Signal Detection for Tracer-Based-Sorting using Deep Learning and Synthetic Data

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Abstract: Increasing environmental awareness and new regulations require an improvement of the waste cycle of plastic packaging. Tracer-Based-Sorting (TBS) technology can meet these challenges. Previous studies show the market potential of the technology. This work improves on the solution approach using artificial intelligence to maximize the number of tracers that can be detected accurately. A convolutional neural network and random forest classifier are compared for classification of each tracer based on signal intensities. The approach is validated on different settings using synthetic data to counter the low amount of available data. The results show that theoretically up to 120 tracers can be classified simultaneously under near-optimal conditions. Under more difficult conditions, the maximum number of tracers is reduced to 45. Thus, the approach can increase the diversity of TBS by increasing the maximum tracer count and enable a broader range of applications. This helps to establish the technology in the field of recycling.

1 INTRODUCTION

Modern societies rely on mass production of all different kinds. One type of material in particular stands out from the crowd: plastic has proven to be extremely useful because it is so easily moldable and versatile which is why it is used almost everywhere. This comes with a prize: production and disposal of plastic generates greenhouse gases and hazardous waste. At 3.22 million tons (2019), plastic sales packaging is one of the most relevant plastic waste streams in Germany alone. They take up over a quarter of all plastic waste and are still mostly thermally recycled. Since the share of plastic recyclate accounts for a total of 13.7% of the processing volume, increasing reuse is a major challenge (Conversio GmbH, 2020). Increasingly, it is precisely the packaging properties that pose barriers to high-quality recycling: packaging is becoming smaller (pre-portioned units), more wide-spread (“to-go” products) and is predominantly equipped with portioning and handling functions as e.g., pump dispensers. Unfortunately, design or durability reasons induce packaging units to be harmful to the circulation (multilayer or black polymers). Packaging waste can be sorted with state-of-the-art machinery (e.g., near infrared (NIR) sorter) only by main polymers and colors and thus can no longer be recycled on an equal basis by its plastic specification (Woidasky et al., 2017). The state of Germany and the European Union address this challenge with the German Circular Economy Act 2012 (Bundesministerium der Justiz, 2012) and the European Circular Economy Action Plan (European Comission, 2018; European Comission, 2020). They aim to establish a sustainable circular economy, which is seen as a solution to reduce raw materials and plastics. A more comprehensible material flow is important to recycle more efficiently. This work helps to establish new ways to more reliably detect material flows, especially plastic materials. To achieve this, a new technology which was developed by Polysecure GmbH called Tracer-Based-Sorting is used in combination with artificial intelligence. This combination enables the detection of many types of materials while maintaining high accuracy.

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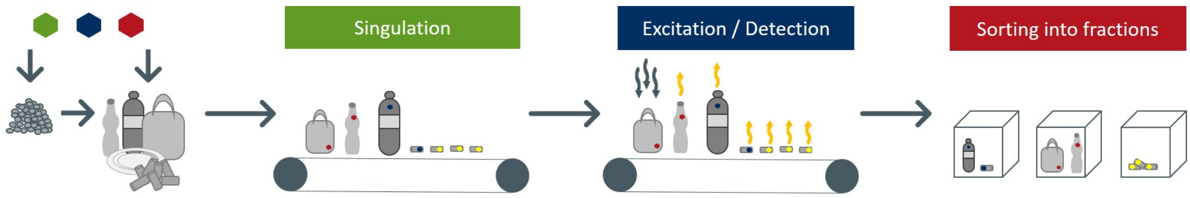

Figure 1: Illustration of the general tracer-based-sorting workflow for plastic waste (source: Polysecure GmbH; based on (Treick, 2019; Gasde et al., 2020)).

1.1 Incentive

Comprehensive recycling is still a major challenge (Conversio GmbH, 2020). The project MaReK (Lang-Koetz and Woidasky, 2021) showed that the establishment of a circular plastic economy can be implemented with Tracer-Based-Sorting (TBS) technology, but not with a state-of-the-art NIR sorter (Schmidt et al., 2021). At the same time, further development needs for innovative approaches were identified for market entry (Schmidt et al., 2022). TBS can help plastics recycling to be more qualitative and economical, enabling more circular economy and environmental protection in terms of global market economy. However, previous studies revealed the importance of optimizing excitation, quantum yield, and differentiability of fluorescence sorting codes (Woidasky et al., 2020a).

