Enhancing biodegradable waste management in Mauritius through real-time computer vision-based sorting

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ABSTRACT

Mauritius faces a significant waste management challenge due to the indiscriminate mixing of biodegradable and non-biodegradable waste. This practice hinders proper recycling and composting efforts, contributing to environmental pollution and resource depletion. This research proposes a computer vision-based system for real-time classification of waste into biodegradable and non-biodegradable categories. Transfer learning approach based on deep learning models, specifically DenseNet121, MobileNet, InceptionV3, VGG16 and VGG19 were evaluated with two different classifiers, the K-nearest neighbors (KNN) and support vector machine (SVM). Our experiments demonstrate that the MobileNet paired with SVM achieves a classification accuracy of 97% for detection in realtime. Compared to other studies, our results demonstrate better performance and realtime classification capabilities through the implementation of a prototype, facilitating automatic sorting of waste.

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1. INTRODUCTION

Mauritius, as a small island developing state, faces significant waste management challenges exacerbated by limited space and a high population density. The island generated 1.4 million tonnes of waste, exceeding the global average in 2020 [1]. To address this, various approaches have been implemented, including a solid waste management strategy focusing on resource recovery, energy generation, and community engagement was implemeneted [2], [3]. Despite such efforts, landfill remains the primary disposal site, handling 97% of the waste, both organic and non-organic [4]. This underscores the urgent need for improved waste separation and management solutions.

The diversity of waste types, influenced by seasonal changes, economic factors, and cultural practices, makes general waste management approaches inadequate, requiring customized solutions. The presence of both centralized and decentralized waste management systems, including informal sector involvement, contributes to inconsistencies and data limitations [5]. To overcome these challenges, this study aims to develop a deep learning prototype, using computer vision to accurately classify waste into biodegradable (bio) and non-biodegradable (non-bio) categories. With the integration of realtime recognition capabilities, the proposed system can assist automatic sorting and improve recycling rates and resource recovery, aligning with Mauritius' commitment to achieving the United Nations Sustainable Development Goals (UN SDG).

Effective waste management is crucial for sustainable development. Separating trash into bio (organic) and non-bio (inorganic) groups is necessary for recycling, reducing landfill dependency, and disposal strategies [6]. However, the diversity of waste material varying in composition, shape, size, texture, and color presents a significant challenge to traditional classification methods, as per Mohammed *et al.* [7]. Deep learning technique with its potential to learn complex patterns from large datasets, including images, can offer a viable solution. Nevertheless, variability in waste appearance due to differences in composition, cultural practices, and geographical locations requires robust algorithms that can generalize across diverse datasets [8]. Traditional methods often struggle with manual feature extraction, leading to inconsistent performance across different waste types [9]. Nevertheless, deep learning models can face the risk of overfitting when trained on limited datasets by capturing too much details. This can result in models that underperform when classifying new, unseen images [10]. Numerous studies have applied convolutional neural network (CNN) algorithms for automatic waste classification, achieving varying levels of accuracy [11]-[13]. Training CNNs from scratch can be time consuming and resource intensive, particularly for large datasets [14]. Transfer learning, which involves the fine-tuning of pre-trained models on specific datasets, has proven to be a valuable approach. Studies have shown that transfer learning can significantly improve classification accuracy while reducing training time. Yang and Thung [15] used a pre-trained InceptionV3 model to classify waste images from the TrashNet dataset, achieving a remarkable accuracy of 83%. Similarly, Bianco *et al.* [16] employed the ResNet50 architecture pre-trained on ImageNet, for the classification of municipal solid waste images, resulting in an accuracy of 95%. These studies highlight the potential of transfer learning in reducing training times and improving model performance. Ferreira *et al.* [17] investigated the use of transfer learning for waste classification by fine-tuning pre-trained models, such as VGG16, ResNet50, and InceptionV3, on a waste classification dataset. They achieved an accuracy of 92% using the ResNet50 architecture, demonstrating the effectiveness of transfer learning in capturing intricate waste features. Rakhra *et al.* [18] study applied transfer learning using the MobileNetV2 architecture for waste classification using a customized ImageNet-pre-trained MobileNetV2 achieving an accuracy of 89%. In 2022, Razzaq *et al.* [19] explored a pre-trained DenseNet12, achieving an accuracy of 93%, thereby demonstrating the model's ability to capture intricate waste features. Recent advancements in deep learning, such as the EfficientNet architecture, have further enhanced waste classification performance. Vijayakumar *et al.* [20] achieved 91% accuracy on the WasteNet dataset using EfficientNet-B0. Transfer learning, with pretrained models like VGG16, ResNet50, and MobileNet, is particularly effective for waste classification. It has been noted that these models can achieve high accuracy, often exceeding 90%, while reducing training times compared to models built from scratch.

