Waste Classification System Using Image Processing and Convolutional Neural Networks

Janusz Bobulski and Mariusz Kubanek(✉)

Institute of Computer and Information Sciences,
Czestochowa University of Technology,
Dabrowskiego Street 69, 42-201 Czestochowa, Poland
{janusz.bobulski,mariusz.kubanek}@icis.pcz.pl

Abstract. Image segmentation and classification is more and more being of interest for computer vision and machine learning researchers. Many systems on the rise need accurate and efficient segmentation and recognition mechanisms. This demand coincides with the increase of computational capabilities of modern computer architectures and more effective algorithms for image recognition. The use of convolutional neural networks for the image classification and recognition allows building systems that enable automation in many industries. This article presents a system for classifying plastic waste, using convolutional neural networks. The problem of segregation of renewable waste is a big challenge for many countries around the world. Apart from segregating waste using human hands, there are several methods for automatic segregation. The article proposes a system for classifying waste with the following classes: polyethylene terephthalate, high-density polyethylene, polypropylene and polystyrene. The obtained results show that automatic waste classification, using image processing and artificial intelligence methods, allows building effective systems that operate in the real world.

Keywords: Deep learning · Waste management · Image processing

1 Introduction

In many European countries waste segregation has already been introduced at the beginning of the recycling path, i.e. at home. Just people divide waste into groups such as plastic, metal, glass and organic/bio. The use of selective automatic techniques for these groups is easier than for municipal solid waste (MSW). Unfortunately, a large part of the waste is still collected in the form of the MSW, which is why the countries strive for the most effective reprocessing of waste materials. In order to do this, the rubbish should be effectively sort into individual factions and materials. Therefore, an important task is to isolate individual

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types of materials from the MSW. Therefore, techniques and procedures for segregating waste are used for the main groups of materials such as paper, glass, metal, wood, plastic and biomass by property system [1,2].

The biggest challenge, however, is the separation of various types of materials within a given group, i.e. sorting different color of glass or different types of plastic. The problem of plastic garbage is interesting and at the same time important due to the possibility of recycling only some types of plastic (e.g. PET). To simplify the recycling process, international labeling of various types of plastics was introduced Fig. 1. These are: 01 - PE (polyethylene terephthalate), 02 - HDPE (high-density polyethylene), 03 - PVC (polyvinyl chloride), 04 - LDPE (low-density polyethylene), 05 - PP (polypropylene), 06 - PS (polystyrene) and 07 (other).

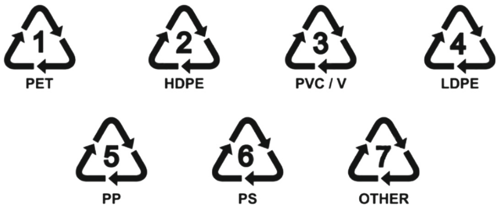

Fig. 1. Labeling of plastic waste

In domestic waste, a significant part is occupied by plastic elements, and within it may be distinguished four dominant types: PET, HDPE, PP, PS. Unfortunately, at this stage of recycling, there is no division into individual types of plastic and they often end up in a group of plastic waste or MSW. There is a problem with the separation of different types of plastics, some of which can be re-used. One of the possibilities is the use of computer vision techniques, in particular image recognition.

2 Review of Methods for Separating Plastic Waste

The whole process of automatic sorting of materials suitable for reprocessing from MSW is complicated. First, the dry waste is separated from the wet, and then the dry waste fraction is subjected to a grinding process. In order to sort materials containing iron, magnetic drum techniques are used. Subsequently, non-ferrous metals are sorted using various indirect sorting techniques, such as eddy current or X-ray radiation. However, for the separation of plastic waste, one of the following methods can be used - direct or indirect [3].