The overarching goal of the project is to increase the economic efficiency of TBS technology. This innovative sorting process is a central building block on the way to a circular economy, as it allows for substantially higher material flow differentiation to be achieved compared to current processes. The paper aims to improve TBS for usage in a circular economy and in addition widens its use to other fields of application. Further extending the differentiable tracer variants is one way to approach this. For that matter, the goal is to develop a signal recognition approach that classifies as many different tracers as possible with as high an accuracy as possible.

1.2 Groundwork

TBS was developed by Polysecure GmbH and is an innovative approach to detection and sorting steps in waste management that enables sorting of materials or products regardless of their physical properties. The technology uses inorganic fluorescent tracers in ppm concentrations. The tracers can be applied in the material or on the surface by printing or using printed labels. They emit bright emission lines in green, red and near-infrared after stimulation with a laser. This signature emission differs depending on the used tracer mixtures. The detection process is done by upconversion. Upconversion is a multiphoton process. Lower energy photons are absorbed and higher energy photons are emitted (Woidasky et al., 2020a). This process practically does not occur in nature, so the measurement is free from background noise.

Previous work showed that 11 out of 15 tested variants could be detected (Woidasky et al., 2020b).

The waste sorting consists of a three stage approach, as sketched in Figure 1: The material waste is collected and transported to the sorting facility, where it is emptied in a waste bunker. During the *singulation* stage, the objects are separated and placed individually on a conveyor belt, tray sorter or similar. This is to ensure that only one item will be scanned at a time during the following stage, in which the fluorescent behavior of the inorganic tracers is triggered by an *electromagnetic stimulus*. The emitted light is captured by a sensitive sensor. The signal is then further processed by a classification model during the *detection* stage as can be seen in the centered *excitation / detection* label in Figure 1. The resulting values are used to distinguish material types in the sorting process and thus enable targeted presorting and subsequent processing into high-quality recyclates (Woidasky et al., 2021).

1.3 Related Work

The following section will give an overview on the research fields and previous work that inspired this paper:

The field of time series classification has been examined in a comparative study by Bagnall et al. (Bagnall et al., 2016) who listed the most commonly used algorithms based on series similarity, phase dependent intervals, phase independent shapelets and dictionaries. Further studies proposed deep learning for time series classification (Ismail Fawaz et al., 2019), analysis of EEG signals (Craik et al., 2019) and feature extraction using convolution and pooling operations (Zhao et al., 2017). Mertes et al. (Mertes. et al., 2020; Mertes et al., 2022) demonstrated data augmentation in an industrial application for images of textile defects. Also, fluorescence imaging was used for plastic waste classification by Gruber et al. (Gruber et al., 2019).

As for garbage detection, Liu et al. (Liu et al., 2021) designed a robot vision system to collect and detect plastic waste and estimate poses using a YOLACT FCN. A related machine vision approach based on hyperspectral imaging for waste identification was introduced by Krasniewski et al. (Krasniewski et al., 2021). Studies addressing signal processing as bearing fault detection was published by Zhang et al. (Zhang et al., 2020).

The authors of this paper confirm that to the best of their knowledge this is the first publication that presents a signal filter augmentation using a convolutional neural network for TBS and packaging waste identification.

1.4 Structure

The remainder of this paper is organized as follows: Section 2 describes the algorithm design and configuration. Furthermore, section 3 elaborates the experimental setup. Section 4 discusses the results accompanied by a critical reflection, before we conclude with an overview of future applications and research goals in section 5.

2 APPROACH

The following section proposes an approach to maximize the tracer count and accuracy for TBS. The approach uses the excited signals from the excitation / detection step illustrated in Figure 1 to classify the tracer variant. For that matter, each signal is preprocessed. The classification method is based on a convolutional neural network (CNN) consisting of 1D-filter operations due to its good performance for time series classification (Ismail Fawaz et al., 2019). For comparison, we use a state-of-the-art machine learning model from the random forest (RF) classifier family. Due to the limited size of available data, we generate synthetic mixtures from real data to enlarge the test and training dataset and to validate different tracer mixture scenarios.

