of industrial waste sorting processes, the architectural advancements introduced in YOLO11 offer substantial advantages over YOLOv8. The incorporation of modules such as the

C3k2 block and the C2PSA attention mechanism enhances feature extraction capabilities, enabling more accurate identification of small, irregular, and visually variable waste objects—challenges that are common in real industrial environments.

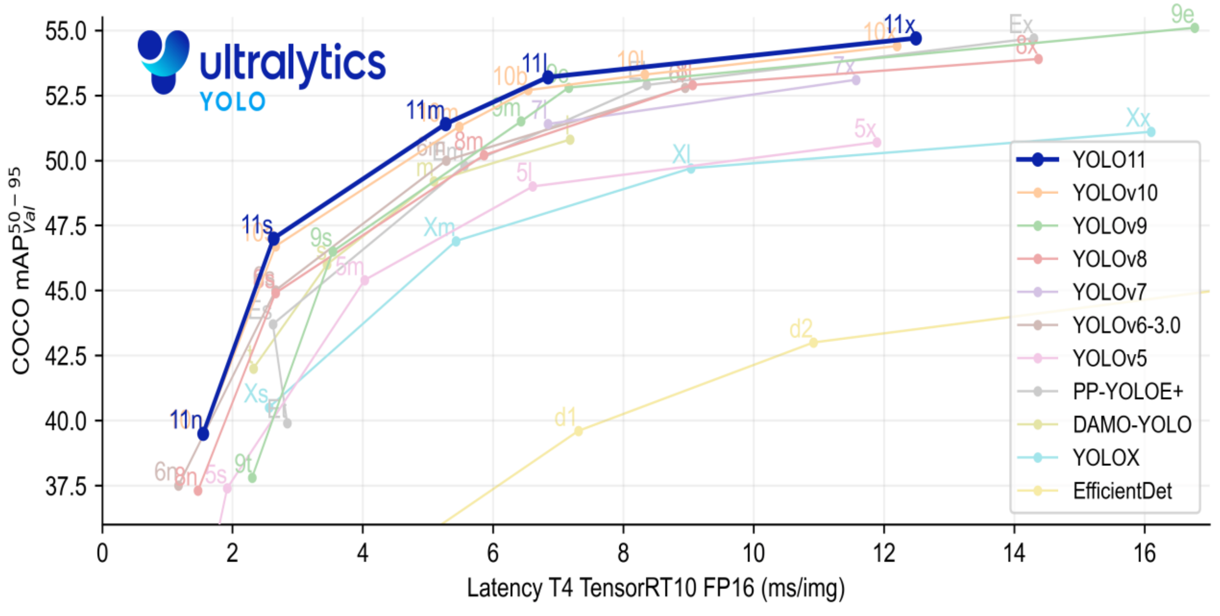


Figure 1. mAP50–95 versus Latency (T4 TensorRT 10, FP16) for several YOLO architectures on the COCO dataset [23]

Such improvements in YOLO11 lead to higher detection accuracy, reduced computational load, and faster inference, which are critical for real-time sorting applications on limited-resource hardware. While YOLOv8 provides a stable and widely adopted baseline, YOLO11 delivers a more optimized balance of speed, precision, and efficiency, making it a superior choice for deploying intelligent, automated waste-sorting systems in industrial settings [24]. These models can be integrated into Android applications using TensorFlow Lite, enabling real-time recognition with minimal computational resources. Such integration aligns with the growing demand for lightweight AI models that support sustainability-oriented innovation in industrial and environmental sectors.

However, most prior research focuses primarily on algorithmic performance metrics—accuracy, precision, recall—without emphasizing practical implementation in real-world scenarios. There remains a gap in developing and validating AI-based waste classification systems that are functionally deployable on mobile devices and directly applicable in industrial waste management environments. Furthermore, public engagement and behavioral change aspects have rarely been addressed, even though they are critical to achieving large-scale adoption of waste-sorting technologies [25]–[27].

This study aims to bridge these gaps by developing a real-time plastic waste detection system that integrates deep learning with a mobile-based platform. The research does not primarily seek to compare algorithms but rather to implement a concrete AI solution that can be used by both individuals and industries. The system employs the YOLO11-Nano architecture [28] trained on a diverse dataset of waste images and deployed through an Android application optimized with TensorFlow Lite. This approach ensures computational efficiency while maintaining accuracy in identifying multiple waste categories, including plastic, glass, paper, metal, electronic, and organic waste.

