Classification of Plastic and Non-Plastic Wastes Using Mobile net and SVM

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Abstract

In recent years, governments across the globe are keen to envisage the use of AI, Deep learning and machine learning methods with the objective of limiting the ill effects of improper waste segregation methods. The current state of technology makes it possible to create a system that can identify plastics and non-plastics automatically from its image. It is necessary to do a feature extraction method in order to take the distinct features of the plastic/non-plastic object that can define the properties of the object in order to provide a more accurate classification.

This study suggests an architecture that uses Mobilenet for feature extraction and the extracted features were classified using Support Vector machine classifier to separate waste items into plastic and non-plastic. Compared to a conventional CNN the proposed approach using Mobilenet requires less training parameters. The dataset employed in this work is a customized one exclusively compiled for this study. The proposed system of separating plastics from other materials requires less manual labour and can be used in smart garbage systems and for plastic segregation in industries.

Keywords: Mobilenet, Support Vector machine, Depth wise separable convolutional neural networks, classification, plastics and non-plastics.

1. Introduction

According to various studies across the globe only minimum percentage of solid waste that is generated is being recycled at present. This is attributed to the absence of an effective system for waste segregation in real time. To achieve the sustainable development goals, we need to keep a clean and green environment, for which we need a clever trash management and sorting system is required. [1-2]. In order to lessen the impact of inappropriate trash disposal, this paper attempts to design and develop an automated plastic waste identification framework employing machine learning methods and deep learning algorithms.

The majority of research on image classification focuses on feature extraction techniques since features are crucial to classification. Due to their capacity for self-learning, self-adaptation, and self-organization, convolutional neural networks can automatically extract features using the prior knowledge of recognized categories, avoiding the time-consuming feature extraction process used by conventional image classification techniques.[3-**5**]. The retrieved features are extremely expressive and effective at the same time.

The computer vision area has seen a lot of success with deep convolutional neural networks, but it is a complex computational model. Convolution is a mathematical operation is a mathematical process in which a k x k kernel slides over the 2D input image/matrix performing matrix multiplication with the part that it is currently on and then summing up the result matrix into a single pixel[6-7].

Several works could be seen in the literature which employs CNN and its variants in object detection and classification. Mentioned below are a few works done by researchers for automatic solid waste segregation which employs deep learning. Glass, paper, cardboard, plastic, metal, and other rubbish are the categories classified by the model developed in [8-10]. Transfer learning was used to create the model from one that had been created using the ImageNet Large Visual Recognition Challenge dataset. In order to categorize images into six types of objects, the authors in [11-13] suggested a method for image classification based on SVM and CNN. Regarding classification accuracy and effectiveness, the authors [10][14] focused on support vector machines and hybrid CNN with SVM. Support Vector Machine (SVM), a machine learning tool that serves as the extractor, and the 50-layer ResNet-50 convolutional neural network model are used to categorize the garbage into several groups and types, such as glass, metal, paper, and plastic, among others, are used in [15-16]. Convolutional neural networks, which offer the highest learning efficiency, require the fewest parameters for training, and offer more accuracy than regular networks, were proposed by [17] as a method for sorting waste items into plastic and non-plastic categories. The authors in [18-19] presented waste image classification to facilitate automatic waste sorting using the Scale Invariant Feature Transform-Principal Component Analysis (SIFT-PCA) and Support Vector Machine (SVM) classification technique.

Due to the massive numerous parameters, large computing load, and numerous memory accesses, it is difficult to adapt the deep convolutional approach to mobile, portable devices with constrained hardware capabilities. Applying the deep convolutional neural network model to real-time applications and portable devices with little memory it is a viable choice to speed and compress deep convolutional neural networks in order to cut back on power, computation, and parameter expenses. A separable convolution is one in which the same output may be obtained by splitting a single convolution into two or more convolutions [20]. Separable convolutions are the foundation of several deep learning algorithms, including Xception [21] and The MobileNet variation known as Mobilenet V1 [22-25]. In this study, a lightweight network called Mobilenet [30]is proposed that deepens the network while minimizing computation and parameters by using depthwise separable convolution.

