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Waste Stratification using Deep Learning

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ABSTRACT

Waste management is one of the most serious problems that practically every country faces. Its goal is to offer sanitary, efficient, and cost-effective solid waste storage, collection, transportation, treatment, and disposal without harming the environment, land, or water system. Waste sorting errors can result in incorrect disposal and the loss of opportunity to recycle or reuse items. Monitoring by hand is inefficient and costly. As a result, deep learning and machine learning play a critical role in categorizing and sorting garbage and rubbish, effectively distinguishing between different types of waste. Many tasks, such as garbage collection and waste classification/ segregation, are partof waste management. One of the most important operations is garbage classification, which is carried out in a varietyof ways based on the nature of the material.

Keywords: *MobileNet Architecture, VGG16model, Accuracy, Data collection, Convolutional Neural Network.*

1. INTRODUCTION

Traditional waste categorization methods haveincluded physical characteristics such as weight, shape, and state of waste such as gaseous, solid, liquid. Many CNN architectures were developed for image classification and Computer Vision approaches have also been applied to detect the type of waste. The main objective of this project is to develop an efficient classification model that could classify and recognize animage passed to the system.

Dataset

The dataset used consists of 8 different categories of waste. It is an extension to the dataset developed by Gary Thung and Mindy Yang which had only 6 different categories: cardboard, glass, metal, paper, plastic and trash. Using web scraping methods on variousstock image websites and real time camera dataset is extended with other two categories i.e., organic waste and ewaste. So, this model can now classify 8 different categories of waste(Link to the dataset).

Data Augmentation

As the main aim is to build a model that recognizes the signs irrespective of its viewingangle and other aspects, the training dataset is passed to the Image data generator which can change the width, height, zoom, shear and rotation range of the images. Hence the modelis trained with an abundance of images.

Architecture

MobileNet architecture has been considered which is a Convolutional Neural Network thatis 53 layers deep. It has been loaded with a pre-trained version of the network that has been trained on over a million images from theImageNet database. The basic unit of this network is depthwise separable convolution,which further has two layers:

A. Depthwise convolution: It performs a single convolution on each input channel.

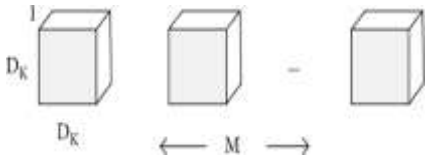
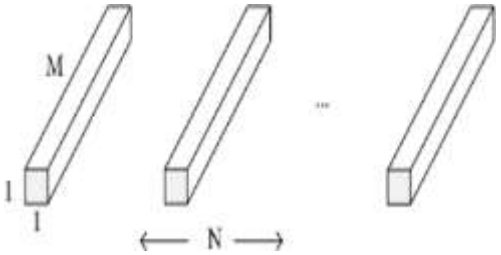


Figure : Depthwise Convolution Filters

B. Pointwise Convolution:It combines theoutput of depthwise convolution linearly with 1*1 convolutions.



Some extra layers and output layers have been added to the model, which included Dense layers along with relu activation function and Softmax activation function that can classify 8 different categories.

