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DEEP NEURAL NETWORKS AS A TOOL FOR ENHANCING THE EFFICIENCY OF PLASTIC WASTE SORTING

Abstract

In the recycling industry, there is an urgent need for high-quality sorted material. The problems of sorting centers related to the difficulties of sorting and cleaning plastic leads to the accumulation of waste in landfills instead of recycling, emphasizing the need to develop effective automated sorting methods. This study proposes an intelligent plastic classification model developed on the basis of a convolutional neural network (CNN) using architectures such as MobileNet, ResNet and EfficientNet. The models were trained on a dataset of more than 4,000 images distributed across five categories of plastic. Among the tested architectures, proposed EfficientNet-SED demonstrated the highest classification accuracy – 99.1%, which corresponds to the results of previous research in this area. These findings highlight the potential of using advanced CNN architectures to improve the efficiency of plastic recycling processes.

Key words: plastic sorting, classification, dataset, deep learning, convolutional neural network (CNN).

Introduction

Sorting garbage, including plastic bottles, and their subsequent recycling are of great importance for Kazakhstan and other countries in the context of sustainable development and environmental protection. Plastic bottles are one of the main sources of plastic waste, which can have a serious impact on nature and living organisms. Micro-plastic and nano-plastic particles penetrate the food chain of animals and humans. Proper sorting and recycling of plastic bottles helps to reduce environmental pollution and conserve natural resources.

There is a need to develop intelligent systems capable of efficiently sorting plastic waste. Current plastic sorting methods face a number of problems, such as low classification accuracy, dependence on the human factor and high operating costs. It is important to create a system that can automatically classify various types of plastic, determine their condition (by type, shape, color, and the presence of residues inside the bottle) and direct waste to appropriate recycling. Solving this problem will improve the efficiency of the recycling process and reduce the likelihood of errors, which is extremely important in the context of growing volumes of plastic waste and the need for sustainable development.

Literature Review

In Kazakhstan, plastic recycling is being tested, but much work remains to be done to increase the level of sorting. Each year, Kazakhstan produces 4.3–5 million tons of solid household waste. The share of recycled and disposed solid waste in 2022 was 25.41%, and only 20% of this amount is plastic waste [1]. Plastic is sorted in major cities and regional centers and processed at factories in Shymkent and Zhanaozen, as well as at small and medium-sized businesses. The government is encouraging plastic collection and recycling by introducing extended obligations for manufacturers. The Ministry of Ecology and Natural Resources of the Republic of Kazakhstan is also implementing the concept of Kazakhstan's transition to a green economy.

Assessing the environmental impact of automated plastic waste sorting systems is critical to assessing their sustainability. Life cycle assessment (LCA) of plastic products was carried out to analyze the overall environmental impact [2,3,4].

There are numerous examples of research on the sorting and classification of plastic wastes using NIR spectroscopy and a hyperspectral visualization system, including optical sorting, magnetic separation and other methods.

NIR spectroscopy has been extensively applied in the field of waste management, particularly for sorting plastic materials. Masoumi et al. (2012) investigated the identification and classification of plastic resins using near-infrared reflectance spectroscopy. Their study highlighted the technology's precision in distinguishing various plastic resins, facilitating more accurate and efficient sorting in recycling operations [5].

Similarly, Wu et al. (2020) demonstrated the effectiveness of NIR spectroscopy in auto-sorting commonly recovered plastics from waste household appliances and electronics. Their research provided significant insights into the application of NIR technology in identifying and separating different plastic polymers, which is crucial for recycling processes [6].

The advancement in hyperspectral imaging systems has further revolutionized the sorting of plastic waste. Zheng et al. (2018) developed a discrimination model using NIR hyperspectral imaging to sort waste plastics. This system proved to be effective in accurately identifying and classifying different types of plastic materials, showcasing the potential of hyperspectral imaging in enhancing waste management practices [7].

The integration of hyperspectral imaging with machine learning algorithms has also been explored to improve the sorting accuracy of plastic waste. Zhu et al. (2019) introduced a plastic solid waste identification system that combines near-infrared spectroscopy with support vector machine algorithms, indicating a significant improvement in the identification and classification of plastic materials [8].