2.1 Direct Methods

The hydrocyclone uses centrifugal force to separate materials of different densities. This method can be used to separate materials such as ABS (acrylonitrile butadiene styrene), PE (polyethylene), HIPS (high impact polystyrene) and PVC (polyvinyl chloride). Different factors affect the buoyancy of a given material, e.g. different density, shape and level of separation from other materials, which is used to separate various fractions from MSW [4–6]. Jigging is using gravity to separate materials that works based on the interaction of buoyancy, resistance, gravity and acceleration. In this process, a mixture of solids and water is placed in a perforated vessel called a pulse bed. The sedimentary bed is shaken to induce vertical currents in the water column. This causes the particles to rise. The currents can be ascending or descending. Materials with higher density settle at the bottom. Segregation takes place according to the density, size and shape of the material [7–9].

Froth flotation technique uses the hydrophobicity of the plastic to separate it from the rest of the waste. The waste is ground into small particles and mixed with water. The air is then dissolved in a mixture of water and waste pulp under high pressure. The dissolved air is then released into the flotation section at atmospheric pressure. This leads to the formation of froth on the surface of the mixture of water and waste. The suspended plastic particles, due to their hydrophobicity, attach themselves to air bubbles in the foam. The combined specific weight of the bubbles carrying the plastic particles is smaller compared to the liquid medium, which causes flotation for separating the plastic from the waste and water mixture [10–12].

2.2 Indirect Sorting

X-ray transmission (XRT) is a fast indirect sorting technique, because X-ray image capture takes a few milliseconds. The imaging module uses a high intensity beam of radiation. Part of this beam penetrates into the material and is absorbed, and a part is passed to the detector below the test material. The radiation captured by the detector is analysed to obtain information about the atomic density of the material. X-ray sorting techniques can be divided into two types: double x-ray energy (DE-XRT) and X-ray fluorescence (XRF) [13,14].

The XRF technician may be used to recover plastic waste fractions. Unfortunately, this technique is only applicable to the recovery of PVC from other types of plastic [15]. The basis of the XRF technique is the induction of individual atoms by an external laser source, which leads to the emission of X-ray photons. The emitted photons form a unique spectral signature corresponding to the atomic weight, which allows to determine the type of material. In the case of plastic, its spectral signature is a superposition of spectral signatures of components that can be identified using machine learning techniques.

Another technique for sorting waste is EDXRF (Energy Dispersive X-ray Fluorescence) that uses markers added to the polymer matrix to sort plastic particles. These labels are formed by many substances dispersed in the material thereby increasing the selectivity of the polypropylene sorting [16]. The X-ray is focused on a small area of material and goes to the detector. The signal from the detector is then sent to the processing unit. This unit controls the radiation source whose spectral signal is analysed and then used to separate materials containing specific quantities of markers. XRF is a non-destructive technique capable of identifying black polymers as well as dirty waste [17].

2.3 Optical Based Sorting

Commonly techniques often used physical features but ignored visual properties like colour, shapes, texture and size for the sorting of waste. In optical sorting, camera based sensors are used for the identification of waste fractions. In this section we present optical sorting techniques.

Sorting technique based on features like shape and colour was proposed by Huang et al. [18]. This method combines a 3D colour camera and laser beam over the conveyor belt. This technique formed triangles over the image from the camera on the base laser beam, so is called triangulation scanning. The technique achieves an accuracy of 99 % for plastic fractions.

Spectral imaging is a combination of spectral reflectance measurement and image processing technologies. We may found several spectral imaging methods using NIR (near infrared), VIS (visual image spectroscopy) and HSI (hyperspectral imaging) [19,20]. A hyperspectral sensor produces images over a continuous range of narrow spectral bands and next system analysis the spectroscopic data. The conveyor system moves the waste fractions beneath the spectral camera acquires images. At the second stage data is pre-processing and reduction. Next to perform material classification a special algorithm is applied. A set of compressed air nozzles is mounted at the end of the conveyor belt and depending upon the classifier decision, one of nozzles are triggered the waste into particular bins [21,22].

Waste classification is also possible using artificial intelligence. In work [23] RecycleNet is carefully optimized deep convolutional neural network architecture for classification of selected recyclable object classes. This novel model reduced the number of parameters in a 121 layered network from 7 million to about 3 million. In paper [24] they provided the concept of automatic processing of plastic and metal waste combined with another mechanism for economic motivation of end users. In work [25] authors propose a multilayer hybrid deep-learning system (MHS) to automatically sort waste disposed of by individuals in the urban public area. This system deploys a high-resolution camera to capture waste image and sensors to detect other useful feature information.

