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Research Article

Automated Waste Image Classification with Weighted Scoring Using MobileNetV2 on the OLSAM Platform

Kartika Nur Anggraeni [1]; Arin Yuli Astuti [2]; Ismail Abdurrozzaq Zulkarnain [3,*]
[1] Universitas Muhammadiyah Ponorogo, Ponorogo 63471, Indonesia, kartikahamad19@gmail.com
[2] Universitas Muhammadiyah Ponorogo, Ponorogo 63471, Indonesia, arinyulias@umpo.ac.id
[3] Universitas Muhammadiyah Ponorogo, Ponorogo 63471, Indonesia, ismail@umpo.ac.id

Correspondence should be addressed to Ismail Abdurrozzaq Zulkarnain; ismail@umpo.ac.id

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Abstract:
This study presents the development of an automated waste image classification system for the OLSAM platform to enhance community participation in waste management. The objective is to integrate a lightweight CNN-based classifier with a weighted point calculation mechanism for five waste categories. A dataset of 1,500 images was used, split into 80% training, 10% validation, and 10% testing. The MobileNetV2 architecture was applied to perform image classification, while a weighted reward mechanism assigned points based on the detected waste type and its weight. The model achieved its best performance at epoch 65, reaching an accuracy of 96.67% and a weighted F1-score of 0.97. These results indicate that combining CNN-based recognition with a weighted point system effectively supports user engagement and promotes sustainable waste-sorting behavior within community waste management systems.

Keywords: Convolutional Neural Network, MobileNetV2, smart waste management, waste classification, weighted approach

Dataset link: https://drive.google.com/drive/folders/1rdH0E7zpMmIYUnXofdLOljCMvCj03Azy?usp=sharing; Kaggle : https://www.kaggle.com/datasets/farzadnekouei/trash-type-image-dataset

1. Introduction

Ponorogo Regency in East Java continues to experience population growth, which has contributed to increasing consumption and a rise in waste generation. According to the Ponorogo Sanitation and Parks Department, the region produced approximately 139,552.49 tons of waste in 2022, yet only 60.92% was managed properly, while the remainder remained unprocessed due to limited transportation and disposal capacity [1], [2]. This condition highlights the need for more effective and sustainable waste management strategies. Waste, as a major by-product of human activities, poses significant environmental, health, and social challenges.

Despite ongoing efforts by the local sanitation department, waste management in Ponorogo remains suboptimal. Key issues include insufficient disposal facilities, low public participation in waste sorting, an imbalance between waste volume and landfill capacity, and an inadequate number of sanitation workers [1], [3]. Indonesia's Waste Management Law No. 18 of 2008 mandates systematic and sustainable approaches to waste reduction, sorting, and treatment, creating an urgent demand for technology-driven solutions [4].

Several studies in Indonesia have explored automated waste classification using deep learning models such as CNN, MobileNet, and EfficientNet. However, these studies primarily focus on improving model accuracy and rely on static benchmark datasets without integrating the models into real digital platforms accessible to the public [5], [6], [7]. Moreover, existing research does not incorporate gamification-based point systems to encourage community participation in waste sorting, nor do they evaluate model performance in real operational environments such as waste collection centers [8], [9]. These limitations indicate that previous research has not yet addressed practical deployment, user engagement, and platform integration forming the research gap targeted in this study.

To fill this gap, this study develops an automatic waste photo detection system using a weighted classification model deployed on the OLSAM (Olah Sampah) website. Users can upload waste photos, which are classified using a Convolutional Neural Network (CNN), and points are assigned based on both the waste type and weight. This mechanism aims to increase user participation and ensure a fair reward system [10].

The contributions of this research are threefold. First, it integrates a lightweight CNN-based classification model into a fully functional community waste management platform (OLSAM), enabling real-time prediction from user-uploaded photos [11]. Second, it introduces a weighted point system as a form of gamification to promote sustainable waste-sorting behavior. Third, the system is tested in a real-world waste collection center in Ponorogo using five recyclable waste types plastic, metal, aluminum, paper, and glassdemonstrating practical applicability beyond laboratory settings [12].

2. Method

This study adopts the prototype development method, which involves several iterative stages, including needs analysis, prototype design, prototype evaluation, system coding, system evaluation, testing, and implementation. This approach enables continuous refinement of the system based on feedback at each phase.

