A Comparative Analysis for Trash Classification

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***Abstract*—In the face of mounting solid waste and unsustainable management practices, traditional manual sorting methods fall short, posing health risks and hindering resource recovery. This study explores the potential of deep learning to revolutionize waste classification, evaluating four prominent models – VGG16, VGG19, DenseNet121 and EfficientNetB0 – for their accuracy in segregating waste images. Trained on both the public TrashNet dataset, EfficientNetB0 shines with an impressive 81% accuracy, surpassing DenseNet121's 79%. This demonstrates the potential of deep learning to address the intricate nuances of waste diversity, paving the way for automated sorting that reduces health risks, streamlines waste management, and fuels efficient recycling for a more sustainable future.**

***Index Terms*—EfficientNetB0, VGG16, VGG19, DenseNet121**

I. Introduction

In our modern world, continuous development of new products is driven by the global economy and population growth. The growing demand results in increased waste production, posing threats of environmental pollution and climate change. A 2020 OECD study revealed that two billion tons of urban trash were produced globally in 2016[1], averaging 270 kg per person.

Currently, over 3.5 million tons of trash are generated daily, and without intervention, this could escalate to 11 million tons by the end of the 21st century[2],potentially causing disposal issues. The United Press International predicts a 70% increase in global waste by 2050.[3].

According to the World Bank, only 13.5% of global waste is recycled, and approximately 33% is improperly discarded without initial classification.[4]. Incorrect classification is a significant contributor to environmental pollution, emphasizing the importance of proper trash sorting to protect the environment. Classifying trash before disposal not only addresses environmental issues but also enhances waste management efficiency. Manual classification, involving humans in the process, can improve trash recycling efficiency by up to 95%. However, dealing with large volumes of trash can be time-consuming and may pose risks of exposure to contaminated and hazardous substances.[5].

Automatic trash classification, utilizing various methods, is a valuable technique. Image-based classification stands out as an effective approach, applicable in numerous applications, including trash classification [6, 7].References. [8, 9] demonstrate the use of images and neural networks to classify bottles on a conveyor.

Our research primarily aims to develop an accurate automatic trash sorting method by enhancing existing datasets. Merging datasets is crucial to improving classification accuracy, enhancing processing plant efficiency, and reducing waste, considering employees may not sort everything with 100

To address challenges associated with large computational models, we adopt a lightweight network. This approach maintains characteristics with high efficiency and accuracy while minimizing computational costs and parameters. Our focus is on reducing feature dimensionality, retaining essential information, and avoiding over fitting, ensuring the model emphasizes waste image features with a minimal number of parameters.

II. Related Works

Correctly determining trash classification is essential for preventing environmental pollution, which is a demanding multidisciplinary task. With the help of developments in computer vision, machine learning, and artificial intelligence, numerous techniques for classification trash have been explored. such as cardboard, paper, glass, and plastic. These motivations have impelled several research