2.1 Preprocessing

For each classifier, we apply an appropriate preprocessing method to prepare data to fit the input specification. The data consist of pulses for three channels in the time domain. As for the CNN, the data is normalized to be in the range of 0 to 1. Furthermore, a down-sampling operation is applied so that

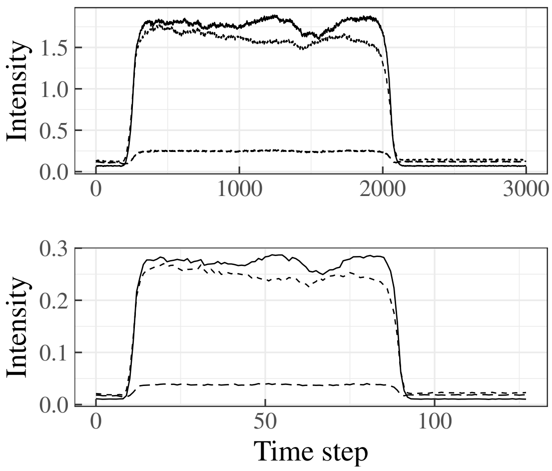

Figure 2: Preprocessing example of the CNN approach: the top chart shows the original signal with three channels, the bottom chart contains the time series after normalization and compression.

each channel is reduced to 128 data points. The compression lowers the complexity by removing redundant information which in turn allows the model to generalize better. Figure 2 presents an example of the signal before preprocessing (top) and after normalization and reduction; as can be seen, the number of time steps is reduced from 3000 to 128. Likewise, the maximum intensity decreases from 1.7 to less than 0.3 due to normalization. However, Figure 2 clearly suggests that the main curve characteristics are preserved.

We then apply preprocessing and feature extraction to prepare data for the RF. Six features are extracted based on process-specific expert knowledge: the *channel ratio* and *peak value* for each channel. The channel ratios characterize a tracer mixture and are derived from the maximum value of a channel. The peak values are needed because the tracer ratios can slightly vary due to the scan object's conditions like deformations and soiling on the packaging. Each feature is subsequently normalized for the range from 0 to 1.

2.2 Generation of Synthetic Data

For this study, synthetic data is created in order to counteract the small amount of mixture data available. The synthetic data helps to validate the approach for more different scenarios and can increase the generalization of the model. Synthetic data is created by scaling the primary (100%) tracer samples from each category linearly and summing up the individual tracers. During this process, each channel of each tracer is augmented randomly by a factor of 0.02 to increase

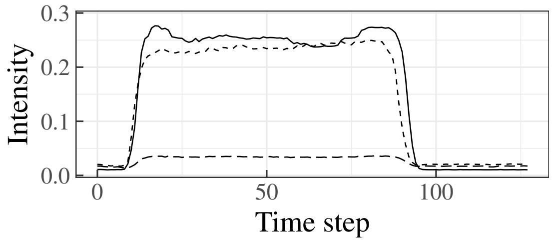

Figure 3: Example of synthetically mixed tracers representing a mix rate of 50% of tracer 1 and 2 and 0% for tracer 3.

the variety of data. For example, a 50% mixture of channel 1 and 2 with no augmentation is calculated by taking 50% of tracer 1, 50% of tracer 2 and 0% of tracer 3. Figure 3 exhibits the output of a synthetic 50% mix rate. This mix rate is equally applied to the signal as for the example presented in Figure 2.

2.3 Convolutional Neural Network

In our approach we apply a CNN based on the residual network (ResNet) kernel for classification (He et al., 2016). The selection of the exact architecture is based on multiple test runs and consists of 5 residual blocks. Each residual block consists of two 1D convolutional layers and one 1D max pooling layer. The architecture is followed by two fully connected layers with 256 and 128 neurons subsequently where each layer is combined with a dropout layer with a probability of 0.4. The last layer is a softmax layer.

The model is trained using the Adam optimizer (Kingma and Ba, 2014) and a learning rate of 0.0001. The batch size is set to 64. Furthermore, the model is trained for 100 epochs where each epoch consists of 3456 synthetic samples.

2.4 Random Forest

A RF ensemble classifier with 100 decision trees is trained for comparison due to its high generalization ability and flexibility (Hänsch and Hellwich, 2016). The number of features to consider when looking for the best split is set to 2 and the Gini criterion is used for the evaluation of splits. The hyperparameter setting is based on default values from scikit-learn (Pedregosa et al., 2011).

