M. Alamgir, S.M.T. Islam and J. A. Saju (Eds.)
ISBN: 978-984-35-4034-8

Proceedings of the Waste Safe 2023 – 8th International Conference on
Integrated Solid Waste and Faecal Sludge Management
25-26 February 2023, Khulna, Bangladesh

TRANSFER LEARNING BASED SOLID WASTE CLASSIFICATION USING THE ORGANIC AND RECYCLABLE WASTE IMAGES

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ABSTRACT

Solid waste is a growing problem, but with the right tools, we can turn it into a resource. Classification of solid waste is a critical step in waste management systems, as it enables the efficient separation and recycling of materials, reducing the environmental impact of waste disposal. One challenge faced by solid waste classification is the large variability in the appearance of different types of waste. This variability can make it difficult for traditional machine learning algorithms to accurately classify waste items from images. In this work, we explored the use of transfer learning for classifying images of solid waste. We compared the performance of popular transfer learning models. Our dataset included images of solid waste, labeled as either organic or recyclable. The results showed that transfer learning can be an effective approach for solid waste classification. However, the choice of model can significantly impact the classification accuracy. The proposed approach has the potential to be integrated into waste management systems to improve the efficiency of waste segregation and recycling, ultimately reducing the environmental impact of waste disposal.

INTRODUCTION

Solid waste classification is a critical aspect of modern waste management systems, as it enables the sorting and processing of solid waste materials in an efficient and effective manner. Solid waste refers to discarded materials that are not liquid or gas and are not intended for further use. These materials may include garbage, construction debris, industrial waste, and other types of discarded materials. According to the United States Environmental Protection Agency (EPA), common examples of solid waste include [1]:

- Municipal solid waste: This includes waste generated by households, businesses, and institutions, such as packaging materials, food waste, paper, yard waste, and other materials.
- Construction and demolition debris: This includes waste generated from the construction, renovation, and demolition of buildings, such as wood, drywall, concrete, and other materials.
- Industrial waste: This includes waste generated by manufacturing and other industrial processes, such as chemicals, hazardous materials, and other materials.

These solid wastes can be broadly classified in organic and recyclable waste. Unclassified solid waste dumping can have significant negative impacts on the environment. According to a study conducted in 2012 by United Nations Environment Program, unclassified waste dumping is more prevalent in developing countries [2] where the 53% of worlds total population live [3]. When solid waste is dumped in an unorganized manner, it can contaminate soil and water, leading to a range of environmental problems [4]. One of the main ways in which unclassified waste dumping can harm the environment is through the release of toxic chemicals and pollutants. Many types of waste, such as electronic waste and industrial waste, contain hazardous substances that can leach into the soil and water when they are improperly disposed of [5]. These chemicals can have detrimental effects on human health and the local ecosystem. In addition, unclassified waste dumping can also contribute to climate change by releasing greenhouse gases into the atmosphere. Landfills are a major source of methane, a potent greenhouse gas, which is produced as organic waste decomposes [6]. Methane emissions from landfills contribute significantly to global warming, and can have significant negative impacts on local air quality.

Accurate waste classification is essential for maximizing the efficiency and effectiveness of waste management systems, as it allows resources to be directed to the most appropriate channels. However, training machine learning models for waste classification can be a challenging task, requiring large amounts of labeled data and computational resources. One approach that has the potential to significantly improve the efficiency of waste classification is transfer learning. Transfer learning is a machine learning technique that allows a model trained on one task to be used as the starting point for a model trained on a related task [7]. This approach can significantly reduce the amount of data and computational resources required to train a new model, as it allows the model to leverage the knowledge learned from the original task [8]. In the context of waste classification, transfer learning could allow a model trained on one type of waste to be used as a starting point for a model trained on a different type of waste, potentially improving the efficiency and effectiveness of the classification process.

The goal of this paper is to explore the effectiveness of transfer learning for waste classification and to improve its performance. For that reason, we have employed different transfer learning models for efficient classification of wastes. Our major contributions are:

- Improving the performance of waste classification using different models of transfer learning
- Comparing the performance of the models
- Comparing our results with existing works.

In this paper, we will begin by reviewing the related work in the field. Next, we will present our experimental setup and describe the datasets and models used in our study. Then, we will present our results and discuss their implications for the use of transfer learning in waste classification. Finally, we will compare our results with existing works and conclude.

