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Computer Vision-Based Automatic Sorting of Non-Biodegradable Waste: A VGG16 Approach for Plastics and Polythene

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Abstract

Sustainability should be an integral part of modern civilization. To cultivate this habit, individuals can make conscious choices such as refusing single-use plastics, segregating and composting waste at home, and fostering awareness about consumption. With rapid industrialization and an increasing population, waste generation is rising significantly. A large portion of this waste is either dumped onto land or disposed of in aquatic ecosystems, leading to severe environmental hazards. Waste can be categorized into two types: (i) Biodegradable and (ii) non-biodegradable. Biodegradable waste, including food waste, green waste, and paper, decomposes naturally. In contrast, non-biodegradable waste—such as plastic, polythene, glass, and metal—persists in the environment. While materials like glass and metal can be recycled, plastics and polythene often pose long-term environmental threats. This paper presents a computer vision-based approach using VGG-16 to detect non-biodegradable waste, specifically plastics and polythene. Geo-tagged & non tagged waste images were collected from two locations in West Bengal, India: Banipur (North 24 Parganas) and Panihati (Kolkata region). The real time dataset was classified into two distinct categories: plastics_data and polythene_data. Experimental result shows that image data sets of geo-tagged and non-geotagged images of two different categories of classes i) plastics and ii) polythene 95%, with training and validation accuracies of 50.3% and 49.7%, is found respectively. The study further analyses classified and unclassified waste images, using Principal Component Analysis (PCA) to visualize the nature of each category. Our approach aims to enhance waste management practices by reducing the consumption of non-biodegradable materials in these two regions, thereby contributing to a more sustainable environment.

Keywords: *Non-biodegradable waste, VGG-16, Image Augmentation, Image Classification, Principle component Analysis (PCA), Sustainable Environment*

1. Introduction

Modernization of recent industries and its impact on socio-economic structure significantly affects a lot to our regular life. The adoption of Industry 4.0 has led to increased waste generation, posing significant environmental challenges [1][2][3]. Waste Management 4.0, also known as smart waste management, focuses on efficient sorting and recycling of metal, plastic, paper, and glass waste [5][6]. The design of the classification of waste system presents the identification of plastic waste material in the aquatic region and land using a machine learning model. The proposed machine learning model detects environmental threats by identifying single-use plastics, polythene, and metal waste in both aquatic and terrestrial regions [7]. Waste can be categorized into three major types: (i) Solid, (ii) Liquid, and (iii) Gas. Additionally, based on moisture content, waste is further classified as Dry or Wet waste [8] [9]. Amount of waste that India produced 60% is recycled (mainly plastics) and the rate is much higher than in other developing countries. Waste management is important because:

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i) 1. It saves the environment, ii) Recycling helps to achieve financial gain, iii) Reduces waste types, and iv) Energy conservation [10][11][12]. Each of them is discussed separately. (Figure 1,2) [1-2]

Figure 1 Epict the Ill Effect of Industrialization Towards the Aquatic Biome

Figure 2 Epict the Ill Effect of Industrialization Towards the Aquatic Biome

- **It Saves the Environment:** The waste products are recycled and it is preserved for future usage. [3-4]
- **Recycling Helps to Achieve Financial Gain:** Recycled materials can be repurposed, leading to financial gains and reduced raw material costs.
- **Reduction of Waste:** Proper waste sorting minimizes landfill waste and promotes sustainability [6]
- **Energy Conservation:** Certain waste materials can be converted into energy sources, such as electricity generation from waste processing

2. Experimental Methods or Methodology

2.1.Preprocessing the Image Data Sets

The dataset consists of images categorized into plastics and polythene, collected from various sources. Data augmentation techniques, such as rotation, flipping, zooming, and brightness adjustment, are applied to increase the dataset size and improve model generalization.

2.2.Phase A: Selection of Study Area

Study area is based on aquatic region i.e. focusing on parts of Ashokenagar, Banipur (North 24 Parganas of West Bengal,India) and Panihati, municipal Area of North 24 Parganas i.e: Agarpara, Kolkata, India.

2.3.Phase B

Sample Data have collected as an Image & Preprocessing the image. (Data Collection):
Firstly, collect the sample data as an image. Sample image can be prepossessed because of getting the specific size. (Figure 3,4) [5]

Figure 3 Separate Polythene Data

Figure 4 Separate Plastic Data

Noise Removal: Median filter can be used for noise removal
Let x= (2, 3, 90, 6, 2, 3) & median filter will be y so

the median filter y will be:
y1= (2, 3, 90) = 3 (as 2,3,90 is in increasing order)
y2 = (3, 90, 6) = med (3, 6, 90) =6
y3= (6, 90, 2) = med (2, 6, 90) = 6
y4= (6, 2, 3) = med (2, 3, 6) = 3
i.e: y will be (3, 6, 6, 3) [7]
For removal of impulse noise in the image:

100	105	120
105	255	105
105	100	105

255 is the maximum value out of this 3d matrix.
So, arranging the value in ascending order: (100, 100, 105,105, 105, 105,105, 120, 255) now 255 is replaced by 105. So,105 is the median value.