With the development of deep learning and computer vision, more accurate and faster methods for recognizing and classifying objects based on images have become possible, making machine learning an ideal tool for automating the sorting of plastic waste. Carrera et al. (2022) focus on the application of machine learning algorithms such as neural networks, the support vector machine and deep learning algorithms for the recognition and classification of plastic materials. These studies emphasize the importance of selecting suitable features for model training and developing effective classification algorithms. [9].

Machine learning algorithms play a vital role in automating the sorting process by classifying plastic materials based on their composition, color and shape. Choi et al. (2023) uses deep learning models such as convolutional neural networks (CNN) and recurrent neural networks (RNN), have demonstrated exceptional performance in image recognition and classification tasks [10].

Problems in the automated sorting of plastic waste persist. These challenges include the diversity of plastic materials, the limitations of real-time processing, and the need for reliable algorithms to handle different waste streams. Abdallah et al. (2022) proposed innovative solutions, such as ensemble learning methods and transfer learning, to improve the adaptability and accuracy of machine learning models in real-world sorting scenarios [11].

Recent studies, such as by Kumar et al. (2021), explore deep learning approaches for waste segregation, notably using the YOLOv3 algorithm within the Darknet framework. This method, tailored for object classification, has shown effectiveness in classifying various waste types, including plastics. Deep learning, especially convolutional neural networks (CNNs), alongside techniques like Support Vector Machines (SVM) and Multilayer Perceptrons (MLP), are increasingly applied in waste management for their accuracy in classifying and segregating waste materials [12]

The research conducted by Bobulski and Kubanek (2021) introduces an advanced classification system for plastic waste, utilizing deep learning methodologies, with an emphasis on the development and evaluation of models capable of identifying various categories of plastic [13]. Their work utilized several deep neural network architectures (AlexNET, MobileNET) to achieve good classification accuracy (comparing across epoch), but in alignment with other studies [14, 15], their focus was aimed at the classification relevant to specific types of plastic materials (PET, PP, PS etc.). Furthermore, these models were additionally employed to identify various categories of municipal solid waste (MSW), including plastics, glass, metals, or alternative refuse [16, 17].

In our study, we conduct a deeper analysis of the application of deep neural network architectures to classify plastic bottles with different levels of residual contamination, including dairy and chemical liquid bottles. The main goal of our work is to improve sorting processes in real-world settings, where plastic waste often contains contamination. This makes the classification task more complex and important for ensuring an efficient recycling process.

Material and methods

In this study, we compared the architectures of deep convolutional neural networks: MobileNet_0.35, ResNet-34, and EfficientNet-B1/SED. These architectures were chosen as a backbone and due to their proven effectiveness in computer vision and image classification tasks, as their performance and ability to identify the most suitable architecture are key for automated plastic sorting.

MobileNet

In the research work of Howard et al. (2017), MobileNet is described as an efficient architecture for mobile devices that uses deep-separated strands and width multipliers to optimize computing resources, providing a balance between accuracy and efficiency, making it suitable for computer vision applications in computing power-limited environments [18].

MobileNet_0.35, a variant of the MobileNet architecture, is designed to operate with a reduced width multiplier of 0.35. This model maintains the use of depthwise separable convolutions, which significantly decrease the number of parameters and computational cost. The architecture starts with an initial full convolutional layer followed by a series of depthwise separable convolutional blocks. Each block comprises a depthwise convolution layer for filtering input channels independently, followed by a pointwise convolution that combines these channels. The stride is adjusted in certain blocks to reduce spatial dimensions, facilitating a reduction in computational load. The architecture concludes with global average pooling and a fully connected layer, terminating with a softmax activation function for classification.

ResNet

In the paper, He et al. (2016) first described the concept of residual blocks and ResNet architecture, which enables deep neural networks with hundreds of layers to be trained, solving the problem of disappearing gradients. The ResNet-34 architecture is notable for its ability to transmit information directly through skip connections, improving learning and providing high accuracy in computer vision tasks [19].

ResNet-34, part of the Residual Network family, is a deep CNN characterized by its use of residual blocks. These blocks incorporate skip connections that enable the direct flow of gradients, effectively addressing the vanishing gradient problem in deep networks. The architecture commences with a large kernel-sized convolutional layer, followed by a max-pooling layer to decrease dimensionality early in the network. The bulk of the network comprises residual blocks with two convolutional layers each, interspersed with batch normalization and ReLU activations. As the network progresses, the number of filters doubles, and the feature map size is halved, providing a pyramidal structure. The final stages include an average pooling layer leading to a dense layer that produces the output via softmax.