LITERATURE REVIEW

Approaches of Solid Waste Classifiction from Images

There are several approaches that have been used for classifying images of solid waste, including traditional image processing techniques, machine learning approaches, deep learning approaches, transfer learning approaches.

Traditional image processing techniques involve the use of algorithms and filters to extract features from images and classify them based on these features. These techniques can be effective for simple image classification tasks, but may be limited in their ability to handle more complex or variable image data [9].

Machine learning approaches, such as support vector machines and random forests, involve the use of algorithms that are trained on labeled data to learn patterns and classify new data based on these patterns. These approaches can be effective for image classification tasks, but may require a large amount of labeled data to achieve good performance [10].

Deep learning approaches, such as convolutional neural networks, involve the use of artificial neural networks with multiple layers of interconnected nodes to classify images based on patterns and features learned from the data. These approaches can be effective for image classification tasks, but may require a large amount of labeled data and computing resources to train the networks [11].

Transfer learning can also be used to classify solid wastes by using pre-trained deep learning models as a starting point to train a new model for the specific classification task. This involves using the weights and representations learned by the pre-trained model as a starting point, and then fine-tuning the model on a dataset of labeled solid waste images. One advantage of transfer learning is that it can leverage the knowledge and representation learned from large, pre-trained models to improve the performance of a new model on a related task [12]. This can reduce the amount of labeled data and computational resources needed to train a new model, making transfer learning particularly useful in cases where labeled data is scarce or expensive to obtain. Another advantage of transfer learning is that it can improve the generalization ability of a model, making it more robust to variations in the data and better able to handle new, unseen data [12]. This is particularly important for solid waste classification tasks, as the appearance of waste items can vary widely due to factors such as wear, damage, and contamination.

Related Works

As we choose transfer learning as our approach, we have limited our literature review to only the recent works used transfer learning for solid waste classification. Several researchers have completed waste image classification using the deep CNN based transfer learning techniques. Qiang Zhang et al. [13], deals with waste image classification using deep CNN based transfer learning model namely Densenet169. The model shows the 82% of accuracy. In [14], the authors applied three TL models named VGG, Inception and ResNet for waste image classification and their highest accuracy is 88.6%. In another paper [15], the researchers moved a waste classification system using SVM and ResNet 50 models along with the highest accuracy of 87%. In [16], the authors raised multilayer hybrid deep method to classify waste images with the accuracy of 90% above. In [17], the authors executed transfer learning system to classify the disposable waste with accuracy of 88.42%. In [18], the researchers presented trash image classification using transfer learning models with accuracy of 93.10%. Lin, K. et al. [19] depicted ResNet structures (ResNet-18, ResNet-34, ResNet-50, ResNet-101, and ResNet-152) for waste image classification with the highest accuracy of 88.8%.

In this paper, we classified the solid waste images into the organic and recyclable images using two transfer learning models named VGG19 and InceptionV3. Our models outperformed than the related works.

METHODOLOGY

Figure 1 depicts the working procedure of the works graphically. To begin with, we collected a solid waste dataset from Kaggle sources. In addition, test-train splitting and augmentation are applied for being suitability for model design. Furthermore, we designed two pre-trained models and classified into the organic and recyclable from the waste images using the pretrained models.