3 EXPERIMENTAL SETUP

The following section describes the available data that is used for the experiments. Furthermore, different scenarios are proposed to validate our approach.

3.1 Data Acquisition and Preparation

The data was collected at Polysecure GmbH based on several test runs with different tracers. Two individual test runs are analyzed in detail. The test runs have to be examined separately as individual datasets due to different recording conditions.

The first dataset contains samples for the three primary tracers and samples for the 50 % mixtures of these primary tracers. In total there are 11793 real samples. In order to synthetically increase the variance in the dataset, the laser intensities for stimulating the tracers for individual recordings are varied. This allows to emulate different conditions like soiling on the packaging and therefore increased absorption which may occur in the real-world environment.

The second dataset consists of recordings of tracers applied to printed white labels placed on black panels. Dataset 2 contains samples for the primary tracers and 50 % mixtures which is analogue to dataset 1. In contrast, however, dataset 2 additionally contains mixtures for 25 % step size. In total the datasets comprise 1660 samples.

3.2 Evaluation Scenarios

To evaluate our approach, we define the following three scenarios:

1. Incremental augmentation
2. Tracer count maximization
3. Synthetic mixture validation

In scenario 1, CNN and RF are compared by incrementally increasing the augmentation on the test data. This becomes necessary because training and testing is performed only on synthetic mixtures due to limited availability of real mixtures. By augmenting the data, the generalization to unknown scenarios can be validated. Three different types of augmentation are tested. In the first one, the noise level is gradually increased. The second augmentation deals with the stepwise shifting of the curve in the time domain. The last augmentation approaches an offset shift of the curve intensity. The experiments are run five times each due to the stochastic nature of the training methods while mean and standard deviation of the accuracy results are recorded.

The second scenario is designed to maximize the tracer count. Hereby, the tracer count is incremented stepwise, while the mean and standard deviation of the related model's accuracy are recorded over five consecutive runs. As before, the training and validation is only applied to synthetic data. A stepwise noise augmentation is utilized on the test data to counterbalance the usage of only synthetic data.

In scenario 3, the synthetic mixtures are validated by training the model only on synthetic mixtures and then validating on real samples. If the synthetic data is similar to real data, then the model should generalize well and achieve high accuracy values on the validation set. The training step is repeated five times.

4 RESULTS AND DISCUSSION

The following section describes the results for the aforementioned experiment in details. At first, RF and CNN are compared to each other. Then, the tracer count is maximized by analyzing different tracer count scenarios and lastly, the quality of the synthetic data is investigated.

4.1 Model Comparison and Evaluation

CNN and RF are compared for a scenario with 45 tracer mixtures and incremental data augmentation. Figure 4 visualizes the results for noise, offset and shift augmentation where the bars show the standard deviation of five test runs. CNN-1 and RF-1 describe the results for dataset 1 and CNN-2 and RF-2 for dataset 2 respectively. The results appear similar but especially for noise augmentation, the CNN exhibits slightly better accuracy values. Nevertheless, the CNN's performance seems to significantly decrease for high shift values. In contrast, high shift values do not affect the RF approach because only the maximum peak values are used for calculating the features and the 40 time steps considered at maximum are not enough to shift the peak of the curve out of the time window.

It should be noted that the results for RF can probably be improved by more detailed hyperparameter tuning and feature engineering. Nevertheless, the key advantage of a CNN is that it automatically extracts features and the model adapts for very complex scenarios if enough data is provided. Further studies are expected to show, that more real data can be collected once the demonstrator is ready for experimentation. Furthermore, problems like shift can be alleviated by using augmentation during training. Therefore, the CNN approach will be further pursued for the previously mentioned tracer maximization scenario No. 2.

