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DEEP LEARNING ENABLED GARBAGE CLASSIFICATION AND DETECTION BY VISUAL CONTEXT FOR AERIAL IMAGES

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Abstract. Environmental pollution by garbage is a biggest problem of most of the developing country, garbage waste processing management and recy-cling is significant for ecological and economic reasons. computer vision techniques are very advance in many application for object detection and classification, we did an extensive study on the use of artificial intelligence for garbage processing and management and it is lagging because of dataset availability which have the top view images of garbage. We create a new da-taset 'KACHARA' which have 4727 images of seven classes Cloths, Decom-posable, Glass, Metal, Paper, Plastic, and Woods. Classification is performed by the transfer learning by popular Deep learning mode MobileNetv3 large with fine tuning the top layers. And archive the classification accuracy of 94.37

Keywords: Deep learning, Object classification, Object detection, Transfer learning, Aerial Images.

1 Introduction

The improper management of solid waste contributes to global environmental contamination. The recent spike in the creation of disposable products has resulted in a huge increase in the amount of waste generated. Waste refers to any materials that have been used yet are considered useless. Waste can be undesired or worthless things; it is also referred to as waste, trash, refuse, garbage, and junk. Millions of tons of waste are produced annually in every country, and this amount is rising quickly. For instance, the industrialized country of America produces 2 kg of munic-ipal solid waste per person each day, which accounts for 55% of residential waste. Moreover, 50% of biodegradable garbage is produced in developing nations, and human waste is present all across the world. Waste management is becoming in-creasingly difficult due to increasing city waste and declining disposal and manage-ment capacity [1] Waste detection and management mechanisms are needed to iden-tify and categories different garbage types in order to improve both the environment and quality of life. Convolutional neural networks have been used in garbage detec-tion in recent years. UAV technology can be used by the government and waste management organizations to manage waste effectively. Many waste management tasks, including garbage collection and landfill monitoring, can be made simpler by UAVs [2].The most widespread and long-term marine environmental harm is caused by macro- and micro plastic waste [3].It is imperative to take action right away to make it easier for responsible trash collection and segregation in order to stop fur-ther environmental pollution and, as a result, protect people and wild animals.

The majority of the garbage collection is located in fixed locations in the open air. There are issues like a poor working environment, high labor intensity, and a poor sorting efficiency. In fact, garbage classification in the context of aerial view has the potential to address the core issue. However, due to low classification aware-ness, the difficulty of classification, and the wide variety of garbage, people rarely actually throw their trash in categories. Machine learning is one method for assisting with waste sorting (ML). Deep learning-based systems that support or entirely cover sorting processes have been put into place recently, speeding up this process as a result. These bins are able to categories a single object at a time if it is placed on a background that is free of clutter [4].CNN-based models are used to train UAVs to identify litterbugs and collect garbage [5].The proposed garbage classification algo-rithm is optimized with multi-feature fusion, feature reuse, and a new activation function [6].Builds a deep neural network model for garbage categorization called DNN-TC. This model is a refinement of the ResNext model that aims to improve the predicted performance of the model [7].ResNet-50 and SVM are used to classify waste into different groups/types [8].

It has long been believed that an automated analytic procedure is required for draw-ing the most accurate findings. Based on the use of symmetry, these automated solu-tions can aid waste management organizations in properly treating trash. Symmetry creates equilibrium, and balance is essential in all aspects of life. Deep learning is used for image retrieval in the present day, and it is a significant difficulty to deliver accurate pictures while neglecting symmetry for feature extraction. Considering this effort, there are a number of unexplored research areas.

- What garbage detection methods have been employed?
- What various performance metrics are employed in this work?
- What sort of information or dataset was used to do this task?

With the use of the symmetry theory, this study intends to provide waste manage-ment firms with a quick, accurate, low-cost solution that is simple to use. The fol-lowing is primary contribution to this article.

- A dataset is made up of images from UAVs and other cameras of garbage from different free datasets.
- MobilenetV3Large with fine tuning is for classification, and a soft attention layer is suggested for the CNN based model for better classification.
- The overall performance of this proposed model was judged based on how it compared to the best models available at the time.

