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Analysis of Machine Learning Recognition Method for Garbage Classification

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Abstract. With the deepening of sustainable development strategies and the growing emphasis on green living, the demand for intelligent and automated waste management has significantly increased. Efficient waste classification systems not only help reduce environmental pollution but also play a pivotal role in promoting smart urban governance. The integration of machine learning and computer vision has emerged as a promising approach to address waste classification challenges, enabling real-time recognition and categorization based on visual and structural data. This study explores two complementary technical approaches: image classification using convolutional neural networks (CNNs) and structured data analysis through statistical methods. It utilizes the publicly available "TrashNet" dataset from Kaggle (approximately 2,500 labeled images across six waste categories) and the "Garbage Classification Dataset," which includes tabular information such as waste type, weight, and material attributes. The goal is to systematically evaluate various models—such as SVM, Random Forest, MobileNetV2, and EfficientNet—based on accuracy, inference time, model size, and interpretability. The findings provide practical insights into selecting suitable algorithms for embedded deployment and propose optimization suggestions that enhance both performance and efficiency in real-world applications of intelligent waste sorting systems.

Keywords: Waste Classification, Machine Learning, Intelligent Recognition

1. Introduction

With the acceleration of urbanization, household waste has grown explosively. Traditional waste disposal methods mainly rely on manual sorting and experience-based judgment, which are inefficient, costly, and error-prone—no longer meeting the development needs of modern urban management. Against this backdrop, the introduction of intelligent waste classification systems has become an important means to improve processing efficiency and precision, and the integration of machine learning with computer vision provides a promising solution.

Extensive literature has shown that automatic waste classification systems based on deep learning and traditional machine learning methods have achieved significant results in multi-category classification tasks. Wang et al. developed an automatic classification device that integrates multi-feature fusion, using the YOLOv5 network combined with fiber optic sensors and transfer learning. The YOLOv5-based detection model includes a Backbone, Neck, Head, and a serial communication

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module. The model was trained and tested on a self-constructed waste dataset, achieving an average accuracy of 0.99 [1]. This end-to-end architecture not only improves classification efficiency but also enables hardware deployment.

Another study implemented a smart waste bin based on STM32 for voice-controlled classification. The system uses the STM32F103C8T6 microcontroller as the core controller, coordinating various modules to achieve voice recognition classification, overflow detection, and alert functionalities. The system features high stability, low cost, low power consumption, and user-friendly operation, enabling intelligent waste sorting through voice commands [2].

Additionally, Howard proposed MobileNetV3 by using platform-aware neural architecture search to balance latency and accuracy. MobileNetV3 demonstrated state-of-the-art performance on mobile devices, making it a strong candidate for lightweight garbage classification tasks [3].

Therefore, this study adopts a data-driven approach to compare traditional machine learning algorithms (SVM, Random Forest, KNN) and lightweight convolutional neural networks (e.g., MobileNetV2, EfficientNet) using publicly available waste image datasets.

2. Method

2.1. Dataset description

2.1.1. TrashNet

This study utilizes the publicly available TrashNet dataset from Kaggle as the core image dataset. TrashNet contains images of six main waste categories. Each image features a single type of waste item in a relatively controlled environment, with a clear background and foreground, facilitating key feature learning by models. Figure 1 shows example images of each waste category in TrashNet.

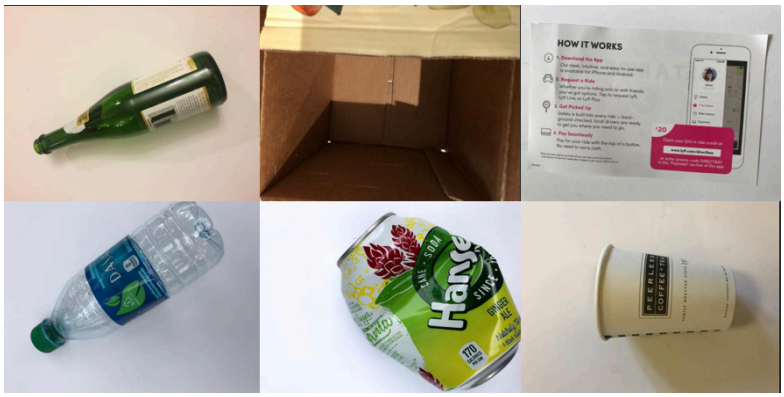


Figure 1. Sample images from TrashNet for each waste category [4]