By combining AI and computer vision, this research contributes to the practical application of intelligent automation for waste management. The developed system is designed to serve not only as a technical innovation but also as a behavioral tool that promotes proper waste sorting habits among users. In the broader context of Industrial Engineering and Rubber and Plastic Processing Technology, the study demonstrates how AI-based solutions can enhance operational efficiency, reduce manual sorting errors, and support sustainable practices across production and waste handling processes.

2. MATERIALS AND METHODS

This research employs a quantitative approach using secondary data obtained from an open-source dataset. The dataset utilized is the WasteIn Dataset, which was downloaded from the Roboflow Universe platform at https://universe.roboflow.com/ai-projects-r9oea/wastein-dataset [29]. The WasteIn Dataset is designed to support research in Computer Vision, particularly for waste detection and classification. It consists of labeled image data divided into three subsets:

- Training set – used to train the object detection model.
- Validation set – used to evaluate model performance during the training process.
- Testing set – used to measure the model's generalization capability on unseen data.

The study begins with an extensive literature review, focusing on theoretical foundations and previous research related to waste management, image recognition, and deep learning-based object detection. This review establishes the conceptual and methodological basis for the present study. Following the theoretical review, the data determination phase is carried out. The dataset is selected according to the study's objectives, focusing on waste image data categorized by material type. The selected data are obtained from publicly available repositories such as Kaggle and the Roboflow Universe, ensuring sufficient diversity for robust model training.

1. Data Collection
   The research starts with the collection and compilation of image datasets that serve as the foundation for training the artificial intelligence model. Images primarily depict various forms of plastic waste but also include other categories such as paper, glass, and organic materials. Data were obtained from two sources open datasets available online, and direct image documentation using a smartphone camera in local environments. Captured images reflect diverse lighting conditions, backgrounds, and waste shapes to ensure that the developed model can operate effectively in real-world conditions. Each image is manually labeled to distinguish between plastic and non-plastic waste categories.
2. Data Preprocessing
   Before training, the dataset undergoes several preprocessing steps to standardize and enhance image quality. These steps include image resizing, to ensure uniform input dimensions; color normalization, to maintain consistent illumination and contrast. The processed data are then split into training, validation, and testing subsets to ensure fairness and reliability in performance evaluation. To increase the training data diversity, random horizontal and vertical flipping transformations with a probability of 0.5 are applied.
3. Model Development and Training
   The deep learning model is designed and trained using a transfer learning approach. At this stage, the model architecture adopted was YOLO11-Nano, a lightweight variant of the *You Only Look Once (YOLO)* family. The YOLO11-Nano model is designed for rapid object detection and classification with low computational complexity. Its efficiency and inference speed make it highly suitable for real-time implementation in mobile applications. The model training process is conducted on cloud-based platforms, namely Google Colab, leveraging GPU acceleration for faster computation. Transfer learning enables the model to adapt pre-trained weights from large-scale datasets to the custom WasteIn dataset.

   The model training process was conducted using the PyTorch framework, which allows flexible construction and management of artificial neural network architectures. Training was performed using the AdamW optimizer due to its ability to balance convergence speed and weight update stability. The initial learning rate was set to 0.001 and dynamically adjusted using a cosine annealing scheduler throughout the training process.

   The loss function used in this study is a composite of three components:
   - Complete Intersection over Union (CIoU) Loss — for bounding box localization accuracy;
   - Binary Cross Entropy (BCE) Loss — for objectness prediction; and
   - Cross Entropy Loss — for object classification.

   Throughout training, the model was periodically evaluated using the validation dataset to compute performance metrics including mean Average Precision (mAP). An early stopping mechanism was applied if model performance did not show significant improvement over several iterations, in order to prevent overfitting. The best-performing model was then saved as a checkpoint, determined based on the highest mAP@0.5 value achieved on the validation set.