Table 1: MobileNet Body Architecture

Type/Stride	FilterShape	Input Size
Conv / s2	3 x 3 x 3 x 32	224 x 224 x 3
Conv dw / s1	3 x 3 x 32dw	112 x 112 x32
Conv / s1	1 x 1 x 32 x 64	112 x 112 x 32
Conv dw / s2	3 x 3 x 64dw	112 x 112 x 64
Conv / s1	1 x 1 x 64 x 128	56 x 56 x 64
Conv dw / s1	3 x 3 x 128 dw	56 x 56 x 128
Conv / s1	1 x 1 x 128 x 128	56 x 56 x 128
Conv dw / s2	3 x 3 x 128 dw	56 x 56 x 128
Conv / s1	1 x 1 x 128 x 256	28 x 28 x 128
Conv dw / s1	3 x 3 x 256 dw	28 x 28 x 256
Conv / s1	1 x 1 x 256 x 256	28 x 28 x 256
Conv dw / s2	3 x 3 x 256 dw	28 x 28 x 256
Conv / s1	1 x 1 x 256 x 512	14 x 14 x 256
5 x Conv dw / s1 Conv / s1	3 x 3 x 512 dw 1 x 1 x 512 x 512	14 x 14 x 512 14 x 14 x 512
Conv dw / s2	3 x 3 x 512 dw	14 x 14 x 512
Conv / s1	1 x 1 x 512 x 1024	7 x 7 x 512
Conv dw / s2	3 x 3 x 1024 dw	7 x 7 x 1024
Conv / s1	1 x 1 x 1024 x 1024	7 x 7 x 1024
Avg Pool/ s1	Pool 7 x 7	7 x 7 x 1024
FC / S1	1024 x 1000	1 x 1 x 1024
Softmax / s1	Classifier	1 x 1 x 1000

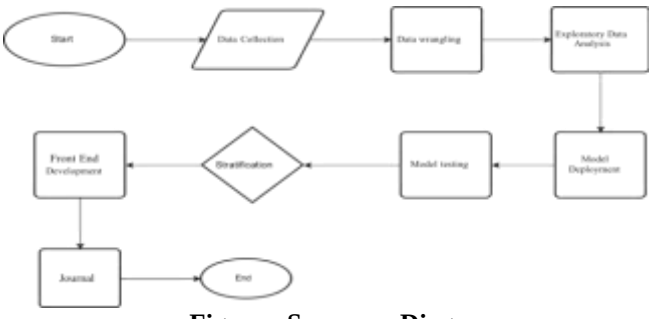


Figure : Sequence Diagram

2. LITERATURE REVIEW

Olugboja adedeji, zenghui wang in 2019 proposedan intelligent waste material classification system,which is developed by using the 50-layer residual net pre-train (ResNet-50) Convolutional Neural Network model which is a machine learning tool and serves as the extractor, and Support Vector Machine (SVM) which is used to classify the waste into different groups/types such as glass, metal, paper, and plastic etc. The proposed system is tested on the trash image dataset which was developed by Gary Thung and Mindy Yang, and is able to achieve an accuracy of 87% on the dataset.

Sai susanth, LM Livingston in 2021 proposed a work 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, suchas 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.

Himanshu Gupta, dristi yadav in 2020 presented a work that investigates a novel approach for waste segregation for its effective recycling and disposal by utilizing a deep learning strategy. TheYOLOv3 algorithm has been utilized in the Darknet neural network framework to train a self-made dataset. The network has been trained for 6 object classes (namely: cardboard, glass, metal, paper, plastic and organic waste).

3. RESULTS

When the model was tested it classified the imagecorrectly with 99.65% accuracy. The classification report of the model was displayed as
follows:

Table 2: Classification Report

	precision	recall	f1- score	support
cardboard	0.98	0.93	0.96	61
ewaste	0.96	0.98	0.97	82
glass	0.98	0.82	0.89	76
metal	0.87	0.97	0.92	62
organic waste	0.98	0.97	0.97	58
paper	0.92	0.94	0.93	90
Plastic	0.85	0.96	0.90	73
trash	0.79	0.71	0.75	21
accuracy			0.93	523
weighted avg	0.93	0.93	0.93	523

4. CONCLUSION

Waste management is a major issue, its purpose isto provide a hygienic environment. A small mistake in waste classification can lead to improper disposal and missed opportunities to reuse and recycle materials. This model is proposed to classify waste materials. This model can currently classify 8 different types of waste. Data was collected and cleaned very carefully before passing it to the model. Also, the dataset can be extended with different types of waste materials and more images. The idea of waste classification can be used in the recycling processof waste if the mode is reliable and accurate.

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