100	105
105	255

(100,105,105, 255) so 155 is the median value.
ii) Image Enhancing:
Image Enhancing is done for getting the better visual representation. In this qualitative enhancement can be done for modification of images that looks more appealing. For Enhancing procedure removal of noises high spatial frequency is considered.
If f(x, y) -> Original image, where f->grey level image & (x, y) ->image coordinates.
If f(t) is a time domain function then its fourier transform will be:

$$F[f(t)] = F(j\Omega) = \int_{-\infty}^{\infty} f(t)e^{-j\Omega t}\, dt$$

This converts its time domain on its frequency domain.
Apply spatial operation on neighborhood pixel of the input image. If the input image is: [4×4] i.e. neighborhood of [2×2] pixel. Output is resultant.
Let us consider a [4×4] matrix apply special function on neighborhood of [2×2] pixel:

c1	c2	c3	c4
c5	c6	c7	c8
c9	C10	c11	c12
c13	c14	c15	c16

i.e: (c1+c2+c5+c6) =e1, (c2+c3+c6+c7) = e2, (c3+c4+c7+c8) = e3, (c5+c6+c9+c10) = e4, (e6+c7+c10+c11) =e5, (c7+c8+c11+c12)= e6,(c9+c10+c13+c14)= e7,(c10+c11+c14+c15)=e8, (c11+c12+c15+c16)=e9
The resultant matrix would be:

e1	e2	e3
e4	e5	e6
e7	e8	e9

So that is the enhanced form of image.
Image detection and Comparing between Real time data set using VGG 16. [8]

2.4.Phase C: Classification of Images

Sample data can be collected as images. We are having two different class's i.e: 1.plastic waste, 2.polythene . Machine learning model are designed to classify on these variants based on features extraction. For classification we have used the VGG 16 model which is a classifier of CNN for getting the better accuracy and performance.
In this study VGG-16 is used for automatic classification of plastic and polythene waste.
Deep but Simple Architecture: VGG-16 consists of 16 weighted layers, mainly using 3×3 convolutional filters to extract fine details of plastic and polythene textures. (Figure 5) [9]

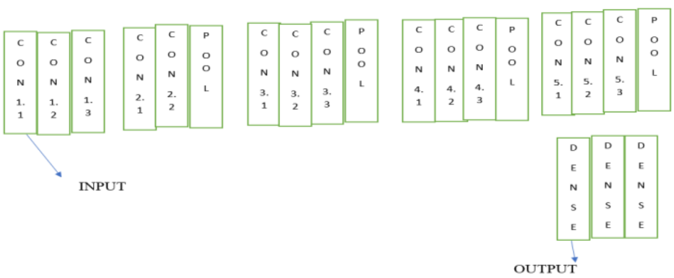

Figure 5 (a) VGG 16 Generic Architecture Labelled C (Convolution), P (Pooling), and D (Dense/FC layer), which Correctly Represents how VGG-16 Processes an Image

2.5.Steps Involving to use VGG-16 for Image Classification

- Load VGG16 (pre-trained on ImageNet)
- Modify the classifier to adapt to binary classification (plastic vs polythene).

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- Compile the model for training. (Figure 6,7)

Layer (type)	Output Shape	Param #
input_layer_4 (InputLayer)	(None, 224, 224, 3)	0
block1_conv1 (Conv2D)	(None, 224, 224, 64)	1,792
block1_conv2 (Conv2D)	(None, 224, 224, 64)	36,928
block1_pool (MaxPooling2D)	(None, 112, 112, 64)	0
block2_conv1 (Conv2D)	(None, 112, 112, 128)	73,856
block2_conv2 (Conv2D)	(None, 112, 112, 128)	147,584
block2_pool (MaxPooling2D)	(None, 56, 56, 128)	0
block3_conv1 (Conv2D)	(None, 56, 56, 256)	295,168
block3_conv2 (Conv2D)	(None, 56, 56, 256)	590,080
block3_conv3 (Conv2D)	(None, 56, 56, 256)	590,080
block3_pool (MaxPooling2D)	(None, 28, 28, 256)	0

Figure 6 VGG 16 Architecture Some Layers Are Mentioned Here

```
Total params: 21,170,497 (80.76 MB)
Trainable params: 6,455,809 (24.63 MB)
Non-trainable params: 14,714,688 (56.13 MB)
```

Figure 7 VGG 16 Architecture

2.6.Small 3×3 Filters for Better Feature Extraction

- Stacking multiple small convolutional filters achieves the same effect as large filters (e.g., 5×5) while keeping the model efficient computation. [11-14]
- This helps in distinguishing between plastic and polythene, which may have almost similar visual properties.

