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Enhancing Waste Classification with MobileNetV2: Adding a Plastic Sachets Class for Sustainable Management

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Abstrack

The issue of waste management remains a critical concern due to its adverse impact on the environment. This research enhances a deep learning-based waste classification model by introducing a new class, namely plastic sachets, to broaden the classification scope and increase the model's relevance to waste types commonly found in the community. The dataset used is an extended version of a previous open-source dataset, comprising 2,968 images divided into seven classes. Data preprocessing steps include stratified data splitting, data augmentation to increase image diversity, and pixel normalization. The model adopts the MobileNetV2 architecture through a transfer learning approach, utilizing 2D Global Average Pooling and Dense layers with softmax activation for multi-class classification. Evaluation using precision, recall, and F1-score demonstrated strong performance, with an overall accuracy of 97%. While the model performs well across most classes, further improvement is needed for minority classes such as plastic sachets. This study highlights the promising potential of deep learning in supporting automated waste sorting to promote sustainable waste management practices in Indonesia.

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INTRODUCTION

The issue of waste has become an increasingly important concern as awareness grows regarding its negative impact on the environment. Improperly managed waste can cause soil, water, and air pollution and also pose risks to public health. According to the Ministry of Environment and Forestry's (MoEF) 2023 National Waste Management System (SIPSN), as of July 24, 2024, national waste generation from 290 districts/cities reached 31.9 million tons. Of this total, 64.3% (20.5 million tons) is managed, while 35.7% (11.4 million tons) remains unmanaged (Sakinah & Aberth, 2024). These figures highlight the significant challenges in achieving effective waste management in Indonesia.

The rapid growth of the population, combined with limited waste disposal and processing facilities, has worsened this condition. Household waste is among the largest contributors, and it is often not properly sorted (May Ningrum & Istiqomah, 2020). This situation adds complexity to waste management and increases the burden on existing systems. While community involvement in household waste segregation is crucial, public awareness and participation remain low, and many overlook the role of segregation in improving waste management efficiency (Wijayanti et al., 2023).

The government plays a vital role in raising public awareness and encouraging active participation in waste management. Collaborative policies and programs between the government, communities, and the private sector are essential to achieve more effective results. Providing adequate infrastructure, such as separate waste bins in strategic locations, along with public education on the importance of recycling, is a good initial step. Incentives for individuals actively participating in waste segregation could also motivate greater engagement (Khoiri et al., 2024).

Waste segregation is one of the most effective ways to support sustainable waste management. Although participation rates remain relatively low, consistent efforts could turn waste segregation into a widespread habit. This small step, when implemented on a large scale, can significantly contribute to environmental sustainability and create a greener world for future generations. However, manual waste segregation is time-consuming, labor-intensive, and prone to errors—especially in contexts with limited human resources and high volumes of waste (Prochazka et al., 2024). One promising approach is the application of computer vision through image-based waste classification. By leveraging visual cues from waste items, such models can rapidly and accurately categorize waste types, enabling efficient sorting at various scales. This is , particularly impactful in urban and industrial settings where real-time waste management is critical. Artificial intelligence (AI), especially deep learning, offers innovative solutions for task(Mustaqim et al., 2020). Such models can automatically recognize various waste types, making the sorting process faster and more accurate.

Previous studies have implemented MobileNetV2-based waste classification models capable of recognizing six waste categories: cardboard, glass, metal, paper, plastic, and trash. MobileNetV2 offers high efficiency and strong generalization, making it suitable for image-based waste sorting applications. However, these models are limited in handling more specific waste types, particularly those prevalent in local environments (Ulfah Nur Oktaviana & Yufis Azhar, 2021) (Qin et al., 2021).

This study extends previous work by introducing a new class—plastic sachets—to address thin plastic waste, such as sachet packaging, which is often overlooked during sorting. By adding this class, the model aims to improve classification coverage, enhance sorting accuracy, and support better environmental sustainability. The proposed model has potential applications from household-level waste management in larger-scale operations, contributing to broader sustainability initiatives.