The TrashNet dataset consists of approximately 2,500 high-quality labelled images. All images were manually screened and annotated to ensure accurate category labels. The dataset was pre-divided into training, validation, and test sets at a typical rato of 70%:15%:15%. Figure 2 shows a bar chart of the number of images for each category in TrashNet

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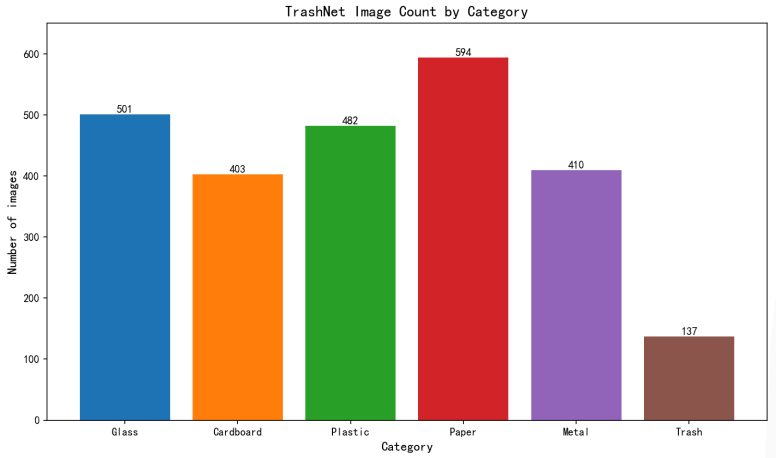


Figure 2. Bar chart showing the number of images per category in TrashNet (picture credit: original)

2.1.2. Garbage classification dataset

In parallel, the "Garbage Classification Dataset" from Kaggle is used, which contains approximately 600 records [5]. Each entry includes fields such as waste category, weight, and material code. The dataset is clean and well-labeled, making it suitable for statistical analysis using SPSSAU (e.g., ANOVA and chi-square tests).

2.2. Indicator selection

2.2.1. Classification accuracy metrics

Accuracy: The proportion of correctly classified samples over all samples, reflecting the overall performance.

Average Inference Time (ms): The time taken for the model to make a prediction on a single image.

Number of Parameters: Indicates the model's complexity and its memory requirements for deployment.

2.2.2. Efficiency and resource consumption metrics

Average Inference Time per Image: Critical for assessing real-time performance, especially in edge computing environments.

Model Size (MB): The storage space required for the trained model, which is crucial for embedded device deployment.

2.3. Method introduction

2.3.1. Traditional machine learning methods

Features such as color histograms, texture (GLCM, LBP), and shape (HOG) were extracted from the images. Then, SVM, Random Forest (RF), and KNN algorithms were used for classification. These methods are fast and easy to deploy but are heavily dependent on the quality of feature design,

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making them more suitable for low-computation environments. Figure 3 shows the workflow of traditional machine learning methods.



Figure 3. Workflow diagram of traditional machine learning approach (picture credit: original)

2.3.2. Subsection titles

Huawei released an open-source waste image dataset in 2019. As shown in Table 1, this study uses MobileNetV2 trained on this dataset and achieves up to 94% accuracy, which is sufficient for urban waste classification needs [6].

Table 1. MobileNetV2 model architecture

Input	Operation	t	c	n	s
224×3	Conv2d	--	32	1	2
112×32	Bottleneck	1	16	1	1
112×16	Bottleneck	6	24	2	2
56×24	Bottleneck	6	32	3	2
28×32	Bottleneck	6	64	4	2
14×64	Bottleneck	6	96	3	1
14×96	Bottleneck	6	160	3	2
7×160	Bottleneck	6	320	1	1
7×320	Conv2d 1×1	--	1280	1	1
7×1280	Avgpool 1×1	--	--	1	--
1×1×1280	Conv2d 1×1	--	K	--	--

To achieve better accuracy and efficiency trade-offs, Tan and Le introduced EfficientNet, a family of convolutional networks that uniformly scale depth, width, and resolution using a compound coefficient. Compared to traditional models that scale only one dimension, EfficientNet achieved state-of-the-art results on ImageNet while using significantly fewer parameters and FLOPs [7].

