Retraction

Retraction: An Intelligent System for Waste Materials Segregation Using IoT and Deep Learning (J. Phys.: Conf. Ser. 1916 012028)

Published 23 February 2022

This article (and all articles in the proceedings volume relating to the same conference) has been retracted by IOP Publishing following an extensive investigation in line with the COPE guidelines. This investigation has uncovered evidence of systematic manipulation of the publication process and considerable citation manipulation.

IOP Publishing respectfully requests that readers consider all work within this volume potentially unreliable, as the volume has not been through a credible peer review process.

IOP Publishing regrets that our usual quality checks did not identify these issues before publication, and have since put additional measures in place to try to prevent these issues from reoccurring. IOP Publishing wishes to credit anonymous whistleblowers and the Problomatic Paper Screener [1] for bringing some of the above issues to our attention, prompting us to investigate further.

[1] Cabanac G, Labbé C and Magazinov A 2021 arXiv:2107.06751v1

Retraction published: 23 February 2022
An Intelligent System for Waste Materials Segregation Using IoT and Deep Learning

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Abstract. Disposing of Garbage is still a hurdle in today’s world and not many waste materials are disposed of correctly as per the requisite procedure. They are rather dumped in landfills and other sources like water bodies causing Pollution. The proposed system amalgamates the Internet of Things with Deep Learning and Image Processing which replaces the conventional waste management system with a smart segregation process. The proposed model consists of a Raspberry Pi camera to scan and detect the object. This detected object is then exported to the Deep learning Model as the input using the ‘Histogram of Oriented Gradients’ algorithm. This is invariable to the geometrical and photometrical changes of the object. The image classification is accomplished using the combination of Faster Regions with the CNN algorithm (RCNN) with contextual information and incremental learning which improves the detection performance under special and extreme conditions, accurately classifying the objects into bio and non-biodegradable waste. Using the Faster R-CNN algorithm, explicit information can be obtained from the different layers of the neural network of Faster R-CNN, thereby proving that the proposed system has a higher accuracy rate.

Keywords: Internet of Things, Deep Learning, Image Processing, Faster Region with Convolutional Neural Network, Histogram of Oriented Gradients, Incremental learning, Contextual Information.

1. Introduction

Waste materials should be properly disposed at a regular basis. But, due to low responsibilities, a lot of wastes get dumped and gathered in landfills and other sources like water bodies causing pollution and damaging the planet earth. The existing waste segregation strategies have also proved to be not fully efficient. First, it is highly crucial to understand the type of the waste materials and its requisite treatment methodology. At present, there is no proper format of a low-cost and efficient waste segregation system that is affordable at the household level.

It is necessary for the waste materials to be separated according to their recyclable efficiency and then be treated. This helps in protecting the people and the environment from the aftereffects of these waste disposals. With the help of developments in the technological sector, automated segregation using advanced technologies would become a useful entity in the near future as the demand rises.
2. Image Processing Algorithm

Object Detection has become an important section of the rising developments in the recent technologies for many purposes like bio-metric detection of human features, forensic investigations and classification of various types of objects. The commonly used Object detection algorithms like YOLO, Single Shot Detector (SSD), Hough transform and optical flow are encountered with flaws of errors and limitations for accurate object detection. However, novice object detection based on deep learning algorithm known as ‘Histogram of Oriented Gradients’ works in the real-time capsule with a very expertise performance rate.

2.1 Histogram of Oriented Gradients

The Histogram of Oriented Gradients is a feature descriptor algorithm of the OpenCV Library of Python, used in the image processing sector to detect objects correctly. This method is initiated by counting the number of occurrences of the gradient orientation in the localized sections of the captured image. An evenly spread high dense grid and local contrast normalization are superimposed to each other which determines high accuracy rate.

The vital explanation for using this feature descriptor is because the local images are defined by the varying intensity in the local gradient orientation and edge direction. This image is further divided into a sequence of small regions called as the cells and are assembled and organized in the local region within each pixel of the image. The descriptor overall is the succession of the histograms obtained by calculating the intensity of the gradient orientation from the wider sections of the image called as the blocks, and this value is then used to measure the contrast normalization of all the cells of the block [1]. This algorithm works well for objects that are of varying size, colour, and dimensions.

3. Deep Learning Algorithm

Deep learning (DL) has revolutionized the future of digital technologies. In recent years, various architectures with different learning paradigm are rapidly introduced to develop machines that can perform similar to human behaviours and are highly useful in major domains like Diagnoses of diseases in the medicine industry, identification of bio-metric features in the forensic industry, weather forecasting, and education sector. Recent algorithms like Convolutional Neural Networks (CNN), Long Short-Term Memory Networks (LSTMs), Recurrent Neural Networks (RNNs) are usually expected to have an inefficient detection rate.

The Faster R-CNN algorithm along with the incremental learning and contextual information feature extraction provide a very high accurate detection and classification rate. The incremental learning algorithm helps mainly in allowing the machine to detect new objects once the pre-training and testing of the machine is completed. Hence, only one-time training and testing of the image is succinct. The contextual feature extraction is used for detecting the objects irrespective of its occlusions [2].

Python libraries like Tensorflow, Numpy, Matplotlib, Pillow, opencv, Matlab etc are used for the implementation.

