Patch-Oriented Anomaly Detection and Segmentation Model

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Abstract

Anomaly detection task is to detect any event that deviates from a normal behavior. In real situations, there is a lack of real anomaly samples, leading to the development of pseudo-anomaly methods to learn unknown anomaly patterns. The recently proposed methods are limited in a way that they learn anomaly patterns in pre-required time because they inserted fewer anomalies per image. To address this, we propose a patch-based anomaly insertion technique that maintains a consistent ratio of normal to anomalous regions within each image. This approach allows for the learning of more anomaly patterns in less time and helps balance the normal and anomalous classes.

Ⅰ. Introduction

The anomaly detection problem in image and video data is defined as the process of recognizing an alteration of visual appearance from the normal presence. These deviations are crucial for identifying abnormal appearances and localizing anomaly regions. Anomaly detection has several significant applications, including fraud detection [1], medical image diagnosis[2], surveillance[3], and industrial defect detection[4].

The design of a deep learning model is dependent upon its specific application. For tasks such as anomaly detection, image reconstruction and segmentation methods, like Autoencoders (AE) and Generative Adversarial Networks (GAN) are widely utilized. These reconstructive models, AE and GAN, are trained to learn the input data by reconstructing the same input image at the output stage [5].

The fundamental concept behind reconstructive methods is to learn the low-dimensional representation of the input training images. During the testing phase, if a portion of the input image deviates from its normal appearance, it will exhibit poor reconstruction at that specific output position. The anomaly region can be identified by subtracting the input image from the output image, resulting in a residual image. This residual image is then utilized to localize and classify the images as either anomalous or normal.

Recent anomaly detection techniques can be classified into two categories. The first category encompasses learning techniques based solely on normal images, utilizing anomaly-free data to train the anomaly detection models.

The second category is a learning technique based on the mixture of normal and anomalous images, which creates pseudo-anomalous data to train the model to differentiate abnormal images from normal images. In this study, we introduce patch-based anomaly detection and segmentation method which localizes the anomaly in MVTec dataset as demonstrated in Fig 1. The presented approach falls into the second category. Fig 1. and learn the pseudo-anomaly patterns by inserting into the patches defined by a patch size.

The second category comprises learning techniques based on a mixture of normal and anomalous images created by generating pseudo-anomalous data to train the model to distinguish abnormal images from normal ones. In this study, we introduce a patch-based anomaly detection and segmentation method, which localizes anomalies in MVTec dataset [6], leather class example as demonstrated in Fig 1. This approach falls into the second category, learning pseudo-anomaly patterns by inserting them into patches defined by a specific patch size.

Ⅱ. Proposed Method

In previous approaches, the entire image is considered for the insertion of pseudo-anomalies, resulting in a low probability of pseudo-anomalies being inserted into each portion of the image. Since anomaly insertion is random, it may occur in any part of the normal image. During the training phase, randomly adding these anomalies to the entire image can help learn anomaly patterns. However, there is a risk that fewer anomalies will be present in the region of interest (RoI). To increase the number of anomalies in the RoI, anomalies can be added independently and randomly to each small portion of the image. This method mitigates the issue of missing RoI and ensures an equal percentage of normal and anomalous regions within an image.

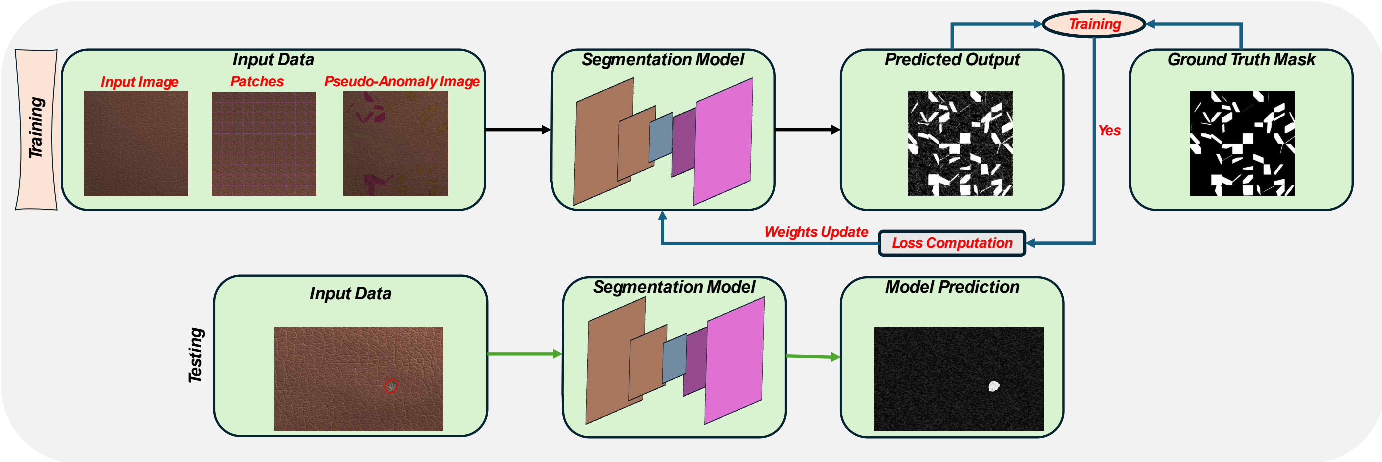

Fig 1. In the initial stage, the input image (640x640) is divided into patches by patch size of 64x64 then the pseudo anomalies are inserted randomly into each patch. The resulting pseudo-anomaly image is fed into the segmentation model to predict these anomaly mask. These predicted masks are compared with the ground truth masks to update model parameters based on the loss value. In second row, during the test phase, the image is directly passes to network to perform prediction.

In the proposed scheme, the image is initially resized to 640x640, a necessary step to ensure uniform image dimensions for deep learning models. During the training phase, as illustrated in Fig 1., the input image of 640x640 dimensions is divided into patches by randomly selecting a patch size from the list [16, 32, 64]. The random patch size selection is to ensure equal representation of different anomaly sizes, as discussed in [4], where representative anomalies can handle small, medium, and large anomalies. In the example shown in Fig 1, the randomly selected patch size is 64, resulting in 64x64 equal-sized patches from the normal image. Each patch can be either normal or anomalous with equal probability. When the probability of inserting an anomaly is high, anomalies are inserted into those patches, and corresponding masks are generated to train the segmentation model. In the final stage, anomalies are predicted by the segmentation model during the training phases, and the loss is updated to learn the anomaly patterns. While, during the testing phase, the complete image is fed to the trained model to predict anomalies.

Ⅲ. Conclusion

In the proposed method, we can generate more anomalies per image to balance both the normal and anomalous portions within an image. This approach also facilitates faster model training convergence. When inserting anomalies into a complete image, there is a risk of missing the insertion of anomalies in the region of interest (RoI). However, this method increases the probability of adding anomalies within the RoI.

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