2.3.3. Sub subsection titles

Prior research has shown that residents' waste-sorting behavior is influenced by physical, socio-cultural, and environmental factors. These can be analyzed through statistical methods like ANOVA and chi-square tests [8].

Using SPSSAU, the following analyses were conducted: Descriptive statistics; One-way ANOVA to compare weight across categories; Chi-square tests to assess the association between material code and waste category

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3. Results and discussion

3.1. Comparison of results

Table 2 shows the classification effect of machine learning methods

Figure 4 shows the classification accuracy and error rate. The models have obvious differences in accuracy, inference speed, and model parameter count.

Table 2. Classification performance of each method

Method	Accuracy (%)	Inference Time (ms/image)	Parameters	Model Size (MB)
SVM	82.5	1.5	-	-
RF	85.0	2.2	-	-
KNN	80.0	4.0	-	-
MobileNetV2	93.0	35	2.3M	14MB
EfficientNet-B0	94.2	42	3.8M	16MB

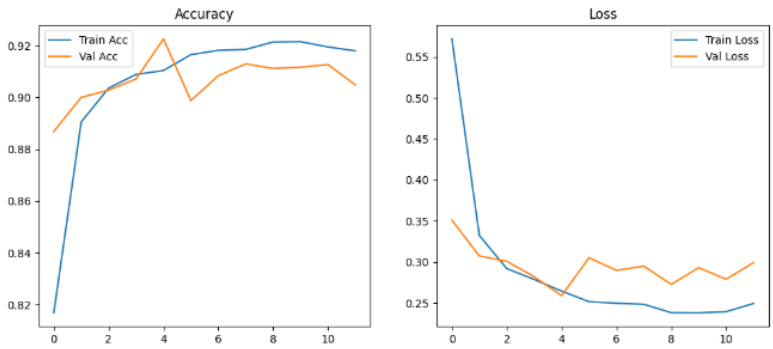


Figure 4. Accuracy and loss comparison across models [4]

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3.2. Challenges of analysis of classification

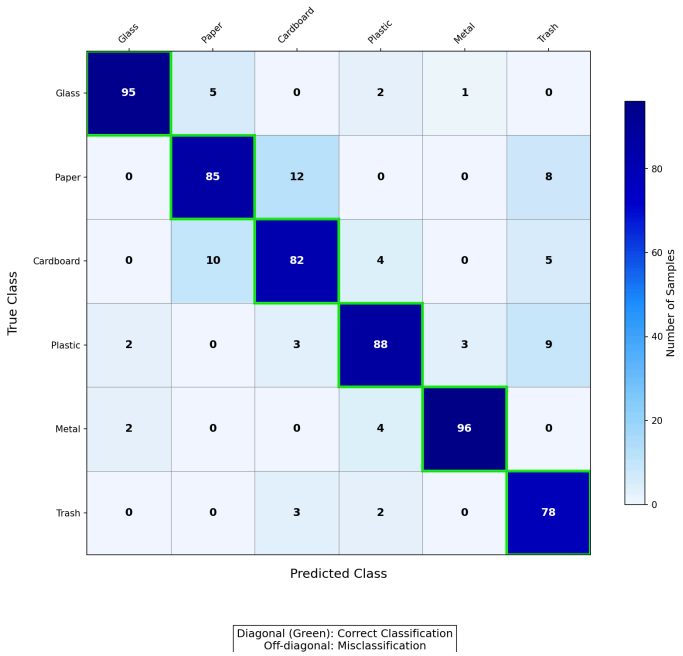


Figure 5. Confusion matrix (picture credit: original)

As shown in Figure 5, the confusion matrix indicates that metal and glass are easier to classify, while paper and cardboard are often confused due to visual similarity. The “trash” category has fewer samples and more ambiguous boundaries, resulting in the lowest accuracy and highest misclassification rate.

This suggests the need for incorporating more discriminative features or using data augmentation techniques to balance category distribution.

