Segmentation of municipal solid waste using artificial neural networks

A St Kozodaev$^1$, N S Kostromin$^2$, P A Kaplenkova$^1$ and A N Sivova$^1$

$^1$Department of Ecology and Industrial Safety, Bauman Moscow State Technical University, 5/1, 2ya Baumanskaya st., Moscow, 105005, Russia

$^2$Department of Automatic Control Systems, Bauman Moscow State Technical University, 5/1, 2ya Baumanskaya st., Moscow, 105005, Russia

*kozodaevs@mail.ru

Abstract. The article discusses the prospects of using neural networks and Waste-to-energy technology to create a rational and efficient waste management culture. The study determines the quality (by metrics) of a trained neural network that determines the type of solid household waste, depending on various parameters of the model. Based on the analysis of the obtained metrics, a conclusion is made about the best parameters for the developed neural network model. This neural network was trained specifically for this study, and as was chosen TACO dataset. Brief theories of neural networks and Waste-to-energy technologies are also discussed. Particular attention is paid to the need to use these tools together to reduce and suspend the formation of new landfills and energy generation. The article will be especially relevant for scientists in those countries where the percentage of recycled waste tends to zero.

Every year, each resident of Russia produces an average of 400 kg of waste, i.e. in total, more than 60 million tons of household waste are delivered to landfills in the Russian Federation per year [17]. Moreover, more than a quarter of the volume of the Russian trashcan is occupied by food waste, almost 20% – paper and cardboard, 17% – glass. Nevertheless, the amount of household waste is also growing: in twenty years, the production of solid household waste (MSW) has doubled [10, 12]. The state authorities say that this is due to the active use of packaging materials: polyethylene, plastic, paper. However, only 8% of waste is recycled, and annually 9 million tons of waste paper, 2 million tons of plastic and 0.5 million ton of glass is sent to landfills [21] – all this can be recycled, but the country does not have a collection system for such waste or special factories [6].

Thus, the paper considers the prospects of using Waste-to-energy technology as a way to reduce the formation of new landfills and energy generation [1]. This technology consists in generating electric and thermal energy because of incineration. Moreover, solid household waste that has been pre-sorted is used as fuel [2]. The waste sorting process is one of the most difficult stages of Waste-to-energy. Therefore, the main task of the work is to develop artificial intelligence to determine the type of waste [18].

Now Russia is facing such an acute environmental problem as excessive accumulation of garbage in landfills. Landfills cause discomfort among the population and cause great harm to the
environment: large fires occur, landfills pollute ground water and soil [9], occupy a large area of industrial zones. Also it is a center of the spread of unpleasant odors in residential areas.

At the end of the 19th century, the first waste incinerators appeared in Europe and the USA. Moreover, by the middle of the 20th century, the technology was developed to clean up dangerous gases released during garbage incineration. Later, the combustion temperature was set, at which the toxins are completely neutralized. Today, incinerators in many developed countries operate on Waste-to-energy technology and are an alternative source of energy, replacing nuclear power plants in some countries.

For example, about 17 such plants are produced annually in Sweden [16]. This is enough for heating a significant part of the country’s territory. The energy that a small Sweden accumulates in a year is approximately equal to the energy produced by an average CHP. At the same time, an ordinary heating plant needs coal, and a Waste-to-energy plant needs garbage. Thus, waste becomes a source of clean energy. However, for the efficient operation of incinerators, proper waste sorting is essential. However, for the efficient operation of incinerators, proper waste sorting is essential. According to the average data in Sweden in 2018, about 15% of waste is organic waste that undergoes biological treatment, 35% of waste is recyclable materials such as glass, metal and plastic. So it is waste that is recycled, 50% of the waste is waste that cannot be recycled for various reasons, and this waste is burned and converted into energy.