4. Literature Survey

4.1. Waste Segregation using Deep Learning Algorithm-R S Sandhya Devi, Vijaykumar VR, M Muthumeena.

In this paper, Convolution Neural Networks algorithm is shaped to segregate and classify objects into bio and non-biodegradable, supported by the object recognition. Python libraries of Spyder like OpenCV is used to identify and classify the waste materials in real-time implementation through a webcam. However, objects susceptible to different dimensions, shapes and invariances is limited for training and testing.

4.2. An Internet of Things Based Smart Wastes Management System Using LoRa and TensorFlow Deep Learning Model - Teoh Ji Sheng 1, Mohammad Shahidul Islam, Norbahiah Misran.
This paper primarily makes use of IoT and Artificial Intelligence (LoRa communication protocol and TensorFlow) to detect the objects using the Raspberry Pi 3 Model B+ camera and classification is done using the Convolution Neural Networks. This object detection also provides the percentage of the relative match of the objects. TensorFlow Package of Python is represented as the main processing unit in figure 1.

5. Flow Diagram

![Flow Diagram](image)

**Figure 1.** Flow Diagram of the work.

6. Model Implementation

| Item                      | Quantity |
|---------------------------|----------|
| Raspberry Pi Camera       | 1        |
| IR sensor                 | 1        |
| Connecting wires          | 1        |
| Bread Board               | 1        |
| I5 core processor system | 1        |

![Raspberry Pi with Wires](image)

**Figure 2.** Raspberry Pi with Wires
The pre-trained object detection model is trained using images of wastes as a training dataset in figure 2 and 3. This method of training is known as transfer learning in table 1. Dataset is used to train the model, and around 15000 images of wastes with different orientations, backgrounds, and lighting conditions are collected. Before the training, images of wastes are labelled by class to perform supervised learning where the data is fed in training data with known classes for the model to perform training. Both the training and testing data each is divided as bio-degradable and non-biodegradable waste products in figure 4 and 5.

![Camera Module](image1.png)

**Figure 3. Camera Module**

6.1. Histogram of Oriented Gradients Algorithm

The images after training and testing are given as input once again and this time the real-time object is detected using the Histogram of Oriented Gradients algorithm of the OpenCV Python library by which the image after the capture by the Raspberry Pi camera is pre-processed and detected in figure 6 and 7.

![Dataset of Bio-Degradable Wastes](image2.png)

**Figure 4. Dataset of Bio-Degradable Wastes**

![Dataset of Non-bio Degradable Wastes](image3.png)

**Figure 5. Dataset of Non-bio Degradable Wastes**
Figure 6. Hog Feature Extraction for Bio Degradable Wastes.

Figure 7. Output of the Hog Feature Extraction

6.2 Faster R-CNN Algorithm

The Faster regions with convolutional neural networks (R-CNN) is put into action by coalescing the rectangular region gradients of the image with the convolutional neural network features of the algorithm. This Faster R-CNN algorithm occurs in two levels.

- The first level detects the subset regions of the object from the detected object.
- The second level classifies the object in each region provided.

The processes involved are as follows:
- The input image is first passed to the Convolutional networks which in return generates a feature map for the image.
- The proposals are extracted by employing the Region Proposal Network (RPN) in the newly generated maps from the previous step.
- The ROI layer is used further to reduce the size of the object proposals that has been extracted in the previous step irrespective of the original size of the images.
- Finally, these proposals are passed to a fully connected deep neural network layer in order to classify the images according to the conditions provided.

6.2.1 Incremental Learning

Incremental learning is a machine learning algorithm where the learning process takes place when new inputs adjust itself to the pre-trained images [3-7]. The incremental learning is exclusively in action.
when a supervised learning is required during the time of training data and when the memory limit is reached [8-10] in figure 8.

Figure 8. Incremental Learning

6.2.2 Contextual Information Extraction
Contextual information is a part of the Recurrent Convolutional Neural Networks (R-CNN). The Recurrent Neural Networks chart the directional features to a two-dimensional vector. By comparing the distance between the vectors, a depiction of semantic information is rendered. The RNNs acquire the nonlinear technique of recursive weight matrix and use it in each step in a loop. The image that is generated in this way has the same size as the output images obtained from the deep convolutional layers. [11-15].

To start the identification of the matrices, there is an activation function that uses a rectified linear unit (ReLU) function, which is specialised in improving the training. The ReLU function together with the RNN is called as IRNN. The calculations of the hidden states are also taken into accounts and are issued in different directional movements in figure 9 and 10. These movements include up, down, left and right.

Figure 9. Screen Display
7. Conclusion
With the rise of advanced Technologies like Internet of Things and Deep Learning, this paper was able to achieve its purpose. The proposed system is an integration of IoT with Deep learning algorithms and Image Processing techniques that uses deep neural networks to pre-train and test the images. The Faster R-CNN framework is combined with incremental learning and contextual information to identify and classify the waste object. After working with a huge dataset containing the bio-degradable and non-biodegradable waste materials, patterns are predicted and are further detected for training the algorithms. However, these results are mandated for optimization and improving the accuracies when it comes to being employed in real-time.

This proposed algorithm has provided with the best detection performance rate including even the detection of extreme conditions like objects that are too small or with different size, shape, color, dimension, rotation and deformation and has successfully classified them into bio-degradable and non-biodegradable waste materials which will be useful at the time of waste disposition. For future scope, there is a possibility to further study the processing speed of the algorithm so that real-time implementation can be met. With emerging urbanization, wastes can be properly segregated and treated for the well-being of the Mother Earth.

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