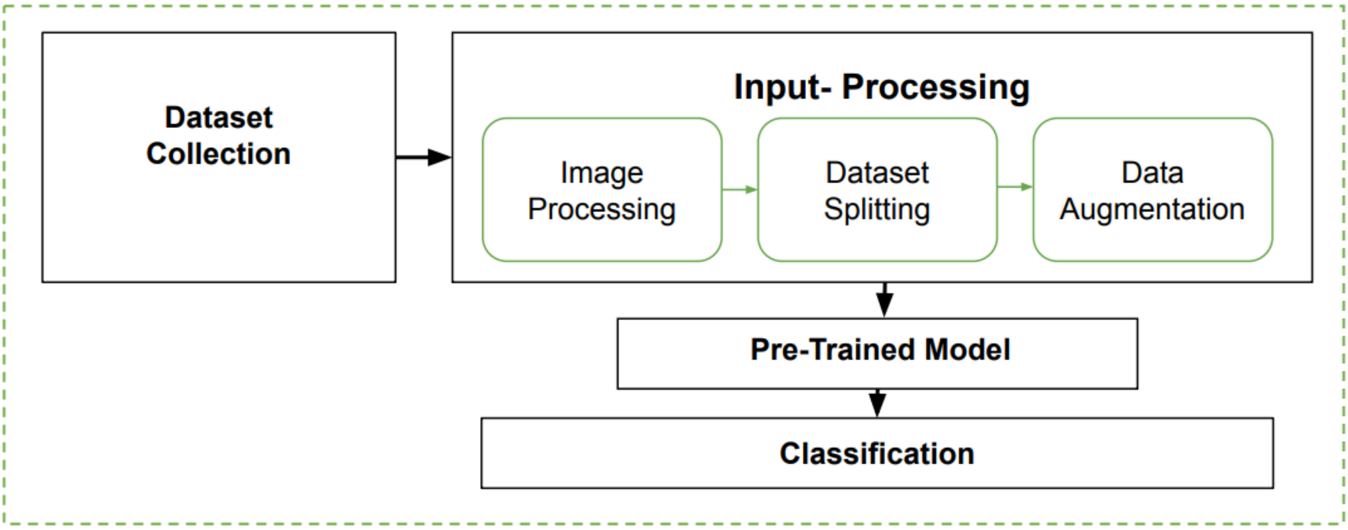

Figure 1: Overall work process of Trash Classification on Trash Images.

papers on trash classification. Here, we have summarized five such works that heavily influenced our investigations.

Mindy Yang et al.[10], proposed a computer vision-based system to classify images of single items of garbage or recycling into six categories: glass, paper, metal, plastic, cardboard, and trash. A new dataset of around 2400 images spread across the six classes, hand-collected by the authors and including data augmentation techniques like rotations and brightness changes.An SVM classifier using SIFT features and a bag of visual words approach, achieving 63% test accuracy. Future work includes improving the CNN, extending to classifying multiple objects in images/video to match real recycling facilities, expanding the dataset, and releasing it publicly.

Sekar Ayu Wulandari et al.[11], proposed a mobile app (”DjunkGo”) to help users identify and sort household waste types to facilitate recycling. The app uses image classification with a VGG16 deep neural network, achieving 90% accuracy in identifying 8 waste categories. - 7100 total images scraped from the web were used, with 2798 organic waste images making up the largest class. The model was deployed on an Android app allowing users to capture images of waste, automatically classify it, save it to lists, and potentially connect it to waste collectors. Evaluating model performance on real-world images. The current model was trained and tested on web images that may not reflect actual trash sorting use cases. Testing on more diverse real images could reveal limitations.

Dashun Zheng et al.[12], propose Focus-RCNet, a lightweight CNN architecture using depth-wise separable convolutions and knowledge distillation from EfficientNet-B4.- Evaluated on the TrashNet dataset, Focus-RCNet achieves 92% test accuracy with only 0.525 million parameters and 418 MFLOPs.1. Limited evaluation datasets. The model was only evaluated on the TrashNet dataset with 6 categories. Additional datasets with more diverse and granular waste categories could reveal limitations.

Hani Abu-Qdais et al.[13], proposed an automated waste classification model using image processing and machine learning techniques to improve waste management. Models tested include traditional machine learning models (SVM, Random Forest) and deep learning convolutional neural networks (CNN). Public dataset TrashNet (2495 images, 6 classes) and locally collected Jordan waste dataset (2656 images) were used.JONET achieved 96.06% accuracy on TrashNet and 94.42% on the local dataset. Traditional ML models performed significantly worse. Real-world factors like occlusion, poor lighting, dirt on items etc. also need to be accounted for through robust models and representative datasets

Ryotaro Harada et al.[14], propose a trash detection algorithm suitable for mobile robots using an improved YOLO model. On their dataset, the models achieve 85-97.5% average precision and over 88% F1 score. On the marine trash dataset, YOLOv5-ghost achieves 86.4% average precision for plastics. The proposed trash detection system shows promise for real-time usage on autonomous mobile robots for trash pickup. Future work includes expanding trash types, improving models, and adding distance estimation. Narrow trash categories: Only 4 common trash types were considered. Expanding categories could improve the applicability

Given these works, we can conclude that there is still room for exploration for developing more accurate deep-learning models for trash classification. We evaluated existing deep CNN models with pre-trained models on a merged image dataset which is more robust and includes various trashes to achieve accurate detection of trash classification. As a result, we classified 12 classes. In this paper, we will explore and compare four deep CNN models on trash classification using this new dataset and determine its effectiveness in detecting trash classification.

III. Methodology

This section describes the methodology of trash classification on trash images in order to retrieve the most relevant and perfect trash classification. The proposed process works in four steps as shown in Figure. 1 First, the Dataset Collection module extracts data (images) from the merged dataset. Second, Input processing does some image processing and augmentation to prepare for the next process. Next, the processed images are used to train the models utilizing pre-trained model. Finally, we used the trained models to classify trash for evaluation. In detail, the methodology is explained below.

