Method for Construction and Demolition Waste Classification Using Two-Factor Neural Network Image Analysis

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Abstract

Method for construction and demolition waste classification using two-factor neural network image analysis has been developed, which allows increasing the classification accuracy to 97.8% for 10 classes of construction waste. High accuracy of object recognition and prevention of misclassifications is achieved due to use of two-factor approach to identification and classification of the construction and demolition waste. Approach consists in combining the use of YOLO11 model for object identification and set of binary ResNet50V2 classifiers for the classification of each of the 10 classes of construction and demolition waste. Method takes into account the results of binary trained neural networks for the classification of construction and demolition waste, and in cases of ambiguous classification, it additionally uses the prediction of YOLO11 arbiter neural network. To ensure the diversity of training dataset and improve the generalization capabilities of classifiers, dataset was expanded using transformations such as rotation, scaling, color change, and reflection; this also significantly increased the accuracy of separation and classification of construction and demolition waste. Comparison of the developed method and known analogues revealed minimum increase in accuracy of 5.2%, maximum increase in accuracy of 32.5%.

Keywords

construction and demolition waste, construction waste sorting, classification, ResNet50, YOLO11

1. Introduction

Classification of construction and demolition waste is becoming increasingly relevant due to the rapid growth in the volume of such materials, which accompanies the processes of urbanization and infrastructure modernization [1]. The construction industry is currently one of the largest sources of solid household and industrial waste, which is a significant environmental problem [2, 3]. Modern waste management strategies require the integration of innovative technologies that can provide prompt and highly accurate identification of materials for their effective recycling, reuse or environmentally safe disposal [4]. Outdated waste management methods, often accompanied by low levels of sorting and disposal, are one of the main causes of environmental degradation, water, air and soil pollution [5]. This creates risks of geological instability, increases the number of dangerous zones, such as landfills, and contributes to the spread of diseases among the population due to exposure to toxic substances. In addition, inefficient waste management exacerbates the problem of depletion of natural resources, as many materials that could be recycled end up in landfills [6, 7].

In this context, recycling of such waste appears as an important mechanism to reduce the volume of landfills, while reducing the need for energy and natural resources required for the extraction and production of new materials [8, 9]. Innovative solutions such as neural network technologies, automated sorting systems and recycling infrastructure aim to minimize these

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negative impacts, ensuring not only the protection of the ecosystem, but also transition to a circular economy [10, 11].

The application of neural network technologies in the classification of construction and demolition waste contributes to the achievement of the UN Sustainable Development Goals, in particular sustainable urban development (SDG 11), responsible consumption (SDG 12), sustainable infrastructure development (SDG 9) and combating climate change (SDG 13) through effective waste management, increased recycling rates and reduced emissions [12, 13]. The aim of the study is to develop a method for classifying the remains of destroyed buildings and construction waste using neural network image analysis, which will allow to increase the accuracy of classification. The main contributions of the article can be summarized as follows:

- Method for construction and demolition waste classification using two-factor neural network image analysis is proposed, which is based on combination of binary classifiers and the YOLO neural network, which allows to increase the accuracy of multi-class classification.
- Approach to refine predictions in case of classification ambiguity is developed, which reduces the number of errors and ensures identification accuracy at the level of 97.8% for 10 classes of construction waste.
- Experimental validation of the method is carried out, which confirmed its effectiveness in real conditions with heterogeneous data.

The next section presents an overview of related works in the field of construction waste and production waste. Section 4 offers an overview of the experiment to investigate the effectiveness of the proposed approach. Section 5 offers an overview of the obtained results with comparisons and discussions. The last section is conclusions.

2. Related Works

Studies have shown that construction and demolition waste (C&DW) constitutes a significant proportion of municipal solid waste (MSW) accumulating in landfills worldwide, posing a significant environmental challenge [14].

The study [15] is devoted to the development of a highly efficient method for fine-grained classification of construction and demolition waste (C&DW), which is an important step for the development of a recycling system and achieving carbon neutrality in the waste management sector. C&DWNet models built on ResNet using knowledge transfer and a cyclic learning coefficient were proposed to classify ten types of construction waste. The results showed that the knowledge transfer method can reduce the training time and improve the efficiency of the model. The average training time increased with the number of layers of the architecture: from C&DWNet-18 (946.7 s) to C&DWNet-152 (1186.6 s). The best Accuracy (73.6%) was achieved on C&DWNet-152, however, the C&DWNet-18 model showed the optimal balance between training time, accuracy, precision and F1-metric. The use of t-distributed stochastic neighbor embedding allowed to clearly distinguish the types of waste.

In [16], an approach to construction waste management is presented using a robotic system to automatically sort and collect construction materials, such as nails and screws, which are difficult to detect manually. The robot uses neural network and computer vision technologies, as well as the Faster R-CNN method for real-time detection and collection of target objects in the work environment.

In the study [17], deep learning approaches for effective waste identification and classification based on an open set of images from the Middle East region were studied. Images of garbage and waste are divided into five categories: paper, plastic, glass, metal and other. Each image contains only one class. Convolutional neural network (CNN) algorithms were used to classify waste, as well as pre-trained models MobileNetV2, ResNet50V2, and DenseNet169. The highest accuracy among the pre-trained models was demonstrated by ResNet50V2 (98.95%), while the proposed CNN model achieved an accuracy of 88.5%, which exceeds the results of previous studies on the same dataset.

