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Garbage Waste Segregation Using Deep Learning Techniques

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Abstract. Waste segregation is one of the primary challenges to recycling systems in major cities in our country. In India, 62 million tons of garbage is generated annually. Of this 5.6 million tons of wastes consist of plastic materials. About 60 percent of this is recycled every year. In addition, 11.9 million tons are recycled from 43 million tons of solid waste produced. Though the numbers sound good, a serious problem in the recycling industry is the segregation of waste before recycling or any other waste treatment processes. In India, at present situation waste is not segregated when collected from households. So a lot of workforce and effort are needed to separate this waste. In addition to this people working in this industry are prone to various infections caused due to toxic materials present in the waste. So the idea is to decrease the human intervention and make this waste segregation process more productive. The proposed work is aimed to build an image classifier that identifies the object and detects the type of waste material using Convolutional Neural Network. In this work, four different models of the CNN, such as ResNet50, DenseNet169, VGG16, and AlexNet, trained on ImageNet, are used to extract features from images and feed them into a classifier to make predictions and distinguish a type of waste from its corresponding category. The experimental results showed that the performance of DenseNet169 was significantly greater than all four models and the performance of ResNet50 is closer to DenseNet169.

Keywords: Convolutional Neural Network, Deep learning, Waste segregation, Pre-trained models

1. Introduction

Recycling is a very important phenomenon in a healthy and green environment. With raising awareness among the citizens of India regarding the importance of using recycling items to decrease the consumption of natural resources and garbage disposal, the recycling industry is booming. People are willing to use more recycled products and also contribute their part to the society by disposing of their waste to recycle. As a result, there is a need to divert more waste to recycling industries which can only be done after proper segregation [1].

Even the non-recyclable waste is treated with methods like burying, combustion, plasma gasification only after waste segregation which removes objects that may destroy the quality of nearby water bodies or soil or air when burnt or burying. Hand-picking is not possible once the amount of waste increased with increasing population



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To counter this problem we can automate the entire process by building an image classifier using a convolutional neural network (CNN) and thereby decrease the time for the waste segregation and make it cost-effective. CNN is an artificial neural network which is very popularly used in analyzing images. CNN relatively minimizes the pre-processing for an image dataset [3]. The key to CNN's success is due to its ability to learn high-level abstractions from raw input image data [5]. There are some automated methods for garbage segregations existing already [7, 12], but they have mainly focused on hardware implementations with less accurate waste classification.

The four pre-trained CNN models used here are ResNet50, DenseNet169, VGG16, and AlexNet. These pre-trained models are previously trained on ImageNet dataset that consists of almost 22,000 object categories for the purpose of computer vision research [4]. The custom CNN architecture requires a large dataset and also takes a lot of time to train. Pre-trained models overcome these issues as its weights are already optimized when trained on the ImageNet dataset. Though the models can't achieve 100% accuracy, it is built to achieve the best possible classifier and to minimize the errors to the maximum possible extent.

The organization of the paper is as follows. Section 2 deals with the Survey of Literature. Dataset collection and modifications are shown in Section 3, and Methodology is presented in Section 4. Findings are presented in Section 5, followed by a conclusion in Section 6.

2. Related Work

Of the existing pre-trained models trained on ImageNet database, AlexNet, which won ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2012 is a highly competent architecture and proven to work efficiently on most image datasets. It is commonly used for the segregation of waste but its efficiency is not comparable to other pre-trained models.

Mindy Yang and Gary Thung [6], collected images for the dataset used Machine Learning and neural networks to segregate waste. Using Support Vector Machine (SVM), they classified waste into six different categories and an 11-layer CNN. SVM performed well compared to CNN with 63 percent accuracy, while CNN is only 23 percent accurate.

Yash Desai et al. [7] proposed a method that uses CNN to classify degradable and non-degradable waste. A flap can be used to insulate the grouped waste into different classifications. Afterward, the computerized order helps throughout the time spent on sanitation. The ordered waste can also be arranged and handled by the companies in a concomitant manner.

Micro-controller based automatic waste garbage segregation is proposed by Pushkar Sathe et al. [12], using custom neural networks. This model classifies waste into four classes namely paper, glass, plastic, and metal. There are four dust bins connected to a servo motor. The type of waste is recognized by the system and the respective dust bin is opened. The drawback here is if there any non-recyclable waste exists, it will be classified into the existing four classes.

Zabir et al.[13] introduced three methods, Convolutional Neural Network (CNN), AlexNet and Bag of Features (BoF). They used the MCIndoor20000 dataset, which consists of doors, signage, and stairs images of Marshfield Clinic. BoF generates almost the same precision as CNN, which shows that machine learning is almost as good as deep learning. Experimental results showed that AlexNet achieves higher precision than CNN and BoF.