2.7.Max Pooling for Dimensionality Reduction

- Max pooling layers reduce the spatial size of feature maps while retaining important features, making classification faster and more accurate.

2.8.Fully Connected Layers for Final Classification

- Extracted features are fed into fully connected layers, mapping them to two distinct categories: Plastics and polythene.

2.9.Transfer Learning & Generalization

- Pre-trained VGG-16 weights (from ImageNet) allow faster training and better generalization, ensuring accurate waste classification across different environments.
- By leveraging VGG-16's deep feature extraction and classification ability, this approach enhances automated waste sorting, promoting efficient waste management and environmental sustainability.

2.10. Classification for the Input Data Sets

We are using VGG-16 for classification for the image data sets.
input image, plastic: = ip
input image, polythene: =io
combined data: = (ip + io)
trainable through augmentation
augmentation: = au> (ip + io)
au, train data: tr, au >tr
train tr to compare
binary categories: ip:=0,io:=1
Each convolutional layer applies a filter w1to the input x with a bias term b:

$$y1=f\,(w1*x+b)$$

where: [15-18]

- is the convolution operation
- f is the activation function (ReLU in VGG16)
- y1 is the feature map output.

Ypooled=max (Yregion)
S=Wf·Yflattened+bf
softmax classification:Sc
Si = Summation index: = ∑ Si,so probability of (Pc) of plastics and polythene, Pc:= eSc/ ∑Si

2.11. Confusion Matrix

- Plastics correctly classified: 107
- Plastics misclassified as polythene: 5
- Polythene correctly classified: 22
- Polythene misclassified as plastics: 74

2.12. Performance Metrics

Class	Precision	Recall	F1 score	Support
Plastics	0.59	0.96	0.73	112
Polythene	0.81	0.23	0.36	96
Overall Accuracy	62%			
Macro Average	0.70	0.59	0.54	208
Weighted Average	0.69	0.62	0.56	208

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3. Results and Discussion

In this section, we present a comparison of the model's accuracy before and after applying data augmentation. Additionally, we demonstrate image classification using the VGG16 model. The dataset is divided into two subsets: training and testing. 70% of the data is used for training, while 30% is allocated for testing to evaluate model performance effectively.

3.1. Basic Dataset

Our dataset consists of images of non-biodegradable waste, specifically categorized into Polythene and plastics. To enhance model performance, we applied data augmentation techniques, as the dataset was small (collected real time image 682 and 189 for validation). We incorporated augmentation techniques, resulting in a significant improvement, with the accuracy increasing to 95%. Binary Classification for plastics 0 and polythene 1. (Figure 8,9,10) [19-20]

```
{'plastics': 0, 'polythene': 1}
```

