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# Robot for plastic garbage recognition

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**ABSTRACT**

Waste and related threats are becoming more and more severe problems in environmental security. There is growing attention in waste management globally, both in developing techniques to decrease their quantity and those correlated to their neutralization and commercial use. The basic segregation process of waste due to the type of material is insufficient, as we can reuse only some kinds of plastic. There are difficulties with the effective separation of the different kinds of plastic; therefore, we should develop modern techniques for sorting the plastic fraction. One option is to use deep learning and a convolutional neural network (CNN). The main problem that we considered in this article is creating a method for automatically segregating plastic waste into seven specific subcategories based on the camera image. The technique can be applied to the mobile robot for gathering waste. It would be helpful at the terrain and the sorting plants. The paper presents a 15-layer convolutional neural network capable of recognizing seven plastic materials with good efficiency.



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## 1. INTRODUCTION

An intensive increase in the consumption of main raw materials causes an increase in waste appropriate for reuse, which absurdly reduces resource use. Due to the constantly growing raw material needs in the industry and construction sector, it is important to gradually increase waste as secondary raw materials as high as possible. The research results presented that the expenses of obtaining raw materials are greater than gathering and regenerating secondary raw supplies acquired from manufacture or post-use waste. Gathering and recyclable old substances also involve minor energy use than producing a new one [1]. We may use municipal and agricultural waste for the production of gas or heat energy. Changing original materials with processed materials also reduce the use of resources, excludes the cost of transferring waste to landfills, maintains, reduces work input, and decreases the production costs of products.

Regulating the mass of produced waste to a quantity ensuring raw material, biological and hygienic balance is impossible without far-reaching harmonisation of knowledge and the way people live with the development and functioning of an ecological arrangement in a given region. Activities goal at decreasing the quantity of waste formed and collected in the environment contain reprocessing raw materials, reducing waste creation through up-to-date low-waste or non-waste technologies, and exchanging used materials [2].

The aim of society for solving fabrication waste polluting is minor and waste-free knowhow. Non-waste technology (NWT) is created with avoiding waste and complete use of substances. It implicates several technical procedures that lead to total supervision and the removal of pollution without damaging effects on the environs. The primary disorder has not deposited the waste. The application of NWT has monetary motivation for the reason of the complete use of materials. Reducing the number of waste permits for improved production and reduces introductions of raw materials. It’s also potential to decrease heat and electricity consuming. The benefits of using non-waste technology include reduced material consumption, reduced environmental losses, and often also reduced operating costs.

An alternative way to reduce garbage volume is recycling. This is an essential task to exploit the use again materials from the past, plus reducing spending on their processing. The recycling procedure occurs in two areas: the fabrication of things and the following production of waste. Its conventions adopt the obligation of the right insolences among producers, favourable to producing the more recoverable resources and creating proper behaviour between beneficiaries. Recycling unwanted elements of post-consumer products may occur, through the repeated usage of raw substantial joint with a change in its composition and shape. It is essential to sort garbage not only by materials such as paper, metal, plastic, glass or bio. It is needed to use a new method to recognize the kind of substation in different groups because not all of them are proper for reprocessing. The simple tactic to recycle one kind of plastic is by separating polyethene terephthalate (PET) and making textiles out of it.

To facilitate the recycling process, introduced the international marking of various types of plastics [3]. These are: i) PET, ii) high density polyethene (HDPE), iii) polyvinyl chloride (PVC), iv) low-density polyethene (LDPE), v) polypropylene (PP), and vi) polystyrene (PS). The division into different kinds of plastics would allow reusing some of them. Some of the possibilities is the combination of artificial intelligence and computer vision methods. We proposed this kind of method, implemented in portable devices. It could help solve urban waste problems at home and in the sorting plants. The process of materials sorting suitable for the process again from the municipal solid waste (MSW) is labour-intensive and complicated. In the beginning, dry and wet parts are parted, and electromagnetic devices are used to remove iron elements. In the next step, visual techniques may be used.

In optical recognition, optical sensors are used to classify diverse waste fractions based on shape, colour or texture [4], [5]. Huang *et al.* [6] proposed a categorisation technique that contains a 3D camera and a laser over a conveyor belt. This technique creates triangles with the camera, the object and the laser, it’s called triangulation scanning [6]. The alternative process is spectral imaging, it’s an arrangement of two technologies spectral reflection measurement and image processing. This group of techniques use hyperspectral imaging (HSI), either visual image spectroscopy (VIS) or near-infrared (NIR) [7]–[9]. The hyperspectral camera obtains pictures in the thin spectral bands, and the next system analyses the data. Then the data is processed using a special procedure. An air jet at the end of the conveyor belt drives the elements into separable containers dependent on the classifier's verdict [10], [11].