EfficientNet

EfficientNet-B0, described in Tan and Le (2019), implements composite scaling, optimizing network depth, width and resolution. This provides high efficiency and accuracy, making B0 fundamental for subsequent EfficientNet models and showing the way to improving the performance of deep neural networks [20].

EfficientNet-B1 is an optimized version of the base model, EfficientNet-B0, which is scaled using a compound coefficient to balance the dimensions of network width, depth, and resolution. The architecture employs MBConv blocks, an advanced version of inverted residual blocks with squeeze-and-excitation optimization, which recalibrates the feature maps adaptively. Unlike other architectures, EfficientNet applies a systematic approach to scaling all dimensions of the network. The B1 model enhances the baseline design with increased depth and width, alongside a higher resolution, leading to improvements in accuracy. The concluding layers of the network resemble traditional CNNs with global average pooling followed by a fully connected layer and softmax activation

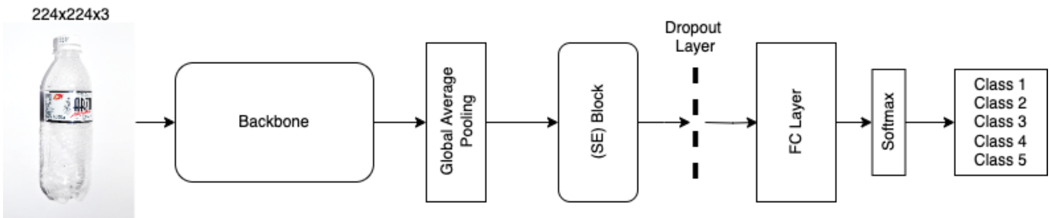

Figure 1 – CNN Architecture

EfficientNet-SED

We investigated three well-known models MobileNet, ResNet, and EfficientNet to assess the success of several backbone architectures for our aim. By means of layer and block experimentation, we created EfficientNet-SED, a new design based on EfficientNet. Following the backbone choice, we included Generalized Average Pooling (GA pooling) and Squeeze-and-Excitation (SE) blocks to improve feature representation. Dropout was used at each layer to provide robust generalization and avoid overfitting. A Fully Connected (FC) layer finishes the network design and allows softmax activation function to enable categorization (Fig. 1). Combining modern pooling and excitation methods with the strengths of every backbone, this methodical approach maximizes the model for higher accuracy and performance.

Data collection

For the purposes of the study, a specialized dataset of images of plastic waste was selected, available on the Kaggle platform called "Bottle Plastic Waste" with 80% for train set and 20% for test set and 200 images were additionally collected manually for the test set. This dataset includes a variety of plastic images, including bottles with contamination from both dairy and chemical (Table 1).

In the process of collecting the database, it was necessary to include several different classifications. The main type of most recyclable plastic in demand today is polyethylene terephthalate (PET) bottles. In order to become a secondary product, plastics undergo several stages of differentiation processes in sorting centers. Among them, plastic is distinguished from general waste products, and then sorted by type of plastic and the level of harmful waste. To obtain a high-quality secondary plastic product, it is necessary to have a bright/transparent color. If the bottle is of a dark color, used for dairy products, used for household chemicals, etc., then it is in the category that the bottle is not suitable for recycling.

Table 1 – Illustration of sample images with their respective class

				
Class1: Bottle transparent & clean	Class2: Bottle Dark color	Class3: Bottle from dairy and oil products	Class4:Bottle from Chemical products	Class5:Bottle from harmful contamination

According to the above classification, cameras, special visual sensors, mobile devices with cameras are used to obtain images of plastic waste. Visual data is collected to classify plastic waste using machine learning models.