The paper [18] describes the development of a methodology to improve the sorting of construction and demolition waste (BDW) using machine learning, using an RGB camera to recognize waste fragments. The main goal of the research is to improve the efficiency of waste sorting through the use of advanced feature extraction methods, which improves the speed and accuracy of classification. The paper compares three classifiers: convolutional neural network (CNN), gradient boosting decision trees (GB), and multilayer perceptron (MLP), where the feature extraction method for GB and MLP showed better results in terms of speed and accuracy compared to the traditional CNN. The results show that the new methodology provides accuracy up to 92.3%, compared to 85.9% for CNN. The paper also provides additional materials, including datasets, codes, and models, which contributes to the transparency and reproducibility of the results.

In [19], a method for detecting construction and demolition waste (CDW) in urban development is considered, taking Beijing as an example. Given the rapid demolition of old buildings, waste has become an important component of the urban pollution problem. Since CDW landfills have unstable contours, it is important to determine their location in a timely and accurate manner to achieve accurate mapping and effective waste management. A method based on change detection and deep learning was proposed to solve this problem. ZY-3 multispectral images from 2016 and 2019, as well as difference images obtained using change detection methods, were used to prepare the initial samples. Sample expansion using the post-classification method allowed to increase the sample by 25.4%, which improved the results. This extended learning environment was used to train the DeepLabV3+ model, and the digital terrain model information was also used to distinguish different types of CDW, such as demolition waste, landfills, and large-scale dumps. The CDW detection accuracy was 91.67%, and the Kappa coefficient was 0.8642. Comparison of the results with the original samples showed that expanding the sample using change data improves the accuracy of the deep learning models, which is also confirmed by the results for the PSPNet and UNet models. This study is the first to effectively distinguish the three main forms of CDW and significantly reduce the errors in the classification of CDW and bare land.

The literature review identified several key issues in the classification of construction and demolition waste. First, most works are focused on classification within already defined objects, which is a simplified task, since one image may contain different fragments, often belonging to different classes, and objects may be superimposed on each other. Second, in multi-class classification, there is still low identification accuracy, which complicates the effective solution of the problem.

3. Method Design

The proposed approach allows to increase the accuracy of classification of construction and demolition waste by applying the developed method, which converts input data in the form of a photo image for analysis, a trained neural network for highlighting fragments of construction remains in the photo image and their basic classification, and a set of trained neural networks for binary classification of fragments of construction remains into output data in the form of an image with highlighted fragments of construction remains and defined classes with probabilities of their belonging. The scheme of the method for construction and demolition waste classification using two-factor neural network image analysis is shown in Fig. 1.

The input data of the method are photo images for analysis, a trained neural network for extracting fragments of construction remains in the photo image, and trained neural networks for binary classification of the selected fragments. YOLO11 [20] was chosen as the neural network for extracting fragments of construction remains in the photo image, and the trained neural networks for binary classification of the selected fragments have ResNet50 architectures [21].

For neural network extraction of objects in the image, the step 1 of preprocessing of the photo image first occurs [22]. The image is scaled to a size of 640x640 pixels. After scaling, the step 2 of extracting fragments of construction remains in the photo image directly occurs.

