Intelligent Waste Classification for Efficient Disposal Using Convolutional Neural Networks

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***Abstract*—Proper waste disposal is critical for effective waste management and environmental sustainability. However, individuals often misidentify waste categories, leading to contamination in recycling streams and reduced processing efficiency. This paper explores image-based waste classification using convolutional neural networks (CNNs) across nine waste categories. We evaluate a custom-built CNN alongside fine-tuned ResNet and AlexNet architectures, trained on a dataset of 4,752 labeled images from the UC Irvine Machine Learning Repository. The best-performing model achieved 90% accuracy, demonstrating the feasibility of deep learning approaches in enhancing waste sorting accuracy.**

Keywords*— *convolutional neural networks, image recognition, transfer learning

I. Introduction

Recycling, as a formal practice, began gaining prominence in the 1970s with the rise of environmental awareness and the first Earth Day in 1970, although informal recycling activities date back to ancient civilizations where materials like bronze and paper were repurposed. In modern times, increasing urbanization and industrialization have led to an exponential rise in waste production, prompting governments and organizations worldwide to institutionalize recycling programs as a means of reducing landfill use, conserving natural resources, and lowering greenhouse gas emissions.

Despite these efforts, the effectiveness of recycling heavily depends on the accurate separation of waste into the appropriate categories, such as paper, plastic, metal, organic, and hazardous materials. Improper sorting, known as contamination, can render entire batches of recyclable materials unusable. For instance, food-contaminated containers or misplaced items like electronics in general waste streams often lead to additional processing costs, inefficiencies, and even the rejection of recyclables.

Furthermore, many individuals face uncertainty about how to properly categorize waste, especially when dealing with mixed materials or less commonly recycled items. This confusion significantly undermines the success of recycling programs and contributes to environmental degradation, increased operational costs for waste management facilities, and reduced material recovery rates.

In light of these challenges, there is growing interest in automating waste classification using image-based recognition systems powered by machine learning, particularly convolutional neural networks (CNNs). Such systems can assist in real-time sorting, improve accuracy, and alleviate the burden on individuals and waste management operators. This paper explores deep learning approaches for classifying waste into nine distinct categories using image data, with the goal of improving sorting efficiency and supporting sustainable waste management efforts.

Recent advancements in computer vision have enabled the automation of complex visual tasks such as object detection and image classification. One of the most widely used techniques in this domain is the Convolutional Neural Network (CNN), a type of deep learning model specifically designed to process grid-like data such as images. CNNs have shown exceptional performance in visual recognition tasks due to their ability to automatically learn spatial hierarchies of features from raw pixel data without manual feature engineering [1].

However, training deep CNNs from scratch typically requires large datasets and significant computational resources. This is particularly challenging in domains like waste classification, where labeled image datasets are limited. To address this, transfer learning has emerged as a practical approach. In transfer learning, a model pre-trained on a large benchmark dataset such as ImageNet is fine-tuned on a smaller, task-specific dataset. This method leverages the general features learned in earlier layers and adapts them to the new task, often resulting in faster convergence and improved performance on limited data [2].

This study investigates the effectiveness of CNN-based waste classification, comparing the performance of a custom-built CNN with two transfer learning models: ResNet and AlexNet. Our objective is to evaluate the feasibility of deep learning techniques in enhancing waste sorting systems.

II. Related work

Recent advancements in deep learning have significantly enhanced the capabilities of automated waste classification systems. Numerous studies have explored various architectures and methodologies to improve classification accuracy and efficiency.

One notable approach is the integration of Internet of Things (IoT) technologies with deep learning models. A study published in Scientific Reports introduced an AI-driven waste classification system that combines IoT-enabled smart bins with blockchain technology to ensure secure and transparent data handling. This system utilizes convolutional neural networks (CNNs) for real-time waste classification, achieving high accuracy and operational efficiency[3].

Moreover, hybrid models combining CNNs with other architectures have shown promise. A study presented in Multimedia Tools and Applications proposed a hybrid CNN-LSTM model that incorporates transfer learning for waste classification, demonstrating improved accuracy and robustness in handling sequential data[4].

