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Automatic Lightweight CNN Waste Identification for Green Campus Program Support

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Abstract

Effective waste management is a key indicator of success for Green Campus Programs and a major factor in the UI GreenMetric World University Rankings. However, many Indonesian universities still face difficulties due to low accuracy in manual waste sorting, particularly for inorganic and hazardous (B3) waste. This study develops a lightweight, high-accuracy automatic waste classification system using the MobileNetV2 Convolutional Neural Network (CNN) architecture. The model was trained via transfer learning on the Kaggle "Trash Classification Dataset" (Sathish, 2023) containing 19,762 images from 10 waste classes: Metal, Glass, Biological, Paper, Plastic, Cardboard, Battery, Shoes, Clothes, and Trash. To align with operational needs of the Green Campus Program, these 10 classes were mapped into three functional categories: Organic, Recyclable, and Inorganic/B3. Experimental results show that MobileNetV2 achieved 93.2% accuracy with efficient inference time (~4.8 ms per image) on a CPU. The prototype, built using Python Streamlit, outputs both predicted waste type and confidence percentage, making it practical for real-time campus waste sorting. The proposed model provides an intelligent, energy-efficient, and transparent solution to support sustainable waste management, addressing key operational challenges in inorganic (WS4) and hazardous (B3) waste (WS5) handling.

Keywords: *Lightweight CNN; MobileNetV2; Waste Classification; Green Campus; Artificial Intelligence.*

I. INTRODUCTION

1.1 Background and Urgency of Campus Waste Management

Rapid urbanization and population growth have significantly increased global waste generation, posing major environmental and public health challenges. Inadequate waste management, particularly through traditional disposal methods such as landfilling and incineration, leads to severe environmental pollution, soil degradation, and water contamination while hindering valuable resource recycling efforts.

Higher education institutions in Indonesia play a critical role in promoting sustainability initiatives through the Green Campus Program. Program success is often measured against international standards, including the UI GreenMetric World University Rankings. The Waste (WS) category is especially significant, covering six sub-indicators such as 3R implementation (Reduce, Reuse, Recycle), reduction of paper and plastic use, organic and inorganic waste processing, and hazardous (B3) waste management.

Despite positive initiatives in areas such as paper and plastic reduction (WS2), operational weaknesses remain in inorganic waste processing (WS4) and hazardous waste management (WS5). Contributing factors include limited sorting facilities, inconsistent operational procedures across campus units, and low community participation. Traditional manual sorting is slow, error-prone, and insufficient for modern campus needs. Intelligent technological intervention is therefore necessary.

1.2 State-of-the-Art and Research Gap

Artificial Intelligence (AI) and computer vision, particularly Convolutional Neural Networks (CNNs), offer promising solutions for automatic waste classification. High-accuracy models, such as DenseNet or ResNet, often require substantial computational resources, limiting real-time deployment on resource-constrained devices.

The research gap lies in balancing high classification accuracy with low computational complexity. For practical Green Campus support, the system must be lightweight and fast, enabling deployment on cost-effective and energy-efficient devices. MobileNetV2 was chosen as a lightweight architecture capable of delivering high performance with minimal computational demand, aligning with Green Campus sustainability values. The study also addresses operational weaknesses (WS4 and WS5) by mapping 10 raw waste classes into 3 actionable categories, ensuring classification results have immediate operational relevance.

1.3 Research Objectives

The objectives of this study are:

- To develop and evaluate the MobileNetV2 CNN using transfer learning for automatic waste image classification.

- To implement a strategic class-mapping method, reducing 10 dataset classes into three main categories (Organic, Inorganic/Residual, Recyclable) with a target classification accuracy ≥92%.
- To deploy the trained MobileNetV2 model into a lightweight Python prototype displaying predicted waste types and confidence levels, facilitating rapid integration into Green Campus operations.

II. RESEARCH METHODOLOGY

The objectives of this study are:

1. To develop a MobileNetV2 CNN model for automatic waste image classification using transfer learning.
2. To design a class mapping scheme that groups 10 Kaggle waste classes into 3 main categories: Organic, Recyclable, and Inorganic/B3.
3. To implement the trained model into a Python-based Streamlit prototype capable of real-time classification with confidence scoring.
4.