The rest of the paper is organized as follows: Part-2 related work part-3 material and Methods part 4 Experiment and Result part 5 paper is concluded.

2 Related works

ResUNet50 successful in locating and classifying floating plastic (F1 score > 0.73) for both underwater and floating targets in various datasets.[2]

Convolutional neural networks with one convolutional layer and a variety of con-volution filters were developed. The classification error ranged from 0.51% to 17.77%.[6]

DNN-TC is a trash classification model use for classification This study collected 5904 images in three classes from the VN-trash dataset. Second, the DNN-TC model used the ResNext architecture with several modifications to improve classification performance, compared the predictive performance of proposed framework and state-of-the-art trash classification methods on Trashnet and VN-trash datasets to demonstrate their efficacy. The Trashnet dataset is small, and most images contain one object, while the VN-trash dataset has many objects in each class. DNN-TC outperformed state-of-the-art methods on Trashnet and VN-trash datasets. DNN-TC achieves 94% trashnet and 98% VN-trash datasets. [9]

SVM as a classifier and trained the CNN model with images from VN-trash da-taset Categorized VN-trash dataset. The pre-trained model can also classify solid waste. The inception module performed 88.6% better than Resnet on the trash net dataset.[10]

Image segmentation n and classification are becoming more and more important for researchers in computer vision and machine learning. Author proposes a system that uses convolutional neural networks to classify plastic waste. The results show that using image processing and artificial intelligence to automatically classify waste makes it possible to build systems that work well in the real world.[11]

Focused on Vgg-16, ResNet-50, and ResNet18 pre-trained models. ResNet-18 val-idated 87.8% of the dataset. Past research on automatic garbage collection has been varied. Garbage removal wasn't enough. Recycling must support garbage collection efforts to reduce waste. Implementing resource recovery systems can increase the sustainability of waste management practices. [12]

Two CNN models, CNN1 and CNN2, were evaluated for solid waste detection. The Adam optimizer performed better than the RMS prop optimizer, with CNN1 achieving a higher accuracy of 94% than CNN2. This study demonstrates the poten-tial of neural networks and symmetry in improving waste management to be eco-nomical and environmentally beneficial for society.[13]

3 Material And Methods

3.1 Dataset

Classification of recycling and decomposable waste is very important for humani-ty and civilization. Recycling waste can be process after some time but for the de-composable waste such as green waste and food waste need to process as early as possible as they are biodegradable, and proper processing of such waste will be con-verted in compost fertilizer.

For detection and classification of such garbage waste A new dataset 'KACHARA' is created with collection of various available dataset images TrashNet [15],[16],[17],[18] and images collected through mobile phone camera.

The 'Kachara' dataset was used for this work .This dataset contains seven classes of cloths, decomposable, glass, metal, paper, plastic, and wood. The images on this dataset consist of photographs of garbage taken on a white background. The different exposure and lighting selected for each photo include the variations in the dataset.

KACHARA dataset contains 4715 images in total. The class wise images of the dataset are given in Table 1.

Table 1. Statistic of KACHARA dataset

Number	Classes	Number of images
1	Cloths	299

2	Decomposable	871
3	Glass	568
4	Metal	819
5	Paper	483
6	Plastic	1230
7	Woods	445

KACHARA dataset have images in different sizes before training the model im-ages are preprocess. Sample images are shown in fig-1.in preprocessing the images of all seven class cloths, decomposable, glass, metal, paper, plastic and woods are consider at the time of capturing the images in different orientation and view point images are in aerial view and oblique view for train the model to classify and detec-tion of garbage in any orientation view each image is resize and rescale to same size of 256x256.