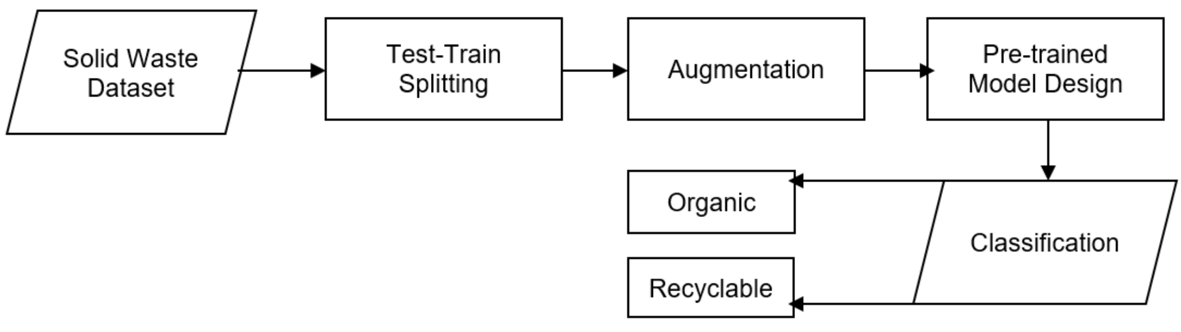


Figure 1 A detailed block diagram of working procedure

Dataset Description

ISBN: 978-984-35-4034-8

For the experimental puposes we used the “Waste Classification Dataset” available in Kaggle website [20]. This dataset consists of images of waste items and labels indicating the type of waste present in each image. The dataset includes images of paper, plastic, metal, cloath and glass waste, as well as mixed waste and organic wastes. The data was collected from various online sources and has been preprocessed to remove low-quality images and to standardize the resolution of the remaining images. The images are divided into two broad categories: Organic and Recycable objects. The data was collected from various websites and databases, including Google Images and Flickr. The data is stored in a collection of JPEG image files. Several organic and recyclabled images is shown in Figure 2.

Figure 2 Some organic and recyclabled images

Test-Train Splitting

The dataset includes 25,077 images. The dataset is folded in two categories named test and train. Again, test and train have two subfolders named organic and recycabled with number of images which is shown in Table 1 briefly. The dataset is divided into training and testing data with a respective ratio of 85:15.

Table 1 Test -Train splitting

	Organic	Recyclabled	Tota
Test	1401	1112	2513
Train	12565	9999	22564
Total	13966	11111	25077

Augmentation

Deep CNN performs very good on big dataset. Data augmentation is a technique to increase the dataset size by various techniques like image rotation, cropping, flipping, noise injection, color space transformation and so on. By using the Image Data Generator function, we have done the augmentation in our work.

Pre-trained Model Design

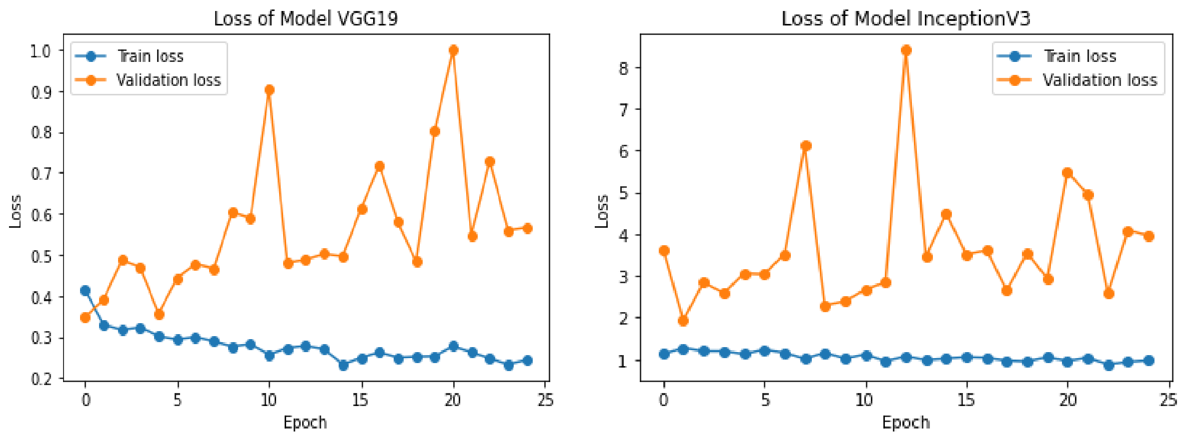
Image classification or image recognition or image segmentation in any field using computer vision is very important due to the prompt solution. Deep learning is good for huge dataset. However, transfer learning also known as pre-trained model performs better in a small dataset. Transfer learning is a method where a model used another model's knowledge. There are several popular pre-trained models named ResNet, DenseNet, AlexNet, Inception v3, GoogLeNet, MobileNet [21-23]. In this paper, we applied two transfer learning models named VGG16 and InceptionV3. The both models are known for its good performance on image classification tasks and have been widely used in a variety of applications

VGG19 is a convolutional neural network model developed by the Visual Geometry Group at the University of Oxford. It was trained on the ImageNet dataset, which consists of over 14 million images belonging to 1000 different classes. VGG19 is characterized by its 19-layer architecture, which includes 16 convolutional layers and 3 fully connected layers [24].