2.1 Data Acquisition and Preprocessing

Data were sourced from the publicly available "Trash Classification Dataset" on Kaggle [Sathish, 2023], comprising 19,762 high-quality waste images across 10 classes: Clothes (5327), Glass (3061), Plastic (1984), Shoes (1977), Cardboard (1825), Paper (1680), Metal (1020), Biological (997), Trash (947), and Battery (944).

Images were preprocessed by resizing to 224×224 pixels and normalized for MobileNetV2 input. Data augmentation techniques, including random rotations, zoom, width/height shifts, and horizontal flips, were applied to improve model generalization and mitigate class imbalance. The dataset was split into training, validation, and test sets.

2.2 Waste Class Mapping (10-to-3 Categories)

To align with Green Campus operational needs, the original 10 classes were mapped into three functional categories:

- Organic: Biodegradable waste suitable for composting.
- Biological (997 images)
- Recyclable: High resource recovery value materials.
- Plastic (1984), Paper (1680), Metal (1020), Glass (3061), Cardboard (1825)
- Inorganic/Residual/Hazardous (B3): Waste requiring special handling.
- Battery (944), Clothes (5327), Shoes (1977), Trash (947)

This mapping aligns with 3R/7R waste management principles and addresses operational challenges in inorganic and hazardous waste processing.

2.3 MobileNetV2 Architecture and Transfer Learning

2.3.1 MobileNetV2: Lightweight Architecture

MobileNetV2 offers high efficiency for mobile and embedded devices through:

- Depth wise Separable Convolutions: Reduces computation and parameters by separating spatial and channel-wise processing.
- Inverted Residual Blocks and Linear Bottlenecks: Expands features, applies depthwise convolutions, and projects back to a lower-dimensional space while preserving essential information and gradient flow.

2.3.2 Transfer Learning Implementation

The model was initialized with ImageNet-pretrained weights. Base layers were initially frozen, and a new classification head (Global Average Pooling, Dropout, and a Fully Connected layer with three softmax outputs) was added. The Adam optimizer with learning rate decay was used for stable convergence.

III. RESULTS AND DISCUSSION

3.1 Classification Performance

After training for 25 epochs with early stopping, the model achieved:

Table 1. Test acuration

Metric	Value
Test Accuracy	**93.2%**
Validation Accuracy	92.7%
Loss (test)	0.174

Table 2. Per-category performance

Waste Category	Precision (%)	Recall (%)	F1-Score (%)
Organic	93.5	93.0	93.2
Recyclable	94.1	93.7	93.9
Inorganic/B3	92.0	91.5	91.7

3.2 Computational Efficiency

Table 3. Parameters

Model	Parameters (Million)	GFLOPs	Device Compatibility
VGG16	138.3	15.4	GPU only
ResNet50	25.6	3.8	Moderate
MobileNet V2 (ours)	**3.47**	**0.30**	✅ Ideal for CPU/Edge

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The model's low complexity enables integration into low-power devices, such as the Raspberry Pi or Jetson Nano, aligning with sustainability goals.

3.3 Prototype Implementation

A Streamlit-based web prototype was developed to demonstrate the classification system. Users can upload a waste image, and the interface displays:

1. Predicted category (Organic, Recyclable, or Inorganic/B3)
2. Confidence percentage

This promotes transparency, environmental awareness, and facilitates practical implementation in campus waste stations.

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IV. CONCLUSION

- Optimal Model Performance: MobileNetV2 with transfer learning on mapped 10-to-3 waste classes achieved 93.5% accuracy.
- High Computational Efficiency: Lightweight architecture ensures real-time classification (<5 ms/image) on CPU, supporting sustainable energy use.
- Institutional Impact: Accurate identification of Inorganic/B3 waste addresses operational weaknesses (WS4, WS5) in Green Campus management.
- Limitations: Further validation is required using campus-specific images to ensure generalization.

V. RECOMMENDATIONS

Domain-Specific Validation: Expand dataset with campus-specific waste images under varied conditions to improve generalization.

Edge Deployment and Physical Automation: Implement on energy-efficient edge devices (Raspberry Pi, Jetson Nano) and integrate with robotic sorting mechanisms.

Advanced Model Optimization: Explore compression techniques (knowledge distillation) or efficient attention mechanisms to balance accuracy and computational simplicity.

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