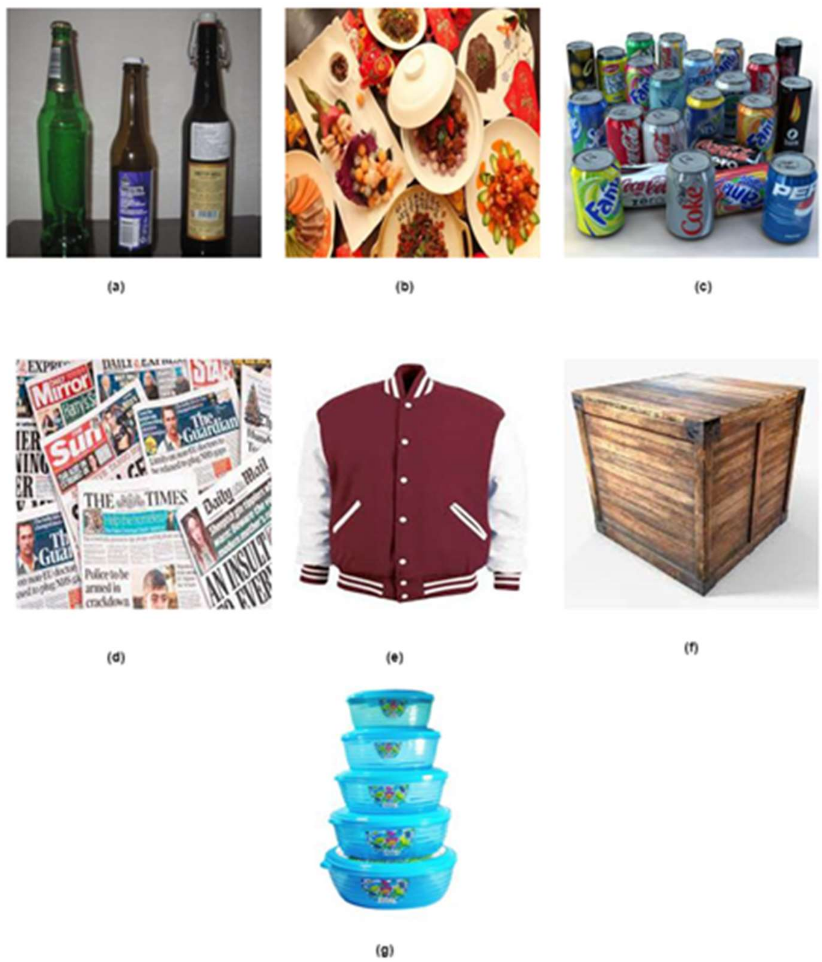

Fig. 1. Sample images of Dataset KACHARA (a) Glass,(b)Decompasable,(c)Metal,(d)Paper,(e)Cloth,(f)Woods,(g)Plastic

3.2 MobileNetV3 large

A number of models have developed by researchers due to the success of deep learning for the image classification and detection VGG16 [20] Efficientnet[21], inception[22],Resnet50[23] accuracy of vari-ous classification model is shown if figure 1.1 and the models MobileNetV3large use for classification with fine tuning.