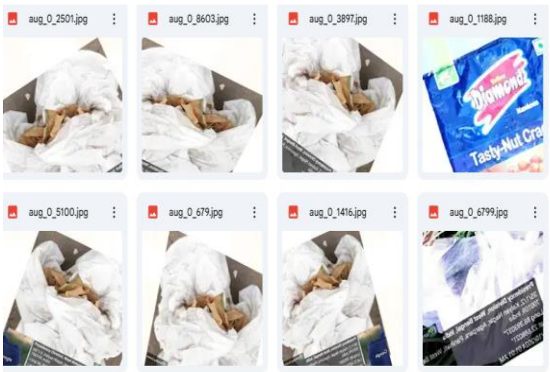

Figure 8 After the Augmentation of Polythene

Figure 9 After the Augmentation of Polythene

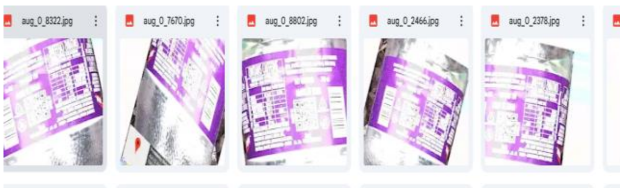

Figure 10 After the Augmentation of Plastic

```
Found 682 images belonging to 2 classes.
Found 169 images belonging to 2 classes.
Epoch 1/10
22/22 ━━━━━━━━━━━━━━━━━━━━ 38s 2s/step - accuracy: 0.7241 - loss: 0.5093 - val_accuracy: 0.8225 - val_loss: 0.4536
Epoch 2/10
22/22 ━━━━━━━━━━━━━━━━━━━━ 24s 1s/step - accuracy: 0.7531 - loss: 0.4472 - val_accuracy: 0.8639 - val_loss: 0.3368
Epoch 3/10
22/22 ━━━━━━━━━━━━━━━━━━━━ 41s 1s/step - accuracy: 0.8756 - loss: 0.3407 - val_accuracy: 0.8935 - val_loss: 0.2610
Epoch 4/10
22/22 ━━━━━━━━━━━━━━━━━━━━ 41s 1s/step - accuracy: 0.8716 - loss: 0.3210 - val_accuracy: 0.8402 - val_loss: 0.3194
Epoch 5/10
22/22 ━━━━━━━━━━━━━━━━━━━━ 26s 1s/step - accuracy: 0.8759 - loss: 0.2933 - val_accuracy: 0.9290 - val_loss: 0.2191
Epoch 6/10
22/22 ━━━━━━━━━━━━━━━━━━━━ 41s 1s/step - accuracy: 0.9205 - loss: 0.2594 - val_accuracy: 0.9231 - val_loss: 0.2401
Epoch 7/10
22/22 ━━━━━━━━━━━━━━━━━━━━ 24s 1s/step - accuracy: 0.9552 - loss: 0.2263 - val_accuracy: 0.9290 - val_loss: 0.1914
Epoch 8/10
22/22 ━━━━━━━━━━━━━━━━━━━━ 28s 1s/step - accuracy: 0.9422 - loss: 0.2198 - val_accuracy: 0.9172 - val_loss: 0.2913
Epoch 9/10
22/22 ━━━━━━━━━━━━━━━━━━━━ 26s 1s/step - accuracy: 0.9430 - loss: 0.1902 - val_accuracy: 0.9467 - val_loss: 0.1882
Epoch 10/10
22/22 ━━━━━━━━━━━━━━━━━━━━ 24s 1s/step - accuracy: 0.9540 - loss: 0.1903 - val_accuracy: 0.9467 - val_loss: 0.1719
```

Figure 11 Validation Accuracy

Figure 12 Graphical Presentation of Training and Validation Accuracy

3.2.Key Observations

- **Steady Increase:** Both training and validation accuracy improve over time, indicating effective learning.
- **Early Convergence:** Validation accuracy quickly reaches above 90%, suggesting good generalization.
- **Minimal Overfitting:** Training and validation accuracy remain close, meaning the model is not overfitting significantly.

Overall, the model performs well, achieving high accuracy with balanced training and validation curves. (Figure 13) [23]

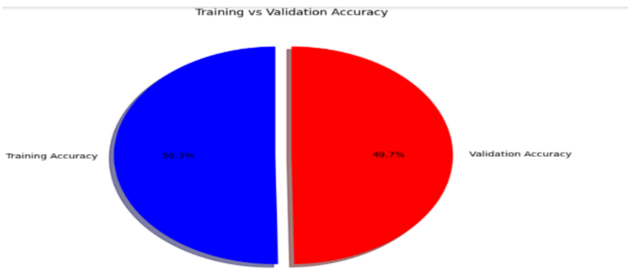

Figure 13 To Show the Proportion of Each Class in the Dataset

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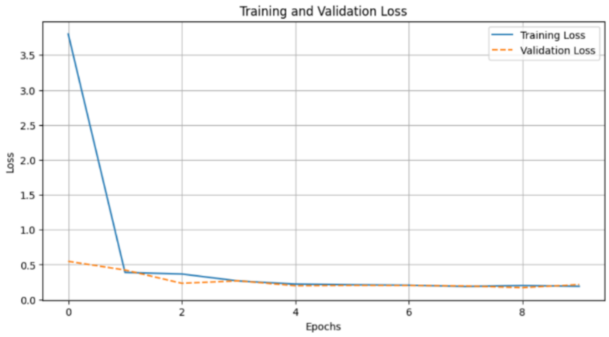

Figure 14 To Show Training and Validation Loss Over Epochs

3.3.Key Observations

- **X-axis:** Number of epochs (iterations over the entire dataset)
- **Y-axis:** Loss value
- **Solid Blue Line:** Training loss (how well the model is learning on the training data)
- Dashed Orange Line: Validation loss (how well the model performs on unseen validation data) [21]

Conclusion

The classification of non-biodegradable waste is crucial for automated sorting systems. Detecting plastics and polythene accurately helps optimize garbage collection and promotes efficient waste management. In this study, computer vision and machine learning techniques are used to classify non-biodegradable waste. A Convolutional Neural Network (CNN) based on the VGG16 architecture is implemented for classification. To enhance model performance, data augmentation is applied to increase the dataset size. Additionally, image quantification is performed separately for the two classes. In the future, to improve classification accuracy, different machine learning classifiers will be compared. Based on this analysis, a new classifier may be designed to enhance detection efficiency, contributing to more effective automated waste sorting systems. [22]

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