2. Depth wise separable convolutional neural networks.

One type of convolution structure made specifically for embedded and mobile devices is depthwise separable convolution. Each input channel is subjected to a filter through depthwise convolution, and the outputs of depthwise convolution are combined using 1x1 pointwise convolution. The standard convolution structure is depicted in Fig.1. and the computational cost is given in Eqn.1.

$$MxNxD_G^2xD_K^2 \qquad [1]$$

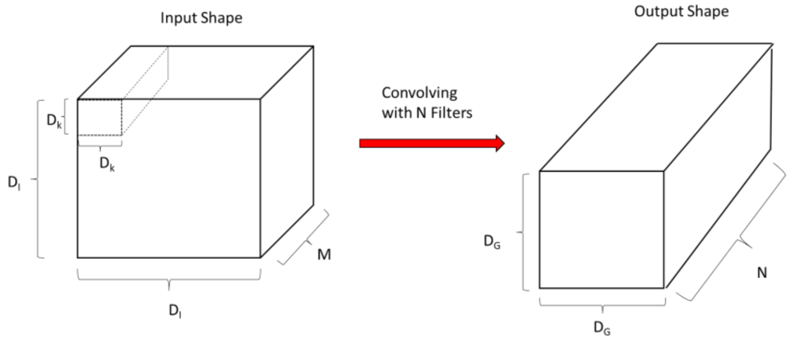
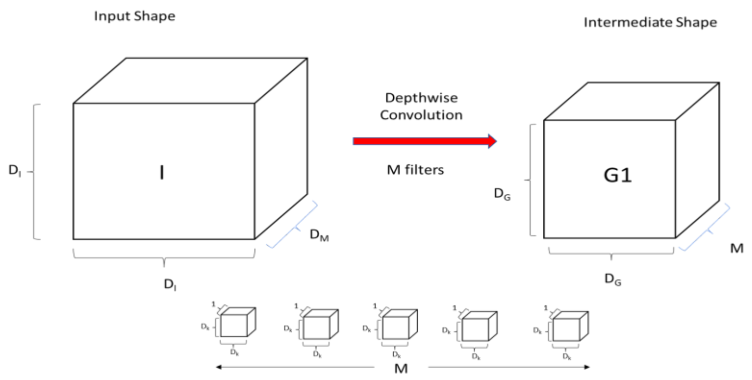
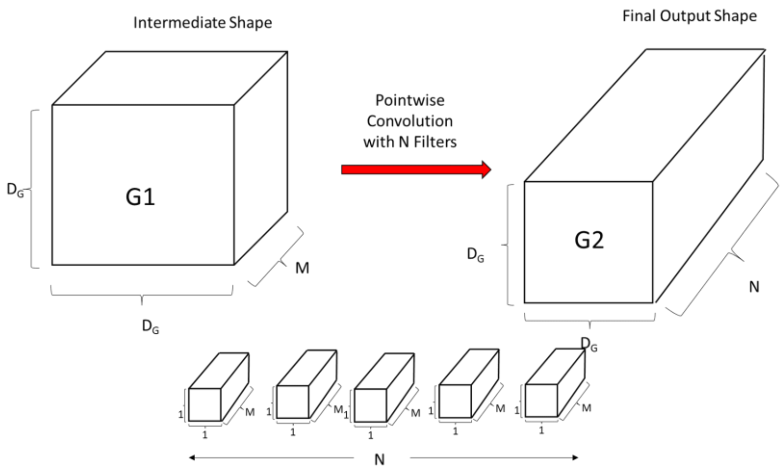


Fig1. Standard convolution structure

Depthwise separable convolution (DSC) structure is shown in Fig.2.



a. Depthwise convolution



b. Pointwise convolution

Fig.2. Separable convolution structure

For depth wise convolution operation, the computational cost is given by Eqn.2.

$$MxD_G^2xD_K^2 \qquad [2]$$

And for point wise convolution operation, the computational cost is given by Eqn.3.

$$MxNxD_G^2 \qquad [3]$$

Total cost is given by Eqn.4.

$$(M \text{ x } D_G^2 \text{ x } D_K^{2)} + (M \text{ x } N \text{ x } D_G^2) \qquad [4]$$

Using the computation loads for depthwise separable convolution and standard convolution as a comparison, we find

$$(M \text{ x } D_{G2} \text{x } D_{K2}) + (M \text{ x } N \text{ x } D_{G2}) \; M \text{ x } N \text{ x } D_{G2} \text{x } D_{K2}^{=1N} \qquad [5]$$

Eqn.5. demonstrates that using a 3x3 depthwise separable convolution kernel (DK=3) results in an eight to nine-fold reduction in parameters and computation with only a tiny reduction in accuracy. This factorization can thereby efficiently reduce computational demands and model size. The benefits of Mobilenet, which is used in this work and uses depth-wise separable convolution, include: (1) They require fewer parameters to be adjusted than standard CNNs, which lessens overfitting. (2) They are appropriate for mobile vision applications because they require fewer computations, which make them cheaper computationally. As the proposed system is expected to be employed in smart garbage systems where the computational resources will be limited, Mobilenet which uses depthwise separable convolution is proposed in this work.

