**Title:** CNN-Based Waste Classification Using BDWaste Dataset

**Abstract**

Waste management is a critical environmental challenge that can benefit significantly from technological innovations, particularly in automated waste classification. This project investigates the use of deep learning techniques, especially Convolutional Neural Networks (CNNs), to classify waste into Digestive and Indigestive categories using the BDWaste dataset. The study implements a custom CNN architecture and evaluates its performance against three pretrained models: VGG16, ResNet50, and MobileNetV2. Extensive experiments were carried out, including hyperparameter tuning for both custom and MobileNetV2 models. Evaluation metrics such as accuracy, precision, recall, F1-score, and confusion matrices are used to assess model performance. The results show that MobileNetV2 and the tuned custom CNN model significantly outperform others in classification accuracy and robustness. This report provides comprehensive insights into the methodology, comparative analysis, and the potential real-world applicability of AI-powered waste management systems.

**1. Introduction**

Waste classification is an essential part of sustainable waste management. Efficient separation of waste at the source can reduce landfill overflow, enhance recycling processes, and contribute to a cleaner environment. Traditionally, waste separation relies heavily on manual labor, which is not only time-consuming but also error-prone. In the modern age, the use of artificial intelligence, especially computer vision and deep learning, opens the door to intelligent, automated systems that can perform waste classification tasks with high accuracy.

Deep learning, a subset of machine learning, has revolutionized the way machines interpret image data. CNNs, in particular, have become the cornerstone of computer vision applications, owing to their ability to extract and learn hierarchical features from images. This project applies CNNs to classify waste into two categories: Digestive (biodegradable) and Indigestive (non-biodegradable), using the BDWaste dataset. In addition to designing and training a custom CNN model, we explore the use of transfer learning via three pretrained networks: VGG16, ResNet50, and MobileNetV2.

The goal of this study is twofold: first, to evaluate how a custom CNN performs on real-world waste classification; and second, to benchmark this against industry-standard pretrained architectures. Additionally, we tune the custom CNN and MobileNetV2 models to explore performance gains through hyperparameter optimization.

**2.Literature Review**

## ****2.1. 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.

## ****2.2. Waste Classification Using Deep Learning****

### **2.2.1 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.

### **2.2.2 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.

### **2.2.3 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.

### **2.2.4 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.

### **2.2.5 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.

## ****2.3. 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**.

**3. Methodology**

**3.1 Dataset Overview**

The BDWaste dataset consists of two categories: Digestive and Indigestive waste. Each image represents a real-world scenario captured under varying lighting, orientation, and background conditions. The dataset was split into training (80%), validation (10%), and test (10%) sets using a stratified approach to maintain class balance.

**3.2 Preprocessing and Augmentation**

To enhance model generalization and handle limited data, image augmentation techniques were applied during training. These included:

* Rescaling
* Rotation (up to 30 degrees)
* Width and height shifts
* Shear and zoom transformations
* Brightness adjustment
* Horizontal flipping

All images were resized to 224x224 pixels to match the input requirement of pretrained models.

**3.3 Custom CNN Architecture**

The custom CNN consisted of three convolutional blocks with increasing filters (32, 64, 128), each followed by batch normalization and max pooling. The classifier used a flattening layer, one dense layer with 256 neurons, dropout of 0.5, and a final output layer with softmax activation. Adam optimizer with a learning rate of 0.001 and categorical crossentropy loss was used.

**3.4 Pretrained Models**

Three pretrained models were used:

* **VGG16:** Known for its simplicity and depth
* **ResNet50:** Introduces skip connections to mitigate vanishing gradients
* **MobileNetV2:** Lightweight model optimized for mobile and embedded applications

These models were loaded with ImageNet weights, frozen for feature extraction, and custom dense layers were added for classification.

**3.5 Hyperparameter Tuning**

Hyperparameter tuning was performed for:

* **Custom CNN:** Learning rate, dropout rate, and optimizer
* **MobileNetV2:** Dropout rate and dense layer units

The tuned models were trained and evaluated for enhanced performance.

**3.6 Evaluation Metrics**

The following metrics were used:

* **Accuracy**: Correct predictions / total predictions
* **Precision**: TP / (TP + FP)
* **Recall**: TP / (TP + FN)
* **F1-score**: Harmonic mean of precision and recall
* **Confusion Matrix**: Matrix showing predicted vs. actual classes

**4. Experiments & Results**

**4.1 Custom CNN Results (Untuned)**

* Training Accuracy: 84.3%
* Validation Accuracy: 86.6%
* Test Accuracy: **80.1%**
* Test Loss: 2.0730
* F1-Score: 0.80

**Confusion Matrix**:

* Digestive: Precision 0.83, Recall 0.79
* Indigestive: Precision 0.77, Recall 0.82

**4.2 Pretrained Model Results**

**VGG16**:

* Test Accuracy: **86.6%**
* Precision: 0.87, Recall: 0.87, F1-Score: 0.87

**MobileNetV2**:

* Test Accuracy: **98.2%**
* Precision: 0.98, Recall: 0.98, F1-Score: 0.98

**ResNet50**:

* Test Accuracy: **64.6%**
* Precision: 0.65, Recall: 0.65, F1-Score: 0.65

**4.3 Tuned Models**

**Tuned Custom CNN**:

* Test Accuracy: **95.7%**
* Precision: 0.96, Recall: 0.96, F1-Score: 0.96

**Tuned MobileNetV2**:

* Test Accuracy: **98.2%**
* Precision: 0.98, Recall: 0.98, F1-Score: 0.98

**5. Analysis & Discussion**

The custom CNN model performed well, demonstrating its ability to learn effective features from limited data. However, its performance was surpassed by pretrained models, especially MobileNetV2. This supports the hypothesis that transfer learning significantly boosts performance by leveraging pre-learned features from large datasets.

Among the pretrained models, MobileNetV2 outperformed both VGG16 and ResNet50, owing to its depthwise separable convolutions which reduce parameters while maintaining accuracy. Interestingly, ResNet50 underperformed, possibly due to overfitting or incompatibility with the specific features of waste images.

Hyperparameter tuning dramatically improved the custom CNN model, raising test accuracy from 80.1% to 95.7%. This shows the importance of optimizing architectural and training parameters.

Visual analysis through confusion matrices revealed that misclassifications mostly occurred between borderline classes, especially where items shared visual characteristics (e.g., food containers that resemble both categories).

Training curves showed good convergence, with MobileNetV2 achieving near-perfect validation accuracy with minimal overfitting. The tuned models, especially MobileNetV2, demonstrated robustness and generalization.

**6. Conclusion & Future Work**

This project successfully demonstrates the potential of CNNs and transfer learning for waste classification. While the custom CNN model achieved satisfactory performance, pretrained models, especially MobileNetV2, delivered exceptional accuracy with minimal training.

Future directions include:

* Extending classification to multiple waste categories
* Deploying models on edge devices for real-time sorting
* Incorporating Explainable AI (XAI) tools like Grad-CAM to visualize feature importance
* Exploring more lightweight architectures for embedded systems

In summary, this study lays the foundation for intelligent waste management systems that are fast, scalable, and highly accurate.

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