Hoque et al. [14] implemented a CNN based system in order to classify the type of waste and open the dustbin when the waste is to be poured into the waste bin. Using this method the separated waste at the basic level becomes easier. They have segregated four categories of waste, namely glass, paper, plastic, and metal.

Osiany et al. [15], designed and made an Automatic Garbage Collector (AGATOR), a rotor robot model to counter the efficiently and effectively flow-free garbage accumulation in the river. The full load pushes up to 5 kg at the garbage receptacle. The Robot average speed when collecting the garbage is 0.26 m/s.

Another project by G.Mittal et al. [16], designed a smartphone application which detects a pile of waste in an image. The authors collected the images in Bing Image search and used the AlexNet model and achieved an accuracy of 87.69%.

Sachin Hulyalkar et al. [17] proposed a system that automatically segregates the waste at the source itself, thereby reducing physical effort. The program is based on Machine Learning principles, image recognition and the Internet of Things (IoT). The aim of this project is to capture images of single waste material and to identify and segregate it effectively into four classes, i.e. metal, glass, paper, and plastic

Olugboja Adedeji and Zenghui Wang have implemented SVM and CNN using ResNet architecture on the same dataset. Clearly, ResNet architecture gave better results compared to SVM and also non-pre-trained CNN models used by Gary Thung and Mindy Yang. So it is proved that pre-trained models are performing better than conventional CNN [18].

Pavithra [19] has developed a smart trash system that aims to use IR sensors and gas sensors where the gas sensors detect if there are any poisonous gases in the waste and IR sensor detects the level of waste-filled. RFID is placed at a municipal corporation office interface with PC. If the trash is filled, the information is sent to the corporate office to empty the bin.

Anjali et al. [20], developed a method of detecting solid waste that uses the motion of an Unmanned Aerial Vehicle (UAV). Here drone is used to detect waste using image processing techniques that detect waste contaminated places and send notification of location coordinates. They have interfaced Arduino that collects images and GPS, GSM modules for communication and location tracking. The scope of this project is only a mass waste detection and segregation is out of scope.

Chandaluru Priyanka & Sri Ramya [2] used Machine Learning models like SVM, KNN, Decision Tree and compared them to CNN. CNN performed well over the mentioned Machine Learning algorithms. Their dataset is better compared to other researchers. Previous researchers used less than 1000 images whereas they have used more than 3000 images to train the model.

3. Dataset and Data Collection

The images used in the proposed work are taken from Gary Thung and Mindy Yang's dataset while working on waste segregation [6]. Initially, this dataset has 2527 images. Since the dataset is very small, we added more images to this dataset from Google Images. Later on in this project, some images collected from Google Images are irrelevant to that particular class as mentioned in Table 1. They are contributing to a less accurate model. So these misclassified images are removed. The dataset contains six classes namely cardboard, glass, metal, paper, plastic, trash with about 4,163 total images.

Table 1. Details of Dataset

Class	Number of images in existing dataset	Number of images of modified dataset
Cardboard	403	651
Glass	501	769
Metal	410	819
Paper	594	909
Plastic	482	878
Trash	137	137
Total images	2527	4163

4. Methodology

Classification is a method by which features are extracted from the dataset. This is achieved by splitting the knowledge into various clusters, based on the characteristics. A novel model is built which performs predictions and classifies it by training it on known data.

The proposed system involves three basic modules such as pre-processing, image augmentation, and feature extraction. Image Augmentation is to increase more pictures by re-sizing, zooming, turning pictures, and so on to build new pictures. With this methodology, the model will be ready to catch a larger number of 'features' than previously and will ready to predict images much better. During feature extraction, the system characterizes the unlabeled data with maximum possible exactness.

4.1 Architecture of proposed system

Figure 1 displays pre-trained models that work on a given dataset. The pre-trained models trained on the ImageNet database are used for the extraction and classification of features after processing and data-augmentation.

