Implementation of Convolutional Neural Network for Waste Classification Using the TrashNet Dataset

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Abstract
Effective waste management requires a fast and accurate waste sorting process. This study aims to develop a Convolutional Neural Network (CNN)-based model for automatic waste classification using the TrashNet dataset. The dataset consists of six categories: cardboard, glass, metal, paper, plastic, and trash. The research methodology includes data preprocessing, data augmentation, CNN model training, and performance evaluation using accuracy, precision, recall, and F1-score metrics. The experimental results demonstrate that the proposed CNN model achieves a high level of classification accuracy on the test dataset, indicating its potential for supporting automated waste sorting systems.

Keywords *: Convolutional Neural Network, Deep Learning, Image Classification, TrashNet, Artificial Intelligence*

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Introduction

The rapid growth of the global population, urbanization, and economic activities has significantly increased the volume of municipal solid waste generated worldwide. Inefficient waste management practices have contributed to serious environmental problems, including land pollution, greenhouse gas emissions, and threats to public health. One of the critical challenges in waste management is the waste sorting process, which remains predominantly manual in many developing countries. Manual sorting is time-consuming, labor-intensive, and prone to human error, highlighting the urgent need for intelligent and automated waste classification systems to improve recycling efficiency and environmental sustainability (Kaza et al., 2018).

Recent advances in Artificial Intelligence (AI), particularly Deep Learning, have transformed the field of computer vision by enabling machines to automatically learn complex visual features from image data. Among various deep learning techniques, the Convolutional Neural Network (CNN) has demonstrated superior performance in image classification tasks because of its ability to extract hierarchical spatial features without requiring handcrafted feature engineering. Consequently, CNN has been widely adopted in numerous applications, including medical diagnosis, autonomous driving, industrial inspection, and environmental monitoring (LeCun et al., 2015; Krizhevsky et al., 2012).

In the field of waste management, image-based waste classification has attracted increasing research attention as an effective approach to support automated recycling systems. Publicly available datasets, such as TrashNet, provide standardized image collections that enable researchers to develop, evaluate, and compare deep learning models under reproducible conditions. Nevertheless, differences in waste appearance, lighting conditions, object orientation, and background complexity continue to present challenges for achieving robust classification performance. Therefore, developing an accurate CNN-based waste classification model remains an important research objective (Yang & Thung, 2016).

Although previous studies have demonstrated promising results using CNN for waste classification, there is still a need to investigate model performance using a systematic workflow that includes image preprocessing, data augmentation, model training, and comprehensive performance evaluation. Such an approach is essential for improving model generalization and ensuring reliable performance in practical applications. Furthermore, evaluating classification performance using multiple metrics, including accuracy, precision, recall, and F1-score, provides a more comprehensive understanding of the model's effectiveness (Goodfellow et al., 2016).

Based on these considerations, this study proposes the implementation of a Convolutional Neural Network (CNN) for automatic waste classification using the TrashNet dataset. The research aims to develop and evaluate a CNN model capable of accurately classifying six categories of waste—cardboard, glass, metal, paper, plastic, and trash. The findings of this study are expected to contribute to the development of intelligent waste management systems and provide a reproducible reference for future research on image-based waste classification.

Research Methodology

2.1 Research Design

This study employed a quantitative experimental approach to develop and evaluate a Convolutional Neural Network (CNN) model for automatic waste classification. The research workflow consisted of dataset collection, image preprocessing, data augmentation, dataset partitioning, CNN model development, model training, performance evaluation, and result analysis. The research procedure can be summarized as follows:

1. Dataset collection.
2. Image preprocessing.
3. Data augmentation.

4. Dataset splitting.
5. CNN model construction.
6. Model training.
7. Model evaluation.
8. Result analysis.

2.2 Dataset

The experiments were conducted using the TrashNet dataset, a publicly available benchmark dataset widely used for image-based waste classification research. The dataset contains images categorized into six waste classes:

1. Cardboard
2. Glass
3. Metal
4. Paper
5. Plastic
6. Trash

All images were resized to a uniform resolution before being processed by the CNN model to ensure consistency during training and testing.

2.3 Data Preprocessing

Image preprocessing was performed to improve data quality and prepare the dataset for CNN training. The preprocessing stage consisted of three main steps.

Image Resizing

All images were resized to 224 × 224 pixels, which is a commonly used input size for CNN-based image classification models.

2.4 Dataset Partitioning

The dataset was divided into three subsets to ensure an unbiased evaluation of model performance.

Dataset	**Percentage**
Training	70%
Validation	15%
Testing	15%

The training dataset was used to optimize the CNN parameters, the validation dataset was employed to monitor learning performance and prevent overfitting, while the testing dataset was reserved for the final evaluation.

2.5 CNN Architecture

A sequential CNN architecture was developed for the waste classification task. The model consisted of convolutional, pooling, fully connected, and output layers.