In addition to architectural innovations, the development of comprehensive datasets has been pivotal. The WaRP dataset, encompassing 28 categories of recyclable waste, has facilitated the training and evaluation of deep learning models, leading to more nuanced and effective classification systems[5].

These studies collectively underscore the potential of deep learning, particularly when combined with transfer learning and IoT technologies, to advance automated waste classification systems. The integration of these approaches can lead to more accurate, efficient, and scalable solutions for waste management challenges.

III. Methodology

A. The Dataset

This study utilizes the RealWaste dataset, available through the UC Irvine Machine Learning Repository. The dataset comprises 4,752 color images of waste items, each captured at the point of reception in a landfill environment. The images are provided at a resolution of 524×524 pixels and are labeled across nine material categories: Cardboard (461 images), Food Organics (411), Glass (420), Metal (790), Miscellaneous Trash (495), Paper (500), Plastic (921), Textile Trash (318), and Vegetation (436). The dataset is complete, with no missing values, and was created as part of an honors thesis investigating the performance of convolutional neural networks on authentic waste materials compared to objects in pure forms. The RealWaste dataset offers a realistic benchmark for evaluating image-based waste classification systems[6].

B. Data Preprocessing

- All images were resized to a resolution of 224×224 pixels to match the input requirements of the pre-trained convolutional neural networks. Data augmentation techniques were applied to reduce overfitting and improve robustness, including random horizontal flipping and random rotations up to 10 degrees. Each image was converted to a PyTorch tensor and normalized using a mean and standard deviation of 0.5 for each RGB channel.
- The dataset was divided into three subsets: 70% for training, 10% for evaluation (validation), and 20% for testing.
- Given the class imbalance in the dataset, especially in categories like Textile Trash and Food Organics, a weighted oversampling strategy was applied to the training data. This approach assigns higher sampling probabilities to underrepresented classes, ensuring that the model receives balanced exposure during training and reducing bias toward majority classes.

C. Model Development

C.1 Custom CNN architecture

To establish a baseline for waste classification, we designed a custom convolutional neural network (CNN) tailored to extract and learn discriminative visual features from waste images. The network consists of four convolutional blocks, each comprising a convolutional layer followed by batch normalization, a ReLU activation function, max-pooling, and dropout for regularization. These layers progressively increase the depth of the feature maps while reducing their spatial resolution, allowing the network to capture increasingly abstract representations of the input images.

After the feature extraction stage, the output is flattened and passed through a fully connected classifier composed of three dense layers with ReLU activations and batch normalization. The final layer maps the features to the target number of waste classes. This deep architecture enables the model to learn complex, non-linear relationships between input images and their respective categories. The design emphasizes regularization and normalization throughout the network to promote generalization and training stability.

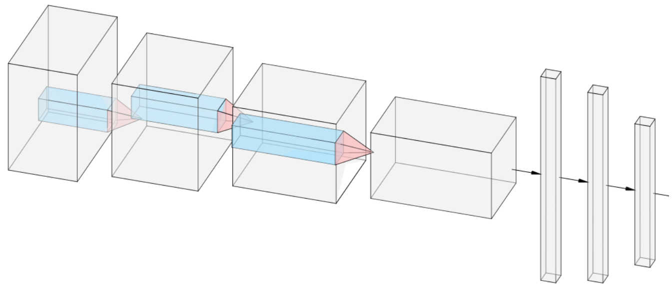

Fig. 1 Custom-built CNN model

C.2 Transfer learning with ResNet and AlexNet

To complement the custom CNN, we explored transfer learning using two well-established convolutional neural network architectures: ResNet and AlexNet. These models serve as strong baselines for image classification tasks due to their proven performance and extensive training on the ImageNet dataset, which contains over one million labeled images across 1,000 classes. Importantly, ImageNet includes object categories such as plastic bottle, paper towel, metal can, cardboard box, and glass bottle, classes that closely align with those in the RealWaste dataset. This overlap in semantic content makes these pre-trained models particularly relevant for waste classification tasks.

