

SR-AnoGAN: You Never Detect Alone. Super Resolution in Anomaly Detection (Student Abstract)

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Abstract

Despite the advance in deep learning algorithms, implementing supervised learning algorithms in medical datasets is difficult owing to the medical data's properties. This paper proposes SR-AnoGAN, which could generate higher resolution images and conduct anomaly detection more efficiently than AnoGAN. The most distinctive part of the proposed model is incorporating CNN and SRGAN into AnoGAN for reconstructing high-resolution images. Experimental results from X-ray datasets (pneumonia, covid-19) verify that the SR-AnoGAN outperforms the previous AnoGAN model through qualitative and quantitative approaches. Therefore, this paper shows the possibility of resolving data imbalance problems prevalent in the medical field and proposing more precise diagnosis.

Introduction

Despite the success of deep learning algorithms, applying those algorithms to medical datasets is challenging due to the characteristics of the medical data (Gao et al., 2020). Since supervised learning algorithms are usually utilized for diagnosing disease, labeling a dataset is vital. However, gathering patient datasets is complicated, which could trigger data imbalance problems (Gao et al., 2020). Therefore, a piece of research proposed an unsupervised learning approach as a solution, which only requires ordinary people's datasets for training. For instance, AnoGAN was proposed as a solution mainly comprising a deep convolutional generative adversarial network (DCGAN) (Schlegl et al., 2017). The DCGAN gets trained with datasets from healthy people and then reconstructs the images to compare and detect abnormal parts from patients' datasets. F-AnoGAN was also a state-of-the-algorithm to secure a faster computation time than AnoGAN by utilizing a novel mapping method (Schlegl et al., 2019). Even though high resolution is vital for AnoGAN, there are still issues with the stable training and resolution of the outputs with a limited number of datasets. Therefore, to resolve the problem mentioned above, an SR-AnoGAN is suggested in this paper, which is moti-

vated by the SRGAN that converts the low-resolution images to a higher one. The remarkable characteristic of this paper is that the SR-AnoGAN emphasizes generating high-resolution images for more accurate diagnosis.

Proposed Method: SR-AnoGAN

SR-AnoGAN mainly consists of three different stages: AnoGAN, SRGAN, and CNN. When the input i is provided, DCGAN reconstructs from the normal dataset, $g(i)$. The CNN model is applied to the generator's output in the second stage. The CNN model only consists of two layers to decrease the size efficiently, and the output is described as $c(g(i))$. The third part, increasing the resolution step, is the most distinctive part of the SR-AnoGAN. The SRGAN is applied to the output of the CNN, $c(g(i))$ to increase the resolution. The SRGAN requires two input data. Therefore, the normal data in the first step is used as higher resolution data, and $c(g(i))$ as lower one, respectively (Ledig et al., 2017). The $c(g(i))$ could be converted to become more like the normal data while getting higher resolution since the target data is the normal one. Even though one of the main shortcomings of the GAN algorithms is generating biased output, this shortcoming is beside the question. Finally, the model from the third stage is merged with the anomaly detector, which finally diagnoses the disease through calculating anomaly score.

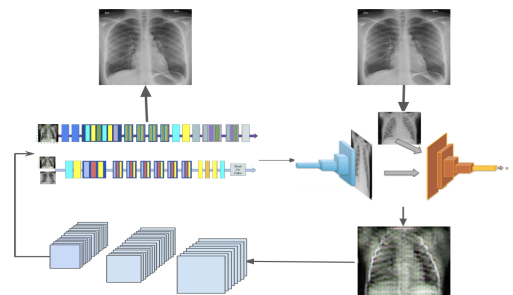


Figure 1: The overall architecture of the SR-GAN consists of three different models: AnoGAN, CNN, and SRGAN

Experimental Setup

Two different X-ray medical data were used in the experiments. The first dataset includes standard and pneumonia X-ray data (Kermany et al., 2018). The second is also an X-ray dataset consisting of standard and covid-19 image data (Cohen et al., 2020). Since the SR-AnoGAN only requires the standard datasets, only normal images were used for training, and each pneumonia and the covid-19 image was utilized as the diagnosis target. The anomaly score was calculated for quantitative evaluation and visualization of qualitative assessment. For image processing, every shot was resized to 128x128 and divided into 255.

Experimental Result

The AnoGAN model was mainly compared to our proposed model. Besides the resolution, Figure 2 below shows that the picture from the AnoGAN contains unnecessary features (sky blue parts), and SR-AnoGAN deletes them and delivers the improved version. With the quantitative approach, AnoGAN yielded an abnormal result. The descriptive statistics of anomaly score from the normal dataset (average 13,035) were higher than that of the pneumonia dataset (average 12,652), as showed in Figure 3. This result implies the wrong result since anomaly score should be low in the normal datasets. However, SR-AnoGAN, could detect abnormal data more efficiently. The result displays a low score in normal data (166,35) and a higher score in both covid-19 (18,381), and pneumonia data (17,240). Therefore, this paper suggests a possibility that could improve the performance of the AnoGAN and diagnose the disease efficiently with limited datasets.

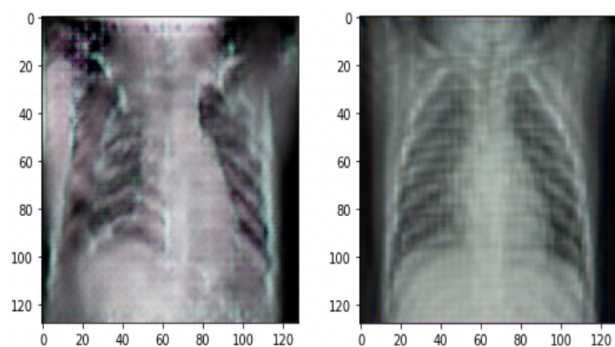


Figure 2: Images generated by AnoGAN (left) and SR-AnoGAN (right)

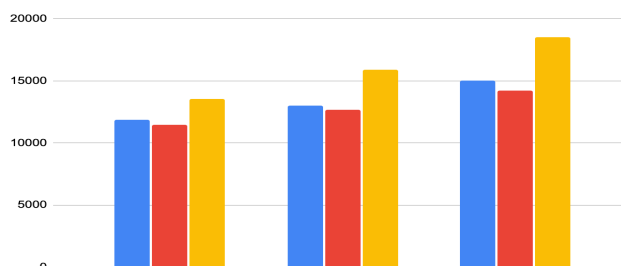


Figure 3 Comparing the outputs from various datasets from AnoGAN. Blue indicates normal one, red indicates pneumonia, and yellow represents covid19 (25%, 50%, 70%, per each column).

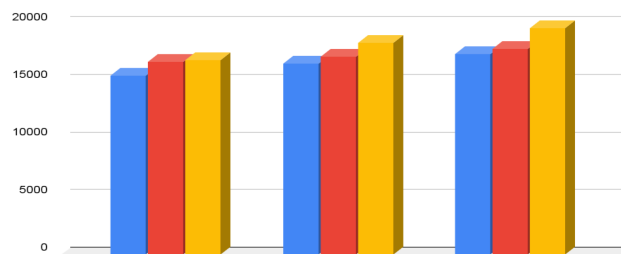


Figure 4. Comparing the outputs from various datasets from SR-AnoGAN. Blue indicates normal one, red indicates pneumonia, and yellow represents covid19 (25%, 50%, 70%, per each column).

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