Table 2 – Description and statistics of Bottle images in the dataset

Class (Type)	Items	*Recyclable	Quantity
Class 1 (PET)	Clean and empty bottles from different brands	+	1,512
Class 2 (PET)	Colored bottles (black, brown, dark purple, etc)	-	805
Class 3 (PET, PP, HDPE)	Bottles from milk products and oil, souse, etc	-	634
Class 4 (PET, PP, HDPE, PVC, LDPE)	Bottles from household chemical products (shampoo, gel, medical containers, etc)	-	630
Class 5 (PET)	PET bottles, but used for storing hazardous liquid (gasoline, antifreezes, domestos, etc)	-	452

***Recyclable.** In fact, all the plastics shown in the table are recyclable. However, there are some problems with collection. It is not profitable for dedicated sorting centers to collect other types of plastic and non-ferrous, dairy and contaminated products, since factories accept large volumes of tons for the production of secondary products. Another reason has to do with the quality of the plastic and, obviously, the price of it. In this regard, it is important to separate PET plastics (class 1) from other plastics (classes 2, 3, 4, 5).

Pre-processing

The following pre-processing process was performed before training the models:

Data normalization. All images were scaled to a single standard size corresponding to the input size of the neural network. Further, the pixel values of each image were adjusted to the range [0.1], which is standard practice to improve learning convergence [21].

$$\text{Normalized Pixel Value} = \frac{\text{Pixel Value}}{255} \quad (1)$$

In addition to scaling pixel values, standardization of data was applied, where the average of each pixel of the image is subtracted from the whole data set and the result is divided into a standard deviation.

$$\text{Standardized Pixel Value} = \frac{\text{Pixel Value} - \mu}{\sigma} \quad (2)$$

where μ is the average pixel value over the dataset, σ is the standard deviation of the pixel over the dataset.

Data augmentation was used to increase the amount of data and improve the generalizing ability of models. This included random image transformations such as rotations, offsets, scaling, and horizontal reflections [22].

The data were divided into training, validation and test samples in standard proportions, allowing the model to be evaluated with unprecedented data and avoiding retraining.

The given methodology of preliminary data processing creates equal conditions for comparison of performance of studied architectures of neural networks, providing accuracy and objectivity of experimental analysis.

The training process

Images are split so that 20% of each class is used for testing. The training process involved the use of stochastic gradient descent (SGD) with an initial learning rate of 0.01, which decreased by an order of magnitude after every two epochs. The training took place over 7 epochs with a package size of 32 samples. Categorical cross-entropy (formula 3) with the addition of L2 regularization with a coefficient of 0.0001 was used as a loss function to prevent overfitting. Data augmentation was applied on the fly using random horizontal reflection and random cropping of images. Dropout was applied with a probability of 0.5 before the last fully connected layer.

$$CE = -\sum_{i}^{C} t_i log(s_i) \quad (3)$$

where:

C – the number of classes;

t_i – the true label, encoded as a one-hot vector (i.e., $t_i=1$ if the true class is *i,* otherwise $t_i=0$);

s_i – the predicted probability of the class *i,* output by the model.

Evaluation metrics

The following metrics were used to evaluate the performance of the models:

The accuracy of the model is calculated using formula (4), where for each sample in the test dataset, the predicted class is compared with the true one. The duration of the model training was recorded from the initiation to the completion of the training procedure, encompassing all epochs, while the duration of model inference was quantified as the mean processing time of a single sample from the testing dataset [23].

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{Total\ Number\ of\ Predictions} \quad (4)$$

The total number of model parameters P is calculated as the sum of the parameters of each layer (5) and calculated using the following formula:.

$$P = \sum_{i=1}^{L} (K_i C_{in,i} C_{out,i} + C_{out,i}) \tag{5}$$

where:

P – the total number of parameters,

L – the total number of layers,

K_i – the kernel size of the package for the i-th layer,

$C_{in.i}$ – the number of input channels in the i-th layer,

$C_{out,i}$ – the number of output channels (or neurons) in the i-th layer.

This formula takes into account the parameters of convolutional layers and fully connected layers without taking into account offsets. To include offsets in the calculation, you just need to add $C_{out,i}$ for each layer to the total number of parameters.

To estimate the computational complexity, the FLOPs metric was used, which represents the total number of multiplication and addition operations required to perform one inference of the model [24].

$$FLOPs = \sum_{i=1}^{L} (2\, K_i^2 C_{in,i} H_{out,i} W_{out,i} C_{out,i}) \tag{6}$$

where:

K_i^2 – the size of the convolution core in layer *i*, squared, which indicates the number of weights in the filter,

$C_{in,i}$ – the number of input channels for the *i*-th layer,

$H_{out,i} W_{out,i}$ – height and width of the output feature map of the *i*-th layer,

$C_{out,i}$ – the number of output channels for the *i*-th layer.