In spectroscopy methods, light is targeted to plastic garbage, and for a different kind of plastic light reflects are unique. NIR and laser instruments detected the reflected spectrum, and the computer recognized the object. Safavi *et al.* [12] developed this type of technique for classifying polyethene (PP) in diverse waste. The HSI method using NIR can be used for PP and PE materials classification [13], [14]. To improve the accuracy of the sorting procedure is used Principal component analysis (PCA) [15]. While the option is a quick way of identifying plastics using a join of mid-infrared spectroscopy (MIR) and independent component analysis (ICA) settled by Kassouf *et al.* in [16]. The approaches have some weaknesses: waste has to be ground, and small elements are problematic to classify. So, techniques without these disadvantages should be settled. Adedeji and Wang [17] proposed the algorithms that are developed for the separation of the accumulated waste constructed with the mixture of support vector machine (SVM) and convolutional neural network (CNN). Another similar method is presented in work [18], [19]. They present a garbage recognition system based on CNN for only 4 types of plastic.

## 2. PROPOSED SYSTEM

### 2.1. Structure of robot

The platform in its basic version is equipped with tracks to move on challenging terrain or the beach. We can remotely control the robot via Wi-Fi, but the advanced version will be provided with a module responsible for autonomous work in the area previously defined by the operator. Optionally, the vehicle may have floats and a water drive instead of tracks. The vehicle is equipped with a platform with a conveyor belt to retrieve objects from the ground. The platform is placed between the tracks, but it will not protrude from the front of the ways to make it easier to overcome the road in uneven terrains, such as on the beach as shown in Figure 1. The robot's caterpillar drive consists of an endless track belt surrounding the three load wheels and a separate drive wheel and idler wheel. The entire system is connected to the vehicle by a suspension [20]. The robot's caterpillar drive consists of an endless track belt surrounding the three load wheels and a separate drive wheel and idler wheel. The entire system is connected to the vehicle by a suspension. The drive consists of two 24 V electric motors with a 200 W. Power supply is of two 12 V 33 Ah gel batteries. An Arduino microcomputer is used to control the drive, while the Wi-Fi standard is used for communication. A trailer with rubbish bins will be pulled behind the primary vehicle. The computer system will control the mechanical arms, directing the waste to the appropriate containers. The waste will be collected from the surroundings using a conveyor belt and then moved under a camera mounted on the principal vehicle. The computer unit will recognize the object based on the camera image as shown in Figure 2.