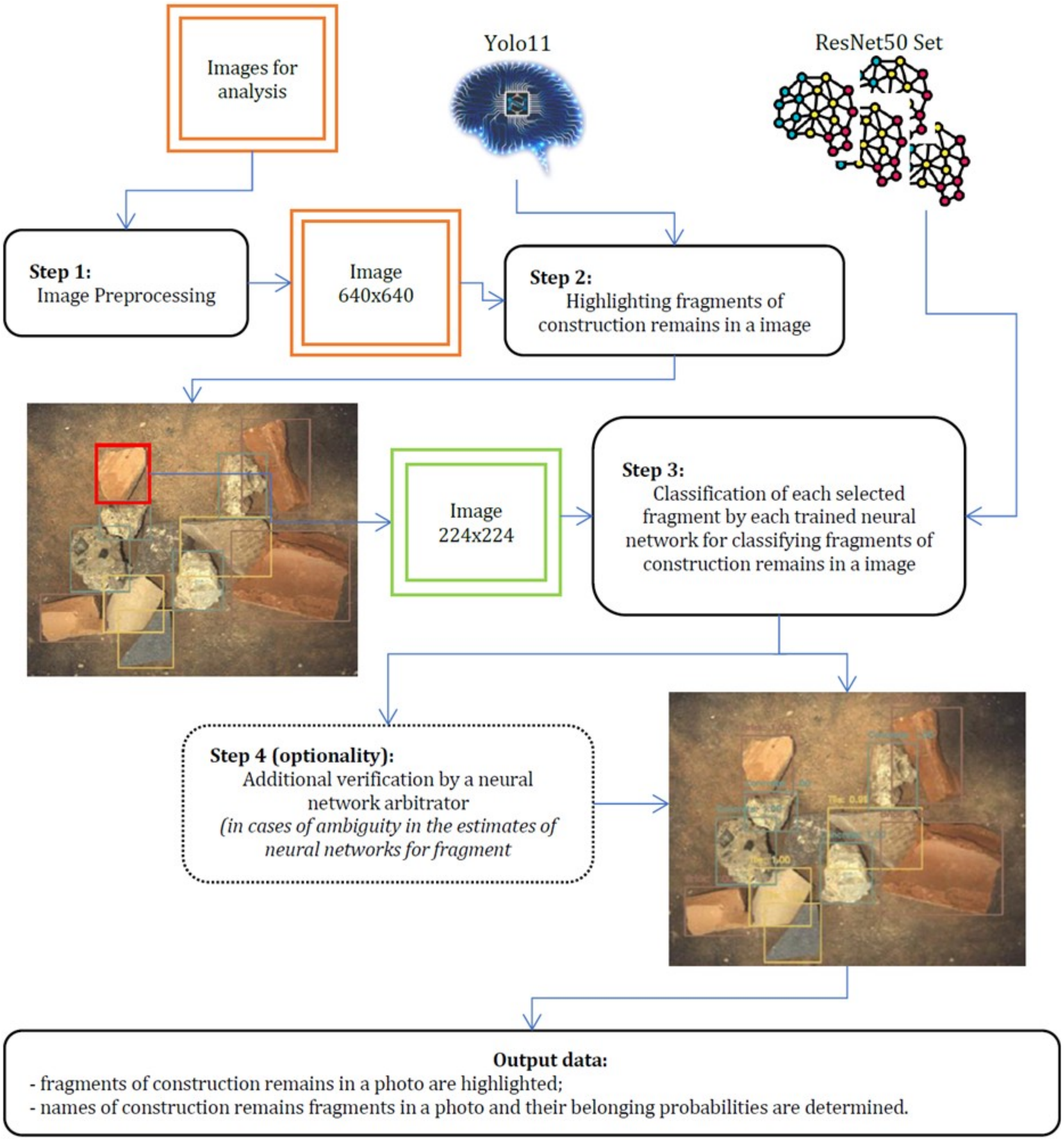

Figure 1: Scheme of the method for construction and demolition waste classification using two-factor neural network image analysis.

For each selected fragment, a preprocessing stage is also performed for the possibility of further classification, which includes scaling to a size of 224x224 (while preserving the aspect ratio) and normalizing the image by subtracting the mean value and dividing by the standard deviation [23]

At step 3, each selected fragment is classified by each of the 10 trained neural networks for classifying fragments of construction remains in the photo image. The following classes are classified in the study: brick, concrete, foam, plastic, general waste, gypsum board, pipes, plastic, stone, tile, wood. Examples of fragments are shown in Fig. 2 (a-k). In the case where the neural networks give the same results, step 4 is performed, which consists of additional verification by an arbitrator. The arbitrator is the YOLO11 classification.

As a result, the output data are the selected fragments of construction remains in the photo and their defined names with membership probabilities.

The developed method was used in this study to analyze separate frames, but it can be integrated into automated demolition waste sorting systems and applied to analyze a video stream in real time.

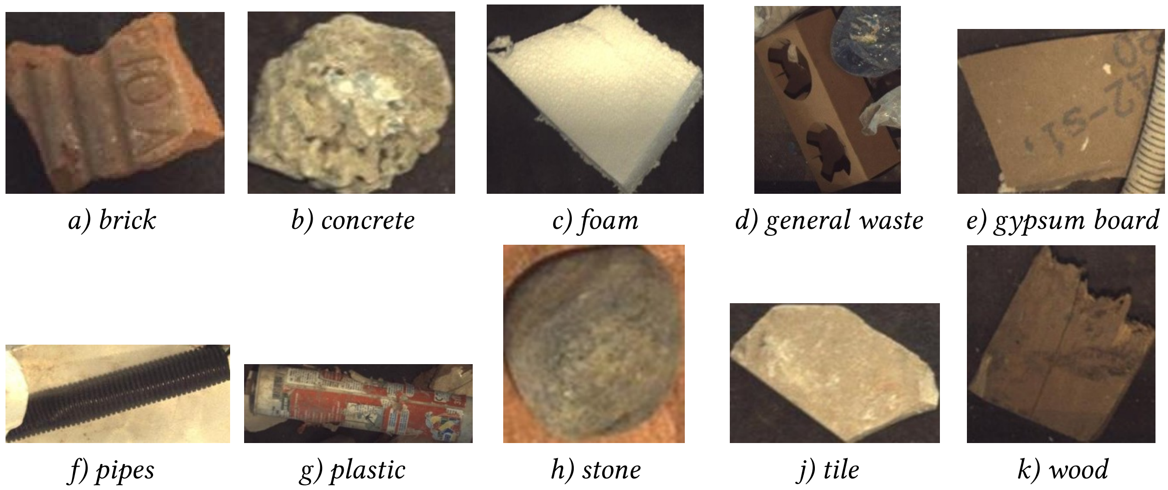

Figure 2: Examples of construction and demolition waste.

Since one of the input data is a set of ResNet50 neural network models for binary classification, Figure 3 shows an example of obtaining a neural network model for brick identification. A similar approach is used to obtain trained models for the remaining 9 classes.