Results and discussion

The results are compared based on the metrics obtained to identify the advantages and disadvantages of each architecture. The analysis includes a discussion of how differences in the structure and complexity of models affect their performance and applicability in different scenarios.

Below is a comparative analysis of these three models and the result obtained where x axis shows number of epoch and y axis shows loss.

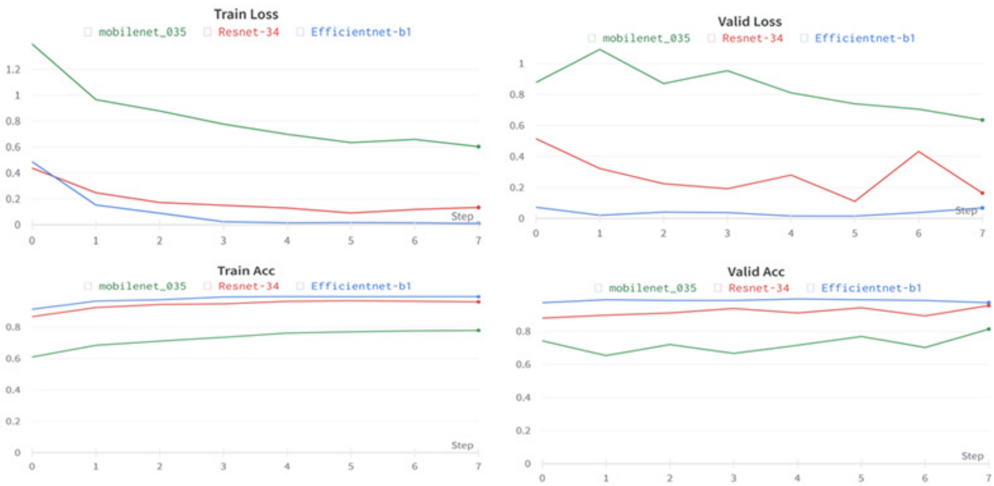

Figure 2 – Comparative analysis of training models

The results of evaluating the training process on the validation data set after seven epochs, providing data on the loss on the training set, loss on the validation set, the error rate and the time spent on each training epoch are shown in the Table 3. Changes in these metrics reflect the model's adaptation during training, highlighting variations in the algorithm's performance as it is optimized.

Train Loss is the average value of the loss function for all samples in the training dataset. For cross-entropy, which is often used for classification tasks, this is calculated as:

$$Train\ Loss = -\frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{C} y_{i,c}\log(\hat{y}_{i,c})$$

where:

N – the number of samples in the training dataset.

C – number of classes.

$y_{i,c}$ – the true class c label for sample i.

$\hat{y}_{i,c}$ – predicted probability of class c for sample i.

Valid Loss is estimated in a similar way to Train Loss, but for a validation dataset:

$$Valid\ Loss = -\frac{1}{M}\sum_{i=1}^{M}\sum_{c=1}^{C} y_{i,c}\log(\hat{y}_{i,c})$$

where:

M – the number of samples in the validation dataset. The other designations are similar to Train Loss.

Error Rate is the proportion of incorrectly classified samples in a dataset:

$$Error\ Rate = -\frac{1}{N}\sum_{i=1}^{N} \mathbf{1}\,(\hat{y}_i \neq y_i)$$

where:

1 – an indicator function that is equal to 1 if the predicted class $\hat{y}_i$ does not match the true class y_i, and 0 otherwise;

N – the number of samples in the dataset (training or validation).

Table 3 – Results of training on validation set

Epoch	Train_loss	Valid_loss	Error_rate	Time
1	1.341781	0.431466	0.123658	00:58
2	0.658234	0.388225	0.145486	00:50
3	0.756324	0.441112	0.098811	00:48
4	0.635198	0.587563	0.140456	00:47
5	0.763405	0.775234	0.278936	00:47
6	0.775418	0.735139	0.2145763	00:47
7	0.603471	0.635423	0.103846	00:47

Table 3 demonstrates the training results of the model over seven epochs, highlighting key metrics such as training loss, validation loss, error rate and time spent per epoch.

