Skip-GANomaly++: Skip Connections and Residual Blocks for Anomaly Detection (Student Abstract)

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Abstract

Anomaly detection is a critical task across various domains. Fundamentally, anomaly detection models offer methods to identify unusual patterns that do not align with expected behaviors. Notably, in the medical field, detecting anomalies in medical imagery or biometrics can facilitate early diagnosis of diseases. Consequently, we propose the Skip-GANomaly++ model, an enhanced and more efficient version of the conventional anomaly detection models. The proposed model's performance was evaluated through comparative experiments. Experimental results demonstrated superior performance across most classes compared to the previous models.

Introduction

In traditional deep learning for computer vision tasks that classify between normal and abnormal, a supervised approach is essential to achieve optimal performance. A supervised approach necessitates a substantial amount of labeled data. However, obtaining a significant volume of labeled data for regions of interest in the real world is a formidable challenge. Consequently, in this study, we propose an Anomaly Detection model utilizing a semi-supervised approach, which obviates the need to consider the balance issue in datasets. This method trains the model using only normal data. Subsequently, during the test phase, it classifies between normal and abnormal. Upon reviewing related studies, GANomaly (Akcay et al., 2019) is an anomaly detection model that leverages the generative adversarial network (GAN) and is composed of a generator, an encoder, and a discriminator. Skip-GANomaly (Akcay et al., 2019), as the name suggests, is an image-based anomaly detection model similar to the GANomaly model but augmented with skip-connections. While skip-connections excel in extracting fine details from the image space and producing high-quality reconstructed images, there's a potential pitfall during training where certain features might be overly emphasized, potentially compromising the model's generalization capability. Therefore, we propose an improved Skip-GANomaly model called Skip-GANomaly++, which employs skip-connections while addressing the generalization issues.

Proposed Method: Skip-GANomaly++

We propose an Anomaly Detection method utilizing a semi-supervised approach. The Skip-GANomaly++ is based on GAN and consists of two subnetworks: a generator and a discriminator. The generator is composed of a single stem block, three encoders, Atrous Spatial Pyramidal Pooling (ASPP) (Chen et al., 2016), and three decoders. Increasing the depth of the neural network is an effective strategy to enhance the model's accuracy. However, as the neural network becomes deeper, it can hinder the training process and induce degradation issues. Thus, we employ residual units (He et al., 2016) in every block. By using both residual units and skip-connections, we can stabilize the gradients, enabling the training of deeper networks. Additionally, we employ ASPP at the junction connecting the encoder and decoder. ASPP, combining atrous convolution and spatial pyramid poling, excels at effectively capturing varied scales and contextual information from fine to broad regions of the image. Consequently, ASPP can effectively address the loss of image information that occurs in the Encoder. The discriminator predicts the class of the given input data. In GAN, the discriminator differentiates between real images and reconstructed images generated by the generator. In this model, beyond the aforementioned role, it is also employed to compute the latent representations of both the real and reconstructed images. Lastly, the Skip-GANomaly++ calculates the similarity between the real image input and the reconstructed image generated by the generator, utilizing this as the anomaly score. Figure 1 shows the architecture of the proposed model.