3. MobileNet Structure

Mobilenet are small, low latency, and low power models that may be tailored to meet the resource constraints of various use cases. With the exception of the first layer, which is a full convolution, the Mobilenet structure is built on depthwise separable convolutions as discussed in the previous section. A batch norm and ReLU are used after each 3x3 convolution layer in the Mobilenet design as opposed to a standard CNN, which is the main difference between the two. MobileNet divides the convolution into a 3x3 depthwise convolution and a 1x1 pointwise convolution, as shown in Fig. 3.

Table 1 provides a definition of the Mobilenet architecture [22-24]. All layers are followed by a batchnorm [25] and ReLU non-linearity [26], with the exception of the final fully connected layer, which has no nonlinearity and feeds into a softmax layer for classification. Both the first layer and the depthwise convolutions manage down sampling using strided convolution. A last average pooling lowers the spatial resolution to 1 before the fully connected layer. If depthwise and pointwise convolutions are regarded as independent layers, MobileNet has 28 layers.

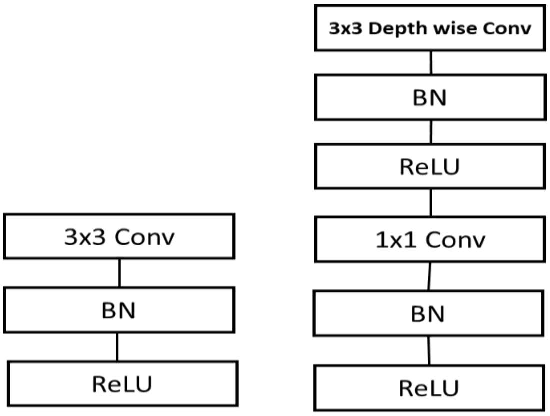


Fig. 3(a) ReLU and batch normalization are applied to a standard convolutional layer. (b) Depthwise separable convolution with depthwise and pointwise layers is followed by batch normalization and ReLU.

Table1 Mobilenet Architecture

Type / Stride	Filter Shape	Input Size
Conv / s2	$3 \times 3 \times 3 \times 32$	$224 \times 224 \times 3$
Conv dw / s1	$3 \times 3 \times 32$ dw	$112 \times 112 \times 32$
Conv / s1	$1 \times 1 \times 32 \times 64$	$112 \times 112 \times 32$
Conv dw / s2	$3 \times 3 \times 64$ dw	$112 \times 112 \times 64$
Conv / s1	$1 \times 1 \times 64 \times 128$	$56 \times 56 \times 64$
Conv dw / s1	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 128$	$56 \times 56 \times 128$
Conv dw / s2	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 256$	$28 \times 28 \times 128$
Conv dw / s1	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 256$	$28 \times 28 \times 256$
Conv dw / s2	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 512$	$14 \times 14 \times 256$
5× Conv dw / s1 Conv / s1	$3 \times 3 \times 512$ dw $1 \times 1 \times 512 \times 512$	$14 \times 14 \times 512$ $14 \times 14 \times 512$
Conv dw / s2	$3 \times 3 \times 512$ dw	$14 \times 14 \times 512$
Conv / s1	$1 \times 1 \times 512 \times 1024$	$7 \times 7 \times 512$
Conv dw / s2	$3 \times 3 \times 1024$ dw	$7 \times 7 \times 1024$
Conv / s1	$1 \times 1 \times 1024 \times 1024$	$7 \times 7 \times 1024$
Avg Pool / s1	Pool 7×7	$7 \times 7 \times 1024$
FC / s1	1024×1000	$1 \times 1 \times 1024$
Softmax / s1	Classifier	$1 \times 1 \times 1000$

4. Methodology

This work focuses on extracting features from the input images using Mobilenet v1 is one of Mobilenet model and then classifying the images of plastic and non-plastic objects using SVM [18]. The network's convolution layer shares the parameters and extracts the majority of the image features. The number of parameters is reduced by using the pooling layer. The final classification outcome is then produced by the SVM classifier which integrates the characteristics that the network had previously collected to produce the overall significance of the image features. The workflow of the plastic and non-plastic waste classification system is shown in Fig.4.

