IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 7, April 2025
Impact Factor: 7.67

A Deep Learning Approach to Intelligent Waste Classification

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Abstract: *As the difficulties associated with waste management escalate due to urban growth and industrialization, there is a growing need for an automated system to classify waste for effective waste management. This research presents an innovative deep learning model that categorizes six distinct types of waste through the Recycling Waste Classification Network (RWCKT), utilizing a dataset of 2,527 trash items. Incorporating advanced conventional neural networks (CNNs) and an adaptive learning methodology, RWCNet achieves an overall accuracy of 95.01%, surpassing current techniques. The model also shows impressive F1-scores across all waste categories, highlighting its strength and dependability. Score-CAM (class activation mapping) is employed to provide visual interpretability, giving clarity into its decision-making process. Furthermore, we advocate for the RWC's incorporation into a real-time waste management framework by merging image, text, and voice recognition for enhanced user engagement. This research emphasizes the diverse possibilities of artificial intelligence in waste management, promoting more effective recycling practices and environmental sustainability*

Keywords: Waste Management, Recycling, Waste Sorting, Multi-Label Sorting, Convolutional Neural Network (CNN), Advanced Learning Techniques

I. INTRODUCTION

The growing interest in natural relaxation stems from population increases globally, along with industrial and economic advancements. Consequently, there has been a notable surge in waste generation. A significant portion of urban refuse is disposed of improperly, primarily through landfilling and incineration, posing risks to environmental systems and public health.

Household waste, particularly plastics, poses severe environmental threats as they take time to decompose. Inefficient waste management practices have led to contamination of both land and water ecosystems. At present, around a third of the world's waste remains unsorted or untreated, presenting a risk of environmental degradation and harm.

To address these issues, local authorities are advocating for the recycling of municipal solid waste as a sustainable solution endorsed by the Environmental Protection Agency. In 2016, the global volume of municipal solid waste reached 5.5 billion tons, projected to rise to 5.9 billion tons, highlighting the need for effective waste management strategies that minimize pollution and encourage sustainable development.

The field of deep learning has advanced significantly due to enhanced computational power and improved algorithms over the last ten years. These advancements have bolstered capabilities in computer vision tasks, including image recognition, object detection, and semantic segmentation. The Convolutional Neural Network has been crucial in refining automated feature extraction and classification precision, proving particularly beneficial for waste sorting and recycling efforts.

Despite the advancements in deep learning, challenges remain in waste classification, including ineffective manual sorting, low public awareness, and the intricacies involved in classification processes. The introduction of datasets like WasteNet, TACO, and AQRUTrash has aided research, though these initiatives face hurdles regarding small sample sizes and accessibility.

This research centers on creating RWC-Net, a deep learning model designed to classify six categories of waste: cardboard, glass, metal, paper, plastic, and general waste. The model employs class activation mapping for enhanced visualization and assessment. By improving precision and efficiency, the goal of this initiative is to enhance recycling efforts and promote sustainable waste management practices.

II. LITERATURE RIVIEW

Effective waste management is becoming a critical issue, necessitating an automated classification system. As urban areas and industries expand, the amount of refuse increases, making it imperative for individuals to sort and recycle waste correctly.

Initially, waste classification relied on conventional machine learning techniques. For instance, early research by Mindi et al. utilized the Support Vector Machine (SVM) algorithm on the TrashNet dataset, achieving an accuracy rate of 63%. Subsequently, in 2018, Bernardo et al. improved classification results by implementing the K-Nearest Neighbors (KNN) algorithm on the same dataset, which resulted in an accuracy of 88%. Additionally, researchers like Mandar experimented with Random Forest (RF) and XGBoost, respectively. Nevertheless, the emergence of deep learning has led to notable advancements in waste classification methods, surpassing the capabilities of traditional machine learning methods.

Recently, Deep Learning models have significantly impacted waste classification. In early 2018, Kennedy et al. presented the Oscarnet framework, which was later refined using VGG 19, achieving an accuracy of 88.42% on the waste dataset. In October 2018, Costa et al. fine-tuned the AlexNet and VGG networks, reaching accuracies of 1% and another percentage, respectively. Furthermore, Rabano et al. introduced the MobileNet architecture, which attained an accuracy of 87.2%.

Further advancements occurred in December 2018 when Rahmani et al. assessed various deep learning frameworks using the garbage dataset. Their study revealed that both Inspect-ResNet V2 and Densenet 121 achieved an accuracy of 89%. Following fine-tuning with an image dataset, Densenet improved its accuracy to 95%, while Inspect-ResNet reached an impressive 94%. By June 2019, Victoria et al. built upon this progress with Inspect-ResNet, attaining an accuracy of 87.71%, while Inspect-ResNet and Racenet achieved accuracy rates of 88.34% and 88.66%, respectively.

These advancements illustrate the shift from traditional machine learning approaches to robust deep learning methods in waste classification. Deep learning models not only enhance the precision of classification but also unveil new opportunities for more effective waste understanding and management.