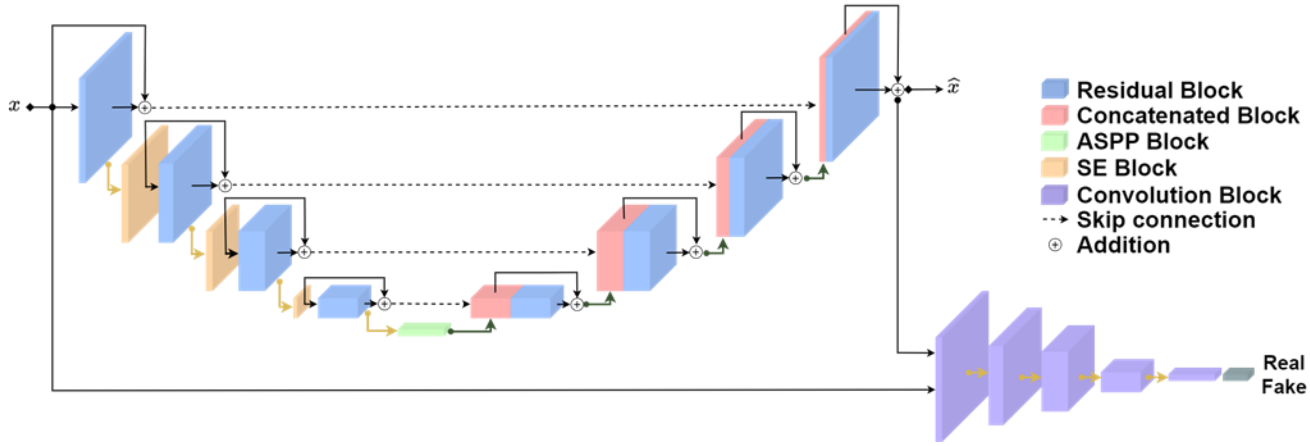

Figure 1: Detailed network architecture of the proposed model

	CIFAR-10									
Model	bird	car	truck	ship	cat	deer	frog	horse	airplane	dog
EGBAD	0.383	0.514	0.555	0.413	0.448	0.374	0.353	0.526	0.577	0.481
AnoGAN	0.411	0.492	0.511	0.567	0.399	0.335	0.321	0.399	0.516	0.393
GANomaly	0.510	0.631	0.617	0.616	0.587	0.593	0.683	0.605	0.633	0.628
Skip-GANomaly	0.448	**0.953**	**0.907**	0.659	0.607	0.602	0.931	0.788	0.797	0.615
Proposed-model	**0.819**	0.891	0.892	**0.998**	**0.907**	**0.998**	**0.999**	**0.832**	**0.984**	**0.818**

Table 1: Comparison results of AUC scores for each class

Experimental Setup

To validate the proof of concept for our proposed model, we conduct evaluations using the benchmark CIFAR-10 dataset. Experiments on the CIFAR-10 dataset follow a one-leave-out approach. The CIFAR-10 dataset comprises 45,000 normal samples for model training and ten distinct test sets, each consisting of 9,000 normal and 6,000 abnormal samples. Additionally, for a quantitative evaluation of our model, we conduct comparative experiments with the GANomaly, Skip-GANomaly, AnoGAN (Schlegl et al., 2017) and EGBAD (Zenati et al., 2018) models. All data used for training and testing are resized to 32x32 dimensions and normalized, scaling the pixel values between 0 and 1. For a quantitative assessment of the model's efficacy, we employ the area under the receiver operating characteristic curve (AUC-ROC) as a key performance indicator. The ROC curve delineates the relationship between the True Positive Rate (TPR) and the False Positive Rate (FPR). Notably, an AUC score approaching 1 signifies optimal model performance.

Experimental Results

The model we propose has been benchmarked against models such as GANomaly, Skip-GANomaly, AnoGAN, and EGBAD. Upon examining the results in Table 1, it is evident that, with the exception of the 'car' and 'truck' classes, our model outperforms the established models across all other classes. Notably, classes like 'bird', 'deer', and 'cat' were ones where prior research consistently failed to yield impressive results. However, our proposed model demonstrated superior performance even in these challenging classes. Conseq uently, this paper proposes a model that not only enhances performance compared to existing models but also effectively identifies anomalies.

References

Akcay, S., Atapour-Abarghouei, A. and Breckon, T.P., 2019. Ganomaly: Semi-supervised anomaly detection via adversarial training. In Computer Vision–ACCV 2018: 14th Asian Conference on Computer Vision, Perth, Australia, December 2–6, 2018, Revised Selected Papers, Part III 14 (pp. 622-637). Springer International Publishing.

Akçay, S., Atapour-Abarghouei, A. and Breckon, T.P., 2019, July. Skip-ganomaly: Skip connected and adversarially trained encoder-decoder anomaly detection. In 2019 International Joint Conference on Neural Networks (IJCNN) (pp. 1-8). IEEE.

Schlegl, T., Seeböck, P., Waldstein, S.M., Schmidt-Erfurth, U. and Langs, G., 2017, May. Unsupervised anomaly detection with generative adversarial networks to guide marker discovery. In International conference on information processing in medical imaging (pp. 146-157). Cham: Springer International Publishing.

Zenati, H., Foo, C.S., Lecouat, B., Manek, G. and Chandrasekhar, V.R., 2018. Efficient gan-based anomaly detection. arXiv preprint arXiv:1802.06222