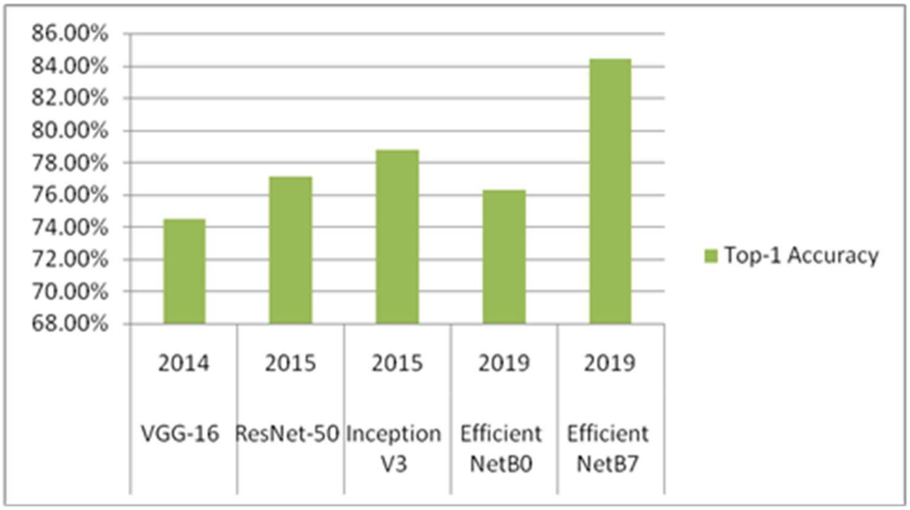

Figure 1.1 Accuracy comparisons of various state of the art models

MobileNetV3Large's deep neural network architecture is optimized for mobile and embedded image classification. It improves performance and reduces computa-tional cost by using new design features from MobileNetV2.The MobileNetV3Large architecture has a convolutional backbone network and classification layers at the end. The backbone network efficiently extracts features from incoming images, while the classification layers classify them.MobileNetV3Large uses the "h-swish" activation function, which is faster and more accurate than the "ReLU" method. The h-swish function is faster and more accurate than ReLU and improves gradient flow during training.MobileNetV3Large additionally uses "squeeze-and-excitation" mod-ules to selectively increase informative features and "hard-swish" activation mecha-nisms to reduce computational cost.MobileNetV3Large is an effective deep learning architecture for image categorization on mobile and embedded devices. [19].

3.3 Metrics

In order to demonstrate the performance of the classification models in a compre-hensive manner, we make use of a number of classification measures. The metrics are defined as the number of True Positives (TP), False Positives (FP), True Nega-tives (TN), and False Negatives (FN), and they are based on the number of True Positives (TP), False Positives (FP), and True Negatives (TN).

$$Accuracy = \frac{True\ postive + True\ negative}{TP+TN+FP+FN} \quad (1)$$

$$Precision = \frac{True\ postive}{True\ postive + False\ Negative} \quad (2)$$

3.4 Proposed Methodology

We are able to represent the problem of waste classification as one of image clas-sification by using a top view camera that captures an aerial image of the waste and feeding that image into a deep neural network in order to determine which class the waste should be placed in.

Intelligent self-sorting trash bins are the solution that is used the most frequently. Garbage object are not any fix feature properties it chang-es time to time to classify the garbage object methodology is proposed in Figure 1