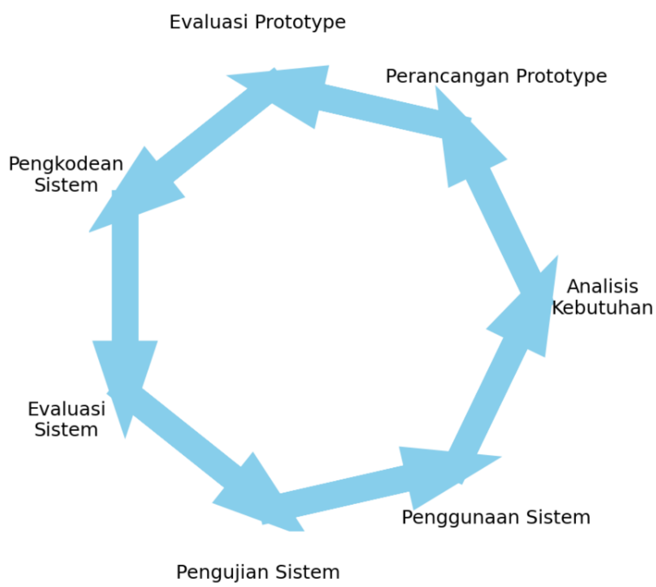

Figure 1: Research Flow

Data Source

This study uses a total of 1,500 waste images across five categories plastic, paper, glass, metal, and aluminum each consisting of 300 images. The dataset was obtained from two sources [13], [14].

a. Primary data: Images captured directly using a smartphone camera under natural outdoor lighting to represent real operational conditions. All images were stored in JPG/JPEG format.
b. Secondary data: Publicly available datasets retrieved from Kaggle and used according to their respective Creative Commons licenses [15], [16].

Since the dataset contains only object-level waste images without any human or sensitive information, no institutional ethical clearance was necessary. Representative sample images for each category are shown in **Figure 2**.

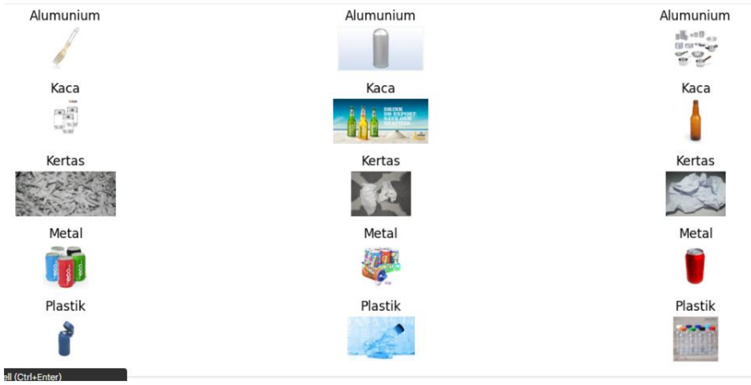

Figure 2. Sample Images from the Dataset

Data collection process:

A total of 1,500 waste images were used in this study, covering five categories: plastic, paper, glass, metal, and aluminum (300 images per category). After preprocessing, the dataset was divided using the splitfolders library into [16]. After preprocessing, the dataset was split using the splitfolders library into training (80%), validation (10%), and testing (10%) subsets. This ensured balanced class distribution and effective model evaluation.

Table 1. Dataset Distribution

	Total	Training	Validation	Testing
Plastic	300	240	30	30
Glass	300	240	30	30
Paper	300	240	30	30
Alumunium	300	240	30	30
Metal	300	240	30	30
Total	1500	1200	150	150

Preprocessing Data

The preprocessing stage standardized all images before model training. The following steps were applied:

a. Resizing all images to 224 × 224 pixels to match MobileNetV2 input requirements [17], [18].
b. Normalization of pixel values to the 0–1 range to stabilize training [19].
c. Conversion to tensors for compatibility with the deep learning framework [20].
d. Directory structuring and class labeling to support automated batch loading [21].

These preprocessing steps ensured uniform input dimensions, reduced computational load, and improved model performance.

Data Augmentation

To increase dataset variability and reduce overfitting, this study applied several image augmentation techniques using the ImageDataGenerator library [22], [23]. The augmentation process included random rotations of up to 30°, horizontal and vertical shifts of up to 30%, shear transformations of up to 30%, and zoom operations of up to 30% to simulate variations in orientation, position, and distance. Horizontal flipping was used to capture symmetrical patterns, while brightness adjustments ranging from 0.8 to 1.2 were applied to reflect outdoor lighting variations [9], [24]. These augmentation strategies provided diverse image transformations and enhanced the robustness and generalization ability of the CNN model in classifying waste categories [25].