The approach began by adapting the original models to our nine-class problem. Specifically, the final classification layer of each model, originally designed to output predictions over 1,000 classes, was replaced with a new fully connected layer producing nine outputs, one for each waste category. However, the decision to use these models was not based solely on their architectural depth or design. A key motivation was the rich feature representations they had learned from the large-scale and diverse ImageNet dataset. Given the limited size of our dataset, training deep architectures from scratch posed a significant risk of overfitting and suboptimal performance.

To evaluate the effectiveness of transfer learning, we implemented two strategies. In the first, we treated the pre-trained weights as an initialization and fine-tuned the entire model on our dataset, allowing the network to adjust all its parameters. In the second approach, we froze the convolutional base of the models and trained only the newly added fully connected layers. This allowed us to leverage the general visual features learned from ImageNet while reducing computational cost and overfitting risk. Both approaches were tested to assess the trade-offs between adaptability and stability in learning from limited data.

D. Model Training

The dataset was divided into training, evaluation, and test subsets to support proper model training, hyperparameter tuning, and final performance assessment. To address the imbalance among classes in the training data, a weighted random sampler was used. This ensured that instances from underrepresented categories were more likely to appear during training, helping the model learn from all classes more effectively.

The model was trained using a standard optimization algorithm suited for deep learning tasks, and cross-entropy was selected as the loss function to guide the classification process. Training proceeded iteratively, alternating between learning from the training data and validating on the evaluation set to monitor progress. An early stopping mechanism was incorporated to halt training when performance on the evaluation set plateaued, thereby reducing the risk of overfitting and saving the best model for final testing. This training strategy helped maintain a balance between accuracy and generalization across all classes.

Different learning rate strategies were applied depending on the model. For transfer learning, a relatively smaller learning rate was found to be beneficial, allowing the pre-trained weights to adjust gradually to the new dataset without overwriting learned representations. In contrast, a comparatively larger learning rate proved useful for training the custom CNN from scratch, enabling faster convergence and more efficient learning during early epochs.

IV. Result and discussion

The goal of this research was to develop and evaluate deep learning-based approaches for multi-class waste classification using image data. Specifically, we aimed to explore the effectiveness of a custom-built convolutional neural network as well as pre-trained architectures such as ResNet and AlexNet through transfer learning techniques.

To comprehensively assess model performance, we employed multiple evaluation metrics: accuracy, precision, recall, F1-score, and specificity. Accuracy provides an overall measure of correctness, but it can be misleading in the presence of class imbalance.

Precision measures the proportion of correctly predicted positive observations relative to all predicted positives, offering insight into the model's ability to avoid false positives. Recall evaluates the model's effectiveness in identifying all relevant instances, reflecting sensitivity to false negatives. The F1-score balances precision and recall, making it especially useful when dealing with uneven class distributions. Specificity complements recall by quantifying the ability of the model to correctly identify negative cases, which is crucial when distinguishing between visually similar but semantically different waste categories.

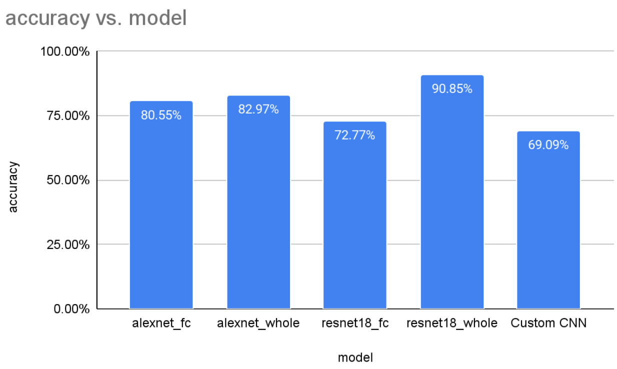

Fig. 2 Accuracy of models

	Model				
	alexnet_fc	alexnet_whole	resnet18_whole	resnet18_fc	custom cnn
Cardboard	0.819	0.851	0.943	0.711	0.884
Food Organics	0.826	0.831	0.909	0.714	0.829
Glass	0.843	0.946	0.947	0.673	0.738
Metal	0.858	0.863	0.934	0.824	0.648
Misc. Trash	0.771	0.798	0.759	0.545	0.422
Paper	0.798	0.941	0.938	0.649	0.738
Plastic	0.735	0.739	0.890	0.778	0.742
Textile Trash	0.719	0.653	0.922	0.622	0.461
Vegetation	0.910	0.951	0.990	0.876	0.798