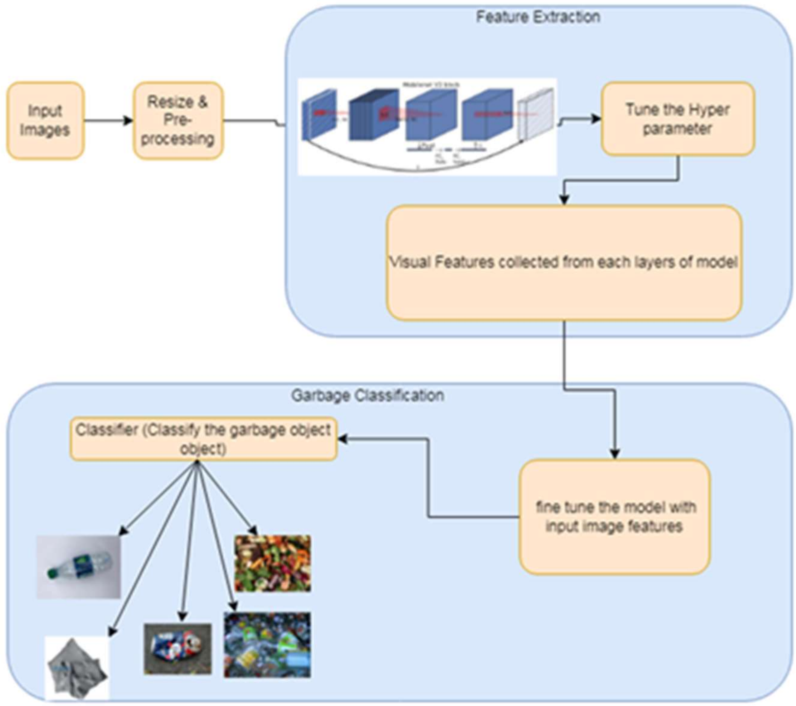

Fig. 2. Proposed Methodology for garbage classification and detection

The model is constructed using the MobileNetV3Large pre-trained model without its original final dense layers. These layers have been replaced with a hidden layer of 256 neurons that receives data from a Global Average Pooling operation, a Batch Normalization layer for fixing internal covariate shift, an ELU activation function, and several Dropouts. The model also contains several Dropouts. After that, the final layer has the same number of neurons as the output classes, which are specified by the number of Classes then, L1 regularization is added to prevent over fitting, which is the primary factor contributing to a lack of generalization. In addition to transfer learning, it is often necessary to unfreeze the final few convolutional layers of the pre-trained convolutional model. This is done in order to optimize the model's per-formance. This process, which is referred to as "Fine Tuning," raises the model's overall performance standards. Just the top six levels of this structure are not frozen. For the purpose of model compilation, a Google Colab environment with a Tesla P100 GPU was used. This was done in order to assign the Sparse Categorical Cross entropy loss function, the Adam algorithm for optimizing all of the network parame-ters, and the accuracy metric. In the final step, the model is trained for a total of fifty epochs. Accuracy graph is shown in figure 4.

4 Results

(a) Classification Test

The following steps are taken to test the model's categorization function: Cloths, Decomposable, Glass, Metal, Paper, Plastic, and Woods are examples of test objects. Gather a huge number of corresponding images. Each item includes over 250 imag-es. These comprise the train data set of this research, which consists of 4715 images in total. After retraining on the KACHARA dataset. The garbage images are evaluat-ed to check if the algorithm can appropriately classify them. The things in the image are accurately classified in the test. Figure 5 depicts the specific test results. The labels for the objects are written in white in the upper left corner. It is clear that the categorization effect is effective. It can meet the requirements of intelligent garbage classification and accurately complete garbage classification shown in the figure 3(Confusion Matrix) with accuracy of 94.37%.