Table 4 – Model performance comparison

Methodology	Model Performance (average acc.)
MobileNet_035	81,33%
ResNet-34	95,55%
EfficientNet-B1	98,5%
EfficientNet-SED	99,1%

Table 4 compares the performance of three deep convolutional neural network architectures as measured by the classification accuracy metric. The results show that the EfficientNet-B1 architecture achieves the highest accuracy of 98.5%, indicating its superiority in the context of classification task compared to others. These findings highlight differences in the performance of architectures and their suitability for specific computer vision applications.

Figure 3 shows the curves in training and validation accuracy for the suggested EfficientNet-SED model. The model showed a strong learning capacity over the training procedure based on the routinely high accuracy values. With a final training accuracy of 0.996 the model clearly learnt the patterns in the training data. With an outstanding value of 0.991, the validation accuracy also demonstrated the great generalizing capacity of the model to unmet data. These findings show how well the EfficientNet-SED design maximizes performance while preserving great accuracy on the validation and training sets.

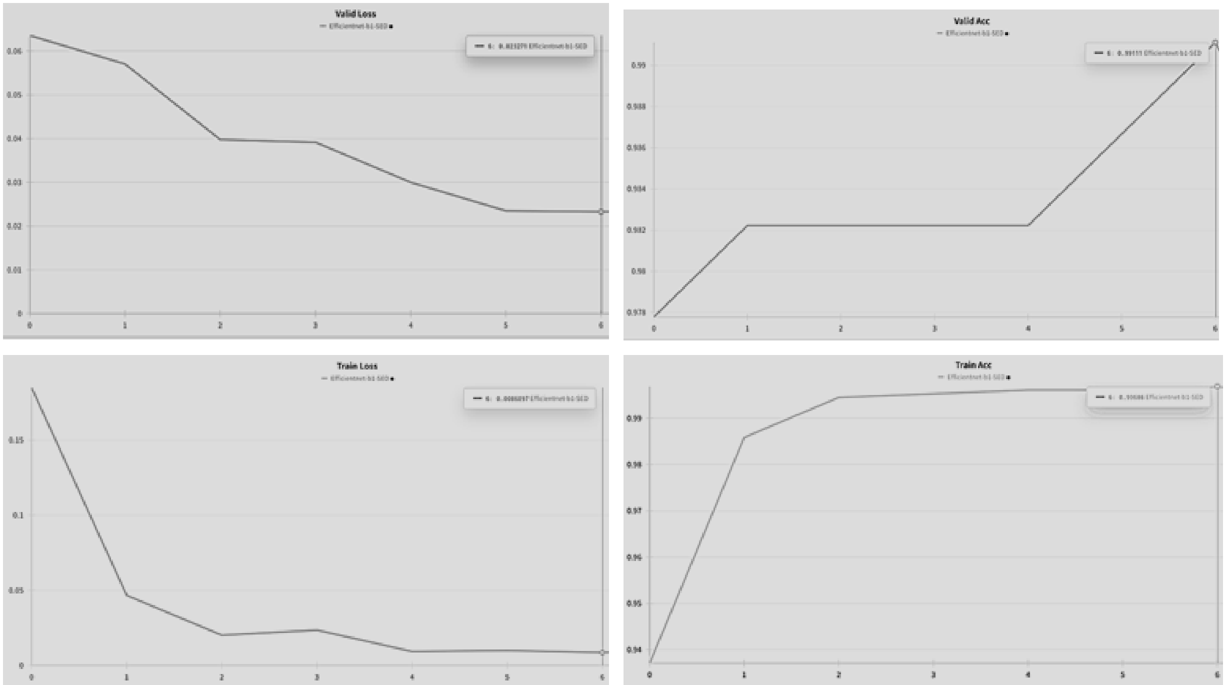

Figure 3 – EfficientNet-SED results

Conclusion

The article analyzes the use of deep neural networks, especially convolutional neural networks (CNN), to improve the sorting of plastic waste, where traditional methods are ineffective, leading to the accumulation of waste in landfills. Tests on a database of more than 4,000 images of plastic waste showed that the EfficientNet-SED architecture achieved the highest accuracy of 99.1%, demonstrating its potential to optimize recycling processes. This study highlights the importance of using advanced CNN architectures to improve plastic sorting accuracy, which is key to environmental sustainability and efficient use of resources. The results of the work allow us to determine the most suitable architecture for computer vision tasks, offering a systematic comparison of models for an objective assessment of their effectiveness.

