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Implementation of CNN Algorithm for Classification of Organic and Inorganic Waste Images

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Abstract

The increasing waste problem necessitates efficient solutions, one of which is automatic classification based on artificial intelligence. This study develops a Convolutional Neural Network (CNN) model for classifying organic and inorganic waste images using a transfer learning approach with the MobileNetV2 architecture. The model was trained in two stages, namely feature extraction and fine-tuning, using a dataset of 25,077 images from a public Kaggle repository. The results show that the model after fine-tuning achieved an accuracy of 92.28%, with a precision of 89.6% for the organic category and 96.4% for inorganic. High recall and F1-score values were also achieved, demonstrating that transfer learning with fine-tuning effectively improves waste image classification accuracy and has potential for implementation in automatic waste sorting systems.

Keywords: *Transfer learning, image classification, organic waste, inorganic waste, CNN, MobileNetV2, fine-tuning*

1. Introduction

Waste management is a global issue that continues to grow, including in Indonesia, in line with population growth and consumption patterns. Inefficient waste management can cause serious impacts such as environmental pollution, health hazards, ecosystem damage, and economic burden [1]. One crucial step in waste management is the separation of organic and inorganic waste. Organic waste, such as food scraps and other natural materials, decomposes naturally and can potentially be processed into compost or alternative energy sources. In contrast, inorganic waste such as plastics, metals, and glass requires more complex recycling processes to prevent environmental contamination [2]. However, manual methods are generally inefficient and prone to errors, as they require substantial time, labor, and accuracy, thus necessitating a more accurate and effective automatic solution.

The advancement of artificial intelligence, particularly Computer Vision, offers opportunities to automate image identification processes. Convolutional Neural Networks (CNNs) are among the most widely used approaches due to their ability to automatically extract complex features without human intervention [3]. Nevertheless, training CNNs from scratch requires large datasets and intensive computational resources, making it impractical for many cases.

To address these limitations, this study employs a transfer learning approach using the MobileNetV2 architecture. This model is chosen for its lightweight and efficient design, suitable for devices with limited computational power [4]. The study uses a dataset of 25,077 waste images categorized as organic and inorganic. The contributions of this study lie in applying both feature extraction and fine-tuning training strategies and performing a comparative analysis of their performance. The findings are expected to support the development of more accurate, efficient, and practical waste classification systems for sustainable environmental management.

2. Literature Review

2.1. Waste Image Classification

Classification is a widely used data mining technique applied across various domains [5]. Image classification is the task of assigning labels to images based on predefined categories [6]. In environmental management, waste image classification is essential as it can facilitate faster and more accurate separation of organic and inorganic waste compared to manual methods. This image-based approach is relevant given the increasing availability of visual data and the growing need for automated solutions to support sustainable waste management systems.

2.2. Convolutional Neural Network (CNN)

CNNs are neural network architectures designed to process grid-like data such as images, aiming to extract high-level features through convolution operations [7]. CNNs are effective in visual pattern recognition as they can learn spatial representations from images without manual feature extraction. Unlike Multi-Layer Perceptrons, CNN neurons are arranged in two dimensions, and their weights are four-dimensional convolutional kernels, making them suitable for images or other structured 2D data [8].

2.3. MobileNetV2

MobileNetV2 is a CNN architecture developed by Mark Sandler et al. in 2018, specifically designed for devices with limited computational resources such as smartphones and embedded systems [9]. MobileNetV2 employs two main operations: Depthwise Convolution (DW) for residual blocks and Pointwise Convolution (PW) for downsampling [10].

2.4. TensorFlow and Keras Frameworks

TensorFlow is an open-source library from Google that supports large-scale numerical computation, particularly for machine learning and deep learning. Keras is a Python-based application programming interface (API) for building deep learning models [11].

2.5. Classification Model Evaluation

Model evaluation aims to measure system performance in image classification. Common metrics include:
a) Accuracy : the percentage of correct predictions over total data.
b) Precision : the accuracy of positive predictions.
c) Recall : the model's ability to identify all positive data.
d) F1-Score : the harmonic mean of precision and recall.
e) Confusion Matrix : a table comparing actual labels with predictions.

These metrics provide a comprehensive view of model quality, considering not only accuracy but also class-wise performance balance.