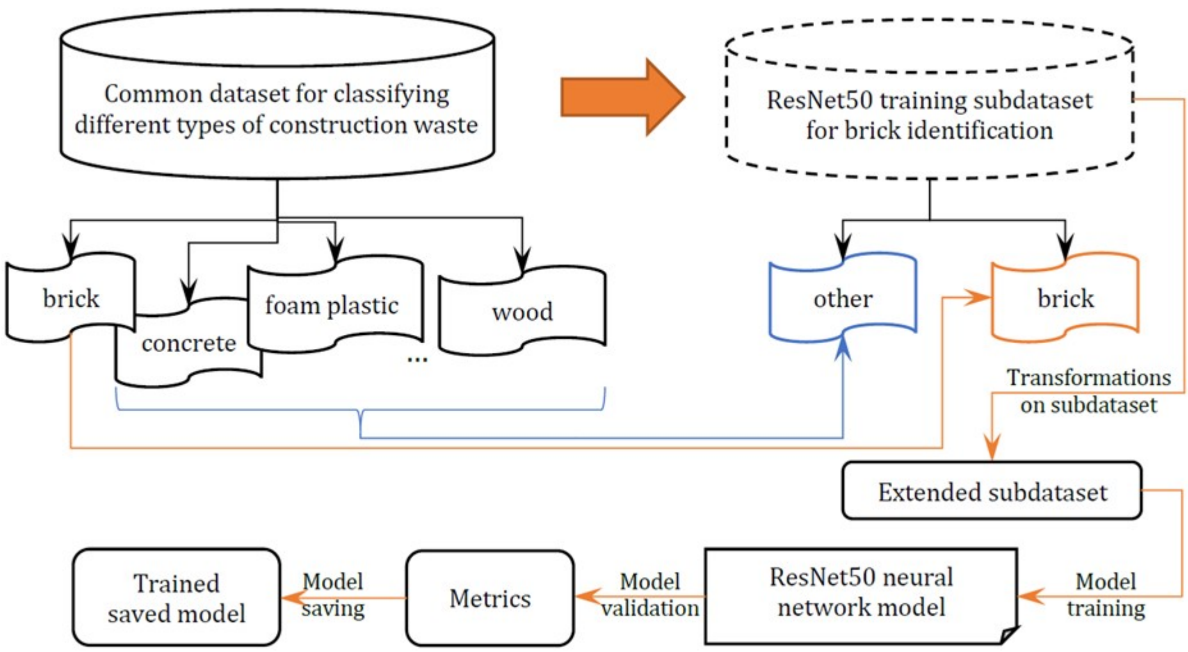

Figure 3: Training scheme of typical ResNet50 model for binary classification.

First, to train binary ResNet50 models from the general dataset for classifying different types of construction waste, subdatasets are formed. All fragments of the subdataset are scaled to 224x224 size while preserving the aspect ratio and converted to RGB format. Since the key problem of multi-class classification is the reduction of identification accuracy, it was decided to use 10 neural network classifiers, separate for each type of construction waste. Datasets are formed according to the rule: all images from the general dataset that correspond to the target category are transferred to the subdataset in the target category. The opposite category of the subdataset is formed by combining in equal parts other types of construction waste and construction residues. Further, each of the fragments is rotated by 45 degrees 4 times, 4 new samples are formed, and for each new inverted sample, a random color change is applied according to the brightness and contrast parameters. Thus, an extended subdataset is formed.

ResNet50 models are trained on the obtained subdatasets, which are validated by the metrics Accuracy, Precision, Recall, F1, after which a typical binary classifier model is saved.

So, a method is proposed that, instead of using the standard multi-class classification, which is typical for the YOLO neural network, uses a set of binary classifiers, each of which determines the belonging of the object to one of the classes. The method takes into account the results of binary trained neural networks for classifying fragments of construction remains, and in cases of ambiguity (equality of estimates between classes), it additionally uses the YOLO forecast. In situations where YOLO and one of the binary classifiers coincide in the estimate, this class is determined as dominant. This approach reduces the number of erroneous classifications and provides higher accuracy of object recognition.

4. Experiment

To research the effectiveness of proposed approach, the software was developed (Fig. 4) that uses pre-trained YOLO11 model and set of ResNet50 models for finding and classifying objects in an image. The PySide [24], TensorFlow [25], and Ultralytics [26] libraries were used to create the software.

Figure 4: Created software for construction and demolition waste classification.

The following datasets were used to train the neural networks, which are the input data of the proposed method and are used in the application:

1) "Construction and Demolition Waste Object Detection Dataset" [27]. The dataset contains 3,129 high-resolution images (1920 × 1200 × 3, RGB) with 16,545 annotated samples covering 10 waste categories. The data were collected at a waste sorting plant in Cyprus. The annotations are provided in PASCAL VOC XML format, including the coordinates of bounding boxes and polygons for accurate object detection. The dataset is divided into subsets for training, validation, and testing.

2) “Dataset-of-stacked-construction-solid-waste” [28] to supplement the images of concrete and wood. The dataset contains 4 types of solid construction waste: concrete, brick, wood, and rubber. Each document contains 25 sample images and label files.

3) “RGB-D construction solid waste” [29]. An instance segmentation dataset for solid waste identification. The dataset includes 4 waste types: concrete, rubber, wood, and brick. It is also used for supplementation.

From the considered datasets, a general dataset was formed, which has the following structure and dimension: “brick” – 1370 samples, “concrete” – 1407 samples, “foam” – 746 samples, “general_w” – 742 samples, “gypsum_board” – 1184 samples, “pipes” – 715 samples, “plastic” – 675 samples, “stone” – 744 samples, “tile” – 1344 samples, “wood” – 1131 samples. This formed dataset was used to create subdatasets for training binary ResNet50 classifiers.

For further training of YOLO11, the following distribution was used: “brick” – 1370 samples contained in 309 files; “concrete” – 1407 samples contained in 311 files; “foam” – 746 samples contained in 126 files; “general_w” – 742 samples contained in 359 files; “gypsum_board” – 1184 samples contained in 126 files; “pipes” – 715 samples contained in 196 files; “plastic” – 675 samples contained in 265 files; “stone” – 744 samples contained in 177 files; “tile” – 1344 samples contained in 308 files; “wood” – 1131 samples contained in 504 files.