4. Model Integration into Mobile Application
   After successful training, the optimized model is converted into TensorFlow Lite (TFLite) format to enable efficient deployment on mobile devices. The model is then integrated into an Android-based application developed using Android Studio. The mobile application is designed with a user-friendly interface that allows users to capture images of waste using the device's camera. The application then processes the image in real-time and displays the classification result—indicating whether the waste is plastic or non-plastic. The TFLite optimization ensures low latency and minimal memory usage, enabling smooth operation even on mid-range smartphones.
5. System Testing and Evaluation
   Once integrated, the application undergoes system testing to evaluate its functional performance, detection accuracy, and user experience. Testing includes three primary aspects are technical validation: verifying the functionality of the camera interface and detection algorithms, model accuracy evaluation: testing the model on previously unseen data to assess its generalization ability, and user experience assessment: gathering user feedback on usability, responsiveness, and visual interface appeal. A group of participants is involved in real-world testing to provide practical insights into the system's performance under varying conditions.
6. Performance Analysis and Improvement
   The final phase involves quantitative and qualitative evaluation of system performance. Quantitatively, the model's detection accuracy and other performance metrics are analyzed, while qualitatively, user feedback is used to assess usability and identify potential improvements. Based on these analyses, several recommendations are formulated for future development, such as expanding classification categories to include more waste types and integrating educational features on plastic recycling practices. Through this structured and iterative approach, the research aims to produce a practical, efficient, and inclusive AI-based mobile system that contributes to smarter and more sustainable waste management practices.

