AI enabled Bio Waste Contamination-Scanner

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Abstract. In Germany Bio waste is collected in separate garbage bins from households in the municipalities (e.g. garden waste, kitchen waste, etc.) and composted. The end result is humus, which is finally fed back into agriculture and closes the organic materials cycle. Waste must be inspected for non-biological contaminants prior to composting, as these can compromise the composting process and damage screening equipment at the recycling facility. Undetected contaminants affect the quality of the humus and can lead to contaminants re-entering the food chain through agriculture. The paper presents a feasibility study of an automatic bio waste Contamination-Scanner aiming to catch contamination early in the recycling process. Image data of bio waste contamination has been collected from a recycling facility. These images were used to design, train and evaluate two Convolutional Neural Networks (CNNs) aimed at detecting contaminants during bio waste collection. One CNN was trained on RGB and the other on greyscale images. The results show an initial surface scan can detect contamination with an accuracy of up to 86% and could form part of a holistic detector attached to bin lorries.

Keywords: CNNs · Contamination Detection · Bio Waste Recycling

1 Introduction

Contamination of bio waste with inorganic material such as plastic is a major challenge in the bio waste recycling industry, since excessive contamination can break filtering machinery (personal communication with RETERRA GmbH). Also filtering machines are not 100% accurate, the higher the contamination the more contaminants remain in the compost. Contaminants in bio waste significantly reduces the purity of the final product (see Figure 1) and can lead to contamination of soils and groundwater with microplastics. Microplastics in soils can lead to a reduction of soil density and the release of additives having negative impact on germination, agriculture and ultimately the food chain. If it were possible to automatically detect plastic materials in bio waste bins during collection, composting contaminated bio waste could be avoided. This paper investigates if it is possible to develop an intelligent Contamination-Scanner for the use during bio waste bin collection.

Fig. 1: Bio waste heavily contaminated with impurities (left image) and resulting compost contaminated with plastic (right image)

The scanner opens two possibilities to tackle the contamination problem: (a) avoidance of contaminated bio waste collection, and (b) to reach out to specific clients or neighbourhoods to raise awareness of the environmental implications of incorrect bio waste separation to improve behaviours. The paper contributes a CNN architecture for the Contamination-Scanner, a trained implementation of this architecture on bio waste images, and (3) an evaluation on real data. The use of CNNs is motivated by recent works utilising CNNs to assess the proportion of recyclables in residual waste [5] and to detect plastic contamination in aquatic environments [8, 1]. The current limitation is that contaminants must be visible on the surface of the collected waste bin. If successful the study may be extended to different types of sensors to also capture contamination deeper inside the bins. The paper introduces the Contamination-Scanner methodology in Section 2, provides an experimental evaluation in Section 3 and conclusions are discussed in Section 4.

2 Contamination-Scanner Methodology

2.1 Data Preparation and Augmentation

The image data was obtained at a bio waste recycling facility near the town of Bohmte (Germany) part of RETERRA Nord GmbH. At the time of data collection the case study was not planned, hence the images were casually taken from different angles, different lighting conditions and distances. This is expected to negatively affect the detection performance results of the methodology. The images were cut into tile sizes of 100x100x3 pixels. Experiments with larger tile sizes of up to 200x200x3 and 300x300x3 have been conducted. However, the detection performance was considerably lower, with around 50%-60% accuracy, and hence these tile sizes have been omitted in the experimental evaluation. In other works detecting plastic debris from vegetation a 100x100x3 tile size has also been proven successful [4], although these pictures are different since they were taken from drones at larger distances. The tiles were manually labelled in two classes whether they contain contamination or not. This resulted in a total number of 2227 tiles (84%) not containing contaminants and 426 tiles (16%) containing contaminants. From these tiles three random samples without replacement were taken for training, validation and testing. Each sample contained 142 tiles for each of the two classes. Please note an equal number of tiles per class was desired to avoid bias of training and evaluation towards non-contaminated tiles as they are over-represented. CNNs typically need a large number of training instances to achieve good results, thus augmentation was applied to the training data only. Here the tiles were flipped randomly horizontally and vertically and also randomly rotated by a 90-degree angle. The probability of a flip, rotation or a combination of these was 75%. This resulted in 852 training tiles for each class, thus 1704 training tiles in total. Data augmentation is a common technique to decreases the overfitting on image processing tasks [6].

2.2 Network Architecture

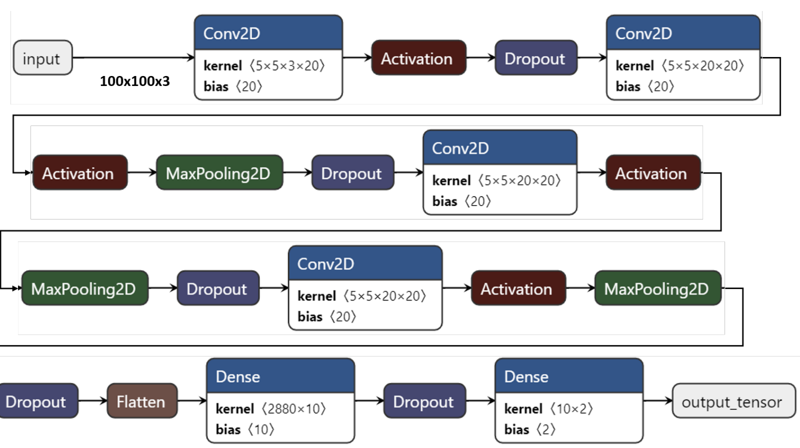


Fig. 2: BioWaScan Architecture

The architecture that yielded the best results has been empirically determined and is illustrated in Figure 2. It consists of four 2D convolutional layers with 20 5 x 5 kernels. These layers work well on image data by preserving some of the pixel's locality [2, 3]. 2 x 2 max pooling and dropout layers with a dropout rate of 0.2 were included in positions indicated in Figure 2. Dropouts in neural networks are known to mitigate overfitting and non-optimal co-adaptation, minimizing generalization uncertainties [2, 7]. The network is completed by a fully connected dense neural network layer with 10 units followed by a fully connected output layer comprising 2 units, since there are two classes (whether there is contamination or not). Various alternative architectures with different numbers of convolutional and dense layers and also larger dens layers and variations and different levels of dropouts have been experimented with in this study. However, the here presented architecture yielded the highest accuracy and reproducible results. A larger number of dense and larger dense layers appeared detrimental to the stability of the validation accuracy.