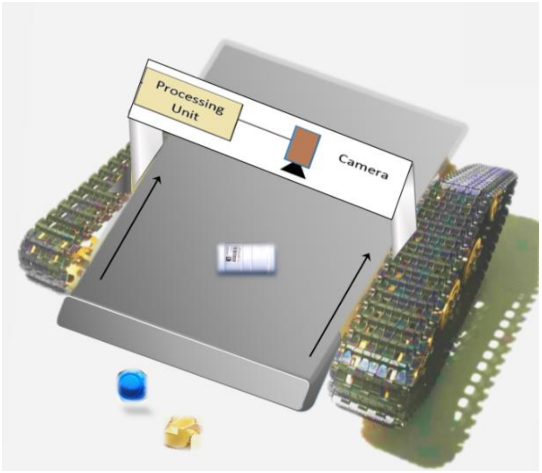


Figure 1. The draft of the robot main part

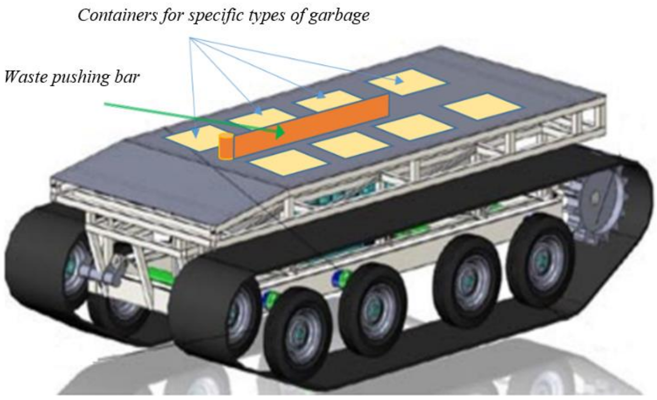


Figure 2. The draft of collecting trailer

### 2.2. Structure of computer system

A computer system dedicated to image processing is used to identify the type of plastic from which the waste is made. This kind of system is embedded on a mobile robot platform. The platform in its basic version is equipped with tracks to move on rugged terrain or the beach. We may remotely control the robot via Wi-Fi, but the advanced version will include a module responsible for autonomous work in the area previously defined by the operator. Optionally, the vehicle may have floats and a water drive instead of tracks. The waste will be collected from the surroundings using a conveyor belt and then moved under a camera mounted on the primary vehicle. The computer unit will recognize the object based on the camera image as shown in Figure 1. Our computer system contains RGB digital camera, a computer and software to recognition plastic waste. The software classifier controls air nozzles to drive the garbage to a correct container. The main element of a classifier is the object recognition procedure used deep learning, CNN and computer vision techniques [21].

The CNN is widely used for image recognition. CNN consists of a few convolutional layers (typical of the sampling step, defining the sub-pattern) followed by one or fully interconnected layers as in a classic multi-layer network, e.g., multilayer perceptron (MLP), SVM, and SoftMax. The deep convolutional network contains many layers. Convolutional networks are easy to train than a typical neural network. They have fewer parameters with an accuracy up to the number of convolutional layers and their size. This type of neural network predestines for computations on 2D structures (i.e. images) [21].

## 3. RESEARCH

### 3.1. CNN structure

Planning the construction of a neural network, the input image size should be well-thought-out an essential component. Too high resolution increases the number of calculations, leading to overworking of the random-access memory (RAM). A further aim was to improve the structure that can be implemented into a RaspberryPi microcomputer. The too-large size of handled pictures would be difficult to process in real-time. On the other hand, the small input images cause impossible to identify the element and achieve the estimated accuracy [22], [23].

Based on preliminary research, we selected images with a size of 60×120 pixels. The next critical component was the choice of CNN layers. According to publications on CNN and image recognition, we decided to develop our structure. We proposed a CNN network be made of 15 layers. The first convolution layer contained 64 filters of size 9×9. Three convolution layers translate information and are next transferred to two fully connected layers. The size and number of filters were chosen experimentally. Table 1 presents the organisation of our network, where ReLU is rectified linear unit. In the last layer, the 7 outputs are represented by 7 types of plastic.

Table 1. Structure of our CNN

| No | Name of layer | Parameters |
|---|---|---|
| 1 | Image input layer | 60×120×3 |
| 2 | Convolution layer | 64 filters, size 5×5 |
| 3 | Max pooling layer | |
| 4 | ReLU layer | |
| 5 | Cross channel normalization layer | |
| 6 | ReLU layer | |
| 7 | Max pooling layer | |
| 8 | Convolution layer | 64 filters, size 5×5 |
| 9 | ReLU layer | |
| 10 | Max pooling layer | |
| 11 | Convolution layer | 64 filters, size 5×5 |
| 12 | Fully connected layer | Inputs 4992, outputs 64 |
| 13 | ReLU layer | |
| 14 | Fully connected layer | Inputs 64, outputs 7 |
| 15 | Classification layer | 7 |

### 3.2. Input data

Correct groundwork over data that will be used for the research is critical in evolving a system for categorising objects in the natural environment. For CNN, gathering as many images as possible for each category (thousands) is necessary [24], [25]. In our case, we obtained waste pictures of previously classified. We implemented a cut-down model in which only one waste exists in the camera lens. This tactic does not replicate natural enclose, but the study desires to provide satisfactory chances to create a correctly operative network.

The images symbolised objects categorised in seven measured classes: PET, PP, PS, high-density polyethylene (PE-HD), low density polyethylene (PE-LD), and PVC. The classification of the object was based on the manufacturer's designation, i.e. recycling stamp (triangle with an arrow) and numbers inside. These images come from the Gadaba database [26], and samples are shown in Figure 3. For the first six classes were selected ten thousand images and 5,000 in the 7th for the reason that it is problematic to find such objects. We used 8,000 images (except 7-Other) for the learning/validation procedure and 2,000 for testing per class. There were images of other items in the group for teaching and validation. We used four thousand pictures for teaching and 1,000 for testing in group number 7.