3. Analysis and Design

3.1. System Analysis

The main problem in waste management is the manual separation process. This method requires human labor, takes longer, and is prone to errors due to fatigue or inaccuracy. Proper waste separation, especially between organic and inorganic categories, is critical for supporting recycling or further processing.

Thus, an automatic, fast, and accurate classification system is needed. Such a system can make the sorting process more efficient and reduce human workload. A suitable approach is CNNs, which have proven effective in extracting visual patterns from images, making them appropriate for classifying waste images into organic and inorganic categories.

3.2. System Design

To implement a CNN-based waste image classification system, a structured design is required to ensure each processing stage meets its objectives, from dataset preparation to building the final predictive model.

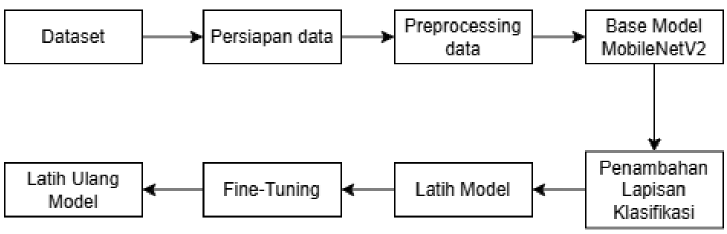

Fig. 1 : System design workflow

The main stages of the waste image classification system are as follows:
1. Dataset: Collection of waste images in two categories: organic and inorganic.
2. Data Preparation: Splitting the dataset into training, validation, and test subsets.
3. Data Preprocessing: Normalization, resizing, and augmentation to improve data quality.
4. Base Model MobileNetV2: Using MobileNetV2 pretrained on ImageNet as a feature extractor.
5. Classification Layer: Adding fully connected and sigmoid layers for binary classification.
6. Model Training: Training the classification layers with the base model frozen.
7. Fine-Tuning: Unfreezing some MobileNetV2 layers for further training.
8. Retraining Model: Final training to achieve optimal performance.

3.3. Dataset

The dataset used was obtained from a public Kaggle repository, containing 25,077 images divided into two main classes: organic and inorganic. All images are in colored JPEG format, allowing the model to learn rich visual features for each waste type.

Table 1 : Data distribution

Subset	Organic	Inorganic	Total
Train	12.565	9.999	22.564
Validation	700	556	1.256
Test	701	556	1.257

This distribution ensures the model can learn effectively from training data, tune hyperparameters using validation data, and finally be evaluated on unseen test data.

3.4. Model Architecture

The CNN architecture used is MobileNetV2, designed with depthwise separable convolutions to reduce parameters without significantly reducing accuracy.

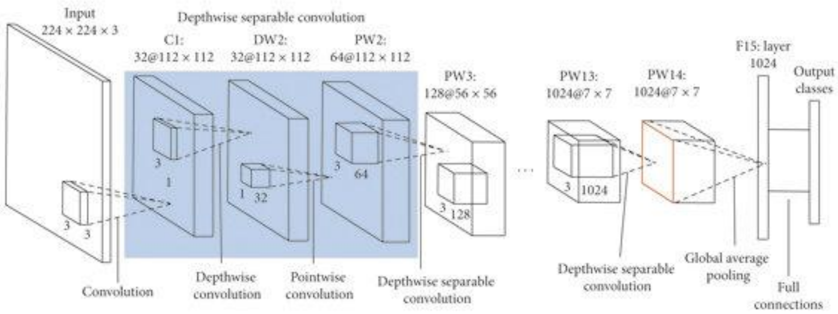

Fig. 2 : MobileNetV2 Architecture

The study uses MobileNetV2 in two stages: feature extraction, where pretrained ImageNet weights are frozen, retraining only the classification layers; and fine-tuning, where some MobileNetV2 layers are unfrozen to be trained alongside the classification layers. This approach allows the model to adapt its feature representation to the characteristics of organic and inorganic waste more effectively.

4. Discussion and Implementation

4.1. Experimental Results

Experiments were conducted in two main stages: feature extraction and fine-tuning using MobileNetV2 pretrained on ImageNet.

During feature extraction, all MobileNetV2 weights were frozen, and only the final classification layer was retrained. The model achieved a validation accuracy of 91.6% and a test accuracy of 91.3%. The confusion matrix showed a high recall for the organic class (96.7%) but relatively lower precision (88.7%) due to some inorganic images being misclassified. Overall, MobileNetV2's pretrained features were sufficient to distinguish organic and inorganic images, even without full adjustment.