Table 1. Precision of models

	Model				
	alexnet_fc	alexnet_whole	resnet18_whole	resnet18_fc	custom cnn
Cardboard	0.827	0.827	0.892	0.688	0.369
Food Organics	0.938	0.914	0.988	0.926	0.850
Glass	0.864	0.864	0.934	0.868	0.832
Metal	0.732	0.803	0.877	0.722	0.779
Misc. Trash	0.640	0.710	0.854	0.350	0.447
Paper	0.798	0.769	0.904	0.759	0.621
Plastic	0.833	0.867	0.909	0.658	0.688
Textile Trash	0.707	0.845	0.881	0.836	0.686
Vegetation	0.942	0.895	0.970	0.929	0.943

Table 2. Recall of models

	Model				
	alexnet_fc	alexnet_whole	resnet18_whole	resnet18_fc	custom cnn
Cardboard	0.823	0.839	0.917	0.699	0.521
Food Organics	0.879	0.871	0.947	0.806	0.840
Glass	0.854	0.903	0.940	0.759	0.782
Metal	0.790	0.832	0.904	0.770	0.707
Misc. Trash	0.699	0.751	0.804	0.426	0.434
Paper	0.798	0.847	0.920	0.700	0.674
Plastic	0.781	0.798	0.899	0.713	0.714
Textile Trash	0.713	0.737	0.901	0.713	0.551
Vegetation	0.926	0.922	0.980	0.902	0.865

Table 3. F1 score of models

	Model				
	alexnet_fc	alexnet_whole	resnet18_whole	resnet18_fc	custom cnn
Cardboard	0.978	0.982	0.994	0.970	0.994
Food Organics	0.982	0.983	0.991	0.966	0.984
Glass	0.985	0.995	0.995	0.963	0.967
Metal	0.976	0.975	0.987	0.968	0.921
Misc. Trash	0.978	0.979	0.967	0.965	0.940
Paper	0.975	0.994	0.994	0.961	0.975
Plastic	0.930	0.929	0.973	0.954	0.934
Textile Trash	0.982	0.971	0.994	0.962	0.954
Vegetation	0.991	0.995	0.999	0.985	0.976

Table 4. Specificity of models

The evaluation of the five models — fine-tuned and frozen variants of ResNet18 and AlexNet, along with a custom CNN, shows distinct performance differences across multiple metrics. Overall, the fine-tuned ResNet18 model achieved the highest performance across all metrics, including precision, recall, F1-score, and specificity. This suggests that leveraging both the architecture and pre-trained weights of ResNet18 allowed the model to adapt effectively to the RealWaste dataset, even with limited training data.

In particular, fine-tuned ResNet18 consistently outperformed other models across all nine classes. It achieved high precision in distinguishing visually similar items like paper, glass, and plastic, and maintained excellent recall, especially in underrepresented classes such as textile trash and food organics. The model's high F1-scores across the board indicate a strong balance between precision and recall. Additionally, its specificity values remained high for all classes, reinforcing its ability to avoid false positives.

In contrast, the custom CNN showed the weakest overall performance. Although it achieved moderate scores in some categories, such as food organics and vegetation, it generally underperformed in recall and F1-score, especially for complex classes like cardboard and miscellaneous trash. This reinforces the limitation of training deep models from scratch on small datasets without leveraging external knowledge.