All the methods cited have their advantages, but they also generate problems with the use of appropriate specific and often expensive technologies (direct sorting, indirect sorting), or demanding high computational efficiency (artificial intelligence). The use of artificial intelligence to classify waste became the main motivator for the authors. The possibilities obtained by neural networks in the field of image classification and recognition show that it is possible to build effective systems also in the field of waste selection, but the complexity of the whole system must be simplified.

3 Proposed System

After extracting plastic garbage from the MSW, a computer system based on image processing can be used to divide it into different types Fig. 2. The method we propose uses an RGB digital camera and a computer with software for classifying plastic waste. In contrast, an air stream is used to direct the waste to a specific container, assuming that the waste will be transported separately on the conveyor belt. The software used in this system uses image processing techniques in the process of image pre-processing. Convolution neural network and deep learning [26,28,29] are used to recognize objects.

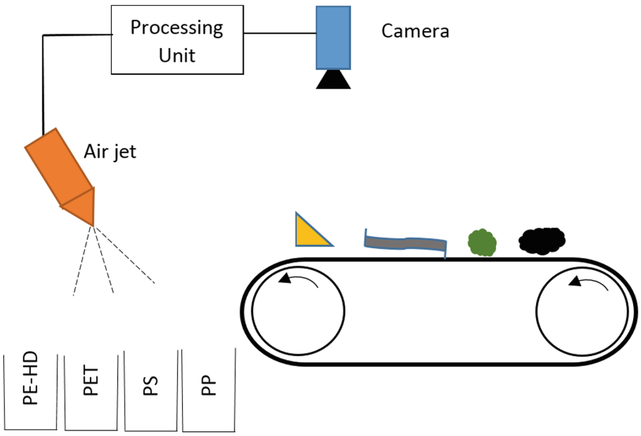

Fig. 2. Proposed system for plastic waste sorting

4 Convolutional Neural Network

Convolutional neural network (CNN) is a feed-forward artificial neural network in which the organization of neurons is similar to the animal visual cortex [27]. In order to recognize the shape of an object, the local arrangement of pixels is important. CNN starts with recognition of smaller local patterns on the image and concatenate them into more complex shapes. CNN was proved to be efficient especially in object recognition on an image [28–30]. CNNs might be an effective solution to the waste sorting problem. CNN explicitly assumes the input is an image and reflects it onto its architecture. CNN usually contains Convolutional layer, Pooling layer and Fully-connected layer. Convolutional layers and Pooling layers are stacked on each other, fully-connected layers at the top of the network outputs the class probabilities.

5 Structure of Research Networks

A number of important factors had to be taken into account when working on the appropriate selection of the network structure. First of all, the size of the input image was an important element. Too high resolution resulted in increasing the number of calculations, which resulted in fairly frequent overload of memory available computing unit. On the other hand, too low resolution of the input data could have prevented the achievement of the expected performance. It was decided to conduct research for images with a resolution of 120×120 pixels and 227×227 pixels. The assumption that the resolution of input images is 227×227 pixels results from the established AlexNet structure [30]. The assumption that the resolution of input images is 120×120 is an experimental assumption. This choice allowed testing for images almost twice smaller than in the case of AlexNet.

Another important element was the selection of the number and types of layers of the CNN network. Two CNN networks were tested, differing in the number of layers and the number and size of convolution filters. The first type of network tested (based on the AlexNet network) contained 23 layers. For this structure, 9×9 convolution filters were used in the first convolution layer. A total of six weave layers were responsible for the appropriate encoding of the input image, which was then fed into a three-layer fully connected layer.

The second type of network, based on the authors' proposals, preceded by preliminary tests (other structures tested achieved worse results, or it was hard to adapt them to the adopted resolution.), contained 15 layers. The first convolution layer consisted of 64 convolution filters with dimensions 9×9. Three layers of convolution encode information, transferred to a two-layer fully connected layer. The network diagram for 120×120 pixel images is shown in Fig. 3. For CNN prepared in this way, tests were carried out with images of various input resolutions.