The fine-tuning stage, where some MobileNetV2 layers were unfrozen for weight updates, achieved a validation accuracy of 90.8% and a test accuracy of 92.3%. Evaluation showed increased recall for the organic class (97.4%) and precision for the inorganic class (96.4%). F1-scores for both classes also improved, indicating better balance between precision and recall.

Training accuracy and loss curves showed stable trends. Feature extraction training accuracy increased rapidly in early epochs and then plateaued, while loss decreased consistently. Fine-tuning showed slightly slower training accuracy improvement due to layer weight updates, but validation accuracy increased and loss decreased, indicating that the model learned more relevant features without overfitting (Figures IV.1 and IV.2).

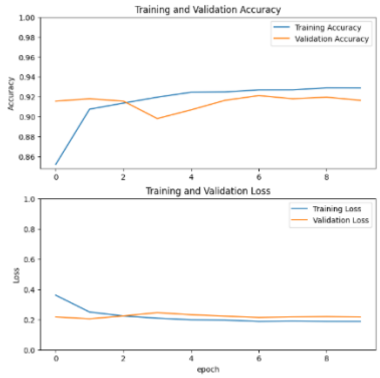

Fig. 3 : Feature extraction accuracy and loss graph

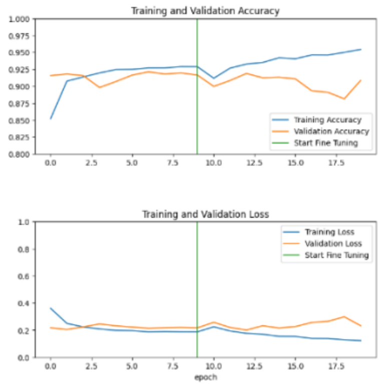

Fig. 4 : Fine-tuning accuracy and loss graph

Comparison of feature extraction and fine-tuning results is shown in the table below. Fine-tuning generally provides better performance, particularly in improving organic recall and inorganic precision.

Table 2 : Feature extraction vs. fine-tuning evaluation

Metric	Feature Extraction	Fine-Tuning
Accuracy	91.3%	92.3%
Precision (Organic)	88.7%	89.6%
Recall (Organic)	96.7%	97.4%
F1-Score (Organic)	92.5%	93.3%
Precision (Inorganic)	95.3%	96.4%
Recall (Inorganic)	84.5%	85.8%
F1-Score (Inorganic)	89.6%	90.8%

4.2. Discussion

The results indicate that the transfer learning strategy using MobileNetV2 is effective for classifying organic and inorganic waste images. Feature extraction already yields high performance with lower computational cost but has limitations, particularly in distinguishing organic images with textures or colors similar to inorganic.

Fine-tuning improves performance in terms of accuracy and other evaluation metrics, confirming that adjusting MobileNetV2's final layer weights enables the model to learn features more specific to the dataset. Training graphs also show stability without signs of overfitting, suggesting good generalization to new data.

In conclusion, transfer learning with MobileNetV2 and fine-tuning is more optimal than pure feature extraction. Although the improvement is relatively small, it is significant for practical applications as it produces a more accurate, reliable model ready for image-based waste classification systems.

5. Conclusions and Recommendations

5.1. Conclusion

This study successfully developed a CNN-based model for classifying organic and inorganic waste images using MobileNetV2 with a two-stage transfer learning strategy: feature extraction and fine-tuning. Experiments show that feature extraction performs well, but fine-tuning achieves optimal performance with 92.3% test accuracy and high precision, recall, and F1-score for both classes. Fine-tuning enhances the model's ability to adapt to dataset characteristics and strengthens generalization.

5.2. Recommendations

For future research, the following directions are suggested:
1. Use more diverse and balanced datasets to improve model robustness and reduce potential classification bias.
2. Explore alternative architectures such as EfficientNet, ResNet, or other lightweight models for performance and efficiency comparison.
3. Deploy the model in real-world applications, e.g., camera-based waste sorting systems, to validate performance under practical conditions.
4. Integrate classification with object detection methods to enable multi-object recognition and classification in a single image.

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