Data analysis methods

In this study, the MobileNetV2 architecture was employed as the base model for waste image classification, combined with a weighted classification mechanism to support the point-based scoring system [26]. The model was trained using the Adam optimizer with a learning rate of 0.0001, a batch size of 32, and a maximum of 80 epochs. To prevent overfitting, EarlyStopping was applied with a patience value of 5, and ModelCheckpoint was used to preserve the best-performing model during training. A fixed random seed (42) was set to ensure reproducibility across experimental runs [27]. All experiments were conducted using TensorFlow 2.12 and Keras 2.12 with Python 3.10 on a laptop equipped with an Intel Core i3-1005G1 processor, 4 GB RAM, and CPU-based execution. Training and validation loss curves were monitored to observe convergence behavior and detect potential overfitting, while a confusion matrix was used to analyze prediction patterns across waste categories [28]. his configuration ensures a stable, reproducible, and computationally efficient environment for implementing MobileNetV2 in real-world waste classification scenarios [29].

Performance Evaluation

The performance of the classification model was evaluated using four standard metrics: accuracy, precision, recall, and F1-score [30], [31]. These metrics were calculated using the confusion matrix values consisting of True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). The formulas are defined as follows:

a. Accuracy

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \tag{1}$$

b. Precision

$$Precision = \frac{TP}{(TP + FP)} \tag{2}$$

c. Recall (Sensitivity)

$$\text{Recall} = \frac{TP}{(\text{TP} + \text{FN})} \tag{3}$$

d. F1 Score

$$\text{F1 Score} = 2 \times \frac{(\text{Precision} \times \text{Recall})}{(\text{Precision} + \text{Recall})} \tag{4}$$

3. Result and Discussion

Results

The results of this study demonstrate the successful implementation of an automatic waste detection system based on a weighted classification model. A total of 1,500 waste images were used, covering five categories: plastic, paper, glass, metal, and aluminum (300 images per category). The dataset was split into training (80%), validation (10%), and testing (10%) subsets to ensure balanced class distribution. All evaluation metrics in this study use the weighted F1-score, not the macro F1-score, to account for differences in class distribution across categories.

The system was developed using a Convolutional Neural Network (CNN) for waste image classification, combined with a point-weighting mechanism for the five waste categories, and integrated into the OLSAM web-based platform. Experiments were conducted with epochs ranging from 30 to 80, achieving the best performance at epoch 65, which balanced learning and generalization. The backend database manages user data and records waste exchange history, including automatically calculated points based on waste type and weight. This integration enables real-time image recognition, category classification, and gamified reward distribution, encouraging public participation in waste management.

Table 2. Training Performance Comparison

Epoch	Training Time (Seconds)	Accuracy (%)	Weighted F1-score	Model Size (MB)
30	5	94.00	0.94	14
65	9	96.67	0.97	14

Table 2 summarizes the overall training performance at epoch 30 and epoch 65, while Figure 3 provides a detailed visualization of the model's precision, recall, and weighted F1-score for each waste category at both training stages.

```
Test Accuracy: 94.00%
150/150 ━━━━━━━━━━━━━━━━━━━━ 5s 26ms/step
              precision    recall  f1-score   support

   Alumunium       0.88      1.00      0.94        30
        Kaca       0.97      0.97      0.97        30
      Kertas       1.00      0.83      0.91        30
       Metal       1.00      0.97      0.98        30
     Plastik       0.88      0.93      0.90        30

    accuracy                           0.94       150
   macro avg       0.94      0.94      0.94       150
weighted avg       0.94      0.94      0.94       150
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Test Accuracy: 96.67%
150/150 ━━━━━━━━━━━━━━━━━━━━ 9s 46ms/step
              precision    recall  f1-score   support

   Alumunium       0.88      1.00      0.94        30
        Kaca       1.00      1.00      1.00        30
      Kertas       1.00      0.97      0.98        30
       Metal       1.00      0.93      0.97        30
     Plastik       0.97      0.93      0.95        30

    accuracy                           0.97       150
   macro avg       0.97      0.97      0.97       150
weighted avg       0.97      0.97      0.97       150
```

Figure 3. Evaluation Model Performance (epoch 30 and 65)

Figure 3 shows the comparison of model performance at two different training stages: epoch 30 (left) and epoch 65 (right). The test set consisted of 300 images per category. At epoch 30, the model achieved a test accuracy of 94.00% with a weighted F1-score of 0.94, indicating strong but still improvable performance. By epoch 65, the model's test accuracy improved to 96.67%, and the weighted F1-score increased to 0.97, demonstrating better overall classification capability across all waste categories.