III. METHODOLOGY

Waste management classification is a structured approach used to categorize waste based on its origin, composition, and its effects on the environment. This classification is essential for identifying the appropriate methods for disposal, recycling, or treatment. The process generally consists of the following key steps:

1. Waste identification

- Classification by source: Categorizing waste according to its origin, such as household, industrial, agricultural, or medical.
- Classification by design: Determining types of waste based on their physical and chemical characteristics, including organic, inorganic, harmful, and recyclable waste.

2. Waste characteristics

- Physical characteristics: Assessment of dimensions, weight, moisture levels, and flammability.
- Chemical characteristics: Detection of chemical makeup, acidity, and presence of harmful substances.
- Biodegradability: Assessing the potential for decomposition and composting.

DOI: 10.48175/IJARSCT-25479

3. Segmentation and classification

- Biodegradable versus Non-biodegradable: Distinguishing between organic matter (such as food scraps and paper) and non-biodegradable materials (including plastic and metal).
- Hazardous versus Non-hazardous: Separating waste that includes toxic, flammable, or infectious materials from other waste.
- Recyclable versus Non-recyclable: Identifying materials that can be reprocessed and reused (like glass, plastic, and metal) as opposed to those that cannot be repurposed.

4. Waste collection and sorting

- Manual sorting: Typically found in smaller or community-driven waste management initiatives.
- Automated sorting: Leveraging artificial intelligence, machine vision, and robotics to categorize waste more effectively.

IV. MODELING AND ANALYSIS

In this study, various advanced educational frameworks were employed to categorize waste into six distinct groups. The evaluation was based on a dataset consisting of 2,527 images of waste. To enhance the training and assessment of the model, this dataset was augmented to contain 15,000 images through data expansion. Subsequently, the images were allocated into 252 for validation and 504 for performance assessment. A training set comprised 70% of the baseline data while allocating 10% for validation and 20% for performance evaluation across five separate cross-validation iterations. This strategy guarantees a comprehensive assessment, utilizing the complete dataset across various testing subsets (5 × 20% = 100%).

I. Quantitative Assessment

This investigation utilized different deep learning models to sort waste into six categories: cardboard, glass, plastic, paper, metal, and broken items. To evaluate the effectiveness of these models, key performance metrics such as accuracy, recall (sensitivity), specificity, and F1-score were employed. The confusion metric was eliminated from the matrix, which included True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) values.

To establish the validity of these findings, a 95% confidence interval (CI) for each metric was computed. The CI was determined using the formula:

r = z metric (1 - metric) / sqrt(metric (1 - metric) / n)

Where N represents the number of examples tested, and Z denotes the confidence level (1.96 for a 95% CI). The comprehensive evaluation was founded on a global confusion matrix, aggregating the results from all testing sets across five iterations of cross-validation.

The equations below outline the evaluation metrics applied in this research:

- Accuracy = (TP + TN) / (TP + TN + FP + FN)
- Precision = TP / (TP + FP)
- Recall (Sensitivity) = TP / (TP + FN)
- Specificity = TN / (TN + FP)
- F1-score = (2 × Precision × Recall) / (Precision + Recall)

Considering the unequal distribution of certain waste categories, weighted values were applied for all metrics apart from accuracy. The average of the confusion metric was calculated over the entire dataset. Additionally, a detailed matrix was generated for the model that performed the best.

II. Qualitative Assessment

To conduct a deeper evaluation of model performance, the class activation mapping (CAM) method was employed. Producing CAM heatmaps assists in visualizing the key components involved in the model's assessments. In this work,

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score-CAM was utilized along with several other sophisticated CAM methodologies like grad-CAM, smooth grad-CAM, and grad-CAM.

Score-CAM was particularly beneficial as it highlights the distinct features learned by the model rather than depending on fixed procedures typical of techniques such as grad-CAM.

By applying score-CAM to test images from each category, the model acquired profound insights into its decision-making process. This qualitative analysis, when paired with quantitative metrics, validated the efficiency of these advanced educational models in the classification of waste

V. CONCLUSIONS

Ultimately, this document examines numerous research studies centered on deep learning pertaining to waste identification and categorization, along with object detection.

This study emphasizes the necessity of recycling to minimize waste levels and enhance waste management strategies. Within this investigation, RWC-Net presents a comprehensive educational model that effectively differentiates between six categories of waste materials. By integrating Deccan 2 and Mobilenet-22, this model achieved an impressive accuracy rate of 95.01% and was compared against various existing approaches. Furthermore, it exhibited robust performance across different dataset divisions, ensuring dependable classification.

Moreover, the score-CAM-based heating technique validated the model's proficiency in accurately defining the waste category. Due to its exceptional accuracy, the RWC-T-T automated waste solution can be integrated into sorting systems, thereby enhancing the efficiency of reuse processes.

Looking ahead, future studies will seek to further elevate classification accuracy, particularly concerning the "waste" category and the utilization of bounding boxes. We intend to assess RWC-NET on waste images collected from diverse locations to analyze the effectiveness of distinct waste management systems.

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