Thereby, using transfer learning for waste classification is particularly relevant for Mauritius, where traditional waste management methods face challenges due to diverse and variable waste materials.

2. METHOD

2.1. Dataset and pre-processing

The "Non-Biodegradable and Biodegradable Waste Dataset " dataset [21] has been chosen as the images closely resemble the types of waste found in the Mauritian context. The dataset comprises of approximately 16,726 images, categorized primarily into two groups, Biodegradable and Non-biodegradable waste, equally distributed. Biodegradable waste encompasses organic materials such as food scraps, plants, and fruits, which naturally decompose and can be converted into compost. This process is essential for recycling nutrients and minimizing landfill use. Conversely, non-biodegradable waste includes substances like plastics and metals that do not decompose naturally.

All the images have been resized to 150 x 150 pixels, and the following data augmentation approaches have been applied: normalizing pixel values, rescaling by 1/255, shear range and zoom of 0.2, and horizontal flipping. A validation split of 20% has been reserved for evaluation.

2.2. Approach

Our approach consists of using traditional pre-trained CNNs and explore the effect of different classifiers on their performance. We designed our experiments to use VGG16, VGG19, MobileNet, DenseNet121, and InceptionV3 with two classifiers, the K-nearest neighbors (KNN) and support vector machine (SVM). The process starts by training the CNN models on the well-established ImageNet dataset in order to establish a baseline. Then, experiments with KNN and SVM are conducted as classification layers. KNN is known to improve accuracy by clustering similar data points and reducing noise, especially in complex datasets [22]. SVM algorithm excels in high-dimensional spaces by maximizing the margin between the classes, and can therefore identify the most effective hyperplane for class division [23].

2.2.1. Base models

Each pre-trained model is adapted for binary classification by importing their pre-trained weights on the ImageNet dataset, excluding the top classification layer, adding custom layers (GlobalAveragePooling2D to reduce spatial dimensions, a Dense layer with 512 units and ReLU activation, an optional Dropout layer with a rate of 0.5 for VGG16 and VGG19, and an output layer with a single unit and sigmoid activation). All layers of the base model are then frozen.

The models are compiled using the Adam optimizer with a learning rate of 0.0001, binary cross-entropy loss function, and accuracy as the evaluation metric, and trained for up to 50 epochs with callbacks for saving the best-performing model and halting training to prevent overfitting.

2.2.2. Customized models

Instead of using the models for direct classification, we focus on these two custom functions to reshape the feature maps generated by the models:

- Transfer Learning with KNN: KNN compares a new image to its most similar neighbors from the training data (using 5 neighbors for balanced accuracy) to determine its class. This simple yet powerful approach is widely used in tasks like facial recognition [24].
- Transfer Learning with SVM: This technique leverages feature maps to classify images using an SVM with a linear kernel. Other kernels can be explored for further optimization. SVMs excel in various image analysis tasks like object detection [25].

3. RESULTS AND DISCUSSION

3.1. Experiments

Results from the experiments are presented in Table 1. A comparison of the different approaches shows significant improvement in performance. While DenseNet121 and InceptionV3 achieve the highest training accuracies at 99.79% and 99.03% respectively, their test accuracies are only 51.0%, indicating potential overfitting. This discrepancy between training and testing accuracy is observed across all models, suggesting the need for further tuning and regularization techniques to improve generalization.

Table 1. Experimental results

Model	Epoch	Train accuracy %	Test accuracy %	Test accuracy %	Test accuracy %
		Without Classifier	Without Classifier	With KNN Classifier	With SVM Classifier
Mobile Net	14	98.89	50.0	95.0	97.0
VGG16	12	95.9	49.0	89.0	95.0
VGG19	20	95.89	50.0	90.0	90.0
InceptionV3	16	99.03	51.0	94.0	96.0
DenseNet121	20	99.79	51.0	96.0	94.0

When paired with classifiers, the models exhibit varying performance. MobileNet achieves the best test accuracy of 97% with the SVM while InceptionV3 performs quite well with SVM, reaching 96.0% test accuracy. The VGG models demonstrate lower training and testing accuracies compared to the other models. The DenseNet121 demonstrates a performance of 96% with the KNN classifier, as compared to only 51% without any classifier. The choice of classifier is significant, with SVM generally outperforming KNN for most models. However, the training accuracy of the DenseNet121 model at 99.79% and InceptionV3 at 99.03% clearly exhibit signs for overfitting.

The experiments employed early stopping to prevent overfitting and ensure model performance during validation. The batch size, which determines the number of images generated for each step of an epoch, increased throughout the experiments. The number of epochs and steps per epoch varied, with fixed values creating trade-offs between early stopping and overfitting risks. The results suggest that larger batch sizes enhance feature identification capabilities by exposing models to a greater variety of images and augmentations during training, but this is constrained by memory limitations, restricting the batch size to a maximum of 256.