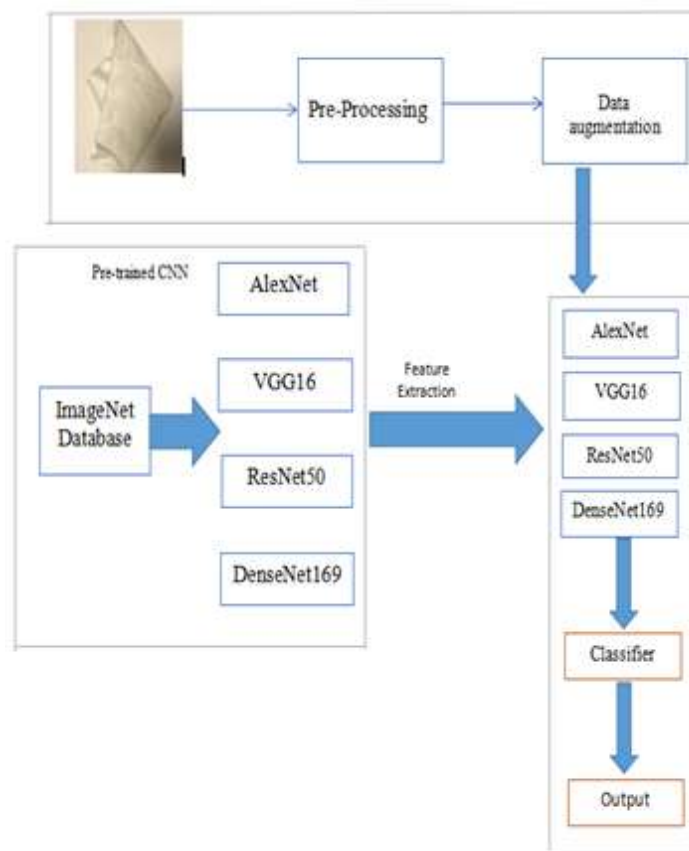


Figure 1. Methodology of proposed work

4.2 Pre-processing and data augmentation

The dataset is relatively small for pre-trained models to handle. Overfitting can be a concern. Therefore some steps must be taken before the training model. Dataset size is doubled by adding images from the Google images. Additionally, certain techniques of augmentation such as Random Re-sized Crop, Random Horizontal Flip, are used.

4.3 Convolutional Neural Network

Convolutional Neural Network (CNN) is prominently used for image analysis. Its hidden layers called convolutional layers to make it more special. Each convolutional layer contains a set of filters. These filters detect patterns or features in the images. A simplest CNN has the following layers:

4.3.1 Convolutional layer: A convolutional layer extracts features of images by using filters. Filters are small matrices of dimensions of our wish filled with random values. These filters detect patterns by striding over the input images after which we get the resultant feature map which is passed to the next layer.

4.3.2 Pooling layer: In this layer, a window normally a size of 2x2 is placed over the feature map and the maximum value is selected in the window neglecting all other values. It results in a decreased picture scale.

4.3.3 Fully connected layer: The actual image recognition and classification happens in this sheet. The shrink images are taken and inserted into a single vector. This vector is compared and the image is classified with the vectors obtained from the trained images. Below are the CNN architectures that are used in this research,

AlexNet. It is eight layers deep, the first five layers being convolutional layers and last three layers are fully connected layers. There is a max-pooling layer after each convolutional layer. It uses Rectified Linear Unit (ReLU) activation function. ReLU is preferred over Tanh to add non linearity. It accelerates speed by eight times without accuracy change. It accepts only images of size of 256x256. If the images are of any other size then they are converted to 256x256 and then used [9].

VGG16. VGG networks are developed to increase the depth of existing CNN architectures though ResNet is introduced later. 3x3 sized filters are used in convolutional layers with a stride of size one, which reduces the number of parameters in the networks. VGG networks are more difficult to train, compared to AlexNet. Here 16 layered VGG network is used for the segregation of waste [11].

ResNet50. Residual Network (ResNet) architecture is considered as a starting point to transfer learning. There are five stages in ResNet50 architecture. Each stage has a convolutional block and an identity block. Each convolutional block has three convolutional layers. It is introduced to simplify training deeper networks. It is eight times deeper than VGG architecture, but still has lesser complexity [8].

DenseNet169. The speciality of DenseNet architecture is each layer is connected to every other layer in a feed-forward way. Each layer will get feature maps from all other previous layers. Due to this, the features are not lost even after passing through lots of layers. In DenseNet architecture, there is a reduction in parameters due to reuse of functions [10].

4.4 Network Training

The dataset is split into 80% training set and 20% testing set. Google Colab is used for this project as it provides GPU free of cost. Google Colab has 1000s of cores running simultaneously. It provides with 12.72 GB RAM and 358.27 hard disk spaces in one run time. We took advantage of Fastai library to train CNN models. The Learning rate is determined after plotting learning rate vs loss graph (Figure 2). From the graph, suitable learning rate is selected and each CNN model is trained for 50 epochs using data augmentation.

4.5 Problems Addressed

The two key concerns that were found most are:

1. The dataset is too small to train. So there can be a problem of insufficient training.
2. There is a problem of overfitting because of less data.

Image Scrapping and removal of misclassified images is performed to combat these problems.

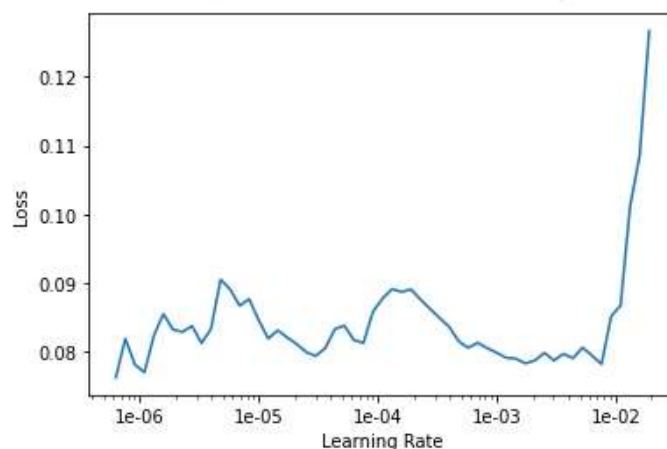


Figure 2. Loss vs Learning rate for DenseNet169

4.6 Image Scraping

The models performed considerably well. Still, there is a scope to increase accuracy. To improve the model's accuracy, image scraping is done to increase the dataset set, and some of the most misclassified images are removed.