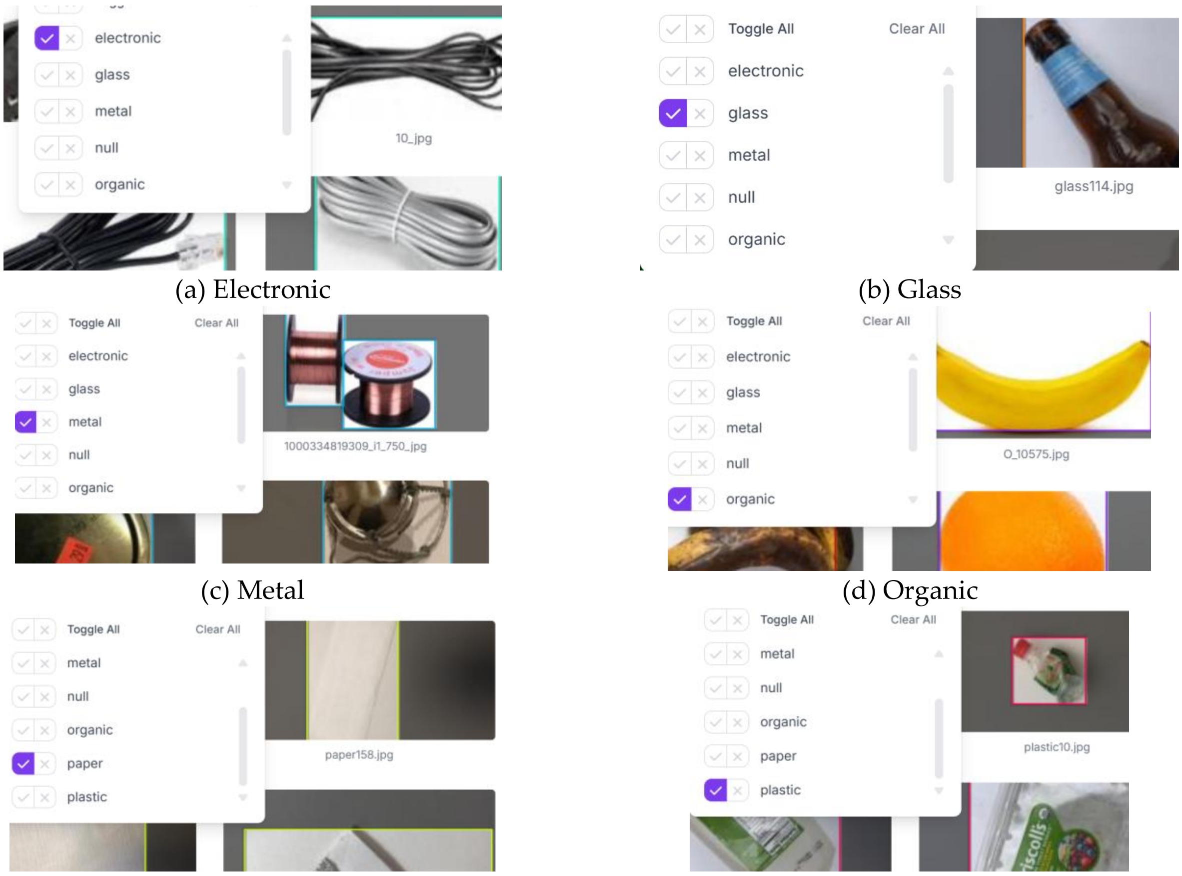
3. RESULTS

3.1. Development of an Automatic Detection System for Plastic Waste Using Artificial Intelligence (AI)

Several examples of images from the WasteIn dataset used in this study are illustrated in Figure 2. The image illustrates examples of annotated data used for training a waste-classification or waste-detection system. Each sub-figure represents a different waste category—Electronic, Glass, Metal, and Organic—accompanied by a labeling interface where annotators assign the appropriate class to each image. The panels show selectable labels such as *electronic*, *glass*, *metal*, *organic*, and *null*, with the correct category highlighted for each object: cables labeled as electronic, glass bottles labeled as glass, metal coils labeled as metal, and fruits labeled as organic. This annotation process is essential for creating a structured and high-quality dataset that enables deep learning models to accurately distinguish between various types of waste in automated waste-sorting applications.

Sub-figures (e) and (f) in Figure 2 represent the Paper and Plastic categories, respectively, with each image displayed alongside a labeling interface that lists selectable waste classes such as *metal*, *organic*, *paper*, and *plastic*. The correct label is highlighted—*paper* for images containing paper materials and *plastic* for images containing plastic waste—indicating that annotators have assigned the appropriate category based on the object present in the image. This annotation process ensures that the dataset is accurately structured, enabling the model to learn clear distinctions between different waste types and improving the performance of automated waste-sorting systems.

Having prepared the dataset, the process continues to the YOLO11-Nano training stage. This stage is critical, as it determines how well the model learns discriminative features from the prepared data. The training time for the object detection model was recorded as 0.784 hours (approximately 47 minutes). The relatively short training duration indicates the computational efficiency of the YOLO11-Nano architecture. The model was trained for 100 epochs, and performance evaluation was conducted on the validation set at each epoch to mitigate the risk of overfitting and to ensure robust generalization capability. This iterative evaluation also provides insight into the model's convergence behavior throughout training. The training results of the YOLO model are visualized through the plots shown in Figure 3.



(a) Electronic (b) Glass

(c) Metal (d) Organic

(e) Paper (f) Plastic

Figure 2. Sample Images from the WasteIn Dataset: (a) Electronic Waste, (b) Glass, (c) Metal, (d) Organic, (e) Paper, (f) Plastic.

Figure 3 illustrates the progressive decrease in the box loss during the training of the YOLOv11n model. At the early stages of training, the box loss values were relatively high, approximately 0.8, indicating limited accuracy in predicting object locations. As the number of epochs increased, the box loss consistently declined, demonstrating the model's improving capability to generate more precise bounding boxes. This reduction reflects a significant enhancement in object localization precision.

Figure 3. The bounding box loss during training

To mitigate overfitting, we also evaluated the bounding box loss on the validation dataset. Figure 4 shows the decreasing trend of the validation box loss (val/box_loss), which reflects the model's ability to predict bounding boxes on unseen data. The initial values were relatively high, at approximately 0.8, and gradually decreased to about 0.4. This decline indicates that the model was able to maintain accurate object localization on unseen data. The stability of this trend suggests that the model did not suffer from overfitting in terms of bounding box prediction.