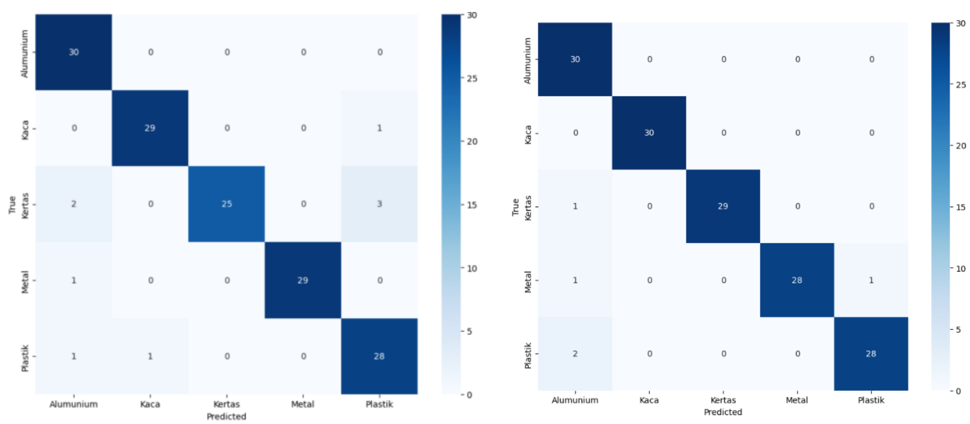

Figure 4. Confusion Matrix

Figure 4 illustrates the confusion matrices for the model at epoch 30 (left) and epoch 65 (right) across the five waste categories: aluminum, glass, paper, metal, and plastic (300 images per category). At epoch 30, some misclassifications occurred, such as three paper images incorrectly classified as plastic, and minor confusion in the glass and plastic categories. Aluminum and metal were classified correctly with minimal error. At epoch 65, all aluminum and glass images were correctly classified, and errors in the paper and plastic categories decreased significantly. This confirms the effectiveness of the CNN-based weighted classification approach in distinguishing between waste types.

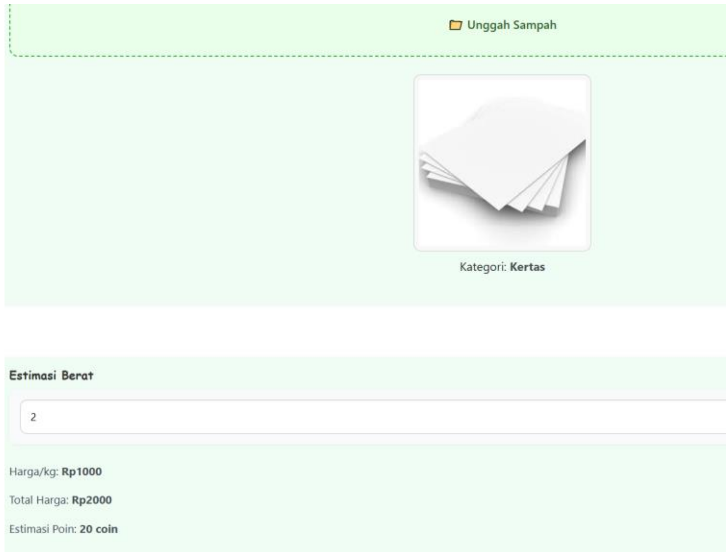

Figure 5. Waste Image Classification and Point Calculation Interface

Figure 5 illustrates the OLSAM web interface, where users can upload a waste image to automatically classify its category. For example, an uploaded image classified as Kertas (Paper) allows users to input the estimated weight (e.g., 2 kg). The system calculates the total price (Rp2,000 in this case) and assigns points according to the waste type and weight (e.g., 20 coins). This gamified mechanism ensures fair reward distribution and encourages participation.

Discussion

The proposed automatic waste detection system using a weighted classification model with MobileNetV2 achieved high accuracy, precision, and weighted F1-score, particularly at epoch 65 (96.67% accuracy, 0.97 weighted F1). This supports previous studies on lightweight CNN architectures and transfer learning for image classification. The point-weighting mechanism provides practical incentives for users to participate in waste sorting. However, the system is currently limited to five categories and may face challenges in diverse real-world environments. Future work should expand the dataset, explore object detection, and develop offline or mobile-based versions to improve accessibility and scalability.

4. Conclusion

This study aimed to develop an automated waste image detection system using a Convolutional Neural Network (CNN) integrated with a weighted point calculation mechanism on the OLSAM platform. The system successfully classified five waste categories plastic, glass, aluminum, metal, and paper with its best performance achieved at epoch 65, yielding an accuracy of 96.67% and a weighted F1-score of 0.97. The classification output is directly linked to the point-exchange feature, allowing users to automatically receive points based on the detected waste type and its weight.

However, the system is limited to five categories, which restricts its ability to handle more diverse waste types in real-world scenarios. For future work, the system can be further developed into a mobile or offline version to improve accessibility and usability in various field conditions.

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