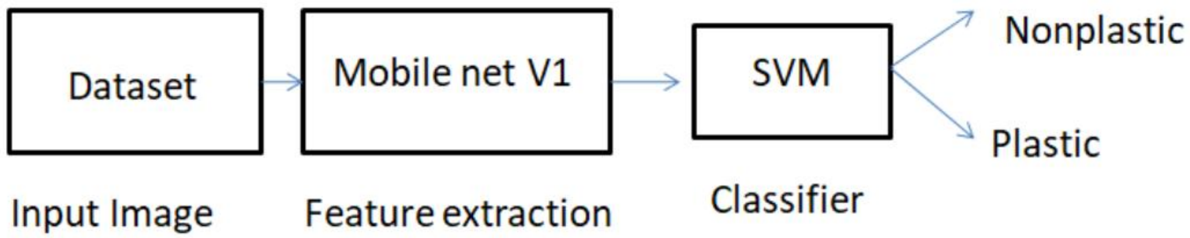


Fig.4. Workflow of the proposed plastic and non-plastic waste classification system

SVM

A supervised learning machine known as an SVM employs kernels and support vectors as its core ideas for a variety of learning tasks. The selection of the kernel functions in kernel machines can be used to complete various tasks in many domains. SVM determines the ideal hyperplane that divides the vector cluster into the target variable on one side and other category on the other. The vectors that are near the hyper-plane are the support vectors.

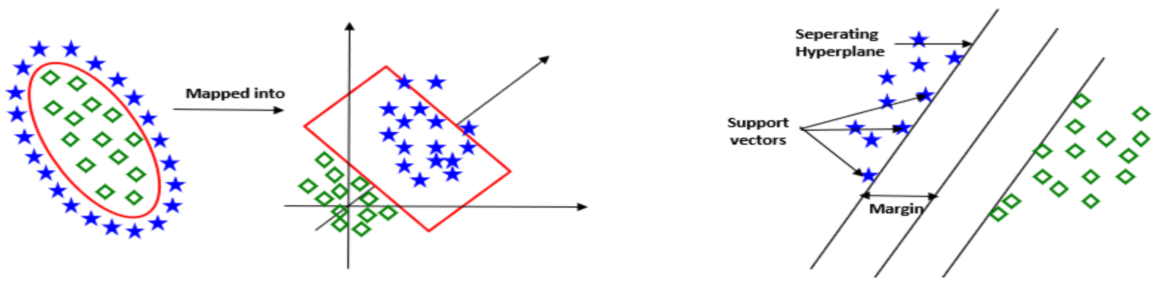


Fig. 5 SVM principle (a) Non-linear data mapped to linearly separable data using kernel function (b) Support vectors and maximum margin hyperplane

The linear kernel function in linear SVM [27] as: $K\,(x, x_i) = x.\,x^{t}$ [6] and

In non-linear SVM [18], popular kernel functions include

a. Kernel for the Gaussian Radial Basis Function (RBF): $K(x, x') = \exp(-\gamma\| x - x'\|^{2})$ [7]

b. Polynomial kernel: $K\,(x, x') = (\gamma(x, x') + r)^{d}$ [8]

c. Sigmoid kernel: $K\,(x, x') = \tanh(\gamma(x, x') + r)$ [9]

All the three kernels were employed for testing the efficacy of the proposed plastic and non-plastic classification system and the results are evaluated and compared [29].

5. Experiments and Evaluation

The custom dataset used include plastic and non-plastic objects totaling 2039 images. In this work, 1143 images of plastic and 896 images of non-plastic were taken for classification.The dataset images collected from the internet is used to train the Mobilenet for feature extraction. The extracted features are then fed into SVM[28], which is used to classify the objects .The confusion matrix and the classification performances of SVMs employing the different kernels are given in Fig. 5. From Fig. 5 we could see that the radial basis function or the Gaussian kernel of SVM was able to categorize plastics and non-plastics with 98% accuracy. The sigmoid kernel depicted the lowest accuracy of 87%, whereas the linear kernel was able to categorize plastics and non-plastics with 94% accuracy. Fig. 6 shows the comparison chart of the various metrics namely accuracy, precision, recall and F-score.