To compare the effectiveness of the studied neural networks, the metrics Accuracy, Precision, Recall, F1-Score [30] and specialized metrics were used, which allowed for a comprehensive assessment of the proposed approaches. The effectiveness study was conducted in the following areas:

- study of the impact of the elapsed training epochs on the accuracy of binary classifiers;
- comparison of the ResNet50 and MobileNetV2 architectures;
- comparison of the efficiency of YOLO11 for classifying production waste objects with the developed method.

5. Results and discussion

To identify construction and demolition waste objects, pre-trained neural network YOLO11 was used, which was further trained on the above-described dataset. This neural network also acts as an arbiter to confirm the predictions of individual neural network binary models [31].

During training YOLO11, the following transformations are performed on the input data:

- horizontal mirroring;
- random scaling;
- random shifting;
- random color changes (brightness, contrast).

These transformations occur over the full image, the fragments are not processed separately. Such transformations allow to increase the correctness of the selection of construction and demolition waste fragments.

To classify the selected fragments, a pre-trained ResNet50 model was taken, which is part of the TensorFlow library and was further trained on subdatasets, separate for each of the 10 models. To study the influence of the passed training epochs on the accuracy of binary classifiers, each of the binary neural network models ResNet50 was trained on different numbers of epochs – from 5 to 20. To train ResNet50, the following manipulations are performed on each fragment:

- the fragments are rotated 45 degrees 4 times, creating 4 new samples;
- a random color change (brightness and contrast) is applied to the new rotated sample.

Before that, the fragments are scaled to 224x224 while preserving the aspect ratio (the original image is centered, the "empty space" is filled with black) and converted to RGB format, if it was BGR or RGBA. The results of the experiments are given in Table 1.

Table 1
The impact of training epochs number on metrics for the ResNet50 neural network

Epochs	Accuracy	Precision	Recall	F1-Score	Class
Epoch 5	0.9738	0.9713	0.9761	0.9737	Brick
Epoch 10	0.9740	0.9624	0.9863	0.9742	
Epoch 15	0.9810	0.9776	0.9845	0.9810	
Epoch 20	0.9775	0.9679	0.9876	0.9776	
Epoch 5	0.9768	0.9643	0.9907	0.9773	Concrete
Epoch 10	0.9785	0.9658	0.9923	0.9789	
Epoch 15	0.9846	0.9855	0.9839	0.9847	
Epoch 20	0.9854	0.9883	0.9826	0.9855	
Epoch 5	0.9818	0.9860	0.9772	0.9816	Foam
Epoch 10	0.9848	0.9871	0.9822	0.9846	
Epoch 15	0.9725	0.9517	0.9950	0.9729	
Epoch 20	0.9877	0.9824	0.9931	0.9877	
Epoch 5	0.9655	0.9473	0.9827	0.9647	General Waste
Epoch 10	0.9643	0.9420	0.9861	0.9636	
Epoch 15	0.9780	0.9766	0.9775	0.9770	
Epoch 20	0.9801	0.9767	0.9818	0.9792	
Epoch 5	0.9454	1.0000	0.8917	0.9427	Gypsum Board
Epoch 10	0.9786	0.9723	0.9856	0.9789	
Epoch 15	0.9765	0.9639	0.9904	0.9770	
Epoch 20	0.9647	0.9410	0.9922	0.9659	
Epoch 5	0.9552	0.9667	0.9410	0.9537	Pipes
Epoch 10	0.9590	0.9479	0.9695	0.9586	
Epoch 15	0.9585	0.9445	0.9724	0.9582	
Epoch 20	0.9599	0.9564	0.9619	0.9592	
Epoch 5	0.9155	0.9033	0.9277	0.9153	Plastic
Epoch 10	0.9378	0.9364	0.9373	0.9369	
Epoch 15	0.9378	0.9381	0.9354	0.9367	
Epoch 20	0.9373	0.9355	0.9373	0.9364	
Epoch 5	0.9793	0.9891	0.9688	0.9788	Stone
Epoch 10	0.9830	0.9851	0.9803	0.9827	
Epoch 15	0.9834	0.9828	0.9836	0.9832	
Epoch 20	0.9850	0.9828	0.9869	0.9848	
Epoch 5	0.9647	0.9755	0.9528	0.9640	Tile
Epoch 10	0.9679	0.9685	0.9667	0.9676	
Epoch 15	0.9647	0.9849	0.9434	0.9637	
Epoch 20	0.9676	0.9558	0.9799	0.9677	
Epoch 5	0.9732	0.9822	0.9638	0.9729	Wood
Epoch 10	0.9787	0.9763	0.9813	0.9788	
Epoch 15	0.9808	0.9849	0.9765	0.9807	
Epoch 20	0.9833	0.9891	0.9774	0.9832	

The data in Table 1 show that increasing the number of training epochs has a positive effect on the performance metrics for most classes. Larger number of epochs allows the model to better adapt to the patterns in the data, although after a certain point the effect can fade or even worsen due to overfitting [32], as seen in the classes "Gypsum Board" and "Plastic". The metrics can also be affected by the characteristics of the data itself [33], such as the distribution between classes, the complexity of the samples, and the level of noise. Thus, choosing the optimal number of epochs is critical and depends on the specifics of the task and the data [34].

To compare the results, a similar experiment was conducted with the MobileNetV2 architecture [35], which is also a pre-trained neural network model. The training results are presented in Table 2.