A. Dataset Collection

In the previous trash classification studies, some researchers created several datasets, such as the Garbage Classification dataset [15] and Garbage Classification dataset [16]. The Garbage Classification dataset consists of six types of classes. The Garbage Classification dataset consists of twelve categories. We merged two datasets to make a robust dataset which can classify trash with more accuracy and precision. Also, we increase the number of data so that can train the model with more data to classify trash more accurately. Our new dataset consists of twelve categories, which contain more types of trash. The twelve categories are defined as battery, biological, brown-glass, cardboard, clothes, glass, green-glass, metal, paper, plastic, shoes, trash, and white-glass.

B. Input Processing

Before training the models, images of our dataset were transformed into 3D arrays and resized to (224 x 224) dimensions with OpenCV. After that, we divided them into two Numpy arrays using Numpy[17]. One is for data and another is for associated class. The processed dataset was split into training and testing sets by a ratio of 80:20. Training part of the dataset was augmented before training the models. We used experimental Keras pre-processing layers in this work for data augmentation [18]. Necessary libraries were loaded and augmentation techniques like rotation, flipping, and zooming were used to develop a basic augmentation model.

C. Pre-Trained Model

The goal behind the pre-trained model is to conduct classification on a related domain by fine-tuning a model that has already been pre-trained on a big dataset using a comparatively small dataset[19].In our work, we used deep CNN models pre-trained on the ImageNet dataset. We have trained and tested four deep CNN structures on our dataset which are: EfficientNetB0, VGG16, VGG19 and DenseNet121. Our decision to choose these Convolutional Neural Network (CNN) models for this task is supported by evidence of their successful completion of image recognition tasks [10, 11, 14]. These models are used as baselines for our task. We froze the feature extraction parts of these models and removed the existing top layers. Then we added a new fully connected hidden layer of 128 neurons and a softmax output layer. The hidden layer has a rectified linear unit activation function and randomly-initialized parameters. We set 12 neurons in the output layer for the 12 target classes of our dataset. Among 6000 images, we used 80% of our dataset for training. Each model was trained for 30 epochs with a batch size of 32. Furthermore, we utilized the Adam optimizer with a low learning rate, to stabilize the training process and help the fully connected layers converge to optimal solutions.

D. Classification

The classification results were obtained and used to evaluate the performance of the trained CNN models on our new dataset. Our dataset was divided into training and testing sets. Among the 18054 images, 20% images are used to test the models after training to classify 12 trash classes. Further analysis of the models is done in section IV.

IV. Experimental Results

This section presents the performances of the selected models as per the results obtained from training and testing the pre-trained models. We conducted our experiments using high-performance systems equipped with GPU support servers for efficient training and analysis of the models. The evaluation involved comparing model performance with and With data augmentation. Metrics such as classification accuracy, precision, recall, and F1-score were utilized to analyze the classification capabilities of the models. Tables I to V illustrate performance metrics for the mentioned models with data augmentation on our trash dataset.

Table I: VGG19 With Data Augmentation

Class	Precision	Recall	F-Measure
Battery	0.92	0.91	0.92
Biological	0.93	0.92	0.92
Brown-Glass	0.73	0.62	0.67
Cardboard	0.92	0.85	0.89
Clothes	0.92	0.97	0.94
Glass	0.25	0.30	0.27
Green-glass	0.83	0.63	0.71
Metal	0.62	0.89	0.67
Paper	0.85	0.85	0.85
Plastic	0.66	0.66	0.66
Shoes	0.93	0.84	0.88
White-Glass	0.44	0.39	0.42
Weighted AVG	0.75	0.73	0.73
Accuracy	0.73		

We compared weighted averages of precision, recall, and F1 score with data augmentation in Figure 2. If we

Table II: EfficientNetB0 With Data Augmentation

Class	Precision	Recall	F-Measure
Battery	0.96	1.00	0.98
Biological	0.97	0.96	0.97
Brown-Glasss	0.79	0.69	0.74
Cardboard	0.92	0.91	0.91
Clothes	0.97	0.99	0.98
Glass	0.24	0.24	0.24
Green-glass	0.82	0.84	0.83
Metal	0.95	0.83	0.89
Paper	0.90	0.91	0.91
Plastic	0.80	0.82	0.81
Shoes	0.97	0.94	0.95
White-Glass	0.52	0.62	0.57
Weighted AVG	0.81	0.81	0.81
Accuracy	0.81		

Table III: DenseNet-121 With Data Augmentation

Class	Precision	Recall	F-Measure
Battery	0.98	0.95	0.97
Biological	0.86	0.94	0.90
Brown-Glass	0.64	0.71	0.68
Cardboard	0.96	0.87	0.91
Clothes	0.99	0.94	0.96
Glass	0.32	0.32	0.32
Green-glass	0.71	0.84	0.77
Metal	0.89	0.76	0.82
Paper	0.82	0.93	0.87
Plastic	0.75	0.79	0.77
Shoes	0.98	0.96	0.97
White-Glass	0.64	0.48	0.55
Weighted AVG	0.79	0.79	0.79
Accuracy	0.79		

consider the weighted average of the F1 score in Figure 2, EfficientNetB0 consistently delivered higher performance (0.81) than most other models on augmented data. DenseNet121 showcased commendable performance (0.79), indicating its reliability. VGG16 displayed potential with a weighted F1 Score of 0.74, while VGG19, lagged behind (0.73) showing its weakness in data augmentation.