InceptionV3 is a convolutional neural network model developed by Google for image classification tasks. It is an updated version of the Inception model and was trained on the ImageNet dataset, which consists of over 14 million images belonging to 1000 different classes. InceptionV3 is characterized by its "inception" architecture, which consists of a series of convolutional and pooling layers arranged in a multi-branch structure [25].

EXPERIMENT AND RESULT DISCUSSION

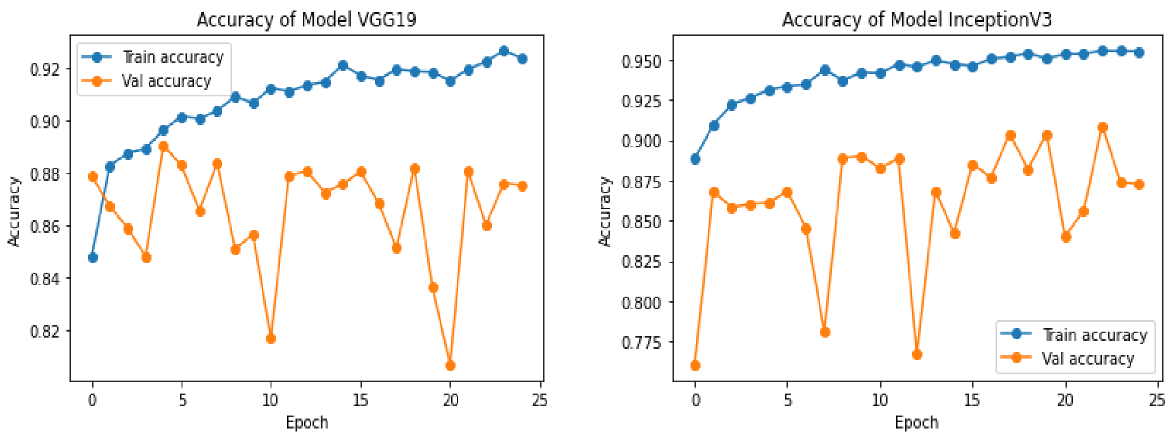
To experiment the work, we used Python 3.8.16 version in google Collaboratory. As a measurement scale, we considered several scales named loss, accuracy and confusion matrix. Figure 3 describes the loss of VGG19 and InceptionV3 models. We have taken total 25 epochs in each model.



(a) VGG19 (b) InceptionV3

Figure 3 Loss of VGG19 and InceptionV3 models

In Figure 4, we shown the accuracy of our used models. There are 25 epochs. The highest training accuracy is 92.63% and 95.56% of VGG19 and InceptionV3 respectively and the highest testing accuracy is 89.02% and 90.89% of VGG 19 and InceptionV3 respectively.