Image scraping is nothing but collecting images from the web and preparing a dataset from those images. In previous work, authors have followed this procedure but later, they neglected due to less accuracy. Therefore, using their expertise, we wanted to use the dataset alongside it by scraping photos from Google images, we doubled the number of images.

We downloaded about 500-600 images for each class and inserted 300-350 manually by removing images that aren't connected at all. We need to be more precise when looking to get more images that are linked and match best.

4.7 Removing the most misclassified images

Scraping the images from the web and adding them to the dataset, sometimes give adverse effects to the dataset. So we need to take necessary precautions while doing web scraping. One is the elimination of the most misclassified images. Therefore, the top 20 most misclassified images are removed from the dataset and instead of them 16 images are newly added during web-scraping.

5. Results and Discussion

Once model is built, the next step is to assess the performance of the developed model using some evaluation metrics. The following metrics were used for performance assessment

Accuracy: Accuracy is the most commonly used and best output metric to compare various models. It is a simple ratio of correctly predicted samples to total number of samples.

$$\text{Accuracy} = \frac{\text{Correctly predicted samples}}{\text{Total number of samples}} \quad (\text{Or})$$

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

True Positives (TP): These are correctly predicted positive values which mean the sample which belongs to a particular class is predicted that it belongs to original class. For example, if an object belongs to the paper class, it is correctly predicted by the algorithm / model.

True Negatives (TN): These are correctly predicted negative values. When a sample is not really part of a class, the model also predicts that the sample is not part of that class. For instance, if an object does not belong to the paper class, the predicted class correctly classifies the same thing.

False Positives (FP): When a sample belongs to a negative class and the prediction model incorrectly classified as positive. For example, when an object is not a plastic material but prediction says it is a plastic material.

False Negatives (FN): When a sample belongs to a positive class and the prediction model incorrectly classified as negative.

Table 2. Confusion Matrix

		Predicted Class	
		Class=Yes	Class=No
Actual Class	Class=Yes	True Positive(TP)	False Negative(FN)
	Class=No	False Positive(FP)	True Negative(TN)

True positive and true negatives are correctly predicted samples whereas false positives and false negatives are incorrectly predicted values and the confusion matrix is shown in Table 2. So we need to minimize false positives and false negatives to build a better model.

Precision: It measures how good the model is at assigning positive events to the positive class. Precision is the ratio of true positive values to total predicted positive values.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

Recall: Recall measures how good the model is in detecting positive events. Therefore, the formula for recall is the same as sensitivity. Recall is the ratio of true positive values to total actual positive values.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

Initially AlexNet, VGG16, ResNet50, DesnseNet169 accuracy and performance are summarized by Table 3. The dataset is too small and there is a problem of over fitting.

Table 3. Initial test set accuracy

Model	Recall (%)	Precision (%)	Accuracy (%)
AlexNet	79.8	82.7	83.7
VGG16	85.1	88.2	86.9
ResNet50	84.2	89.6	89.7
DesneNet169	92.1	92.1	92.6

After bulking up images by adding images and removing misclassified images, the models performed considerably well, the results are summarized in Table 4.

Table 4. Accuracy after Scraping

Model	Recall	Precision	Accuracy
	(%)	(%)	(%)
AlexNet	84.4	88.8	89.3
VGG16	86.6	90.1	91.7
ResNet50	88.2	90.6	93.4
DenseNet169	92.5	94.5	94.9

Though there is no considerable change of accuracy in DenseNet169, it is nearly 6% high in AlexNet, 5% in VGG16 and 4% in ResNet50. Thus the web scraping and elimination of misclassified images performed well to develop models with low accuracy.

Table 5. Evaluation metrics for AlexNet

Material	Precision	Recall
Cardboard	0.98	0.95
Glass	0.82	0.77
Metal	0.80	0.88
Paper	0.90	0.85
Plastic	0.83	0.83
Trash	0.69	0.88

Looking at the precision and recall Table 5, cardboard, paper is predicted well by the model. Trash is not predicted well as the number of images is not sufficient to train the model. Glass, Plastic and Metal's performances are satisfactory. Below graph (Figure 3) shows how accuracy increases with the number of batches processed in AlexNet Model.

