UNSUPERVISED ANOMALY DETECTION IN 3D BRAIN MRI USING DEEP LEARNING WITH IMPURED TRAINING DATA

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ABSTRACT
The detection of lesions in magnetic resonance imaging (MRI)-scans of human brains remains challenging, time-consuming and error-prone. Recently, unsupervised anomaly detection (UAD) methods have shown promising results for this task. These methods rely on training data sets that solely contain healthy samples. Compared to supervised approaches, this significantly reduces the need for an extensive amount of labeled training data. However, data labelling remains error-prone. We study how unhealthy samples within the training data affect anomaly detection performance for brain MRI-scans. For our evaluations, we consider autoencoders (AE) as a well-established baseline method for UAD. We systematically evaluate the effect of impured training data by injecting different quantities of unhealthy samples to our training set of healthy samples. We evaluate a method to identify falsely labeled samples directly during training based on the reconstruction error of the AE. Our results show that training with impured data decreases the UAD performance notably even with few falsely labeled samples. By performing outlier removal directly during training based on the reconstruction-loss, we demonstrate that falsely labeled data can be detected and that this mitigates the effect of falsely labeled data.

1. INTRODUCTION
Brain MRI is commonly used for the diagnosis and treatment of neurological diseases. 3D MRI-scans allow for the detection and delineation of brain abnormalities without the need for harmful radiation. In clinical practice, the MRI-scans are assessed by trained physicians. This is time-consuming and especially for unexpected anomalies this can be error-prone [1].
Supervised deep learning methods have shown promising results for the detection and segmentation of anomalies in brain MRI-scans [2], relying on large-scale annotated data sets. However, the requirement of large-scale data sets with voxel-level annotations represents a hurdle since they are costly and time-consuming to obtain. Furthermore, the flexibility to detect rare diseases is limited as training of supervised methods is challenging in the case of unbalanced data [3]. Deep learning for unsupervised anomaly detection follows the concept of identifying abnormalities by learning from a reference data set of healthy data. Different deep learning models have been used within the UAD framework, mainly focusing on autoencoder-based approaches [4], generative adversarial networks [5] or the combination of both [6]. Typically, a convolutional neural network (CNN) learns to compress and reconstruct the anatomical features of healthy brains but fails to reconstruct unseen anomalies. Afterwards, detection can be performed by considering the reconstruction errors. Thus, in theory, UAD methods can detect arbitrary anomalies but require a large-scale training data set that solely contains healthy samples. However, data labelling is affected by human errors [1], leading to impured training data sets. In contrast to that learning with impured data sets enables UAD methods to learn to compress and reconstruct also unhealthy samples which conflicts with the fundamental concept of UAD methods.

In this work, we study how impured training data affects UAD performance in brain MRI-scans and evaluate a first approach to counteract this problem directly during training. We use 3D autoencoders (AE) as a well-established baseline and systematically evaluate UAD performance on different data set compositions, containing different amounts of unhealthy samples. As a first step towards outlier removal from the impured training data, we identify and remove outliers based on the loss function of the AE directly during training.

2. METHODS
2.1. Data Set
For training, we use two publicly available data sets and combine 496 T1-weighted healthy samples from the OASIS-3...
NATURE is shown in Figure 1. The loss function is formulated as 

\[ L_{AE} = L_{Rec}(x, \hat{x}) = \frac{1}{N} \sum_{k=1}^{N} |x_k - \hat{x}_k| \]  

with \( N \) for the number of samples in the training set, \( x \in \mathbb{R}^{h \times w \times d} \) and \( \hat{x} \in \mathbb{R}^{h \times w \times d} \). \( h, w, d \) are the height, width, and depth of the volumes. Having trained the AE, the reconstruction error between input and reconstruction can be used as an anomaly score. For samples that are similar to the training data set, the reconstruction error is assumed to be small, compared to samples that differ from the training data set. Therefore, the reconstruction error can be used to detect unhealthy samples as outliers [6].

Several approaches have been proposed to identify out of distribution samples in anomaly detection scenarios [11, 12, 13]. In this work, we adapt the general concept of Xia et al. [11] to perform outlier removal directly during training. For images of the natural image domain, Xia et al. [11] show that \( L_{AE} \) can be used to discriminate and cluster between images of different classes directly during training. We adapt this method and investigate whether it is feasible to identify and remove unhealthy samples from MRI-scans of human brains within an impured training data set. Our hypothesis is that for few unhealthy samples, the reconstruction error is high compared to healthy samples already during training. Hence, we perform outlier removal based on \( L_{AE} \) to discriminate unhealthy samples from healthy ones during training. Therefore, we modify the training of the AE and remove samples from the training set every 5 epochs. Samples are removed based on an adaptive threshold, above which the samples are identified as outliers. The adaptive threshold is determined by \( T_{\text{remove}} = \gamma \cdot L_{AE} \), where \( L_{AE} \) denotes the current loss of the entire training set in the current epoch \( i \) and \( \gamma \) denotes a weighting factor which determines the boundary between outlier and normal sample during training. We reinitialize the network’s parameter after 50 and 100 epochs. This aims to reduce the effect of outliers on the final model while removing outliers from the training data set. The number of epochs have been determined, based on prior experiments using the validation set. After the last re-initialization, we train the network for another 400 epochs, again by removing outliers every 5 epochs. We use Adam for optimization, a learning rate of \( lr = 10^{-3} \) and a batch size of \( bs = 32 \) for our experiments and train our models on an NVIDIA GTX 1080ti graphics card.