It should be noted that Waste-to-energy plants are less efficient than conventional CHP plants. In terms of energy output, two tons of garbage is equivalent to one ton of coal, that is, you need twice as much garbage as coal. The cost and maintenance of waste-to-energy plants is significantly higher than conventional incinerators [20], which are able to provide energy only to the needs of the enterprise and are equipped with a one-stage gas cleaning system [7, 4]. However, CHP flue gases contain [14] oxides of carbon, nitrogen, sulfur, hydrogen chloride, hydrogen fluoride, heavy metal compounds, emissions of toxic furans, dioxins formed during the combustion of chlorine-containing polymeric materials [27]. Waste-to-energy plants use three-stage flue gas cleaning systems, which provide for secondary combustion of gases and leaching of buried ash. Thus, waste-to-energy plants are energy efficient and more environmentally friendly. Waste is carefully sorted before incineration [15], which prevents batteries, thermometers, and mercury lamps from entering the raw materials. For sorting waste [11], it is proposed to use artificial neural networks (ANN). This is one of the most widely used areas of artificial intelligence [8, 13]. It is worth noting that the quality of solving problems of detecting the boundaries of objects (waste) by ANN’s models is equal or even superior to human efficiency [23, 29].

The study used the Python programming language [19]. The RCNN Mask was chosen as the model architecture, which solves the problem of segmentation of an object instance [28]. This architecture is based on Faster RCNN, to which an additional block is added. This block outputs segment masks of objects. You can see functional diagram of the architecture in figure 1.

![Functional diagram of the Mask RCNN architecture](image-url)
Main components of the architecture:

1. Feature extraction unit: it receives an image as input, a feature map is formed at the output. For example, an EfficientNet or ResNet101 network without fully connected layers can act as such a block.

2. Region Proposal Network (RPN): this network, having received a feature map as an input, generates a number of regions in which there are supposedly objects.

3. Fully connected layers: for each selected area, using the feature map, it selects objects, designates bounding boxes, and classifies each object.

4. Segment mask generation block - defines a binary mask for each object.

The TACO dataset was used as a dataset TACO dataset [24] consisting of more than 1500 images with annotations for segmentation and object detection tasks. The database includes photos of various garbage items that are divided into 10 classes: can, pop Tab, plastic container, bottle, and others. Examples of a marked-up image can be seen in figures 2 and 3.

![Figure 2. Example # 1 of a TACO dataset image marked up by people dataset.](image1)

![Figure 3. Example # 2 of a TACO dataset image marked up by people dataset.](image2)

In the model used, the ResNet50 [26] network as part of the Feature Pyramid Network was used for feature extraction Pyramid Network [22]. The choice is due to high quality indicators of this network [3] due to the use of identity links in ResNet, which allow you to compensate for vanishing gradient in layers and train deeper networks. The network architecture block is shown in figure 4. The choice of architecture is also due to the ability to use a pre-trained model on the data set used as a first approximation.

![Figure 4. ResNet network block.](image3)
The performance indicators of the trained model are shown in Table 2, where the variable parameters (to improve the quality of the neural network) were [25]:

1. IoU-intersection over the union, which is an evaluation metric (indicator) used to measure the accuracy of the object detector in a particular data set

Mathematically, this metric is calculated as:

\[
\text{IoU} = \frac{\text{area of intersection}}{\text{area of union}} = \frac{\text{square}(B_p \cap B_{gt})}{\text{square}(B_p \cup B_{gt})} \tag{1}
\]

**Figure 5.** Example of detecting a stop sign in an image. Where the green rectangle is the true border and the red one is the one found by the model.

**Figure 6.** Calculating the intersection over the union.

2. area – the detected size of the object (takes the values: all, small, medium, large)
3. maxDets – the maximum number of detections for calculating the metric

The quality of models was compared using two neural network metrics:

* Average Precision – the average accuracy of all pictures, which shows the proportion of objects called positive by the classifier and at the same time really positive

* Average Recall – the average completeness of all pictures, which shows the proportion of objects that are really a positive class of all objects of a positive class that the algorithm found.

To express these metrics in mathematical terms, we use the concept of an error matrix (Table 1).

| Y is the algorithm's response to the object | y=1                              | y=0                              |
|-------------------------------------------|----------------------------------|----------------------------------|
| Y = 1                                     | True Positive (TP)               | False Positive (FP)              |
| Y=0                                        | False Negative (FN)              | True Negative (TN)               |

\[
\text{Average Precision} = \frac{\sum n \text{TP}}{\sum n \text{TP} + \text{FP}} \tag{2}
\]

\[
\text{Average Recall} = \frac{\sum n \text{TP}}{n} \tag{3}
\]

n – number of photos.
The ideal case is when both metrics are equal to 1. For each class, we calculate AP and AR at different IoU thresholds (0.5, 0.75, 0.5-0.95 in increments of 0.05) and calculate their average value, to get the value of the metric of this class. The average value of metrics for all classes is shown in table 2.

