Literature Review: CNN-Based Waste Classification Using BDWaste Dataset

1. Introduction

Waste classification is a crucial step in waste management, ensuring efficient recycling and environmental sustainability. Traditional waste sorting methods rely on manual labor, which is inefficient, time-consuming, and prone to errors. Recent advancements in **deep learning, particularly Convolutional Neural Networks (CNNs)**, have led to significant improvements in **automated waste classification**. This literature review examines **state-of-the-art CNN models** used for waste classification, their effectiveness in different datasets, and the role of data preprocessing, augmentation, and model optimization techniques.

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2. Waste Classification Using Deep Learning

2.1 BDWaste Dataset and Its Importance

The **BDWaste dataset**, introduced by Rahman et al. (2024), is one of the most comprehensive datasets for waste classification. It consists of **2,625 images** categorized into **21 waste classes**, covering both **digestible and indigestible** waste types (Rahman et al., 2024). The dataset has been tested with **MobileNetV2 and InceptionV3**, achieving **classification accuracies of 96.7% and 99.7%**, respectively.

BDWaste serves as a benchmark for evaluating different CNN models in waste classification, making it highly relevant to this research. However, previous studies have not fully explored a **comparative analysis of multiple CNN architectures** on BDWaste, which this study aims to address.

2.2 Transfer Learning for Waste Classification

Transfer learning is widely used in waste classification, as it enables models trained on **large datasets (e.g., ImageNet) to be fine-tuned** for specific tasks. Various studies have explored CNN architectures such as **VGG16, ResNet50, MobileNetV2, EfficientNet, and DenseNet**:

- **Huynh et al. (2020)** applied **ResNet101, EfficientNet-B0, and EfficientNet-B1** to classify waste images, achieving a peak accuracy of **94.11%**.
- **Srinilta et al. (2019)** tested **VGG16, ResNet50, MobileNetV2, and DenseNet-121** for **municipal solid waste segregation**, with **ResNet50 achieving the highest accuracy of 94.86%**.
- **Poudel & Poudyal (2022)** compared **VGG19, ResNet50, DenseNet201, and InceptionV3**, concluding that **InceptionV3 provided the highest classification accuracy**.

These findings confirm that **transfer learning significantly enhances classification performance**, supporting its inclusion in this research. However, further studies are needed to analyze **the computational efficiency and training time** differences among these models.

2.3 Custom CNN Models for Waste Classification

While transfer learning models perform well, **custom CNN architectures** tailored for waste classification have also been explored:

- **Song et al. (2020)** proposed **DSCR-Net**, a CNN model inspired by **InceptionV4 and ResNet**, achieving **94.38% accuracy**.
- **Gyawali et al. (2021)** conducted a comparative analysis of **ResNet, VGG, DenseNet, and MobileNet**, highlighting that deeper architectures improve classification accuracy.
- **Rayhan & Rifai (2024)** developed a **custom CNN model** optimized for **multi-class waste classification**, demonstrating competitive accuracy against **MobileNetV2 and DenseNet121**.

These studies reinforce the **importance of custom CNN models**, supporting this project's approach of **comparing a custom CNN against transfer learning models**. However, more research is required to determine **the optimal number of convolutional layers and kernel sizes** for BDWaste-specific classification.

2.4 Data Preprocessing and Augmentation for Model Performance

Data preprocessing and augmentation techniques are essential for improving CNN performance:

- **Rahman et al. (2024)** emphasized the need for **standardized image dimensions and augmentation techniques** such as **rotation, flipping, and brightness adjustments** to improve model generalization.
- **Mao et al. (2021)** demonstrated that **data augmentation, combined with Genetic Algorithm (GA) tuning, significantly enhances CNN accuracy**.

This research integrates **data preprocessing and augmentation** to ensure robust model training. However, additional studies are needed to explore **the impact of different augmentation techniques on CNN performance** for BDWaste.

2.5 CNN Model Optimization and Hyperparameter Tuning

Various optimization techniques have been explored to enhance CNN performance:

- **Kaya et al. (2023)** optimized **VGG19, DenseNet169, ResNet101, Xception, and EfficientNetV2** using **GridSearch-based hyperparameter tuning**, achieving a **96.42% accuracy and 96% F1-score**
- **Mao et al. (2021)** used **DenseNet121 + Genetic Algorithm (GA) optimization**, achieving **99.6% accuracy**.

These findings validate the use of **hyperparameter tuning and optimization** as a key strategy for improving CNN model performance. However, research is still needed to determine **the most effective hyperparameter combinations for BDWaste classification**, which this study will investigate.

3. Conclusion and Research Gaps

Key Findings

The reviewed studies confirm that CNN-based models are highly effective for **waste classification**, with **transfer learning models (ResNet50, EfficientNet, and InceptionV3) achieving the highest accuracy**. However, **custom CNN models can achieve comparable performance** with proper **fine-tuning and optimization**.

Identified Research Gaps:

- **Explainability in CNN Models:** Few studies explore **Explainable AI (XAI)** techniques to interpret **how CNNs make classification decisions**.
- **Computational Efficiency:** Most studies do not analyze the **training time, memory usage, or inference speed** of different CNN architectures.
- **BDWaste-Specific Performance Analysis:** While some studies utilize **BDWaste**, there is **no extensive study comparing multiple CNN models on this dataset**—this project aims to **fill this gap**.

Final Thoughts

This literature review strongly supports our project by:

1. **Confirming BDWaste as a suitable dataset for waste classification**.
2. **Highlighting the effectiveness of transfer learning models (VGG16, ResNet50, MobileNetV2, EfficientNet)**.
3. **Demonstrating the potential of custom CNN architectures**.
4. **Emphasizing the importance of data augmentation and preprocessing**.
5. **Validating hyperparameter tuning as a key strategy for performance optimization**.

By leveraging insights from these studies, this project aims to **train and compare a custom CNN model against leading pretrained architectures, optimizing the best-performing model for waste classification using BDWaste**.

4. References

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