Table 2

The impact of training epochs number on metrics for the MobileNet neural network

Epochs	Accuracy	Precision	Recall	F1-Score	Class
Epoch 5	0.9601	0.9583	0.9659	0.9621	Brick
Epoch 10	0.9587	0.9706	0.9500	0.9602	
Epoch 15	0.9508	0.9749	0.9301	0.9520	
Epoch 20	0.9564	0.9692	0.9469	0.9579	
Epoch 5	0.9765	0.9691	0.9872	0.9781	Concrete
Epoch 10	0.9785	0.9810	0.9785	0.9798	
Epoch 15	0.9766	0.9715	0.9849	0.9782	
Epoch 20	0.9772	0.9794	0.9775	0.9785	
Epoch 5	0.9726	0.9824	0.9662	0.9742	Foam
Epoch 10	0.9670	0.9517	0.9884	0.9697	
Epoch 15	0.9726	0.9871	0.9614	0.9741	
Epoch 20	0.9814	0.9762	0.9894	0.9828	
Epoch 5	0.9540	0.9502	0.9608	0.9555	General Waste
Epoch 10	0.9461	0.9275	0.9710	0.9487	
Epoch 15	0.9628	0.9714	0.9556	0.9634	
Epoch 20	0.9579	0.9662	0.9514	0.9587	
Epoch 5	0.9610	0.9570	0.9692	0.9631	Gypsum Board
Epoch 10	0.9591	0.9451	0.9788	0.9617	
Epoch 15	0.9613	0.9522	0.9752	0.9636	
Epoch 20	0.9699	0.9659	0.9770	0.9714	
Epoch 5	0.9406	0.9574	0.9278	0.9424	Pipes
Epoch 10	0.9421	0.9165	0.9784	0.9465	
Epoch 15	0.9548	0.9379	0.9784	0.9578	
Epoch 20	0.9534	0.9585	0.9522	0.9553	
Epoch 5	0.8994	0.8844	0.9293	0.9063	Plastic
Epoch 10	0.9104	0.9025	0.9293	0.9157	
Epoch 15	0.9094	0.9163	0.9101	0.9132	
Epoch 20	0.9154	0.8968	0.9474	0.9214	
Epoch 5	0.9564	0.9326	0.9877	0.9594	Stone
Epoch 10	0.9726	0.9793	0.9680	0.9736	
Epoch 15	0.9726	0.9707	0.9770	0.9738	
Epoch 20	0.9701	0.9682	0.9746	0.9714	
Epoch 5	0.9468	0.9436	0.9565	0.9500	Tile
Epoch 10	0.9523	0.9404	0.9714	0.9556	
Epoch 15	0.9540	0.9525	0.9608	0.9567	

Epoch 20	0.9530	0.9394	0.9739	0.9563	
Epoch 5	0.9627	0.9593	0.9700	0.9646	Wood
Epoch 10	0.9647	0.9680	0.9646	0.9663	
Epoch 15	0.9679	0.9664	0.9726	0.9695	
Epoch 20	0.9657	0.9744	0.9598	0.967	

The impact of training epochs number on metrics for the MobileNet neural network-Score is observed at the 20th epoch, while for the "Plastic" class, the qualitative indicators remain lower, regardless of the number of epochs, probably due to the more complex data structure.

The stability of the metrics at the 15th and 20th epochs for many classes indicates that the network achieves optimal learning, although some fluctuations, for example in the "Pipes" class, may be caused by overfitting or insufficient generalization. The overall result indicates the importance of fine-tuning the number of epochs for each specific class to avoid performance loss.

A comparison of the best results from Tables 1 - 2 of alternative neural network options for binary classification is shown in Figure 5.

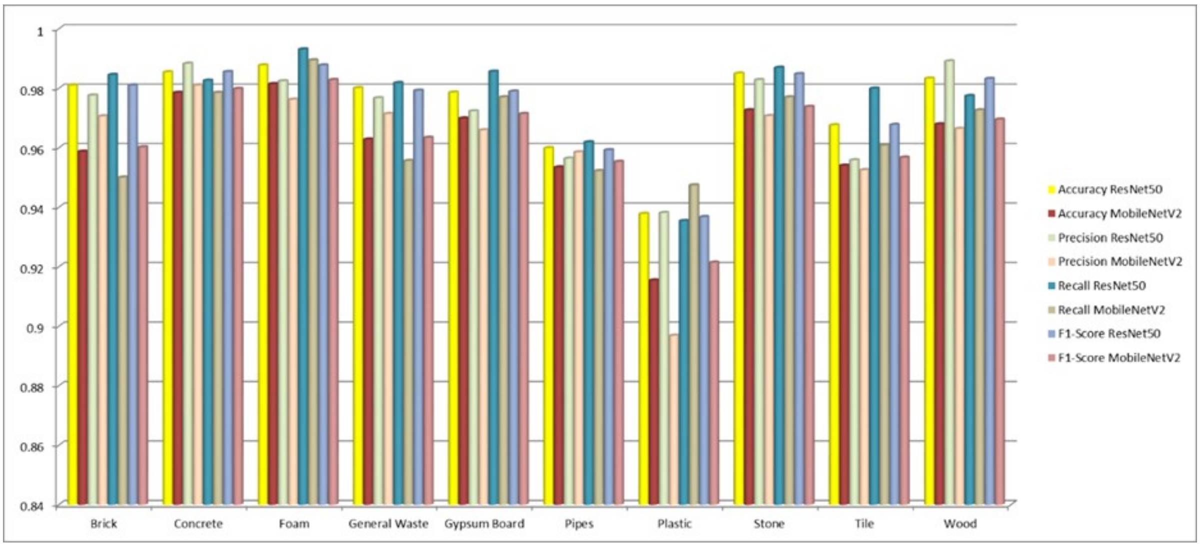

Figure 5: Comparison of the performance of neural networks ResNet50 and MobileNetV2

The results of the performance comparison of the ResNet50 and MobileNetV2 models demonstrate significant differences, which are due to the architectural features of these neural networks. ResNet50, being a deeper and more complex model, shows higher Accuracy indicators and harmoniously balanced Precision, Recall and F1-Score for most classes, in particular for "Foam", "Stone" and "Wood". This indicates its ability to effectively generalize patterns even in complex data.

