A Transfer Learning Approach For Efficient Classification of Waste Materials

Abstract—**The authors of this study used the Waste Classification Dataset to build a highly accurate model that classified rubbish into two distinct groups in an effort to address the problem of waste classification for various classes of discarded material. VGG16, MobileNetV2, and a baseline 6 layer CNN model were used in the experiments. The VGG16 model achieved 96.00% accuracy, while the MobileNetV2 model achieved 95.51%, and the baseline CNN model achieved 90.61% accuracy. The garbage in the input picture can be correctly classified by the neural network model. The experimental findings are compared to other studies in the same area. This investigation's experimental applications are geared on facilitating more precise trash classification.**

Index Terms—**VGG16, CNN, MobileNetV2, Transfer Learning, waste classification, deep learning**

I. Introduction

If we do not take action to prevent it, the accumulation of non-recyclable waste in landfills around the world and the length of time it takes for the majority of its materials to biodegrade will affect our lifestyle in the near future. Accumulation of waste can facilitate the transmission of disease by flies, mosquitoes, and other insects. Landfill construction and deforestation destroy natural habitats and contaminate soil and water with toxic chemicals. Pollution can also wreak havoc on the food chain, leading to an increase in human and animal health problems. There are three primary reasons why waste has accumulated over the past fifty years. First, there are not enough recyclable items on the market, despite the fact that businesses are developing more environmentally friendly products. Overpopulation is the second contributing factor. A large population requiring a variety of resources poses a complex logistical challenge when dealing with waste generation; consequently, more recyclable products end up in landfills or the ocean, affecting tens of thousands of marine species. Third, the lack of involvement of our society in issues such as climate change. The global population generates 7 to 9 billion tons of waste annually, of which 70 per cent is mishandled and ends up in landfills, polluting natural environments and posing new health risks such as microplastics in the ocean. This is the total amount of used, unwanted, and discarded items created by humans. Municipal Solid Waste (MSW) is composed solely of trash from urban areas and their influence zones. MSW accounts [1] for approximately 33% of the 2 billion tons of urban waste produced annually. Each individual generates 0.1 to 4.5 kg of waste per day, with an average of 0.7 kg. Population growth and the need for intensive use of natural resources for industrial development and the survival of our civilization are expected to increase MSW to 3,4 billion tons by 2050. A model of a circular economy that is fully implemented could solve the accumulation problem, climate change, and supply crises in certain regions of the world. Its three principles (reducing waste and pollution, reusing materials, and regenerating nature) result in a more efficient method of managing natural resources, which are not always valued. The execution of a complex plan is hampered by technological, engineering, and logistical constraints.

In this paper we have applied both transfer learning and convolutional neural network (CNN) approches to compare their performance on waste classification dataset. VGG16 and MobileNetV2 have been fine tuned to their best performance. In what follows, I will outline how the remainder of this paper is structured. In Section 2, we provide a brief overview of the existing literature on waste classification; in Section 3, we explain the study methodology, the structure of the deep learning model of waste classification, the transfer learning technique, and the model assessment procedure. The experimental findings and model comparison are presented in Section 4. Section 5 concludes with a brief summary and future projections.

II. Related Works

As a burning issue for climate change, waste management has grown to be a significant concern in recent years. Waste management is directly impacted by climate change. Recycling, reuse, and waste reduction are essential practices for effective waste management. Waste classification is required in the modern era in order to manage waste and carry out these activities with the aid of technology. Many researchers have suggested various methods to accumulate this process, with machine learning and deep learning being the most popular. Olugboja Adedeji and Zenghui Wang [2] have discussed a system in which a 50-layer residual Convolution Neural Network (ResNet-50) has been proposed to classify trash images into a variety of different groups. The proposed model makes use of Gary Thung and Mindy Yang's trash image dataset [3], which they developed in order to facilitate the model. Without involving any humans in the process, this method achieved an accuracy of 87% when categorizing images of trash. ConvNext was the main architecture used in a different study [4] to categorize various waste images. The proposed Mask R-CNN with Convnext by the authors outperformed the currently used waste classification techniques. The study used a customized dataset that was collected and consisted of 1660 images, with about