Table 2. Values of model metrics depending on parameters.

| Metric          | Modifiable model parameters | Metric values |
|-----------------|-----------------------------|---------------|
|                 | IoU                         | area          | maxDets |  
| Average Precision | 0.50:0.95                   | all           | 100     | 0.169 |
|                 | 0.50                        | all           | 100     | 0.270 |
|                 | 0.75                        | all           | 100     | 0.189 |
|                 | 0.50:0.95                   | small         | 100     | 0.074 |
|                 | 0.50:0.95                   | medium        | 100     | 0.080 |
|                 | 0.50:0.95                   | large         | 100     | 0.261 |
| Average Recall  | 0.50:0.95                   | all           | 1       | 0.243 |
|                 | 0.50:0.95                   | all           | 10      | 0.294 |
|                 | 0.50:0.95                   | small         | 100     | 0.075 |
|                 | 0.50:0.95                   | medium        | 100     | 0.155 |
|                 | 0.50:0.95                   | large         | 100     | 0.3922 |

Based on Table 2, we can conclude that it shows the highest accuracy on "large" objects, but still has low values of metrics on average. This is due to the small volume of the training dataset and labeling errors. However, visual analysis of the result of a set of test images showed that the model is able to distinguish between objects of objects in cases of overlapping objects. This can help in the design of a marshalling yard in a recycling environment (large accumulation of class waste on a belt). Waste results using the model in figure 7.

Comparing the existing SOTA (state-of-the-art - advanced and considered the best) model with the developed one, we can absolutely say that SOTA is not trained to detect specific objects - scattered waste, an example of their segmentation is shown in figure 8, 9.

Figure 7. Segmentation of waste using the Mask RCNN model.

Figure 8. Segmentation of waste using the Yolov3 model.
The model developed in the course of the study shows the following results (figure 7): it searches and detects more waste. Thus, we can conclude that the developed model shows the best results of solid waste segmentation.

During the research, the neural network was trained to determine the type of MSW based on the TACO dataset. It should be noted that the joint use of the above technologies (waste segmentation using the developed neural network, waste processing and Waste-to-energy) is extremely convenient and effective. After segmentation using the developed neural network of solid household waste in the sorting workshop, the waste must be sent for recycling or to the Waste-to-energy plant. In addition, it should be borne in mind that the technology of converting waste into energy is less preferable than processing waste into secondary raw materials.

References
[1] Aleksandrov A, Akatev V, Metelkin E and Baryscheva E 2019 Develop a model to study the energy distribution of cascades of atomic collisions Herald of the Bauman Moscow State Technical University, Series Natural Sciences 82 pp 27-36
[2] Anashkin I and Klinov A 2017 Thermodynamic behavior of charged Lennard-Jones fluids Journal of Molecular Liquids 234 pp 424-429
[3] Banerjee I, Ling Y, Chen M, Hasan S, Langlotz C, Moradzadeh N, Chapman Br, Amrhein T, Mong D, Rubin D, Farri O and Lungren M 2019 Comparative effectiveness of convolutional neural network (CNN) and recurrent neural network (RNN) architectures for radiology text report classification Artificial Intelligence in Medicine 97 pp 79-88
[4] Eboh Fr, Andersson B and Richards T 2019 Economic evaluation of improvements in a waste-to-energy combined heat and power plant Waste Management 100 pp 75-83
[5] Ek Cl and Miliute-Plepiene J 2018 Behavioral spiillovers from food-waste collection in Swedish municipalities Journal of Environmental Economics and Management 89 pp 168-186
[6] Epifanov A, Kudriavtceva R, Mironova Sv and Kulik S 2018 Legal aspects of economic regulation in the field of waste management SGEM 18 pp 553-560
[7] Habibollahzade A, Houshfar E, Ashjaee M, Behzadi A, Gholamian E and Meh dizadeh H 2018 Enhanced power generation through integrated renewable energy plants: Solar chimney and waste-to-energy Energy Conversion and Management 166 pp 48-63
[8] Haenlein M and Kaplan A 2019 A Brief History of Artificial Intelligence: On the Past, Present, and Future of Artificial Intelligence California Management Review 61 pp 5-14
[9] Klinov A, Fedorov M, Malygin A, Minibaeva L 2014 Properties of an aqueous solution of ionic liquid [Emim][Cl] at standard atmospheric pressure Russian Journal of Physical Chemistry A 88 pp 1682-1688
[10] Ksenofontov B, Kozodayev A, Taranov R, Vinogradov M 2020 Improvement of efficiency of waste water treatment from metals using flotation combines Ecology and Industry of Russia 24 pp 4-7
[11] Lienig J and Bruemmer H 2017 Recycling Requirements and Design for Environmental Compliance Fundamentals of Electronic Systems Design 1 pp 193-218

