**Abstract**

**Introduction**

Environmental sustainability is greatly impacted by waste management, a crucial worldwide concern. Efficient recycling, avoiding landfill trash, and lowering environmental contamination all depend on properly classifying waste items. However, classifying garbage by hand is frequently labor-intensive, time-consuming, and prone to errors. In recent years, automated waste classification systems have drawn a lot of interest as a solution to these problems.

In this work, we investigate how Convolutional Neural Networks (CNNs) and cutting-edge deep learning architectures can be used to automatically classify waste into 12 different categories: biological, trash, brown-glass, cardboard, clothing, green-glass, metal, paper, plastic, shoes, and white-glass. In order to reflect actual waste situations, these categories were chosen to include a wide variety of recyclable and non-recyclable products.

In picture classification challenges, deep learning models like MobileNetV2, VGG16, EfficientNet, and ResNet have shown impressive performance. These models are appropriate for trash classification tasks because they use their unique architectural features to extract significant patterns and features from visual data. For example, ResNet adds residual connections to address the issue of vanishing gradients in deep networks, whereas MobileNetV2 is renowned for its computational efficiency, which makes it perfect for contexts with limited resources. As early deep learning benchmarks, VGG16 and EfficientNet offer a solid basis for feature extraction and categorization. Our goal is to determine the best architecture for trash classification by using and contrasting these models.

This research paper presents a detailed comparative analysis of these CNN-based architectures, evaluating their performance in terms of accuracy, computational efficiency, and generalization ability. The dataset used for this study consists of high-quality labeled images representing the 12 waste categories. Through extensive experiments and evaluation, we aim to develop a robust waste classification system that can contribute to automated waste management solutions. The findings of this study have the potential to enhance waste recycling processes, reduce human intervention in waste segregation, and promote environmentally sustainable practices. Furthermore, the insights gained from this research can be applied to other image classification domains, showcasing the versatility and utility of deep learning architectures in addressing real-world challenges.

**Literature Review**

**Methodology**

The dataset utilized for waste classification in this study has been sourced from Kaggle. It comprises 12 distinct classes, namely: 'plastic' (865 images), 'green-glass' (629 images), 'shoes' (1977 images), 'biological' (985 images), 'clothes' (5325 images), 'white-glass' (775 images), 'cardboard' (891 images), 'paper' (1050 images), 'trash' (697 images), 'battery' (945 images), 'metal' (769 images), and 'brown-glass' (607 images). Figure 1 provides sample images from the dataset, while Figure 2 depicts a bar graph representing the distribution of images across the classes.

Further, the dataset was divided into training and testing subsets in an 80:20 ratio. This split resulted in the training dataset containing 12,409 files across the 12 classes, while the testing dataset comprised 3,106 files.

Distribution of Images in the Training Dataset:

* Battery: 756 images
* Biological: 788 images
* Brown-glass: 485 images
* Cardboard: 712 images
* Clothes: 4260 images
* Green-glass: 503 images
* Metal: 615 images
* Paper: 840 images
* Plastic: 692 images
* Shoes: 1581 images
* Trash: 557 images
* White-glass: 620 images

In contrast to other classes, the 'clothing' class had a disproportionately large number of photos in the training dataset, indicating an imbalance. We used the ImageDataGenerator to increase the size of the minority classes to equal that of the majority class (the "clothes") in order to rectify this imbalance. To provide varied synthetic samples for the minority classes, augmentation techniques like flipping, zooming, rotating, and brightness modifications were used. Class weights were calculated using the dataset's original distribution prior to data augmentation. In order to prevent the model from becoming biased in favor of the majority class, these weights were applied during model training to penalize misclassifications of minority classes more severely. The model was then trained using the enlarged training dataset and the calculated class weights.

By using class weights to adjust for the original data distribution, this method made sure the model was trained on a balanced dataset. As a result, the model's accuracy and generalization across all classes improved.

**Result**

**Conclusion**

**Future Scope**

**References**