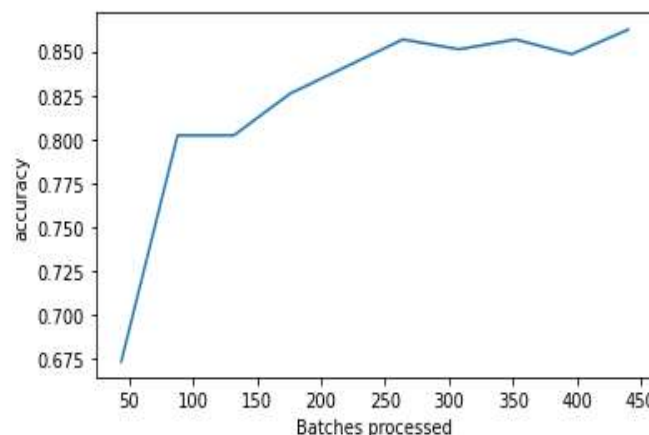


Figure 3. Batches processed vs Accuracy of AlexNet model

A confusion matrix is a table often used to define a classification model's output on a collection of test data for which the true values are known. It enables the output of an algorithm to be visualized.

Confusion matrix of AlexNet model on the **test dataset** is given in Figure 4. It is the least performing model of all four models.

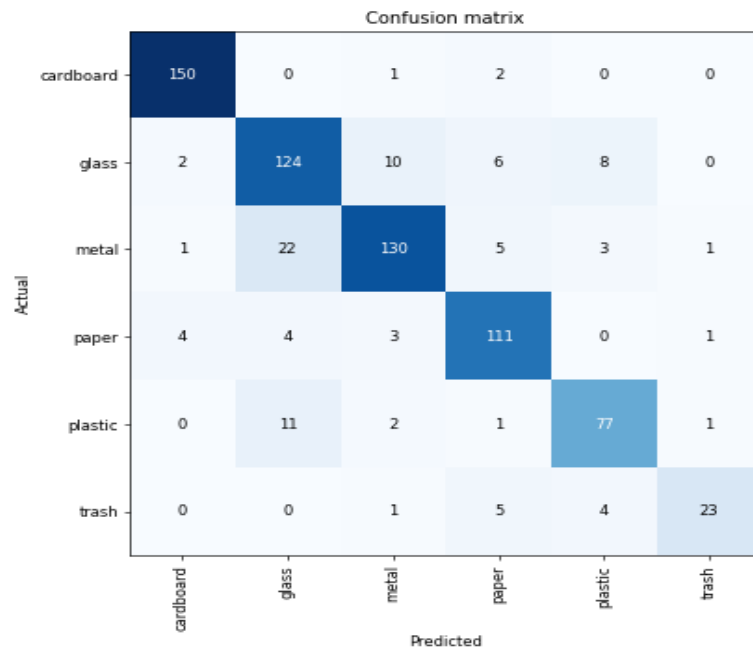


Figure 4. Confusion matrix of AlexNet model

Table 6. Evaluation metrics for VGG16

Material	Precision	Recall
Cardboard	0.98	0.93
Glass	0.91	0.91
Metal	0.91	0.89
Paper	0.94	0.95
Plastic	0.92	0.92
Trash	0.61	0.84

From the above precision and recall Table 6, we can conclude that the model with VGG16 architecture performed well for almost all the class except trash class. Below graph (Figure 5) shows how accuracy increases with the number of batches processed with respect to VGG16.

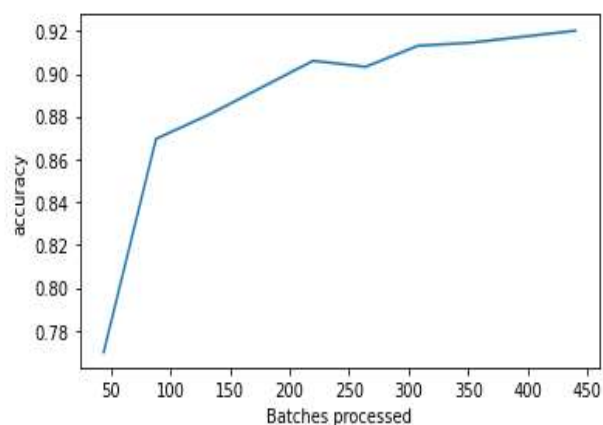


Figure 5. Batches processed vs Accuracy of VGG16 model

Figure 6 displays Confusion matrix of model VGG16 on **test dataset** and it really performed well for cardboard and Paper.