MobileNetV2, on the contrary, is focused on optimizing computational resources and has less depth, which explains its lower performance in the cases of complex classes such as "Plastic" or "Tile". Its advantages become noticeable in tasks with less complex data, where it is able to achieve acceptable metric values with minimal resource costs.

The pre-trained YOLO11 neural network is also capable of performing not only the separation of construction debris and construction residues, but also the identification of the separated objects. After further training on the specified dataset, the neural network obtained the metric values shown in Table 3. The metrics results for YOLO11 demonstrate significant variability in classification performance for different classes of construction and demolition waste, confirming the feasibility of implementing binary classifiers to improve accuracy and consistency of results. The macrometrics show a moderate overall Accuracy of 0.601 and F1-Score of 0.7508, however, there is a clear gap between high performance for some classes (e.g., "brick" and "concrete") and significantly lower results for others (e.g., "foam", "pipes", "plastic"). Most critically, for classes such as "foam" (Accuracy 0.373, F1-Score 0.544), "pipes" (Accuracy 0.289, F1-Score 0.45) and "plastic" (Accuracy 0.294, F1-Score 0.455), Recall values are either not high enough or excessively exceed Precision. This indicates problems with the differentiation of these classes, which may be due to overlapping features between classes, imbalance in the amount of data, or the complexity of the objects themselves to be classified.

Table 3
Metrics of YOLO11

Class	Images	Instances	Accuracy	Precision	Recall	F1-Score	mAP50	mAP50-95
MACRO	570	3236	0.601045	0.803	0.705	0.750816	0.746	0.669
Brick	86	372	0.889290	0.988	0.899	0.941401	0.940	0.876
Concrete	86	364	0.882799	0.965	0.912	0.937752	0.977	0.910
Foam	49	295	0.373196	0.409	0.810	0.543544	0.613	0.502
General Waste	121	287	0.542018	0.702	0.704	0.702999	0.768	0.689
Gypsum Board	30	276	0.875393	0.989	0.884	0.933557	0.904	0.839
Pipes	55	260	0.289945	0.719	0.327	0.449547	0.490	0.383
Plastic	97	306	0.294285	0.493	0.422	0.454745	0.401	0.320
Stone	43	245	0.467000	1.000	0.467	0.636673	0.590	0.539
Tile	84	346	0.770411	0.811	0.939	0.870319	0.921	0.871
Wood	190	485	0.667783	0.954	0.690	0.800803	0.854	0.765

The introduction of binary classifiers allows you to optimize the performance for each class separately, adapting the model to the specifics of each type of object. For example, the use of separate binary classifiers for "plastic" and "pipes" allowed you to focus on the characteristic features of these classes, minimizing the impact of the heterogeneity of features of other classes in the overall model. This, in turn, improved the Recall and F1-Score for classes with low performance, while increasing the overall level of consistency of the metrics.

The mAP50 and mAP50-95 metrics are used to evaluate the quality of the YOLO11 model in classifying and localizing construction debris and construction waste objects in images. The overall mAP50 score is 0.746, indicating a high ability of the model to detect objects at a moderate threshold of match between the predicted and actual frame (IoU ≥ 50%). At the same time, mAP50-95 with an average value of 0.669 shows reduced performance under stricter evaluation conditions that take into account localization accuracy at higher IoU thresholds. This difference is expected, since mAP50-95 is a more stringent metric that reflects the ability of the model to accurately localize objects. Analysis of the results by individual classes shows that for objects with clear visual features, such as "brick", "concrete", "gypsum board" and "tile", the model demonstrates consistently high performance, even under strict conditions. This indicates a reliable ability of YOLO11 to recognize objects with minimal variations in shape or texture. At the same time, classes with heterogeneous characteristics, such as "plastic", "pipes" and "stone", are characterized by significantly lower indicators. This indicates the need for optimization, in particular, increasing the number of training samples, improving data quality or applying specialized approaches to their processing.

However, despite the classification problems, this neural network copes with the task of object selection at a fairly high level, as evidenced by the MioU metric of 0.897.

Regarding the task of classifying the selected objects, a comparison of the obtained metrics for YOLO11 and ResNet50 and their delta results is given in Table 4. A comparison of the metrics of YOLO11 and ResNet50 shows significant advantages of ResNet50 in object classification accuracy and overall model performance. The data in the table shows that ResNet50 significantly outperforms YOLO11 in all key metrics – Accuracy, Precision, Recall and F1-Score. The largest gains are observed in metrics for classes such as "foam", "pipes" and "plastic", where the difference reaches more than 0.6, indicating significant improvements in the ability of ResNet50 to correctly classify these objects and determine their belonging to the corresponding classes.

The average value of the indicators (MACRO) also demonstrates significant advantages of ResNet50, where the overall increase in Accuracy is 0.374, Precision – 0.169, Recall – 0.272, and F1-Score – 0.223. This indicates that ResNet50 is not only more accurate in class detection, but also better at reducing missed (False Negative) or incorrectly identified (False Positive) objects.