400 images per class. Waste is divided into four categories: dry waste, wet waste, hazardous waste, and recyclable waste. The authors claim to achieve 79.88% accuracy in waste classification using their method. An approach to classifying solid waste using five layer DCNN architectures was suggested in [5], which was written by its author. When classifying the waste dataset, both a four-layer and a five-layer deep convolution neural network architecture were utilized; however, the five-layer architecture performed significantly better than the four-layer architecture. After being cleaned, the images in the waste dataset, which included pictures of paper, glass, plastic, and organic waste, were converted to a size of 224 by 224 pixels. According to the findings of this research, the DCNN architecture, which consists of various layers, was able to achieve 70% accuracy when distinguishing between various types of waste.

With regard to performing convolutional neural networks on a waste image dataset, Qiang Zhang and his co - authors [6] primarily focused on a DensNet169 pre-trained model and transfer learning approach. NWNU-TRASH has used the waste image dataset to examine the model. This dataset, which the authors claim is well balanced and diverse, consists of 18911 images of various classes. The image classification models AlexNet, VGG, and GoogLeNet were chosen for this study to use on this dataset. Accordingly, AlexNet, VGG 16, and GoogleNet V2 had accuracy scores of 68.78%, 70.12%, and 75.42%. The DenseNet169 deep learning model was also tested by the authors, both with and without a transfer learning strategy. The outcomes demonstrate that accuracy of 82.80% was significantly higher with the use of DenseNet169 with transfer learning than the other approaches. This analysis demonstrates that DenseNet169, following transfer learning, is a better image classification algorithm.

III. Methodology

A. Dataset Description

There are 24,705 photos in the dataset, split evenly between organic (13,880) and recyclable (10,825) solid trash. This dataset is known as "Waste Classification Dataset" [7]. These data have been reorganized and represented from the original dataset created by Sashaank Sekar and hosted at https://www.kaggle.com/techsash/waste-classification-data. Out of the first 25,077 photos in the Kaggle dataset, 13,966 are organic and 11,111 are recyclable. Figure 1 shows some the sample data from our dataset.

B. Dataset Preprocessing

To facilitate training, testing, and validating our deep learning models, we have shrunk our photos to 224 × 224. We have also separated our data into a training set, a validation set, and a test set. There were a total of 19764 pictures in our training set, 2470 in our validation set, and 2471 in our test set. Our models are complete after training and validation on the data we provided. The models never saw the test set before, but it was used to compare their results using a variety of metrics.

Fig. 1. Sample images from datset. Organic (upper), and Recyclable (bottom)

As a solution to the problem of our dataset's lack of data, we have normalized our models by dividing the pixel values by 255 in order to get better accuracy from the models, and we have enhanced the photos.

C. Model Architectures

In this study, we used a 6 layer baseline convolutional neural network (CNN) in addition to two pretrained convolutional neural network (CNN) models: VGG16 [8] and MobileNetV2 [9]. For the models, we have used the pretrained weights obtained from ImageNet. In order to eliminate any kind of bias during our quantitative comparison of the different models, we have used the exact identical process to customize each of these three models so that they can categorize garbage. An Adam optimizer with a learning rate of 0.00001, binary cross entropy as the loss function, and a sigmoid activation function were used in the output layer, which was comprised of 2 neurons.