RESEARCH METHODS

This research method consists of a series of stages carried out systematically to classify waste images into seven distinct classes. This stage aims to ensure that the data is ready for use in the model training process. Figure 1 illustrates the overall research method used in this study.

A. Data Collection

In this study, the data used is an open-source dataset developed from previous research. This dataset contains images of garbage grouped into several classes, with the addition of new classes to expand the scope of garbage classification (Huang et al., 2020). The addition of this class aims to enrich the waste classification model with more variations and higher relevance to the types of waste in the community.

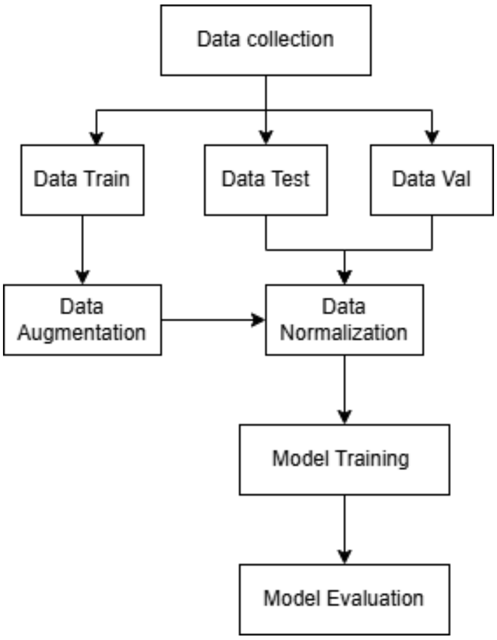

Figure 1. Research methods

B. Data Pre-Processing

Pre-processing is an important stage in data processing that aims to ensure the data is ready to be used in the machine learning model training process. The following are the steps performed in pre-processing.

1. Splitting Data

After data cleaning, the dataset is divided into three subsets, namely training data, validation data, and test data, using the Stratified Random Splitting method. This method ensures that the distribution of images in each category remains proportional within each subset, so that the model gets a balanced representation of all classes (Skula & Kvet, 2024).

2. Data Augmentation

In the dataset, data augmentation is performed using various image transformation techniques. These augmentation techniques aim to expand the diversity of patterns in the dataset without manually adding new data, so that the model can better recognize variations in waste types in real-world conditions.

Some of the augmentation techniques applied include: rotation, to rotate the image at a certain angle to add orientation variation; width/height shift, which shifts the position of the image horizontally or vertically; shear transformation, to geometrically deform the image; zoom, to enlarge or reduce the image area; and horizontal flip, which flips the image horizontally (Shi et al., 2022). By applying these techniques, the dataset becomes more diverse, which in turn increases the model's robustness in detecting and classifying waste types (Heenaye-Mamode Khan et al., 2022).

3. Normalization

Data normalization is the process of transforming data into a specific range, generally between 0 and 1, to improve the efficiency and accuracy of machine learning models. The process involves converting the pixel values in the dataset to a uniform scale, thus preventing the dominance of certain features due to scale differences. In the context of image data, normalization helps to reduce irrelevant pixel intensity variations, so that the model can focus more on important patterns in the data (Mohammed et al., 2022).

C. Transfer Learning

Transfer learning is an approach in machine learning that leverages pre-trained models to accelerate training and improve performance on new tasks. In this study, transfer learning is applied using MobileNetV2, a lightweight and efficient deep learning architecture pre-trained on the ImageNet dataset. The pre-trained weights enable the model to recognize common visual patterns—such as edges, textures, and shapes—before being fine-tuned for waste classification (Putra et al., 2023).

MobileNetV2 was selected as the base architecture due to its balance of accuracy and computational efficiency, making it ideal for enabling deployment on devices with limited resources while maintaining high performance. It employs depthwise separable convolutions, which significantly reduce the number of parameters without sacrificing accuracy (Akay et al., 2021). This design allows the model to be both fast and resource-efficient, which is particularly important for waste classification systems intended for real-time applications or use in developing regions where computing power may be limited.