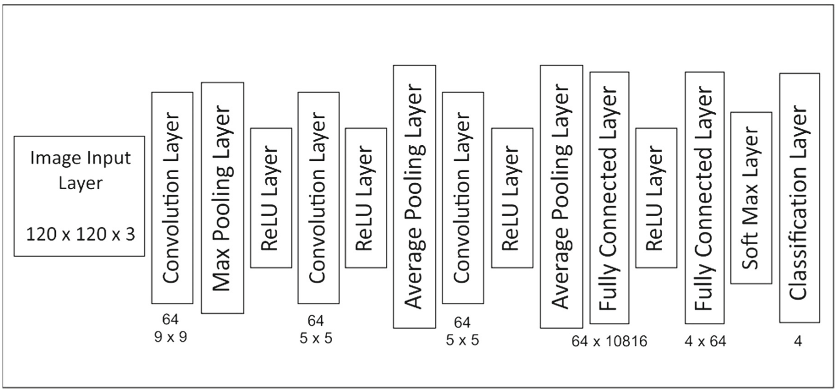

Fig. 3. The structure of our networks - 15 layers

Preparation of input data for the learning and testing phase was important in the context of correct classification of objects in natural working conditions. In the case of deep neural networks, as many data as possible should be collected for each identified class. In our case, it was necessary to collect photos of classified waste. We adopted a simplified model where there could be only one waste within the camera lens. This approach does not reflect the natural working conditions, but for research needs it gives sufficient opportunities to generate a properly functioning network. All collected images represented objects classified into four considered classes: PS, PP, PE-HD and PET. These images came from the WaDaBa database [31], and their samples may be seen on Fig. 4. Due to the availability of research facilities, it was easiest to create a PET class due to the largest amount of this type of waste that can be recycled. This resulted in the fact that a different number of images assigned to individual classes was collected. To increase the number of images in individual classes and to obtain a similar number of images for each class in the final stage, it was necessary to make copies of images rotated by different angles of rotation within each class. Such set of data (about 33 000 simulated images per class) was sufficient to properly teach the prepared network structures.

Fig. 4. Samples images of plastic waste

6 Results and Discussion

The research phase consisted in training two prepared CNN network structures and determining the accuracy of classification at different divisions of input data into training and test data. Four divisions were used: - 90% (training data) - 10% (test data), 80% (training data) - 20% (test data), 70% (training data) - 30% (test data) and 60% (test data) training data) - 40% (test data). The numerical distribution of photos for individual classes is shown in Table 1.

For the learning data prepared in this way, the CNN network learning process was carried out (parameters of the test computer: Intel (R) Core (TM) i7-5820K

Table 1. Numerical division of data into training data and test data

Number of division	Type of division	PE-HD Training/Test	PET Training/Test	PP Training/Test	PS Training/Test
1	90% - 10%	32400/3600	29700/3300	29952/3328	33696/3744
2	80% - 20%	28800/7200	26400/6600	26624/6656	29952/7488
3	70% - 30%	25200/10800	23100/9900	23296/9984	26208/11232
4	60% - 40%	21600/14400	19800/23200	19968/13312	22464/14976

CPU 3.30 GHz, RAM 64 GB, GPU NVIDIA GeForce GTX 960). Training was carried out for two pre-prepared network structures, with input image resolutions of 120×120 pixels and 227×227 pixels. Learning was carried out for a variable value of learning coefficient, starting from 0.001 and decreasing every subsequent 4 epoch. 1064 iterations for one epoch were considered.

Table 2 summarizes all tests carried out for a stratified network using images with a resolution of 120×120 pixels.

Table 2. Learning results of a 15-layer network (image resolution 120×120 pixels)

Number of division	Type of division	2 epochs accuracy [%]	Time [min]	4 epochs accuracy [%]	Time [min]	10 epochs accuracy [%]	Time [min]
1	90% - 10%	93,27	29	97,43	61	**99,92**	217
2	80% - 20%	92,71	27	96,97	57	98,69	203
3	70% - 30%	90,74	24	93,68	52	97,78	184
4	60% - 40%	86,57	20	90,25	49	92,77	167

Table 3 presents all tests carried out for a stratified network using images with a resolution of 227×227 pixels.