3 Experimental Evaluation

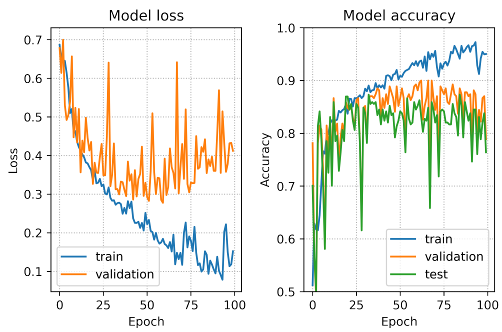
This Section presents the preliminary experimental evaluation including experimental setup in Section 3.1 and Dicussion of Results in Section 3.2.

3.1 Experimental Setup

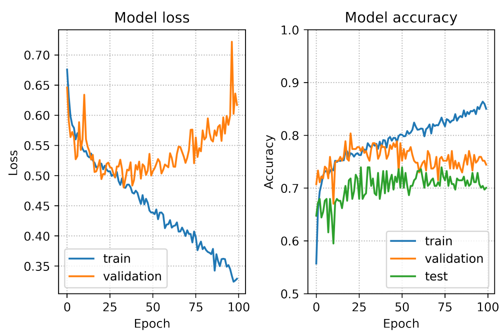
The data tiles were separated into a training, validation and test dataset, each comprising 142 image tiles for each class. The training data was augmented as described in Section 2.2 resulting in 852 training tiles for each class, thus 1704 training tiles in total. Validation and test data were not augmented. The training and validation data were used to train the network and tune hyperparameters. The test data was used to evaluate the training accuracy, after each epoch, however, it was not used as feedback to the training process. Two CNNs were trained, one on greyscale versions of the tiles and one on RGB colour versions of the tiles. The reasoning for training two CNNs is to assess the bias of the method towards bright colours, since contaminants are often plastic wrappings or bin bags containing bright colours. With respect to the batch size an empirical evaluation revealed that batch size of 15 combined with the SDG optimiser yielded best results on the data and these settings have been used in the results presented in Section 3.2. In the 2D convolutional and the first dense layer Rectified Linear Unit (ReLU) activation functions were used, whereas a softmax activation function was used for the second dense layer. The advantage of ReLU activation function is that they usually yield shorter training time compared with alternative activation functions like tanh units [2].

3.2 Results

The experiments using the RGB and the grayscale images were repeated 10 times each. The configuration with the highest validation accuracy of each of the 10 models was used for calculating the accuracy of the test images. Hereby the RGB trained Contamination-Scanner achieved an average validation accuracy of 0.89 and a test accuracy of 0.86. The greyscale trained Contamination-Scanner achieved an average validation accuracy of 0.73 and a test accuracy of 0.71. The results of a typical training run with the RGB version of the Contamination-Scanner are illustrated in Figure 3 (a). The model loss is decreasing until 52 epochs and then the model starts to overfit, validation accuracy is also increasing up to epoch 52 to 0.89. The measured test accuracy on unseen test data is 0.84 indicating a small amount of overfitting.



(a) Trained with RGB images



(b) Trained with greyscale images

Fig. 3: Contamination-Scanner trained with RGB and greyscale images

The results with the greyscale version of the Contamination-Scanner are illustrated in Figure 3 (b). The model loss is decreasing until 40 epochs and then the model starts to overfit, validation accuracy is also increasing up to 0.78 at epoch 40. The measured test accuracy on unseen data is slightly lower at 0.73 indicating a small amount of overfitting. Overall, it was observed that training with greyscale images is starting to overfit sooner than for RGB tiles at about 40 epochs and achieves a lower accuracy on test data. Also the training with RGB tiles results in larger fluctuations on the validation and test accuracies compared with training on greyscale tiles. The tiles have thus been examined qualitatively. It was found that contaminants are often plastic bin bags and/or have bright colours. It was also found that a large portion of non-contaminated tiles contain garden waste which often has brown or green colours. Therefore, it is possible that RGB trained networks are to some extent biased towards bright and green colours, which is indicated by the accuracy difference of 0.11 compared with greyscale images. Nevertheless, if some bias towards colours achieves a higher accuracy in identifying contaminants, it is not inconceivable to use RGB images or a combination of RGB and greyscale images. However, more research would need to be conducted to establish a larger and more robust dataset. I.e., collection during different seasons to obtain more representative data, i.e., it is expected that there is less garden waste during winter months). Yet, the presented results show the feasibility to develop a robust and accurate bio waste Contamination-Scanner.

4 Conclusions and Future Work

The paper presented a feasibility study showing that it is possible to automatically detect contamination in bio waste bins at collection point through RGB and greyscale images. For this study a CNN was created and trained on image tiles of bio waste collected at a recycling facility. Evaluation showed an accuracy of up to 84%. Ongoing work aims to establish a more robust image dataset reflecting seasonal changes and future work envisions the use of bio matter penetrating sensors to extend the study to contaminants deeper inside the bins.

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