We use the reconstruction error between input volume and reconstructed volume as an anomaly score to discriminate between healthy and unhealthy samples during evaluation. To assess the model’s performance independent of a chosen operation point, we report the AUROC. Furthermore, we report the ratio of samples removed during training relative to the number of total samples in the training data, for healthy and

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1https://brain-development.org/ixi-dataset/
unhealthy samples respectively. Across our experiments, we evaluate and report $\gamma$ in the range of $\gamma \in [1.3, 1.35, \ldots, 1.5]$.  

3. RESULTS

The anomaly detection performances for different ratios of unhealthy samples in the training set and for different values of the weighting factor $\gamma$ are shown in Figure 2. Considering the baseline AE without outlier removal, the AUROC decreases from 93.46 to 88.89, 83.51 and 80.42 for 3%, 6% and 12% of outliers, respectively. Across all experiments, outlier removal during training leads to an increased or similar detection performance across all values of $\gamma$ with notable performance improvements for Train$_{3\%}$ and Train$_{12\%}$. For all choices of $\gamma$, the fraction of removed healthy samples is higher compared to the fraction of removed unhealthy samples. Overall, smaller values for $\gamma$ increase the number of removed samples for both, healthy and unhealthy samples. Exemplary healthy samples that are removed when performing outlier removal with Train$_{\text{clean}}$ are shown in Figure 3.

As a first step towards analyzing the training data, we investigate the feasibility of removing outliers directly during training. Our results in Figure 2 demonstrate that unhealthy samples can be detected already during the training process. By removing the samples identified as outliers, the anomaly detection performance can be improved notably, especially for training data with larger quantities of unhealthy samples. Outlier removal during training reduces the adaptation of the AE to the unhealthy samples in the training set and thus improves the ability to detect unhealthy samples in the evaluation. As it is shown in Figure 2, smaller values of $\gamma$ result in larger fractions of removed healthy and unhealthy samples. While our results demonstrate similar or improved performance for all values of $\gamma$, in practice the level of impurity of a given training data set is unknown and $\gamma$ can be considered a hyperparameter, where different values can be evaluated easily. In our experiments, healthy samples from the clean data set that are removed during training show a varying appearance of brains. These removed samples are not necessarily unhealthy especially for older patients, see Figure 3. Thus,

4. DISCUSSION

Training with unhealthy samples decreases the UAD performance notably, see Figure 2. This demonstrates that the AE rapidly adapts to overseen anomalies during training, even in small quantities. Hence, even though less labelling effort is required for UAD, our findings highlight that precise data labelling is vital. This indicates that while deep learning for UAD can detect any anomaly in theory it is limited to those that are strictly not present during training.

Fig. 2. From left to right, data sets with different levels of impurity are evaluated. Top row: For different values of $\gamma$ the UAD performance regarding the AUROC with and without outlier removal is reported. Note that the baseline is independent of $\gamma$ and shows a constant AUROC. Bottom row: For different values of $\gamma$ the relative fraction of removed healthy and unhealthy samples is reported.

Fig. 3. Exemplary slices of two healthy MRI-scans that are removed by our algorithm (left: IXI, right: OASIS-3).
they contain information, e.g., of the homogeneity and possible imbalances of the training data set regarding the age distribution or scanners and could be inspected by experts to post-screen and maintain UAD training data sets. While differences in the age distribution can effect outlier removal, age information could be included in the training process similar to [14]. Outlier removal could be applied to more anomaly detection scenarios and diseases. However, a large-scale public benchmark anomaly detection data set of various disease types which would help our work and the field of UAD in general is missing [6].

5. CONCLUSION

We study the effect of impured training data sets on UAD performance. Our results demonstrate that even few falsely labeled samples have a critical impact. To counteract, we evaluate an outlier removal approach directly during training. Our findings show that falsely labeled samples can be detected and removed during training. This mitigates the effect of impured training data sets and helps to revise UAD training data sets regarding domain shifts and imbalances. For future work, the effect of impured data to other UAD methods like Adversarial autoencoders or generative adversarial networks could be elaborated together with outlier removal approaches.

Ethical approval: This work relies on publicly available OASIS-3, IXI and BraTS19 data sets. For use of this data sets, no ethics statements are necessary.

Funding: This work was partially funded by Grant Number ZF4026303TS9

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