4.2 Maximizing Tracer Count

Next, we tested the model's limitation on an increasing number of tracers. Therefore, we applied the

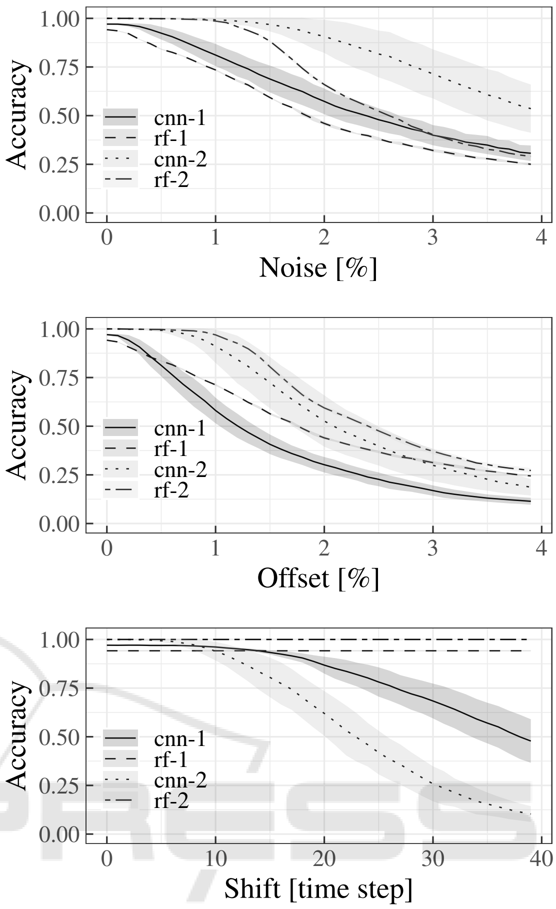

Figure 4: Comparison of CNN and RF model configurations: accuracies are measured for scenarios of varying noise, offset and shift with 45 tracer mixtures.

CNN to different tracer counts by reducing the scaling step width. Figure 5 shows the results, where the top chart shows the results for dataset 1 and the bottom accuracy values for dataset 2. Due to limited space, the figures only display the values for noise augmentation. Nevertheless, the results for offset and shift are similar. As can be seen, the accuracy clearly decreases for an increasing number of tracers. The degradation of accuracy values between both datasets derive from the use of different laser intensities during data acquisition of dataset 1 which synthetically increased the complexity in order to simulate real-world conditions. Further results are shown in Table 1 for dataset 1 and in Table 2 for dataset 2. In the tables, more detailed results are illustrated for smaller tracer numbers, whereas the previous plot had higher spacing between tracer numbers to highlight the general trend. Up to 45 tracers in dataset 1 and 120 tracers in dataset 2 can be classified with high accuracy. For these cases, the accuracy is greater than 97%. Nev-

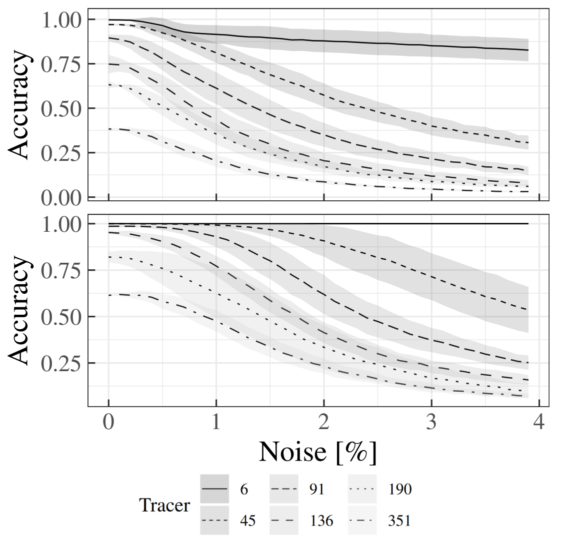

Figure 5: CNN packaging material classification accuracy for different numbers of tracer mixtures; Top: classification accuracy for dataset 1. Bottom: classification accuracy for dataset 2.

Table 1: CNN packaging material classification accuracy for dataset 1.

Tracer count	Noise 0 %	1 %	2 %	3 %	4 %
6	0.997	0.915	0.879	0.851	0.827
21	0.992	0.943	0.816	0.696	0.586
45	0.970	0.811	0.573	0.399	0.307
78	0.907	0.658	0.395	0.236	0.159
120	0.817	0.522	0.284	0.177	0.119
171	0.652	0.331	0.171	0.105	0.073

Table 2: CNN packaging material classification accuracy for dataset 2.