The AlexNet models showed mixed results. The fully fine-tuned version of AlexNet performed notably better than its frozen counterpart, demonstrating that adapting the entire model to the target domain yields better results. However, both versions of AlexNet were outclassed by ResNet18, highlighting the latter's deeper and more expressive architecture.

These findings affirm the effectiveness of transfer learning, especially when the source domain (ImageNet) shares semantic similarities with the target task. The results also illustrate the importance of allowing model weights to adapt during fine-tuning. Relying solely on pre-trained feature extractors without updating them can limit a model's capacity to generalize to new domains. Ultimately, fine-tuned ResNet18 stands out as the most reliable model for image-based waste classification in this study.

V. Conclusion

This study set out to investigate the effectiveness of deep learning models in the task of image-based waste classification, with the goal of improving the accuracy and automation of waste sorting systems. We explored both a custom-built convolutional neural network and transfer learning approaches using pre-trained ResNet18 and AlexNet models. Each model was evaluated on a publicly available dataset, RealWaste, which contains real-world images spanning nine distinct waste categories.

To measure performance comprehensively, we employed multiple evaluation metrics, including accuracy, precision, recall, F1-score, and specificity. These metrics provided a balanced view of the models' ability to correctly classify diverse waste types, handle class imbalance, and generalize to unseen data. While accuracy offers an overall measure of correctness, precision and recall highlight the model's strengths in avoiding false positives and negatives, respectively. F1-score combines both aspects into a single measure, and specificity further ensures that negative instances are correctly identified, which is especially important in a multi-class setting with visually similar classes.

The results clearly demonstrated that the fine-tuned ResNet18 model outperformed all others across nearly every metric. It effectively leveraged both its architectural depth and the knowledge encoded in its pre-trained weights. In contrast, the custom CNN, despite being carefully designed and trained from scratch, struggled to match this performance, particularly in underrepresented or visually ambiguous categories. The AlexNet models showed moderate success, with fine-tuning again proving more effective than using frozen weights.

These findings reinforce the value of transfer learning in scenarios where labeled data is limited and suggest that adapting pre-trained models to domain-specific tasks can yield significant improvements over training from scratch. Ultimately, this study highlights the practical potential of deep learning for supporting smarter, more sustainable waste management systems.

VI. Future work

While the models demonstrated strong performance on the test portion of the RealWaste dataset, they performed relatively worse when evaluated on waste images outside the dataset. This drop in accuracy can be attributed to the controlled nature of the original dataset, which primarily contains isolated waste items rather than mixed or overlapping materials commonly encountered in real-world scenarios. Moreover, most images in the dataset were captured under consistent lighting conditions, limiting the models' ability to generalize to images taken in varying environments. Future work should focus on extending the dataset to include more complex and diverse scenes, such as mixed waste, occlusions, and a broader range of lighting conditions. This would allow models to learn more robust and adaptable features, improving their effectiveness in practical deployment settings.

References

1. Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436–444, 2015.
2. Pan, S. Y. (2010). Q.: A survey on transfer learning. IEEE Transactions on Knowledge and Data Engineering, 22(10), 1345-1359.
3. Alabdali, A.M. Blockchain based solid waste classification with AI powered tracking and IoT integration. Sci Rep 15, 15197 (2025). https://doi.org/10.1038/s41598-025-97030-2
4. Lilhore, U.K., Simaiya, S., Dalal, S. et al. A smart waste classification model using hybrid CNN-LSTM with transfer learning for sustainable environment. Multimed Tools Appl 83, 29505–29529 (2024). https://doi.org/10.1007/s11042-023-16677-z
5. Sayem, F.R., Islam, M.S.B., Naznine, M. et al. Enhancing waste sorting and recycling efficiency: robust deep learning-based approach for classification and detection. Neural Comput & Applic 37, 4567–4583 (2025). https://doi.org/10.1007/s00521-024-10855-2
6. S. Single, S. Iranmanesh, and R. Raad. "RealWaste," UCI Machine Learning Repository, 2023. [Online]. Available: https://doi.org/10.24432/C5SS4G.
7. He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 770-778).