Table 4
Metrics comparison for YOLO11 and ResNet50

Class	Accuracy		Precision		Recall		F1-Score	
	YOLO11	ResNet50 (delta)	YOLO11	ResNet50 (delta)	YOLO11	ResNet50 (delta)	YOLO11	ResNet50 (delta)
MACRO	0.601	0.975 (+0.374)	0.803	0.972 (+0.169)	0.705	0.977 (+0.272)	0.751	0.974 (+0.223)
Brick	0.889	0.981 (+0.092)	0.988	0.978 (-0.01)	0.899	0.985 (+0.086)	0.941	0.981 (+0.04)
Concrete	0.883	0.985 (+0.102)	0.965	0.988 (+0.023)	0.912	0.983 (+0.071)	0.938	0.986 (+0.048)
Foam	0.373	0.988 (+0.615)	0.409	0.982 (+0.573)	0.810	0.993 (+0.183)	0.544	0.988 (+0.444)
General Waste	0.542	0.980 (+0.481)	0.702	0.977 (+0.275)	0.704	0.982 (+0.278)	0.703	0.979 (+0.276)
Gypsum Board	0.875	0.979 (+0.104)	0.989	0.972 (-0.017)	0.884	0.986 (+0.102)	0.934	0.979 (+0.045)
Pipes	0.290	0.960 (+0.67)	0.719	0.956 (+0.237)	0.327	0.962 (+0.635)	0.450	0.959 (+0.509)
Plastic	0.294	0.938 (+0.644)	0.493	0.938 (+0.445)	0.422	0.935 (+0.513)	0.455	0.937 (+0.482)
Stone	0.467	0.985 (+0.518)	1.000	0.983 (-0.017)	0.467	0.987 (+0.52)	0.637	0.985 (+0.348)
Tile	0.770	0.968 (+0.198)	0.811	0.956 (+0.145)	0.939	0.980 (+0.041)	0.870	0.968 (+0.098)
Wood	0.668	0.983 (+0.315)	0.954	0.989 (+0.035)	0.690	0.977 (+0.287)	0.801	0.983 (+0.182)

Particular attention should be paid to the classes with low performance of YOLO11, such as "foam", "pipes", "plastic" and "stone". For these classes, YOLO11 shows significantly lower Accuracy, which may be due to the difficulty of object detection due to non-uniform texture or shape features. ResNet50 significantly improves the results for these classes, indicating its ability to better capture object features even in complex cases.

However, for some classes, such as "brick", "gypsum board" and "stone", the Precision of YOLO11 exceeds ResNet50 or has minimal loss. This may indicate that YOLO11 does a good job of identifying specific, well-defined objects, although the overall performance of the model is lost due to low Recall, which indicates frequent omissions. That is why this model was used for classification only as an arbiter neural network, and its main role is to select objects.

A comparison with existing scientific research was also made. Comparing the results obtained with a similar study of the classification of construction debris and construction waste conducted in [15], an improvement in Accuracy to 0.975 was achieved, compared to the authors' value of 0.736 for classification by ten classes. In the study [17], ResNet50V2 was also used, which achieved an Accuracy of almost 0.99, however, the study was conducted only for five classes, and the objects in the images were contained one at a time, the authors did not conduct a study of object identification, but only classification. In the study [18], the classification of construction waste into four classes was carried out and the Accuracy of 0.923 was achieved, which is lower than the results obtained by the proposed method. The proposed method also performed better than in [19] (the authors obtained Accuracy of 0.917).

Thus, the proposed implementation of binary classifiers is reasonable approach to improve the quality of classification in tasks with high variability of performance between classes.

6. Conclusions

The method for construction and demolition waste classification using two-factor neural network image analysis has been developed, which allows increasing the classification accuracy to 97.8% for 10 classes of construction and demolition waste. This effect is achieved by using a two-factor approach to identifying and classifying the remains of destroyed buildings and construction waste, which consists in combining the use of YOLO11 for object identification and as a neural network-arbitrator and a set of binary classifiers ResNet50V2 for classifying each of the 10 classes of construction waste. The method takes into account the results of binary trained neural networks for classifying fragments of construction remains, and in cases of ambiguity (equality of estimates between classes), it additionally uses the prediction of the YOLO11 neural network-arbitrator. In situations where YOLO11 and one of the binary classifiers coincide in the estimate, this class is determined as dominant. This approach reduces the number of false classifications and provides higher object recognition accuracy.

As data for further training of YOLO11 and binary classifiers ResNet50V2, a composite dataset based on the datasets "Construction and Demolition Waste Object Detection Dataset", "Dataset-of-stacked-construction-solid-waste" and "RGB-D construction solid waste" was used.

The use of transformations such as rotation, scaling, color change and reflection significantly increases the accuracy of construction waste separation and classification. This provides a variety of training dataset and promotes generalization of models. Comparison of the developed method and known analogues showed an increase in accuracy in the range from 5.2% to 32.5%, reaching an indicator of up to 97.8%.

The developed method contributes to the achievement of the UN Sustainable Development Goals, in particular SDG 11, SDG 12, SDG 9 and SDG 13 through effective waste management, increased recycling and reduced emissions. The presented approach can be used to automate the sorting of construction waste, which will reduce time and increase the efficiency of waste processing. Further development includes refining the models to better handle complex classes such as "Plastic" and "General Waste", as well as implementing active learning mechanisms to adapt to new data. Another direction for further research is method's integration into automated waste sorting systems and real-time analysis of the method's performance. The priority direction of further research is to expand the dataset with additional image classes and scaling developed method up to a wider range of building materials.

Declaration on Generative AI

The authors have not employed any Generative AI tools.

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