Tracer count	Noise 0 %	1 %	2 %	3 %	4 %
6	1.000	1.000	1.000	1.000	1.000
21	1.000	1.000	0.994	0.959	0.895
45	1.000	0.992	0.908	0.714	0.536
78	0.976	0.867	0.621	0.379	0.252
120	0.972	0.839	0.517	0.285	0.178
171	0.906	0.697	0.351	0.186	0.111

ertheless, the accuracy values decrease sharply with increasing noise values. For dataset 1 and 45 tracers the accuracy drops to 81% and for dataset 2 and 120 to 84% for a noise level of 1%. These results suggest that considering both datasets, a maximum of 120 tracers is possible under near-optimal conditions. Whereas under more difficult conditions 45 tracers are accurately classifiable. Detailed results for 45 tracer are in the aforementioned Figure 4.

Nevertheless, the results have to be viewed with some caution. The reason for this is that only synthetic data is used for validation. The incremental augmentation can only counter this problem to some degree and further studies have to confirm these results with more real data.

4.3 Validation of Synthetic Mixtures

As for the last scenario, a training is applied only to the synthetic mixtures and the validation on the real mixture samples to validate how well the synthetic data represents the real-world data. Figure 6 shows the results for this scenario. CNN-1 and RF-1 exhibit the results for dataset 1 validated on the according model while CNN-2 and RF-2 show the related result for dataset 2. In summary, the outcome suggests that real mixtures can be mapped well for small numbers of tracers. But as the number of tracers increase, the accuracy significantly decreases.

This effect can be explained as follows: even though we perform the experiments on augmented data, we use the same overall dataset and partition it in smaller subsets. Therefore, the tolerance range becomes smaller with each additional mixture setting which results in a potentially higher error rate. In the previous validation scenario, this effect was not as strong, but was already present. The small deviation to the previous validation scenario shows that synthetic and real data are not identical, but especially the high accuracy values at low tracer counts indicate that the synthetic and real data have similar properties. We consider this relation sufficient for initial theoretical analysis.

5 CONCLUSION AND OUTLOOK

The recycling of plastic waste is a ubiquitous challenge due to the incredible mass deployed around the world each day. In this paper, we propose a technique

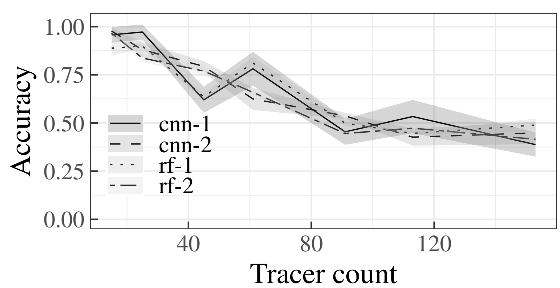

Figure 6: Validation of models trained exclusively on synthetic data and validated on real data.

for improving the efficiency of packaging waste recycling by means of TBS. Our approach builds upon signal data from fluorescent emitting tracers which can be combined in any way to indicate the type of plastic. We applied two different classification models, a RF and CNN to distinguish between the tracer combinations by signal intensity per channel. Due to the limited size of the training and test data, we used synthetic data which we generated by artificially varying the tracer channels and their mixture. We then compared the RF and CNN in different evaluation scenarios in order to compare and assess the models.

The results show that although model performance decreases for theoretically high numbers of tracers, their accuracy still remains high enough for classification decisions up to a tracer count of 120 under near-optimal conditions. In more difficult conditions, the maximum number of tracers is reduced to 45.

Furthermore, RF and CNN seem to provide similar results at first sight; however, the experimentation suggests that the performance of the CNN is likely limited due to the low variation in the dataset and the small amount of available data. It should be mentioned that this problem could be alleviated by attaining more training data and using further data augmentation methods while training. The experiments suggest that synthesized data from tracer data represent the real-world data well enough for first insights. Nevertheless, further studies with more real data are needed to confirm our results. Especially the effects of contamination on the surface need to be studied more in detail on real data.

In view of the dataset size and tracer quality, this study reveals the potential of future TBS applications. In addition, the use of computer vision algorithms in combination with our signal processing approach would increase the search space and add to the available features which would certainly allow to better distinguish between different tracers. The authors plan to continue the work presented in this paper and improve the field of TBS. Further studies are intended to increase the economic efficiency of a circular economy of plastic packaging by means of AI innovation.

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