In Figure 3, The accuracy of models is compared by classifying the trash utilizing our dataset. We can see that EfficientNetB0 had the highest accuracy (0.81), followed by DenseNet121 (0.79) with data augmentation. With accuracies of 0.74 and 0.73, respectively, VGG16 and

Table IV: VGG16 Without Data Augmentation

Class	Precision	Recall	F-Measure
Battery	0.86	0.94	0.90
Biological	0.86	0.95	0.90
Brown-Glass	0.68	0.61	0.64
Cardboard	0.94	0.78	0.85
Clothes	0.96	0.95	0.96
Glass	0.26	0.28	0.27
Green-glass	0.82	0.64	0.72
Metal	0.73	0.78	0.76
Paper	0.81	0.87	0.84
Plastic	0.70	0.74	0.72
Shoes	0.91	0.91	0.91
White-Glass	0.48	0.46	0.47
Weighted AVG	0.75	0.74	0.74
Accuracy	0.74		

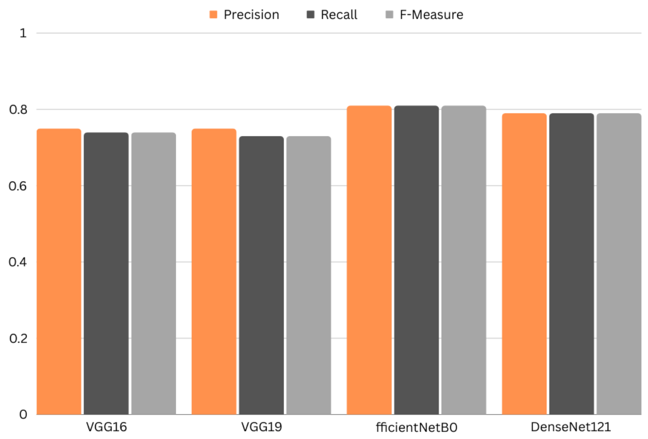

Figure 2: The Comparison Study of Different Models Precision, Recall and F-Measure With Data Augmentation.

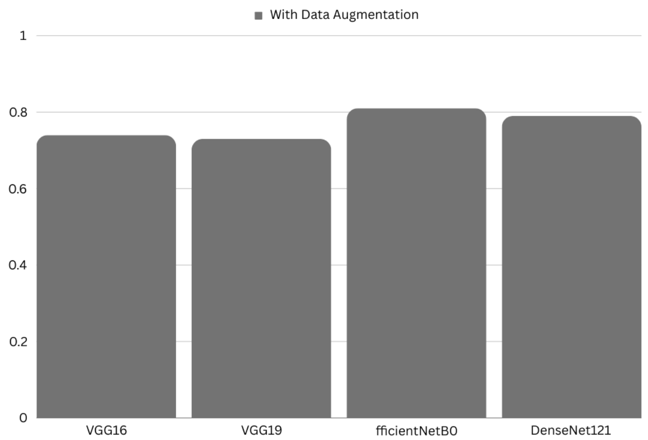

Figure 3: The Comparison Study of Different Models Accuracy With Augmentation.

VGG19 also performed well.

In a nutshell, after analyzing Figures 2 and 3, we conclude that EfficientNetB0 are suitable when data augmentation is applied.

V. Conclusion and Future Works

This research work used pre-trained model on actual images of trash. We make a dataset of over 6000 images into safe and distracted driving scenarios. In this study, we employed four deep CNN models and evaluated them to ensure the quality of trash Classification. The experiment result depicts that EfficientNetB0 exceeded other models with 81% accuracy on test data with augmentation.

Our study has certain limitations. The model's performance could be impacted by the class imbalance. This imbalance, along with the small dataset size of 6000 photos, may make it difficult to generalize trash classification. Another limitation is that our dataset fails to cover every region's images, which might cause problems when attempting to classify trash in different regions. Despite these limitations, our research highlights the necessity for further enhancements in trash classification. Future research should focus on improving class balance by increasing the dataset size enriching the dataset with more trash images and make more diverse in different regions.

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