Following the MobileNetV2 backbone, a 2D Global Average Pooling (GAP) layer is used instead of traditional fully connected layers. GAP compresses each feature map into a single value by averaging all its spatial elements, effectively reducing the number of parameters and thus lowering the risk of overfitting. This is especially beneficial for this study, given the relatively small dataset. Moreover, GAP helps retain the spatial information from the feature maps, ensuring that important visual cues—such as the texture and shape differences between materials like cardboard, glass, and plastic sachets—are preserved before classification (Dogan, 2023).

Finally, a Dense layer with softmax activation is employed to perform multi-class classification across the seven waste categories, including the newly added plastic sachets class. This combination of a pre-trained MobileNetV2 backbone, GAP for dimensionality reduction, and a fine-tuned Dense output layer ensures that the model can achieve high accuracy while remaining computationally efficient.

D. Early Stopping

This technique is used to prevent overfitting of the model during the training process. In this case, training is automatically stopped if there is no significant improvement in the model's performance on the validation data within a few consecutive epochs. This is done to prevent overtraining, which can reduce the model's generalization ability. Early stopping helps save training time and ensures that the model does not learn too much from the training data, which can lead to overfitting and reduced performance on new data (Al-rimy et al., 2023).

E. Model Evaluation

Model performance evaluation is conducted to measure the extent to which the model can classify data accurately and effectively. In this study, the evaluation is done using several metrics, including the classification report, which includes precision, recall, f1-score, and accuracy for each class. In addition, the confusion matrix is used to provide a visual representation of the model predictions and classification errors that occur between the actual and predicted classes (Tan et al., 2021). These metrics provide a deeper understanding of the model's performance in detecting litter across different categories and help in the assessment of whether the model is sufficiently optimized or needs further improvement.

RESULT AND DISCUSSION

A. Data Collection

The dataset used in this study is an extended version of the dataset from previous research. This dataset was obtained from Gary Thung's GitHub repository, which contains images of garbage grouped into six classes. This research adds one new class, plastic sachets, to expand the scope of waste classification and increase relevance to the types of waste that are often encountered in the community. The distribution of data for each class is presented in Table 1.

Table 1. Distribution of Data Counts

Label	Data Count
Cardboard	550
Glass	500
Metal	500
Paper	594
Plastic	505
Plasticsacheet	119
Trash	200

With the addition of the plastic bag class, the dataset contained a total of 2,968 images. The addition of this class aims to enrich the waste classification model with more variations and increase its relevance to the types of waste commonly encountered in the community. Figure 2 shows example images from each class, including the newly added plastic sachets class.

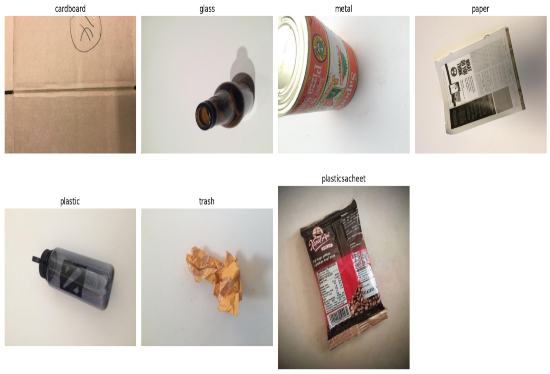

Figure 2. Example of data

B. Data Pre-Processing

1. Splitting Data

Following data cleaning, the dataset was divided into three subsets — training, validation, and test — using the Stratified Random Splitting method. This ensured a proportional class distribution within each subset, allowing for balanced representation of all categories. The dataset was split into 70% training, 15% validation, and 15% testing, as shown in Table 2. Training data was used to fit the model, validation data was used to evaluate performance during training, and test data was used to assess the generalization capability on unseen samples. This division was designed to reduce bias and mitigate issues related to data imbalance (Nguyen et al., 2021).