3.3. Statistical analysis

Table 3. Descriptive statistics of waste categories

Name	Mean ± SD	Variance	Sum	Median	standard error	Mean 95% CI (LL)	Mean 95% CI (UL)
Category	6.500±3.606	13.000	3.250	6.5000	9.750	1.041	4.460
Weight_grams	206.667±284.264	80806.061	42.50	90.000	237.500	82.060	45.83
Material_Code	6.500±3.606	13.000	3.250	6.500	9.750	1.041	4.460

ANOVA results ($p < 0.05$) show significant differences in weight across waste categories. Chi-square test results ($p < 0.01$) indicate a strong association between material codes and waste categories.

Table 4. ANOVA results visualization

Weight_grams (Mean ± variance)										
10(n=1)	30(n=1)	40(n=1)	50(n=1)	70(n=1)	80(n=1)	100(n=1)	150(n=1)	200(n=1)	250(n=1)	500(n=1)	1000(n=1)
1±null	8±null	5±null	9±null	11±null	7±null	4±null	3±null	6±null	2±null	12±null	10±null

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As shown in Table 3 and Table 4, these findings confirm that structured data (e.g., weight and material type) can serve as valuable supplementary inputs for image-based models to improve interpretability and performance.

3.4. Discussion

Deep models are suitable for embedded deployment; although traditional methods have small models and fast speed, their accuracy is generally low. The application of intelligent waste classification systems has extended beyond static bins. For example, a study developed a waste-sorting vehicle equipped with a vision system combining OpenCV and CNNs, capable of real-time recognition and sorting [9]. Another study designed a floating waste-cleaning device using visual recognition and 3D modelling to assist in environmental cleanup, validating its effectiveness in real-world deployment [10].

4. Conclusions

This study comprehensively evaluated the performance of traditional machine learning methods and lightweight CNNs for waste classification using the TrashNet image dataset and structured tabular data. MobileNetV2 and EfficientNet models demonstrated excellent performance for edge computing scenarios. Additionally, statistical analysis of tabular data confirmed significant correlations between waste category, weight, and material, providing insights for future smart classification system designs.

MobileNetV2 and EfficientNet offer a balance between accuracy and efficiency, making them ideal for embedded deployment. Traditional machine learning methods, while simpler and less resource-intensive, are suitable for low-power scenarios. The integration of structured data can further enhance model performance and interpretability.

References

[1] Wang, J., Mao, Y., Guo, L., et al. (2024). Design of a Multi-type Garbage Automatic Classification Machine Based on Machine Vision. *Machinery*, (08).
[2] Jia, Y., Zhu, X., et al. (2025). Design and Implementation of a Voice-Controlled Smart Waste Bin Based on STM32. *Electronic Production*, (03).
[3] Howard, A., Sandler, M., Chu, G., et al. (2019). Searching for MobileNetV3. arXiv preprint arXiv: 1905.02244.
[4] TrashNet. (2025, July). Retrieved from [https: //ww w.kaggle.com/datasets/feyzazkefe/trashnet]
[5] Garbage Classification Dataset. (2025, July). Retrieved from [https: //www.kaggle.com/datasets/arshnoor738 9/garbage-classification-dataset]
[6] Zhang, M., Sun, X. (2024). Garbage Image Classification Algorithm Based on Transfer Learning Using MobileNet V2 Model. *Journal of Hubei Polytechnic Institute*, 2024(10).
[7] Tan, M., & Le, Q. V. (2019). EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks. Proceedings of the 36th International Conference on Machine Learning (ICML), 6105–6114.
[8] Wen, J., Zhang, Y., Fang, X. (2019). Study on Urban Residents' Domestic Waste Classification Behavior: Based on a Survey of Five Provinces in China. *Journal of Arid Land Resources and Environment*, 33(07), 96–101.
[9] Wang, F., Cai, X., et al. (2024). Development and Design of Smart Garbage Sorting Vehicle Based on Machine Vision. *Science and Innovation*, 2024.
[10] Shen, L., et al. (2024). Design of Surface Waste Cleaning Device Based on Visual Recognition. *Henan Science and Technology*, 2024.