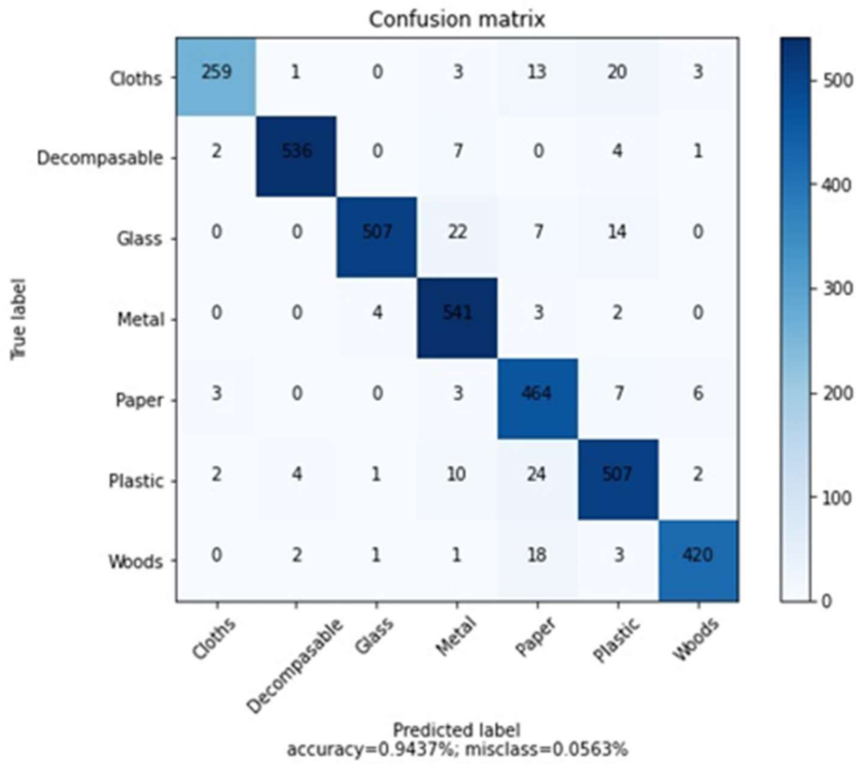

Fig. 3. Confusion matrix

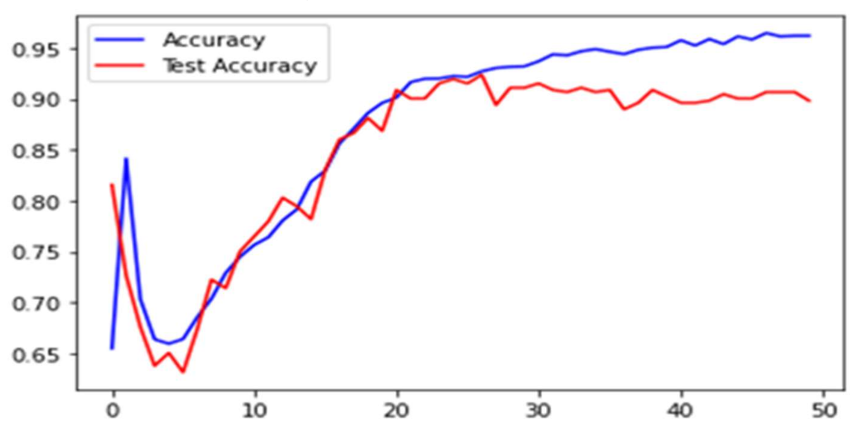

Fig. 4. Accuracy graph

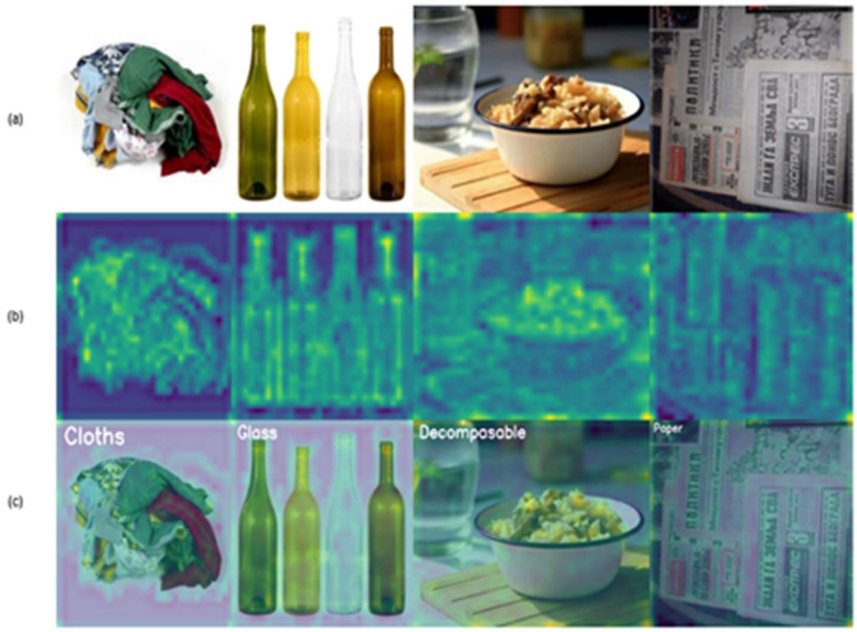

Fig. 5. Result on proposed dataset

In this research our proposed method give the accuracy of 94.37% where number of classes are 7 which is maximum in garbage classification shown in the table 2 where in [12] it was 6 and total number of images are 5000 and it have 90% Accura-cy in [14] CNN1 Model have only 2 classes of 6000 images and it have 94% accura-cy our proposed model is more accurately classify the object classes with accuracy of 94.37%

Table 2. Result compression

Citation	CNN Based Model	Number of Class	Number of Images	Accuracy %
2	Scratch CNN Model	2	1312	83.33
9	VGG 16	4	2527	86.6
10	ANN	3	3046	67
11	Dense Net	5	600	83.7
12	Multilayer Hybrid System (MHS) Alex Net	6	5000	90
13	VGG16, Alex Net	4	2400	93
14	CNN1 Model	2	6000	94
Proposed Model	**MobileNetV3Large**	**7**	**4727**	**94.37**

5 Conclusion

KACHARA dataset is proposed in the paper for the garbage classification for the seven classes and MobileNetv3 large with transfer learning is for the classification which shows promising results for garbage classification how ever more accurate framework is required for the real-time garbage segmentation when single image containing multi classes garbage, in future we propose multi class garbage segmen-tation model for effective garbage segregation.

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