Table 2. Splitting Data

Label	Train	Test	Val
Cardboard	386	82	82
Glass	350	75	75
Metal	350	75	75
Paper	416	89	89
Plastic	355	75	75
Plasticsacheet	85	17	17
Trash	140	30	30

2. Data Augmentation

To increase the amount and variety of data in the dataset, data augmentation was performed only on the training data. This step aims to expand the diversity of patterns in the dataset without manually adding new data, so that the model can better recognize variations in waste types in real-world conditions. The application of augmentation only on the training data is done to prevent overfitting, where augmentation helps the model learn more diverse patterns and not just memorize the limited training data (Cui et al., 2023). In addition, augmentation provides much-needed additional variation to the training data, so that the model has the ability to recognize waste types in a variety of conditions. With this variation, the generalization ability of the model to new data that has never been seen, such as validation and test data, can be significantly improved (Yoo & Kang, 2023).

Some of the augmentation techniques applied include rotation to rotate the image at a certain angle to add orientation variation, width or height shift that shifts the position of the image horizontally or vertically, shear transformation to geometrically change the shape of the image, zoom to enlarge or reduce the image area, and horizontal flip that flips the image horizontally as seen in Figure 3. These techniques ensure that the training dataset becomes more diverse and realistic, making the model more robust in detecting and classifying waste types (Buslaev et al., 2020).

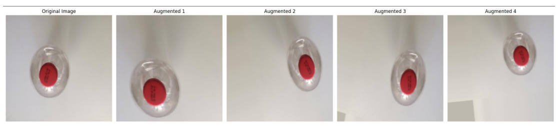

Figure 3. Data augmentation

3. Normalization

The pixel values of the images were normalized from the range [0, 255] to the range [0, 1]. This step aims to speed up the model training process by ensuring the input values are in a consistent range and match the scale used by the learning algorithm in the neural network. In addition, normalization can help prevent , numerical problems, such as gradient exploding or vanishing during training (Usman et al., 2021).

In addition, normalization also helps to speed up model convergence as standardized data is easier to process by activation functions such as ReLU. The combination of normalization with the augmentation process and image size adjustment ensures that the data is ready to be used in the model training process, allowing the model to learn feature representations more optimally.

The image size was standardized to 224 × 224 pixels to match the standard input dimensions of the MobileNetV2 architecture used as the base model. Image size equalization is important to avoid dimensional incompatibility issues and ensure all data has a uniform representation in the network. This process is performed using the image resize technique, which preserves the original aspect ratio to reduce visual distortion. Thus, the model can focus more on the relevant visual features for classification.

C. Model Architecture

The proposed model adopts MobileNetV2 as its base architecture, pre-trained on the ImageNet dataset for feature extraction.

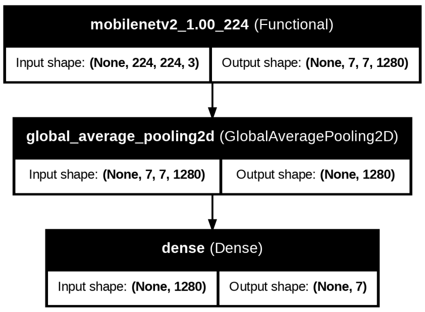

Figure 4. Model architecture

Figure 4 illustrates the model used for feature extraction, yielding an output with dimensions (None, 7, 7, 1280), which represents the features of the processed image. To reduce the dimension and number of parameters, a 2D Global Average Pooling layer is added, which converts the output into a feature vector with dimensions (None, 1280). Next, a Dense layer with 7 neurons is added for litter classification, with softmax activation to generate class probabilities. The model has a total of 2,266,951 parameters, of which most parameters (2,232,839) are trainable, while the remaining 34,112 parameters are not trainable. Hyperparameter settings, such as a low learning rate for the Adam optimizer, were used to ensure stable convergence and optimize model performance on the waste dataset used.

D. Model Training

The model was trained for a maximum of 80 epochs with an augmented data generator. A custom callback was used to halt training early if the training accuracy reached 100%, ensuring efficiency and preventing overfitting.

E. Model Evaluation

The evaluation results indicate that the model built with the MobileNetV2 architecture as the base model performs satisfactorily in classifying litter images into seven target classes. After training, with a total of 2,266,951 parameters, the model achieved high accuracy along with other evaluation metrics that demonstrate good generalization to the test data. The integration of the 2D Global Average Pooling layer proved effective in reducing feature dimensions without losing critical information, which was subsequently passed to the Dense layer with softmax activation for class prediction. The use of a low learning rate with the Adam optimizer contributed to stable convergence, minimized overfitting risk, and allowed the model to optimally capture patterns in the waste dataset.