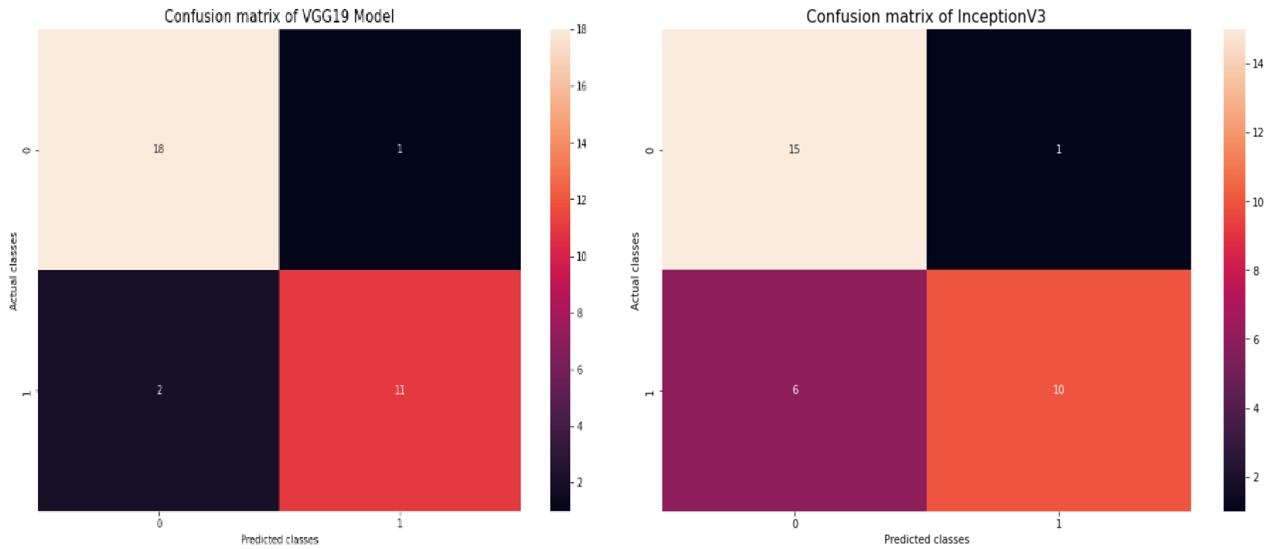


(a) VGG19 (b) InceptionV3

Figure 4 Accuracy of VGG19 and Inception Models

ISBN: 978-984-35-4034-8

We also shown the confusion matrix. From the confusion matrix, accuracy is calculated. Figure 5 shows the confusion matrix of our utilized models.



(a) VGG19 (b) InceptionV3

Figure 5 Accuracy of VGG19 and Inception Models

Our findings are summerized in Table 2. We run both VGG19 and InceptionV3 for 25 epochs. The minimum train accuracy achieved by VGG19 was 84.79% in epoch 1. And the maximum training accuracy achieved by VGG19 was 92.63% in epoch 24. The minimum and maximum test accuracy achieved by VGG19 were 80.66% in epoch 5 and 89.02% in epoch 21 respectively. On the otherhand, InceptionV3 achieved minimum train accuracy of 88.85% in epoch 1 and maximum train accuacy of 95.56%. Again, minimum and maximum test accuracy achieved by Inception3 were 76.04% in epoch 1 and 90.89% in epoch 23 respectively. If we compare the two models we can see that, the minimum test accuracy achieved by InceptionV3 is lower than VGG19. But, in other respects, InceptionV3 is the clear winner.

Table 2 Comparison of maximum, minimum accuracy of training and validation during 25 epochs TL models

Model	Train/ Test	Max. Accuracy (%)	Epoch for Max. Accuracy	Min. Accuracy (%)	Epoch for Min. Accuracy
VGG19	Train	92.63	24	84.79	1
	Test	89.02	21	80.66	5
InceptionV3	Train	95.56	23	88.85	1
	Test	90.89	23	76.04	1

Some tasks has been published for classifying the waste images. Table 3 shows the comparison with the existing works with our work. The transfer learning models used in existing works are: VGG, VGG19, Inception, Densenet169, SVM, Multilayer hybrid deep method, MobileNetV2, ResNet, ResNet-18, ResNet-34, ResNet 50, ResNet-101, and ResNet-152. Our proposed method includes VGG19 and InceptionV3. Existing works that used VGG19 achieved highest accuracy of 90% whereas our highest accuracy with VGG19 was 92.63%. However, the highest accuracy compared to existing works is achieved by our proposed methot with InceptionV3 (95.56%).

Table 3 Comparison with existing works

S.L. No	Source, Year	Method	Highest accuracy (%)
01	[13], 2021	Densenet169	82
02	[14], 2019	VGG, Inception and ResNet	88.6
03	[15], 2019	SVM and ResNet 50	87
04	[16], 2018	Multilayer hybrid deep method	90
05	[17], 2018	VGG19	88.42
06	[18], 2023	ResNet152, DenseNet169, and MobileNetV2	93.10
07	[19], 2022	ResNet-18, 34, 50, 101, and 152	88.8
08	Proposed	VGG19 and InceptionV3	95.56

CONCLUSION

In conclusion, our study demonstrates the effectiveness of transfer learning for classifying images of solid waste into organic and recyclable categories. By comparing the performance of two popular deep learning models, VGG19 and Inception V3, on a dataset of labeled solid waste images, we were able to achieve a high classification accuracy of 95.56% with Inception V3. This result is the highest reported in the literature and suggests that Inception V3 is a promising model for solid waste classification tasks. Our findings have important implications for the development of efficient and accurate solid waste classification systems, which can play a key role in reducing the environmental impact of waste disposal.

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