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IV. Result Analysis

By making predictions on our test set, we have evaluated the efficacy of our models using quantitative performance evaluation metrics such as accuracy (1), precision (3), recall (3), and f1 score (4) and confusion matrix.

$$Accuracy = \frac{T_N + T_P}{T_P + F_P + T_N + F_N} \tag{1}$$

Here, TN = True negative, TP = True positive, FN = False negative, FP = False positive.

$$Precision = \frac{T_P}{T_P + F_P} \quad (2)$$

Here, TP = True positive, FP = False positive.

$$Recall = \frac{T_P}{T_P + F_N} \quad (3)$$

Here, TP = True positive, FN = False negative.

$$F1Score = \frac{2 * Precision * Recall}{Precision + Recall} \quad (4)$$

A comparative analysis between VGG16, MobileNetV2, and baseline CNN in the basis of these evaluation parameters is depicted in Table I.

TABLE I
A COMPARISON TABLE BETWEEN VGG16, MOBEILENETV2, AND CNN ON PERFORMANCE EVALUATION METRICS

Model	**VGG16**	MobileNetV2	CNN
Accuracy	**96.00%**	95.511%	90.61%
Precision	**96.00%**	95.00%	90.38%
Recall	**96.00%**	96.00%	90.75%
F1 Score	**96.00%**	95.00%	90.51%

After analyzing our data on various models, we discovered that some performed admirably, achieving high accuracy with impressive precision, recall, and F1-score rate. CNN and MobileNetV2 have the lowest accuracy among all models at 95.51% and 90.61% respectively, as shown in table I. The highest accuracy is 96.00% for model VGG16. Precision, recall, and F1 all have very high scores of almost 96% in both the VGG16 and MobileNetV2 models. CNN has the lowest Precision, Recall, and F1 scores, with 90.38, 90.75, and 90.51 percent, respectively. As we can see from the table, even though the CNN model has the lowest accuracy, the overall model has over 90% accuracy, which is quite impressive.

In fig.2 our proposed VGG16 correctly classified 1347 organic and 1023 recyclable waste. On the other hand fig. 3 MobileNetV2 misclassified 69 and 42 for both organic and recyclable respectively. In addition, baseline CNN also performs well to classify organic and recyclable waste which is shown in fig. 4.