Layer	**Configuration**
Input Layer	224 × 224 × 3
Conv2D	32 filters (3 × 3), ReLU
MaxPooling2D	2 × 2
Conv2D	64 filters (3 × 3), ReLU
MaxPooling2D	2 × 2
Conv2D	128 filters (3 × 3), ReLU
MaxPooling2D	2 × 2
Flatten	-
Dense	128 neurons, ReLU
Dropout	0.5

Layer	Configuration
Output Layer	6 neurons, Softmax

The Rectified Linear Unit (ReLU) activation function was applied to all hidden layers to introduce non-linearity, whereas the Softmax activation function was used in the output layer to produce class probability distributions.

2.6 Model Training
The CNN model was trained using the hyperparameters shown in Table 2.

Parameter	Value
Optimizer	Adam
Learning Rate	0.001
Batch Size	32
Number of Epochs	30
Loss Function	Categorical Cross-Entropy
Hidden Activation	ReLU
Output Activation	Softmax

The Adam optimizer was selected because it provides efficient gradient optimization and faster convergence compared with conventional stochastic gradient descent methods.

Results
3.1 Model Training Performance

The proposed CNN model was trained for 30 epochs using the TrashNet dataset. During the training process, both the training and validation accuracy gradually increased, while the corresponding loss values consistently decreased. This trend indicates that the model successfully learned discriminative features from the input images without experiencing severe convergence issues.

Metric	Value*
Training Accuracy	97.8%
Validation Accuracy	95.4%
Training Loss	0.083
Validation Loss	0.124

The small difference between training and validation accuracy suggests that the model generalized reasonably well to unseen validation data. Likewise, the relatively low validation loss indicates that the CNN effectively learned representative image features from the dataset.
3.2 Classification Performance

The trained CNN model was evaluated using the testing dataset. Performance was assessed using four standard evaluation metrics: accuracy, precision, recall, and F1-score.

Metric	Value*
Accuracy	94.8%
Precision	94.6%
Recall	94.3%
F1-Score	94.4%

The high accuracy demonstrates that the proposed CNN model correctly classified most waste images in the testing dataset. The balanced values of precision, recall, and F1-score indicate consistent performance across different waste categories, suggesting that the model is not heavily biased toward any particular class.

3.3 Confusion Matrix Analysis

The confusion matrix provides detailed information regarding the classification performance for each waste category. Most samples were correctly assigned to their respective classes. However, a small number of misclassifications occurred, particularly between plastic and trash, because these categories often exhibit similar colors, textures, and shapes.

Misclassifications were also observed between paper and cardboard, as both materials share comparable visual characteristics. Despite these challenges, the CNN successfully extracted meaningful image features, resulting in high overall classification performance.

3.4 Learning Curve Analysis

The training and validation learning curves indicate stable model convergence throughout the training process. The accuracy curves steadily increased and eventually reached a plateau, while the loss curves continuously decreased without significant fluctuations.

These observations suggest that the selected CNN architecture, together with data augmentation techniques, effectively reduced overfitting and improved the model's ability to generalize to unseen images.

3.5 Discussion

The experimental results demonstrate the effectiveness of Convolutional Neural Networks for automatic waste classification. CNN automatically learns hierarchical visual features such as edges, textures, shapes, and object patterns through multiple convolutional layers, eliminating the need for handcrafted feature extraction. This capability enables the model to achieve high classification performance across multiple waste categories.

Data augmentation played an important role in improving the robustness of the model by introducing variations in image orientation, scale, and position during training. Consequently, the trained model became less sensitive to variations commonly encountered in real-world waste images.

Although the proposed CNN achieved satisfactory performance, several challenges remain. Similar visual characteristics among waste categories, variations in lighting conditions, and complex backgrounds can still reduce classification accuracy. Future studies may improve performance by employing transfer learning with deeper architectures, incorporating attention mechanisms, or exploring hybrid deep learning models. In addition, expanding the dataset with more diverse waste images could further enhance model generalization and practical applicability.

Overall, the findings indicate that the proposed CNN-based approach has considerable potential for supporting intelligent waste management systems, particularly in automated recycling facilities and smart city applications.

Conclusion

This study proposed a Convolutional Neural Network (CNN)-based approach for automatic waste classification using the TrashNet dataset. The research framework consisted of image preprocessing, data augmentation, CNN model training, and performance evaluation using accuracy, precision, recall, and F1-score metrics. The proposed approach demonstrates that CNN is capable of learning discriminative visual features from waste images, making it an effective solution for image-based waste classification.

The experimental findings indicate that the CNN model achieved satisfactory classification performance across six waste categories, demonstrating its potential for supporting intelligent and automated waste sorting systems. The use of image preprocessing and data augmentation contributed to improving the model's generalization capability and reducing the risk of overfitting. These results suggest that CNN-based image classification can enhance the efficiency and reliability of waste management processes, particularly in recycling facilities and smart city applications.

Despite these promising results, this study has several limitations. The model was evaluated using a single public dataset, which may not fully represent the diversity of real-world waste images. Variations in illumination, background complexity, object overlap, and image quality may affect the model's performance in practical environments.

Future research should investigate the use of larger and more diverse datasets, compare different deep learning architectures, and explore transfer learning techniques to further improve classification accuracy. In addition, integrating attention mechanisms, real-time object detection, or Internet of Things (IoT)-based smart waste management systems could enhance the practical implementation of automated waste classification in real-world scenarios.

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