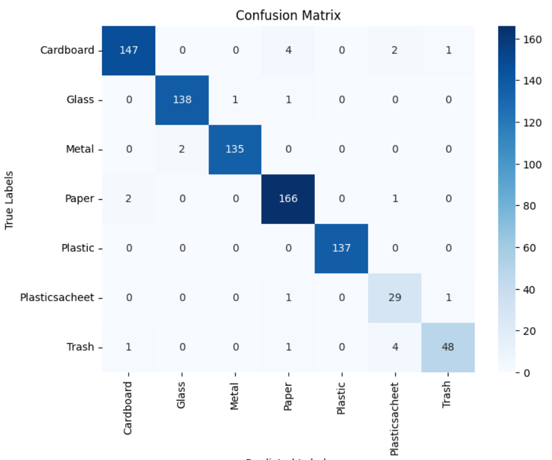

Figure 5. Confusion matrix

The confusion matrix in Figure 5 illustrates the distribution of predictions for each class. The model exhibits high accuracy for most classes such as cardboard, glass, metal, paper, and plastic, with correct predictions dominating the diagonal of the matrix. However, notable misclassifications occur in the minority classes, particularly trash and plastic sachet. For the trash class, several samples were incorrectly classified into other categories such as cardboard or plastic, which suggests that the visual features of trash items may overlap considerably with those categories, especially when objects are irregularly shaped or partially occluded.

	precision	recall	f1-score	support
cardboard	0.98	0.95	0.97	154
glass	0.99	0.99	0.99	140
metal	0.99	0.99	0.99	137
paper	0.96	0.98	0.97	169
plastic	1.00	1.00	1.00	137
trash	0.81	0.94	0.87	31
plasticsacheet	0.96	0.89	0.92	54
accuracy			0.97	822
macro avg	0.95	0.96	0.96	822
weighted avg	0.97	0.97	0.97	822

Figure 6. Classification report

As shown in Figure 6, the majority classes, such as plastic and glass, achieve f1-scores close to 1.00, indicating the model's strong performance for these categories. In contrast, the trash class shows a precision of 0.81 despite a high recall of 0.94. This discrepancy means that while the model is able to correctly detect most trash images (high recall), it also produces a relatively large number of false positives—classifying items from other categories as trash. This may be due to the trash class having highly heterogeneous visual features, making it harder for the model to distinguish it from other waste types. Moreover, its smaller sample size compared to the majority classes limits the model's ability to learn distinctive patterns.

With an overall accuracy of 97% and a weighted average precision, recall, and f1-score near 0.97, the model demonstrates a strong capability for litter classification tasks. Nonetheless, improving minority class performance remains a challenge. Future work could focus on addressing class imbalance through techniques such as oversampling, synthetic data generation (e.g., using GANs), or implementing class-weighted loss functions. Additionally, incorporating more diverse and high-quality images for minority classes could help the model better distinguish visually ambiguous cases, thereby reducing false positives and improving precision for classes like trash.

CONCLUSION

This research has successfully developed a waste classification system by adding a new category, namely plastic bags, to expand the scope of classification and increase relevance to the types of waste that are often encountered in the community. The use of MobileNetV2 architecture equipped with a 2D Global Average Pooling layer and a Dense layer with softmax activation proved effective in producing accurate feature representations for all classes, including the new class of plastic bags. With good model performance, this system can be the first step in supporting more effective waste management and supporting technology-based innovation in waste management in Indonesia.

However, this study has certain limitations, such as the relatively small dataset size for the newly added plastic bag category and the absence of testing in real-world scenarios with varied lighting and background conditions. Future research could address these limitations by expanding the dataset, applying data augmentation for more diverse conditions, and exploring lightweight model optimization for deployment on mobile devices or IoT-based waste monitoring systems.

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