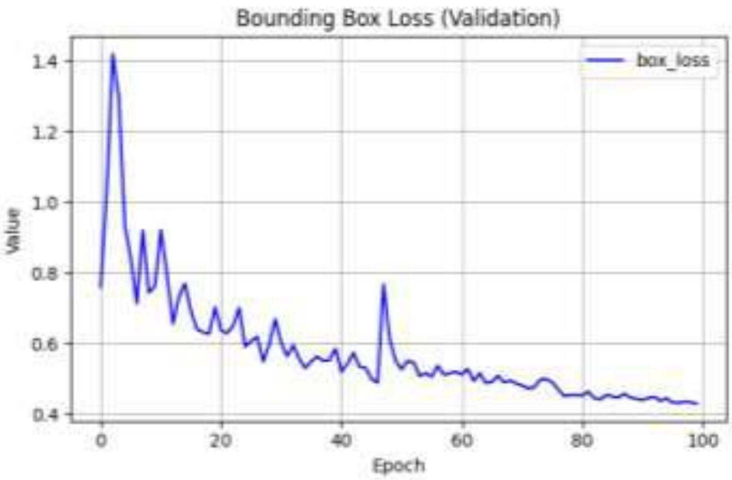


Figure 4. The bounding box loss during validation

As the validation results indicated that the model did not suffer from overfitting, we proceeded to the testing phase. The testing stage was performed using a hold-out test set comprising 10% of the total collected dataset. Figure 5 presents the precision–recall curve of the YOLOv11n model for the object detection task. The curve demonstrates consistently high precision and recall across most classes, achieving a mean Average Precision (mAP@0.5) of 0.930. Most classes maintain high precision over a wide range of recall values, indicating that the model produces reliable predictions even as the detection threshold becomes more permissive.

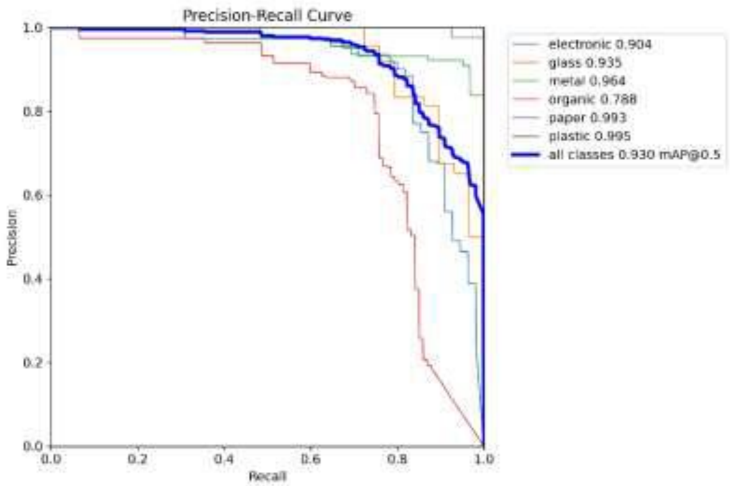


Figure 5. The Precision-Recall Curve of the Model on the Test Set.

The plastic and metal classes exhibit the best performance, with AP values of 0.995 and 0.964, respectively. Their PR curves remain close to the top-right region of the plot, reflecting both high precision and high recall. This suggests that the visual characteristics of these materials are consistently learned by the model, enabling robust discrimination from other waste classes. The electronic and glass categories also show strong performance, with AP scores of 0.904 and 0.935. Although their curves show a gradual decline at higher recall ranges, precision remains relatively high, indicating stable detection under most conditions. These results imply that the model can generalize well to objects with reflective or complex surface properties.

In contrast, the organic class shows comparatively lower performance (AP = 0.788). Its PR curve drops more sharply at higher recall values, suggesting a higher rate of false positives when attempting to detect all relevant instances. This behavior can be attributed to the greater intra-class variability of organic waste, such as differences in shape, texture, and color, which makes the class harder to model consistently. Despite these challenges, the overall stability of the PR curves across most classes indicates that the YOLOv11n model achieves a strong balance between precision and recall. These findings demonstrate the model's robustness and suitability for real-world waste-sorting applications, particularly in mobile-based and resource-constrained deployment scenarios.