### 3.3. Training

We used the back-propagation algorithm with two methodical modernises. Classical back-propagation algorithms yearn to compute altered partial derivatives of weights going to the neurons in the filter; but, these need be equal. Consequently, results of the loss function regarding weights of neurons due to the feature map are summed up together [27]. The bring up-to-date back-propagation that one is when allocating with max-pooling layers. The back-propagating error is transmitted only to those neurons which were not filtered with max-pooling [28]. Hyperparameters used for training: i) InitialLearnRate: 0.001, ii) LearnRateDropFactor: 0.1, iii) LearnRateDropPeriod: 15, iv) L2Regularization: 0.004, v) MaxEpochs: 30, and vi) MiniBatchSize: 100. They were selected experimentally, and some of the research results are presented in Table 2.

Figure 3. Sample images used in the experiment

Table 2. Learning results

| No | Initial learn rate | Learned rate per period | Max epoch | Regularization | Accuracy [\%] |
|---|---|---|---|---|---|
| 1 | 0.0001 | 10 | 20 | 0.1 | 81 |
| 2 | 0.001 | 5 | 20 | 0.1 | 86 |
| 3 | 0.0001 | 5 | 20 | 0.1 | 84 |
| 4 | 0.0001 | 15 | 20 | 0.1 | 82 |
| 5 | 0.001 | 10 | 30 | 0.1 | 87 |
| 6 | 0.01 | 10 | 30 | 0.1 | 34 |
| 7 | 0.001 | 10 | 30 | 0.1 | 81 |
| 8 | 0.001 | 10 | 30 | 0.1 | 85 |
| 9 | 0.001 | 10 | 30 | 0.01 | 84 |
| 10 | 0.001 | 15 | 30 | 0.01 | 83 |

## 4. RESULTS AND DISCUSSION

During analysis of the experiment, we establish that for the proposed network and images size of 60×120 pixel, it is required to learn for 20 epochs, and a thousand iterations per epoch. The value of the parameter Initial learn rate has to be less than 0.01, while regularization should be 0.1. The test uses the cross-validation method using three data sets and gain an average value of the accuracy of 87%.

Related to comparable studies [23], the efficiency of our network is worse. But we recognize seven classes instead of that which identifies four and achieved results 91%. Table 2 presents learning stages conducted for our network using images with 60×120 pixels resolution. Analyzing the obtained results, we see our network reach good results for the fifth stage when it achieved 87%. Twenty epochs were sufficient to get a good level of accuracy of 86% (row 2). Further learning to 30 epochs gives us 87% accuracy. Regarding the other learning parameters, we obtained the best results for Initial learn rate 0.01, Learned rate per period 10, Max epoch 30, and Regularization 0.1. The last parameter did not have a strong influence on accuracy. The most significant impact on the change of accuracy was the change in the Initial learns rate to 0.1. We achieved the highest recognition result with a sensitivity of 0.94 and specificity of 0.

## 5. CONCLUSION

The research results indicate that our 15-layer network reaches good results for images with 60×120 pixels resolution. The sorting of garbage into seven groups is, generally, at a suitable level, average 87%. The best results were achieved for hyperparameters equal to: initial learn rate=0.001, learned rate per period=10, and regularization 0.1 with 30 learning epochs.

The results can not compare with other CNN-based methods because they do not yet publish similar studies. However, when comparing the proposed CNN structure to other networks regarding the number of parameters that we have to determine in the learning process, our network has 222M, the popular Alex Net - 4G, and MobileNet2 - 6G. These values show that the proposed network is better suited for a microcomputer application. Further work will implicate extending the separated waste image to contain waste images under real situations. Later the labours obtain approval from companies dealing with waste sorting for tests on a belt conveyor. Environmental protection is essential and this type of robot would contribute to cleaning up already littered areas, both on land and in seas and oceans. The production costs of this type of robot are small compared to the benefits that we can bring by the utilization and recycling of the plastic lying around in our surroundings.

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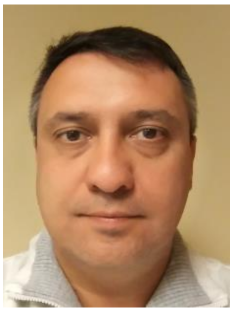

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