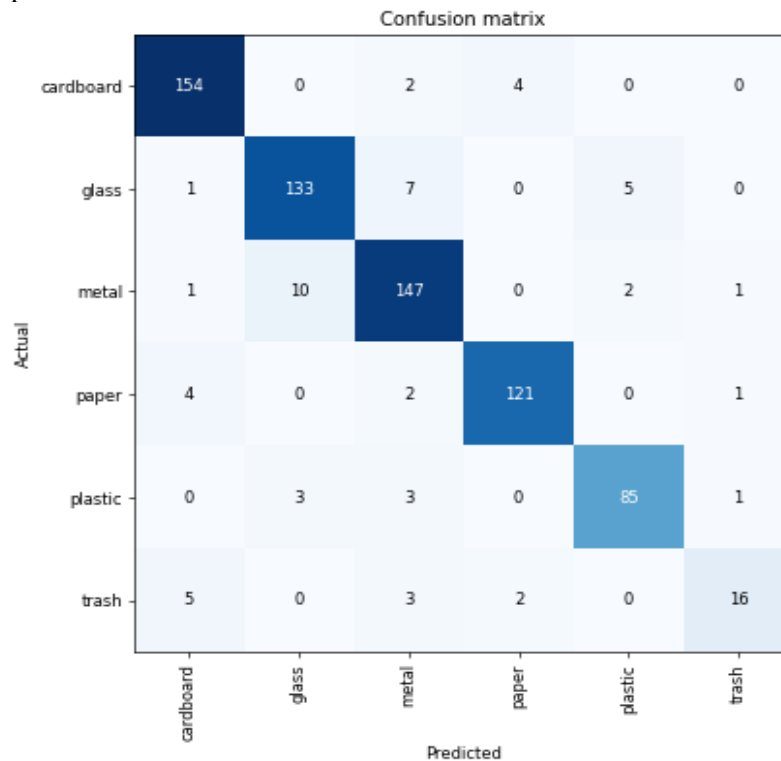


Figure 6. Confusion matrix of VGG16 model

Table 7. Evaluation metrics for ResNet50

Material	Precision	Recall
Cardboard	0.96	0.97
Glass	0.83	0.86
Metal	0.88	0.85
Paper	0.90	0.86
Plastic	0.85	0.86
Trash	0.44	0.57

Looking at the precision and recalling Table 7, we can conclude that ResNet50 model worked well for cardboard and Paper. Its performance on Glass, Metal and Plastic is satisfactory. Like the other models, the model couldn't detect Trash as well. Graph (Figure 7) shows how accuracy increases with the number of batches processed in ResNet50 model.

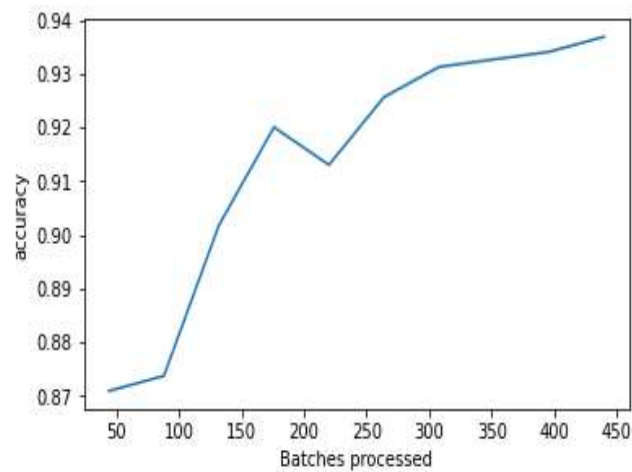


Figure 7. Batches processed vs Accuracy of ResNet50

ResNet50's performance is very nearer to that of DenseNet169. Confusion matrix ResNet50 model on **test dataset** is given in Figure 8.

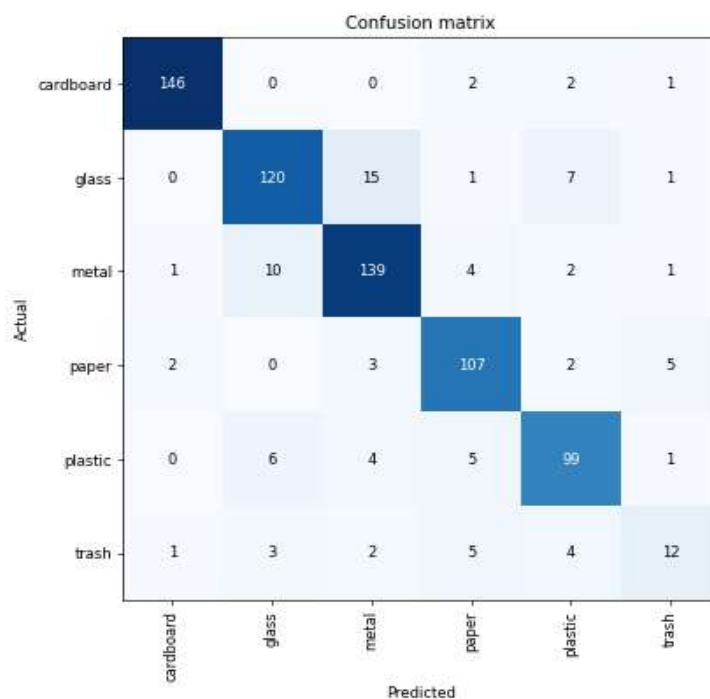


Figure 8. Confusion matrix of ResNet50 model

Table 8. Evaluation metrics for DENSENET169

Material	Precision	Recall
Cardboard	1.00	0.99
Glass	0.93	0.87
Metal	0.95	0.90
Paper	0.93	0.95
Plastic	0.83	0.88
Trash	0.80	0.80

Assessing the above table 8, DenseNet169 predicts all the classes reasonably well. Trash and Plastic are the most mispredicted classes. Graph (Figure 9) shows how accuracy increases with the number of batches processed with respect to DenseNet169 model.