Although the algorithms used in the study are well known, the significance of our contribution lies in their adaptation and application to specific conditions of classification not only by types, but also by colors and different classes are shown in Table 2. The scientific novelty of the study is demonstrated in the comparison of the performance of different CNN architectures under conditions where plastics have different levels of contamination.

Future work

This work is a part of the main scientific project sponsored by the Science Committee of the MSHE of the RK, which is divided into 3 stages. The results presented in this paper focused on the use of a dataset of images captured by the camera. The next stage in the process is to analyze the spectral data of different types of plastic obtained using the NIR spectrometer, which will allow for more accurate classification into categories in the context of waste recycling. The third stage plans to use hyperspectral imaging technologies that will provide the ability to more accurately identify plastic bottles containing hazardous substances inside the bottles.

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ТЕРЕҢ НЕЙРОНДЫҚ ЖЕЛІЛЕР ПЛАСТИКАЛЫҚ ҚАЛДЫҚТАРДЫ СҰРЫПТАУ ТИІМДІЛІГІН АРТТЫРУ ҚҰРАЛЫ РЕТІНДЕ

Аңдатпа

Қайта өңдеу өнеркәсібінде сапалы сұрыпталған материалға шұғыл қажеттілік туындауда. Сұрыптау орталықтарының мәселесі ретінде пластмассаны сұрыптау және тазалау қиындықтарына байланысты қалдықтар, қайта өңдеудің орнына полигондарда жиналуда. Бұл тиімді автоматтандырылған сұрыптау әдістерін дамыту қажеттілігін көрсетеді. Осы зерттеу жұмысы MobileNet, ResNet және EfficientNet сияқты архитектураларды қолдана отырып, конволюциялық нейрондық желіге (CNN) негізделген пластмассаларды жіктеудің интеллектуалды моделін ұсынады. Модельдер пластиктің бес санатына бөлінген 4000-нан астам кескіннен тұратын деректер жиынтығында оқытылды. Сыналған архитектуралардың ішінде EfficientNet-SED классификацияның ең жоғары дәлдігін көрсетті – 99,1%, бұл осы саладағы алдыңғы зерттеулердің нәтижелеріне сәйкес келеді. Бұл нәтижелер пластикті қайта өңдеу процестерінің тиімділігін арттыру үшін жетілдірілген CNN архитектураларын пайдалану әлеуетін көрсетеді.

Тірек сөздер: пластикалық сұрыптау, класификация, мәліметтер қоры, терең оқыту, конволюциялық нейрондық желі (CNN).

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ГЛУБОКИЕ НЕЙРОННЫЕ СЕТИ КАК ИНСТРУМЕНТ ПОВЫШЕНИЯ ЭФФЕКТИВНОСТИ СОРТИРОВКИ ПЛАСТИКОВЫХ ОТХОДОВ

Аннотация

В индустрии вторсырья наблюдается острая потребность в качественном сортированном материале. Проблематика сортировочных центров, связанная с трудностями сортировки и очистки пластика, приводит к накоплению отходов на свалках вместо их переработки, подчеркивая необходимость развития эффективных автоматизированных методов сортировки. В этом исследовании предлагается интеллектуальная модель классификации пластиков, разработанная на основе сверточной нейронной сети (CNN) с использованием таких архитектур, как MobileNet, ResNet и EfficientNet. Модели были обучены на наборе данных, состоящем из более чем 4000 изображений, распределенных по пяти категориям пластика. Среди протестированных архитектур EfficientNet-SED продемонстрировала самую высокую точность классификации – 99,1%, что соответствует результатам предыдущих исследований в этой области. Эти результаты подчеркивают потенциал использования передовых архитектур CNN для повышения эффективности процессов переработки пластика.

Ключевые слова: пластиковая сортировка, классификация, набор данных, глубокое обучение, сверточная нейронная сеть (CNN).

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