Linear Kernel- SVM

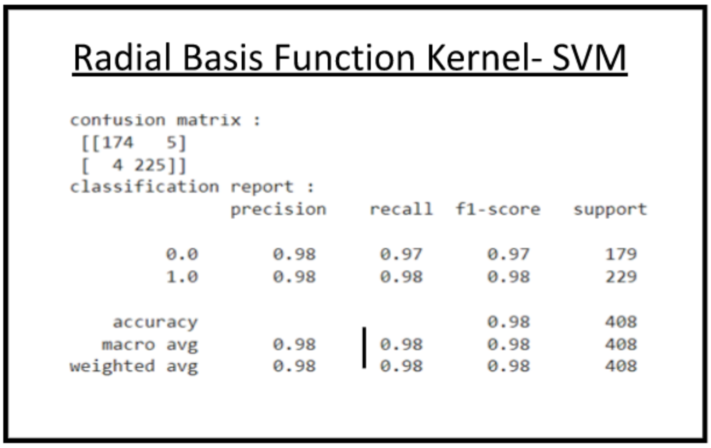
```
confusion matrix :
 [[168  11]
 [ 14 215]]
classification report :
```

	precision	recall	f1-score	support
0.0	0.92	0.94	0.93	179
1.0	0.95	0.94	0.95	229
accuracy			0.94	408
macro avg	0.94	0.94	0.94	408
weighted avg	0.94	0.94	0.94	408

Sigmoid Kernel-SVM

```
confusion matrix :
 [[148  31]
 [ 24 205]]
classification report :
```

	precision	recall	f1-score	support
0.0	0.86	0.83	0.84	179
1.0	0.87	0.90	0.88	229
accuracy			0.87	408
macro avg	0.86	0.86	0.86	408
weighted avg	0.87	0.87	0.86	408



Radial Basis Function Kernel- SVM

```
confusion matrix :
 [[174   5]
 [  4 225]]
classification report :
              precision    recall  f1-score   support

         0.0       0.98      0.97      0.97       179
         1.0       0.98      0.98      0.98       229

    accuracy                           0.98       408
   macro avg       0.98      0.98      0.98       408
weighted avg       0.98      0.98      0.98       408
```

Fig.5. Confusion matrix and Performance metrics of linear, sigmoid and RBF kernel of SVM

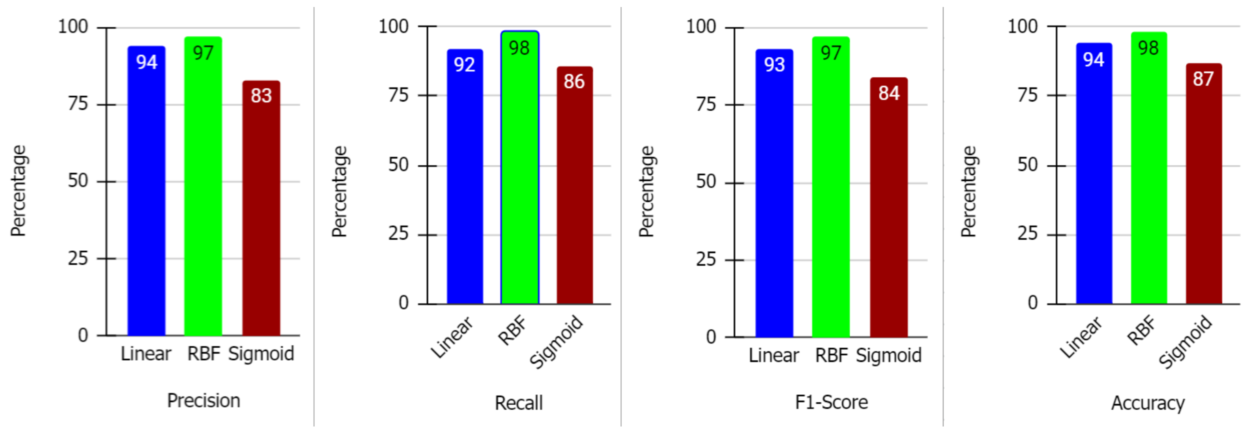


Fig. 6 Comparison chart of the various performance metrics

6. Conclusion

The findings of this study show that deep learning algorithms and computer vision techniques can effectively address the problem of plastic classification. In this study, 1143 images of plastic and 896 images of non-plastic were classified. The images gathered from the internet were used to train Mobilenet for feature extraction. After that, the extracted features are fed into an SVM for classification. Using Google Colab was used as the training environment because it produces outputs that are reliable, accurate, and error-free. Gaussian kernel of SVM produced an accuracy of 98%, the linear kernel was able to categorize plastics and non-plastics with an accuracy of 94% while the sigmoid kernel showed the lowest accuracy of 87%.

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