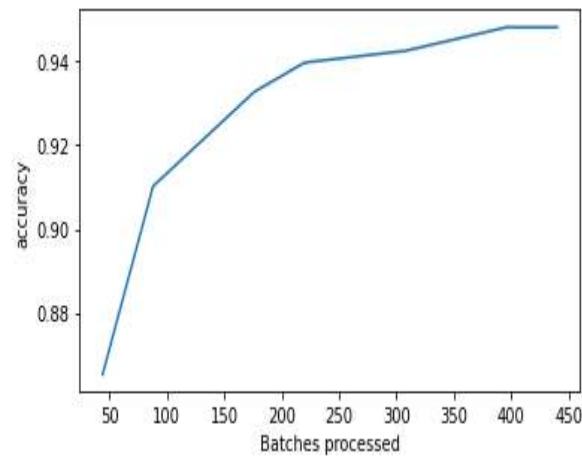


Figure 9. Batches processed vs Accuracy of DenseNet169

We can assess more by understanding confusion matrix of best performed model DenseNet169 using **test dataset**.

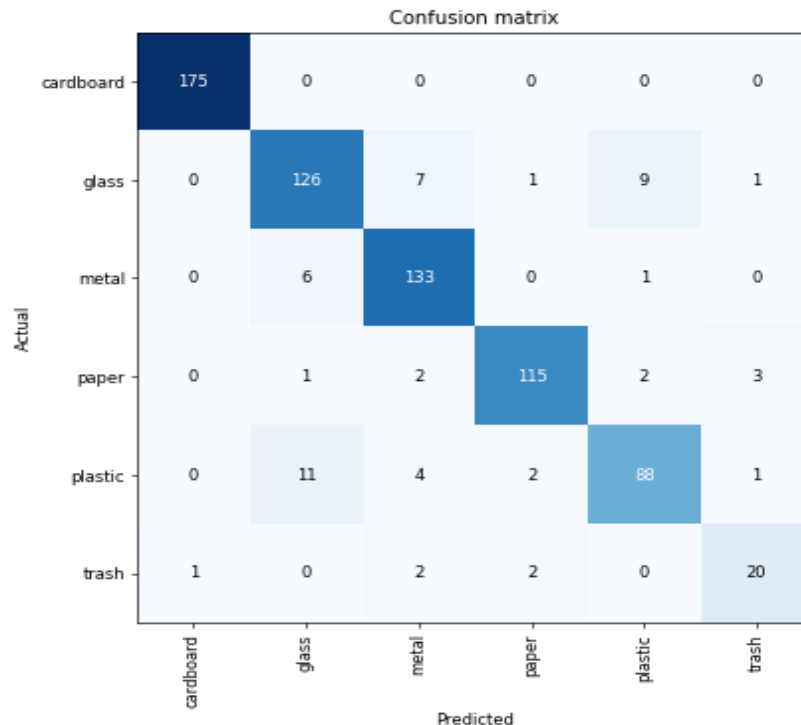


Figure 10. Confusion matrix of DensNet169

It is clear from confusion matrix (Figure 10) that glass is frequently confused. So glass is the area of concern and improvisation to be made in classification of glass.



Figure 11. Some of the mis-classified images

Sometimes glass is classified as plastic or metal and in some cases metal or plastic is classified as glass (Figure 11). Also trash is often misunderstood because of insufficient learning.

6. Conclusion

In this research, our goal is to segregate the waste materials using machine learning. We made use of the pre-trained architectures and six waste classification categories to accomplish this goal. Web scraping is done for removal of misclassified images and it has been working well in developing low precision models. Compared with other versions DenseNet169 performed better. The output of ResNet50 is likewise closer to DenseNet169. The most misclassified or misunderstood of the six categories is 'glass.' We need to add more and clear 'glass' images to enhance the model.