[12] Lomakina G 2020 Role of Biofilms in Microbiologically Influenced Corrosion of Metals Herald of the Bauman Moscow State Technical University. Series Natural Sciences 1 pp 100-125

[13] Lu H, Li Y, Chen M, Kim H and Serikawa S 2018 Brain Intelligence: Go beyond Artificial Intelligence Mobile Networks and Applications 23 pp 368-375

[14] Ma Ch, Li B, Chen D, Wenga T, Ma W, Lin F and Chen G 2019 An investigation of an oxygen-enriched combustion of municipal solid waste on flue gas emission and combustion performance at a 8 MWth waste-to-energy plant Waste Management 96 pp 47-56

[15] Makarichi L, Jutidamrongphan W and Techato K 2018 The evolution of waste-to-energy incineration: A review Renewable and Sustainable Energy Reviews 91 pp 812-821

[16] Malinauskaite J, Jouhara H, Czajczynska D, Stanchev P, Katsou E, Rostkowski P, Thorne R, Colon J, Ponsa S, Al-Mansour F, Anguilano L, Krzyzynska R and Lopez I 2017 Municipal solid waste management and waste-to-energy in the context of a circular economy and energy recycling in Europe 141 pp 2013-2044

[17] Minakova I, Bukreeva T and Timofeeva O 2018 Improvement of solid waste management: Organizational and technological aspects Journal of Applied Engineering Science 16 pp 99-103

[18] Ngiam K and Khor I 2019 Big data and machine learning algorithms for health-care delivery The lancet Oncology 20 pp 262-273

[19] Raschka S, Patterson J and Nolet C 2020 Machine Learning in Python: Main Developments and Technology Trends in Data Science, Machine Learning, and Artificial Intelligence Information 11 pp 193-237

[20] Safiullin M, Chekhlonin S, Aksyanova A 2019 A system approach to assessing the effectiveness of regional innovation systems in the concept of statistical sustainability Humanities and Social Sciences Reviews 7 pp 562-569

[21] Starostina VL, Damgaard A, Eriksen M and Christensen Th 2018 Waste management in the Irkutsk region, Siberia, Russia: An environmental assessment of alternative development scenarios Waste Management & Research 36 pp 309–310

[22] Tayara H and Chong K 2018 Object Detection in Very High-Resolution Aerial Images Using One-Stage Densely Connected Feature Pyramid Network Sensors 18 3341

[23] Tkachenko Y 2017 On the possibility of using artificial ecosystems for maintenance of human life Theoretical and Applied Ecology 2 pp 114-119

[24] Wang T, Cai Y, Liang L and Ye D 2020 A Multi-Level Approach to Waste Object Segmentation Sensors 20 pp 3816-3838

[25] Xiao Y, Tian Z, Yu J, Zhang Y, Liu Sh, Du Sh and Lan X 2020 A review of object detection based on deep learning Multimedia Tools and Applications 79 pp 23729-23791

[26] Yan Ch, Xiao Y, Lei Y, Mikhailov S and Zhengkui W 2020 Automatic Image Captioning Based on ResNet50 and LSTM with Soft Attention Wireless Communications and Mobile Computing pp 1-7

[27] Yaroslavtsev V 2019 Ensuring the Quality of Treatment of Holes in Products from Polymeric Composite Materials Herald of the Bauman Moscow State Technical University. Series Mechanical Engineering 3 pp 78-88

[28] Zhang Y, Chu J, Leng L and Miao J 2020 Mask-Refined R-CNN: A Network for Refining Object Details in Instance Segmentation Sensors 20 pp 1010-1026

[29] Zhao Z, Zheng P, Xu S and Wu X 2019 Object Detection With Deep Learning: A Review. IEEE Transactions on Neural Networks and Learning Systems 30 pp 3212-3232