3.2. Development of a Mobile Application Prototype for Real-Time Plastic Waste Detection

The next phase of this research involved the development of a mobile application prototype capable of recognizing plastic waste in real time through a smartphone camera. The application was developed using Android Studio as the primary Integrated Development Environment (IDE), chosen for its efficiency in Android-based development and its seamless integration with various machine learning libraries. The trained YOLO11-Nano architecture was exported into TensorFlow Lite (TFLite) format to ensure optimal performance on mobile devices with limited computational resources, such as smartphones. For the sake of reproducibility, we have made the TFLite model available at https://bit.ly/TFLite_waste. The converted TFLite model was then integrated into the Android application using the TensorFlow Lite Interpreter API, enabling direct real-time inference from the device's camera feed. Figure 6 illustrates the Android Studio interface used during the development process, while Figure 7 presents an example of the successful import of the YOLO11-TFLite model into Android Studio.

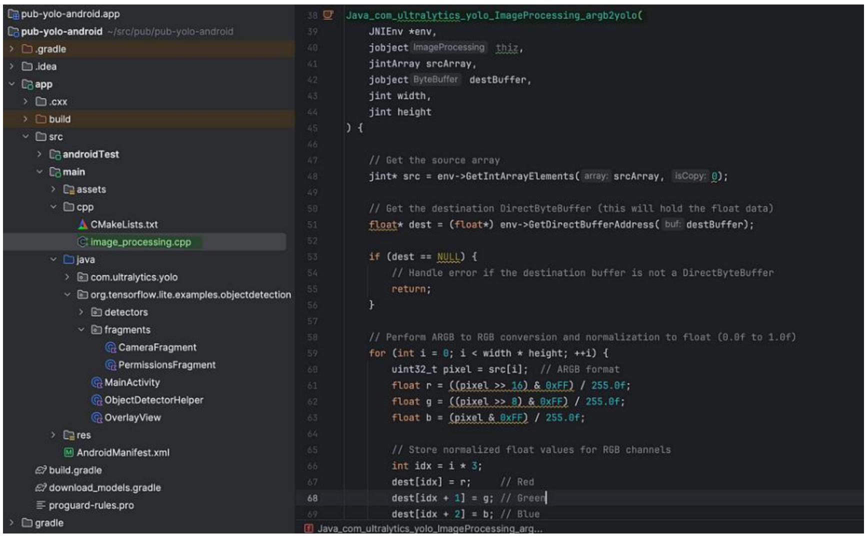


Figure 6. Android Studio interface during the application development process

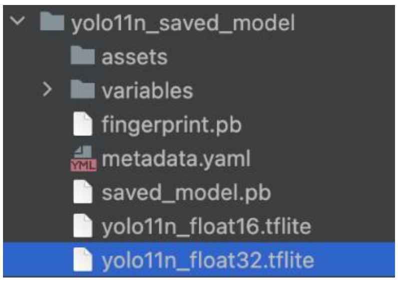


Figure 7. Example of the successful import of the YOLO11-TFLite model into Android Studio.

The mobile application was developed with minimal dependency on external libraries such as Flutter and OpenCV to ensure efficiency and simplicity. Additional optimization was carried out during the preprocessing stage by transferring image conversion operations from Java to C++ through the Java Native Interface (JNI). This modification significantly reduced processing time from approximately 30 milliseconds to only 1–2 milliseconds, enabling faster and more responsive inference performance.

After completing the mobile interface development, the model was tested in real time using the smartphone camera to verify direct on-device inference capability. The testing was performed by pointing the camera toward various waste objects, where the application automatically detected and displayed the corresponding waste type label along with its confidence score.

The real-time testing results demonstrated that the YOLO11-Nano–based model achieved fast and stable detection performance, with an average inference time of less than 100 milliseconds per image. This indicates that the trained and optimized model can be effectively implemented on mobile devices with limited computational resources. The successful completion of the design and training phases confirms that the deep learning approach using the YOLO11-Nano architecture, built on the PyTorch framework and converted to TensorFlow Lite (TFLite), can produce an efficient and accurate automatic waste classification system. Moreover, the implementation supports user-friendly Artificial Intelligence (AI) solutions that contribute to smart, technology-driven environmental management.

During the development process, the user interface (UI) was designed to be simple and intuitive, allowing users to easily direct the camera toward waste objects. Real-time validation was conducted under various lighting conditions, viewing angles, and background environments to ensure consistent detection accuracy and speed. The cumulative results of this validation process are presented in Table 1.