References

- [1] Miranda, Ruben, Blanco and Angeles. 2010. "Environmental awareness and paper recycling". *Cellulose Chemistry and Technology*. Vol. **44**. pp. 431-449.
- [2] Chandaluru Priyanka, Sri Ramya P. 2020. Image Based Classification of Waste Material Using Convolution Neural Network, *International Journal of Advanced Science and Technology* Vol. **29**, 5, pp. 2967 - 2975
- [3] Albawi S, Mohammed T A and Al-Zawi S. 2017. "Understanding of a convolutional neural network," *International Conference on Engineering and Technology (ICET)*, Antalya, pp. 1-6
- [4] Deng J, Dong W, Socher R, L.-J. Li, Li K, and Fei-Fei L. 2009. "ImageNet: A Large-Scale Hierarchical Image Database", *IEEE Conference on Computer Vision and Pattern Recognition*, pp. 248-255.
- [5] Bakator M, Radosav D. 2018. "Deep Learning and Medical Diagnosis: A Review of Literature", *Multimodal Technologies and Interaction*. Vol. **2**, 47, pp. 1-12.
- [6] Thung, Gary and Ming Xiang Yang. 2016. "Classification of Trash for Recyclability Status.", *Corpus Id-27517432*.
- [7] Yesha Desai, Asmita Dalvi, Pruthviraj Jadhav, Abhilasha Baphna. 2018. "Waste Segregation Using Machine Learning", *International Journal for Research in Applied Science and*

- Engineering Technology (IJRASET)*, ISSN : 2321-9653, Vol. 6, pp. 537-541.
- [8] He K, Zhang X, Ren S and Sun J, 2016. "Deep Residual Learning for Image Recognition", *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Las Vegas, NV, pp. 770-778.
 - [9] Alex Krizhevsky, Ilya Sutskever and Geoffrey E Hinton, 2010. "ImageNet Classification with Deep Convolutional Neural Networks", *ImageNet Large Scale Visual Recognition Challenge*.
 - [10] Gao Huang, Zhuang Liu, Laurens van der Maaten and Kilian Q Weinberger. 2017. "Densely Connected Convolutional Networks", *IEEE Conference on Computer Vision and Pattern Recognition*. pp. 4700-4708.
 - [11] Karen Simonyan and Andrew Zisserman. 2015. "Very Deep Convolutional Networks for Large-Scale Image Recognition", *International Conference on Learning Representations (ICLR)*. pp. 1-14.
 - [12] Pushkar Sathe, Omkar Tawade, Tanmay Kale, Syed Samar Abbas and Diksha Thakur. 2019. "Waste Segregation using Convolutional Neural Network", *International Journal for Research in Applied Science and Engineering Technology (IJRASET)*, Vol. 7, pp. 932-937.
 - [13] Zabir M, Fazira N, Ibrahim, Zaidah, Sabri and Nurbaity. 2018. "Evaluation of Pre-Trained Convolutional Neural Network Models for Object Recognition". *International Journal of Engineering and Technology(UAE)*. Vol. 7. pp. 95-98.
 - [14] Shanjenbam Brojendro Singh, Abu Salah Muslaha Uddin Laskar, Biltu Roy, Aminul Hoque Choudhury, Zahidul Islam, Jakir Hussain Mollah, Shadeed Masood Hoque, Mohsin Ali and Pranav Kalita. 2016. "Design of Municipal Dry Waste Segregating Machine Using Conveyor", *International Journal of Innovative Research in Science, Engineering and Technology (IJIRSET)*, Vol. 5, pp. 7156-7162.
 - [15] Nurlansa, Osiany, Dewi Anisa Istiqomah and Mahendra Astu Sanggha Pawitra. 2014. "AGATOR (Automatic Garbage Collector) as Automatic Garbage Collector Robot Model". *International Journal of Future Computer and Communication*, Vol. 3, pp. 367-371.
 - [16] Mittal Gaurav, Kaushal B Yagnik, Mohit Garg and Narayanan C Krishnan. 2016. "SpotGarbage: smartphone app to detect garbage using deep learning". *Proceedings of the ACM International Joint Conference on Pervasive and Ubiquitous Computing*. pp. 940-945.
 - [17] Hulyalkar Sachin, Rajas Deshpande, Karan Makode and Siddhant Kajale. 2018. "Implementation of Smartbin using Convolutional Neural Networks". *International Research Journal of Engineering and Technology (IRJET)*, Vol. 5, pp. 3352-3358.
 - [18] Adedeji, Olugboja, and Zenghui Wang. 2019. "Intelligent Waste Classification System Using Deep Learning Convolutional Neural Network." *Procedia Manufacturing*. Elsevier B.V., Vol. 35. pp. 607–612.
 - [19] Pavithra. 2014. "Smart Trash System: An Application using ZigBee", *International Journal of Innovative Science, Engineering & Technology*, Vol. 1, pp. 319-323.
 - [20] Anjali Pradipbhai Anadkat, Monisha B V, Manasa Puthineedi, Ankit Kumar Patnaik, Shekhar R and Riyaz Syed. 2019. "Drone based Solid Waste Detection using Deep Learning & Image Processing", *Alliance International Conference on Artificial Intelligence and Machine Learning (AICAAM)*, pp. 357- 364.