Table 3. Learning results of a 15-layer network (image resolution 227×227 pixels)

Number of division	Type of division	2 epochs accuracy [%]	Time [min]	4 epochs accuracy [%]	Time [min]	10 epochs accuracy [%]	Time [min]
1	90% - 10%	69,43	79	80,25	183	**91,72**	540
2	80% - 20%	66,76	76	77,80	174	88,34	527
3	70% - 30%	63,89	70	73,69	171	84,64	504
4	60% - 40%	60,70	69	70,45	159	80,23	498

Table 4 summarizes all tests conducted for a 23-layer network using images with a resolution of 120×120 pixels.

Table 4. Learning results of a 23-layer network (image resolution 120 × 120 pixels)

Number of division	Type of division	2 epochs accuracy [%]	Time [min]	4 epochs accuracy [%]	Time [min]	10 epochs accuracy [%]	Time [min]
1	90% - 10%	73,29	63	92,31	125	**96,41**	364
2	80% - 20%	70,08	61	90,83	121	93,39	347
3	70% - 30%	67,13	57	86,24	114	90,29	311
4	60% - 40%	62,44	55	83,04	106	88,46	301

Table 5 summarizes all tests conducted for a 23-layer network using images with a resolution of 227 × 227 pixels.

Table 5. Learning results of a 23-layer network (image resolution 227 × 227 pixels)

Number of division	Type of division	2 epochs accuracy [%]	Time [min]	4 epochs accuracy [%]	Time [min]	10 epochs accuracy [%]	Time [min]
1	90% - 10%	62,38	73	86,83	214	**99,23**	725
2	80% - 20%	60,44	71	84,21	199	97,51	707
3	70% - 30%	59,21	69	80,49	192	97,92	642
4	60% - 40%	58,94	64	72,84	165	93,45	549

Analyzing the obtained results, it can be seen that in the case of a stratified network, for our training data composed of images with a resolution of 120 × 120 pixels, 4 epochs are sufficient to obtain an acceptable level. Further learning, even with a reduced learning rate, no longer significantly affects accuracy. Accuracy at 4 epochs of 97.43% is a very good result as a fairly small number of iterations. After 10 epochs, this accuracy is still increasing and amounts to almost 100%. Of course, this is for the division, where up to 90% of images are used to teach the network. For images with a resolution of 227 × 227 pixels, the computation time is almost doubled. In addition, accuracy at 91.72% at the first assumed division into training and test data is not acceptable for the proper functioning of the system in real conditions.

The training process is slightly different in the case of a 23-layer network, for which the same division into training and test data was used, as in the case of a 15-layer network. It is able to achieve an accuracy index of 99.23 for the first training data sharing and 227 × 227 pixel image resolution, but a learning time of 725 min compared to 217 min makes the learning process inconvenient. This is quite important information in the context of the learning process of the system, which is to function in real conditions. In the case of training images with a resolution of 120 × 120 pixels, the 23-layer network after 10 epochs did not reach the level that was obtained for the 15-layer network.

7 Conclusion and Future Works

The conducted research has shown that the 15-layer network proposed by us allows achieving high efficiency for images with a resolution more than twice lower than the available 23-layer network with a dedicated resolution of 227×227 pixels. Classification of segregated waste into four main classes takes place in most cases without error. Of course, this is to a certain extent caused by the artificially increased number of individual class representatives. Further work will mainly consist of extending the database of segregated waste images with photos of waste in more realistic conditions. Hence, efforts to obtain recordings of waste on a conveyor belt from enterprises dealing with waste segregation. Another noticeable thing is the definitely shorter learning time for a 15-layer network compared to a 23-layer network, especially for 120×120 pixel images. Our research in the future will assume the possibility of training the network while working in real conditions, which is possible to implement with our proposal. After introducing modifications to the training database, we also want to determine the accuracy for real images of waste taken from the conveyor belt during the segregation process.

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