Table 1. The results of the validation process

Evaluation Number	Actual Image	Detected Image	Description
1	Glass waste	Glass waste	Match
2	Glass waste	Glass waste	Match
3	Glass waste	Metal waste	Missmatch
4	Glass waste	Glass waste	Match
5	Glass waste	Paper waste	Missmatch
6	Glass waste	Glass waste	Match
7	Organic waste	Organic waste	Match
8	Organic waste	Organic waste	Match
9	Organic waste	Organic waste	Match
10	Organic waste	Organic waste	Match
11	Organic waste	Organic waste	Match
12	Organic waste	Organic waste	Match
13	Paper waste	Paper waste	Match
14	Paper waste	Paper waste	Match
15	Paper waste	Paper waste	Match
16	Paper waste	Paper waste	Match
17	Paper waste	Paper waste	Match
18	Paper waste	Paper waste	Match
19	Metal waste	Metal waste	Match
20	Metal waste	Metal waste	Match
21	Metal waste	Metal waste	Match
22	Metal waste	Metal waste	Match
23	Metal waste	Metal waste	Match
24	Metal waste	Metal waste	Match
25	Electronic waste	Electronic waste	Match
26	Electronic waste	Electronic waste	Match
27	Electronic waste	Electronic waste	Match
28	Electronic waste	Electronic waste	Match

Evaluation Number	Actual Image	Detected Image	Description
29	Electronic waste	Electronic waste	Match
30	Electronic waste	Metal waste	Missmatch
31	Plastic waste	Plastic waste	Match
32	Plastic waste	Plastic waste	Match
33	Plastic waste	Plastic waste	Match
34	Plastic waste	Plastic waste	Match
35	Plastic waste	Plastic waste	Match
36	Plastic waste	Plastic waste	Match

Based on the testing results of 36 waste images consisting of six main categories—namely glass, organic, paper, metal, electronic, and plastic—a general overview of the performance of the developed detection system was obtained. Figure 8 illustrates examples of matching results between the actual waste objects and the system's detected outputs.

Figure 8. Several examples of images with correct detection

The performance of the architecture is calculated as follows.

$$\text{Accuracy} = \frac{\text{Number of Images with Correct Detection}}{\text{Total Number of Test Images}} \times 100\% \quad (1)$$

From the overall test data, 31 images were correctly detected according to their actual classes, while five images were misclassified. Accordingly, the system's accuracy rate was calculated at 91.67%. This result indicates that the deep learning–based system implemented using the YOLO11-Nano model demonstrates satisfactory detection performance at the prototype stage, particularly in identifying various types of waste in real time through a mobile application.

The misclassification errors primarily occurred in categories with similar visual characteristics, such as glass and metal waste, which both exhibit reflective surfaces, as well as electronic and metal waste, which share metallic elements. These misclassifications are summarized in Table 2.

Table 2. Misclassifications occurred in our experiment.

No	Actual Image	Detected Image	Type of error	Possible Cause
3	Glass waste	Metal waste	Misclassification between reflective materials	Similar color/texture due to light reflection between glass and metal
5	Glass waste	Paper waste	Shape/texture misidentification	Reflective or blurred paper image
30	Electronic waste	Metal waste	Similarity in	Presence of metallic

No	Actual Image	Detected Image	Type of error	Possible Cause
			shape/material features	components in electronic waste
Other	Two similar cases in glass and electronic categories	-	Class overlap	Training dataset not sufficiently representative

Another contributing factor to the observed misclassification errors is uneven lighting conditions, excessive light reflections, and the limited diversity of training data for certain waste categories. Nevertheless, the experimental results indicate that the system was able to maintain consistent detection performance in the organic, paper, and plastic categories, achieving perfect classification accuracy for these classes.

The confusion matrix graph at Figure 9 provides a detailed overview of the model's classification performance across six waste categories: Glass, Organic, Paper, Metal, Electronic, and Plastic. The strong diagonal values indicate that the model correctly classified the majority of samples in each class, with perfect accuracy achieved for Organic, Paper, Metal, and Plastic waste—each showing six correct predictions and no misclassifications. Glass waste shows two misclassifications, being incorrectly detected as Metal and Paper in isolated cases. Similarly, Electronic waste has one misclassified instance that was predicted as Metal. These off-diagonal errors suggest that the model occasionally confuses visually similar materials, such as electronic components and metal objects. Overall, the confusion matrix demonstrates high model reliability, with only a small number of misclassifications, indicating strong performance in multi-class waste detection.