The classification report for the best-performing, MobileNet model with SVM Classifier demonstrates a high precision (0.96 for Bio, 0.99 for Non-bio) and recall (0.99 for Bio, 0.96 for Non-bio), leading to an F1-score of 0.97 for both classes. Both categories showed equal support with 1672 instances each, contributing to an overall accuracy of 97%. The consistent macro and weighted averages, both at 0.97, underscore the balanced and effective performance of this model combination across the categories.

The confusion matrix from Figure 1, indicates a strong performance in both classes with high numbers of true positives. The model has a higher rate of false negatives for 'Biodegradable', where it misclassified 75 instances as 'Non-biodegradable', compared to 17 instances of 'Biodegradable' misclassified as 'Non-biodegradable'. This suggests the model might be slightly more conservative in predicting items as 'Non-biodegradable', leading to a few more errors in classifying 'Biodegradable' items incorrectly. Overall, the model achieves high accuracy in distinguishing between the two classes.

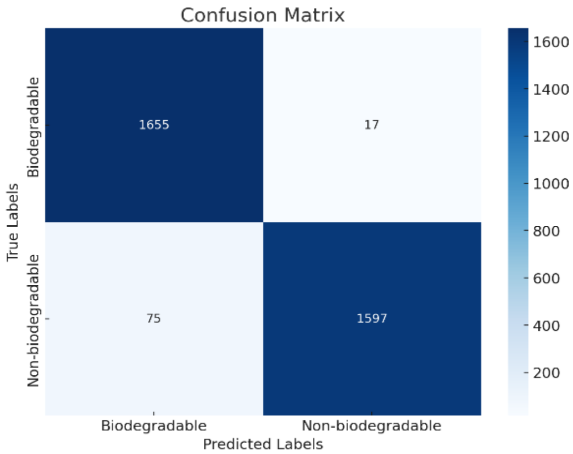

Figure 1. Confusion matrix for MobileNet with SVM

3.2. Real-time application

The MobileNet model with SVM classifier model was integrated into a web application for testing in real time scenarios. The system was designed to work with background images, and out of several possible waste objects, accurate results were noted. Figure 2 shows some of the test cases and the responses of the system.

Figure 2. Real time test cases

3.3. Comparative analysis

In contrast, Rad *et al.* [26] enhanced performance by incorporating batch normalization and dropout layers, achieving an 87% accuracy across six waste classes. While these studies underscore CNNs' potential, they also reveal limitations in training from scratch, such as time consumption and resource demands, especially for vast datasets [14]. Yang and Thung [15] achieved 83% accuracy with the InceptionV3 model, while Bianco *et al.* [16] reported 95% accuracy using the ResNet50 architecture. These results illustrate transfer learning's efficiency in capturing intricate waste features. Recent studies have extended these findings. Ferreira *et al.* [17] demonstrated significant accuracy improvements through transfer learning, achieving 92% with ResNet50. Rakhra *et al.* [18] further validated MobileNetV2's effectiveness in real-time applications, achieving 89% accuracy, and Razzaq *et al.* [19] highlighted DenseNet121's capabilities with 93% accuracy.

By integrating KNN and SVM with transfer learning models, we have achieved higher accuracy levels than the mentioned previous works, significantly surpassing traditional CNN benchmarks. Additionally, the inclusion of real-time recognition capabilities distinguishes our method from many existing models, enabling immediate waste sorting and thereby improving recycling processes and resource recovery rates.

4. CONCLUSION

This study demonstrates the effectiveness of our classification approach for waste management. The pre-trained MobileNet combined with the SVM classifier, achieved an accuracy of 97% in classifying biodegradable and non-biodegradable waste. This approach offers a better solution to traditional methods, enhancing recycling and resource recovery. While still a proof of concept, this approach can be integrated in a system of automatic waste classification. At this stage, the limitation remains the relatively high training accuracy, which can be resolved with more images, and the challenge of capturing several waste products from a video stream of images. Overall, the results highlight the potential of machine learning to address waste management challenges which can be adapted for Mauritius and other developing regions.

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AUTHOR CONTRIBUTIONS STATEMENT

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Geerish Suddul	✓	✓		✓	✓	✓			✓	✓		✓	✓	
Avitah Babajee	✓	✓	✓			✓	✓	✓	✓	✓	✓			
Nundjeet Rambarun	✓	✓	✓			✓	✓	✓	✓	✓	✓			
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C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data used for this study is available from Rayhan Zamzamy, on Kaggle: “Non- and-biodegradable waste dataset”. Source: https://www.kaggle.com/datasets/rayhanzamzamy/non-and-biodegradable-waste-dataset

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