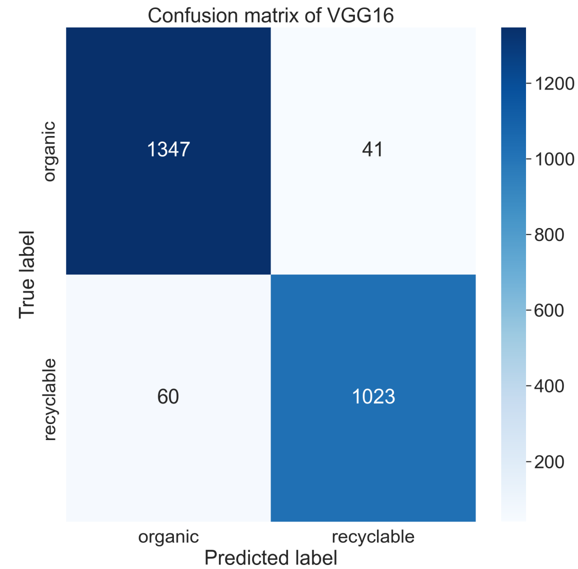

Fig. 2. Confusion matrix of VGG16

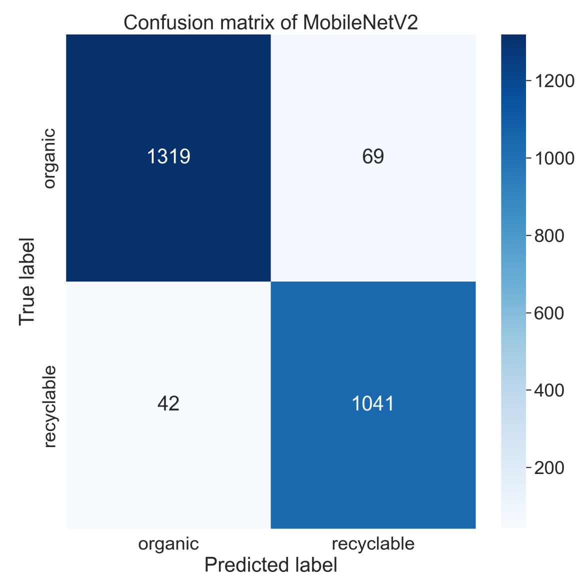

Fig. 3. Confusion matrix of MobileNEtV2

V. CONCLUSION

Finally, we suggested a deep learning-based approach to waste categorization that can effectively identify and isolate individual waste components. One can use this technique to automatically sort trash, which will cut down on human labor and help avoid contamination and pollution. Using the results, VGG16 was able to achieve an accuracy of 96% on the waste classification dataset. Assembling Two Entities

without or with little human intervention, adopting our technology will make garbage disposal quicker and more intelligent. Increases in system accuracy are possible when more images are added to the collection. More waste items will be sorted into categories in the future as we work to refine our system by adjusting some of the current parameters. In addition, we will implement XAI to make our model more explainable.

REFERENCES

[1] D. G. Solla, "Advanced waste classification with Machine Learning," https://towardsdatascience.com/advanced-waste-classification-with-machine-learning-6445bff1304f, jan 14 2022, [Online; accessed 2022-12-1].

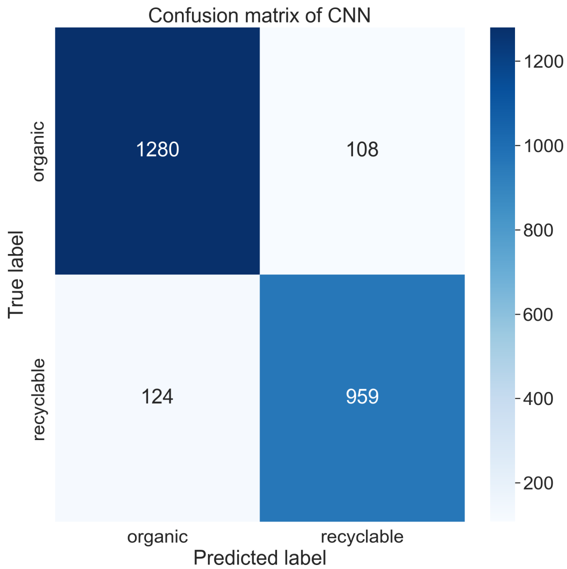

Fig. 4. Confusion matrix of CNN

[2] A. Olugboja and Z. Wang, "Intelligent waste classification system using deep learning convolutional neural network," *Procedia Manufacturing*, vol. 35, pp. 607–612, 01 2019.

[3] G. Thung and M. Yang, "Classification of trash for recyclability status," 2016.

[4] J. Qi, M. Nguyen, and W. Yan, "Waste classification from digital images using convnext," in *Pacific-Rim Symposium on Image and Video Technology*, 2022.

[5] A. Altikat, A. Gulbe, and S. Altikat, "Intelligent solid waste classification using deep convolutional neural networks," *International Journal of Environmental Science and Technology*, vol. 19, no. 3, pp. 1285–1292, 2022.

[6] Q. Zhang, Q. Yang, X. Zhang, Q. Bao, J. Su, and X. Liu, "Waste image classification based on transfer learning and convolutional neural network," *Waste Management*, vol. 135, pp. 150–157, 2021.

[7] N. Nnamoko, J. Barrowclough, and J. Procter, "Waste Classification Dataset," /datasets/n3gtgm9jxj/2, [Online; accessed 2022-12-01].

[8] M. H. K. Mehedi, E. Haque, S. Radin, M. Rahman, M. T. Reza, and M. G. R. Alam, "Kidney tumor segmentation and classification using deep neural network on ct images," 12 2022.

[9] M. H. K. Mehedi, A. S. Hosain, S. Ahmed, S. T. Promita, R. K. Muna, M. Hasan, and M. T. Reza, "Plant leaf disease detection using transfer learning and explainable ai," in *2022 IEEE 13th Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON)*, 2022, pp. 0166–0170.