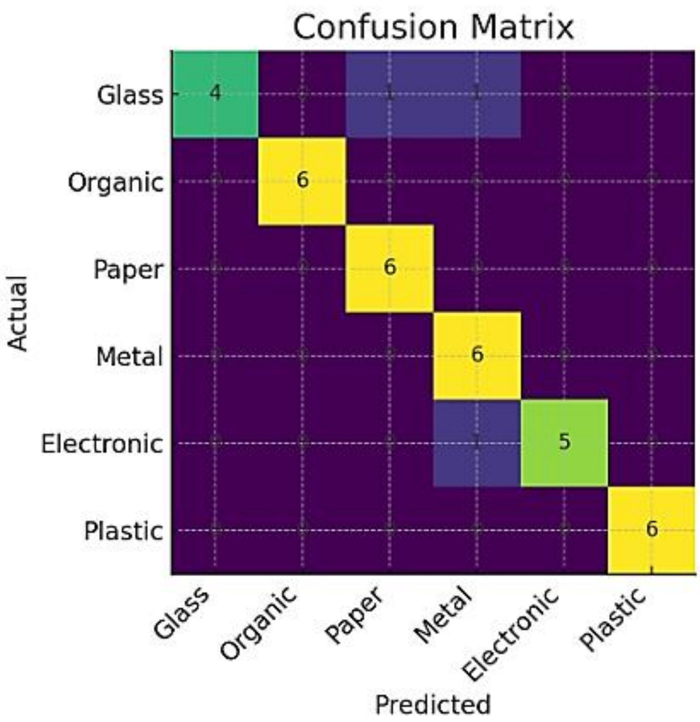


Figure 9. Confusion Matrix

Besides detection accuracy, it is also important to evaluate the inference time of the developed system. According to Table 3, the developed detection system demonstrated stable performance, with an average inference time of less than 100 milliseconds per image, enabling real-time implementation on mobile devices. This finding confirms that the integration of Artificial Intelligence (AI) and Computer Vision technologies can effectively support the automation of waste-sorting processes in both industrial environments and public applications. From the perspective of Industrial Engineering and Rubber and Plastic Processing Technology, these results provide evidence that the application of AI has the potential to enhance waste management efficiency, reduce human error in material sorting, and promote sustainability through more environmentally friendly production systems.

Table 3. The overall performance of the developed system

Evaluation Criteria	Result / Assessment	Description
Detection Accuracy	91.67%	Satisfactory for the prototype stage
Inter-Class Result Stability	High	Most categories detected consistently
Dominant Error	On reflective objects (glass, metal)	Requires improvement in training data quality
Inference Time /	<100 ms per image (based on testing)	Supports real-time detection
System Response	Fast and interactive	Suitable for mobile applications

4. CONCLUSION

This study presents the development of an intelligent mobile-based waste detection system capable of identifying plastic waste in real time. The integration of the YOLOv11-Nano architecture and TensorFlow Lite optimization enabled efficient deployment on resource-constrained mobile devices. Based on evaluations conducted on 36 sample images, the proposed system achieved an overall accuracy of 91.67%, demonstrating its potential as a promising proof-of-concept, particularly for the detection of plastic, paper, and organic waste. An average inference time of less than 100 milliseconds per image further supports the feasibility of real-time operation on mobile platforms. While the results indicate encouraging performance, this study represents an initial prototype rather than a fully validated production system. The findings suggest that the integration of Artificial Intelligence and Computer Vision can potentially enhance automation in waste management and reduce human error in classification tasks, supporting sustainability-oriented initiatives in both industrial and community contexts.

Future work will focus on expanding the dataset with more diverse visual conditions and additional waste categories to improve generalization performance. Further optimization through advanced model quantization and pruning is expected to enhance computational efficiency without compromising detection accuracy. Moreover, the integration of cloud-based analytics and Internet of Things (IoT) connectivity could enable scalable deployment for smart waste management. Incorporating educational features within the mobile application could also promote public awareness and participation in proper waste segregation practices, contributing to a more sustainable environment.

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