Enhancement of Anomaly Detection Using Two-Stage Anomlay Segmentation Model

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***Abstract*—For the anomaly detection task, previously presented deep learning approaches suffer from one potential issue in the testing stage, the resultant output image has noise and missing anomaly area. To deal with this issue, we present a novel two-stage convolutional neural network (CNN) for anomaly detection. In the training stage, the first model is trained by inserting pseudo-anomalies, while the second model is trained by a superpixel technique which segments the image refined by the first model. The superpixel technique can recover partially visible anomaly patterns and suppress noise outside the recovered anomaly patches. We trained the proposed model using an industrial dataset MVTec and compared its performance with state-of-the-art pseudo-anomalous method [11]. Our method shows comparable pixel based percentage area under the receiver operating characteristic (%AUROC) of 96.0% which is only 1.3% less than the performance of DRAEM. However, our model uses four times less number of parameters.**

Keywords*—*Anomaly detection, Segmentation model, Convolutional Neural Network

I. INTRODUCTION

The anomaly detection task in the case of visual data is defined as the identification of deviation of a visual appearance from the normal presence. These characteristics play a key role in identifying the unusual appearance of images and localizing the regions of anomaly. It included the practical applications like, fraud detection [1], medical diagnosis [2], surveillance [3], and industrial defect detection [4].

Deep learning shows promising results in several areas of computer vision like image classification [5], image segmentation and detection [6], object tracking [7], and anomaly detection [8].

The design of a particular deep learning model is application dependent. In a case of anomaly detection, reconstructive models are popular. These models are conventionally designed using autoencoder (AE) [8] and generative adversarial network (GAN) models [9]. The reconstructive models like AE and GAN learn the given data during training stage by reconstructing the same input image at the output. The key idea behind the reconstructive methods is to learn the low-dimensional representation of the input training images. In a testing phase, when tested with an image with a region that deviates from the training images, it still reconstructs the normal image that is similar to the training images it had learned. That anomaly region can be identified by subtracting the input and output image that is termed as a residual image. So, we utilize the residual image to localize and classify an image as anomalous or normal.

The recent methods [8, 9] can be broadly divided into two categories. In the first category, the methods utilize the anomaly-free data to train their models. In the second category, the methods create pseudo data to learn the normal and anomalous behavior.

II. METHODOLOGY

A. Proposed Model

The proposed two stage anomaly detection model is introduced to detect anomaly at two stages as shown in Fig. 1. In first stage, the model trains on normal and psudeo-anompous images to get the residual image at the output. After optimizing the first model, in the second stage, the model is trained by taking the input image refined by the first model. The input image region is extracted by applying a superpixels technique simple linear iterative clustering (SLIC) on an input image. The superpixeling of the input image helps in extracting a complete patch instead of pixels' locations provided by the predicted ground truth at the output of first model. In a case, if some portion of the anomaly is missed at the output of the first model, we get the complete anomalous patch to train the second model. So, the second model is trained on small patches of input image to generate noise free output image with recovered anomalous region.

B. Proposed Approach

As part of the second category, our approach introduces the idea of training the model on normal and abnormal images to generate the residual image at the output of model. Since the anomalous data is often unavailable or hard to get enough amount for training, we insert pseudo-anomaly image patches to normal images to train our two-stage deep learning model as shown in Fig. 1. In our work we take advantage of a pseudo anomaly method [10], which creates perlin noise based random patterns and adds it to the normal images. In order to increase the variation of pseudo-anomalies, a new superpixel-based anomaly addition method is introduced in Fig.2.

The main contribution of our work is to introduce the following techniques to improve the anomaly localization and detection performance:

- The novel superpixel based pseudo-anomaly method is introduced to increase the pseudo-anomaly pattern variations.
- The two-stage anomaly detection model is introduced to capture the anomaly at two level. In case when the noise is produced or the anomaly part missed by first model, the second model can recover the missing anomaly patches and suppress the noise detected as anomaly.

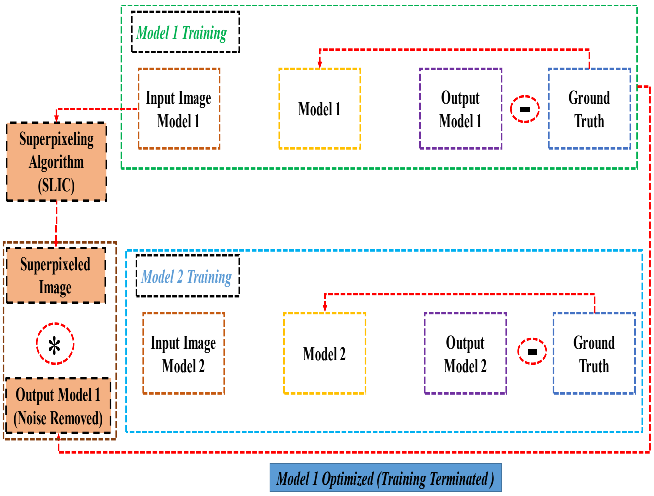

Fig. 1: Proposed two stage-model: The first-stage model is on the top, while second-stage model is on the bottom, which processes the output image produced by the first-stage model.

C. Training Methodology

We introduce a two-stage CNN model for anomaly detection as shown in Fig. 1. In the first stage, the model is trained with normal and pseudo-anomalous images in a supervised fashion. It then applies an anomaly insertion method shown in Fig. 2, which consists of two methods: (1) inserting pseudo anomaly based on Perlin noise similar to [10] and (2) inserting superpixel-based anomaly patterns.

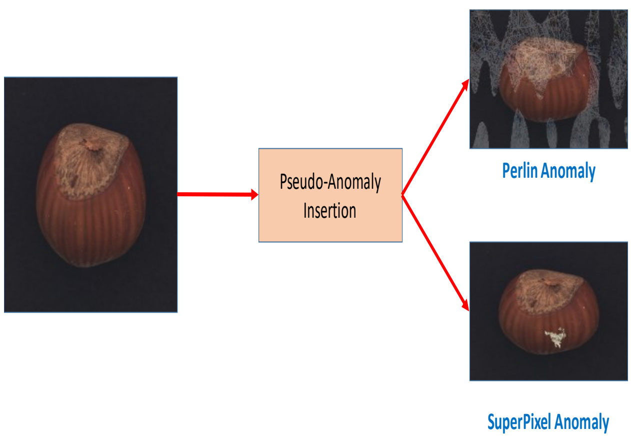

Fig. 2: The proposed pseudo-anomaly insertion method: The left side is a normal image, while the right side shows anomalous images produced by using perlin-noise and superpixel-based anomaly insertion method, respetively. The mask of inserted anomaly serves as a ground-truth mask in training.

The output of the pseudo anomaly generation is also reused as the ground truth labels which denote normal region of images by zero value while expressing anomalous region by high pixel value. In second stage, the model is trained using the output images of first model. We extract small anomaly patches by comparing the pixel of the predicted anomaly patterns with the superpixeling of input image as shown in Fig. 1. The second model is trained on such small patches to accurately detect the anomalies and reduce the false positive predictions.

For both models, the output image is compared with the masks of generated ground truths in an unsupervised manner to compute the loss function.

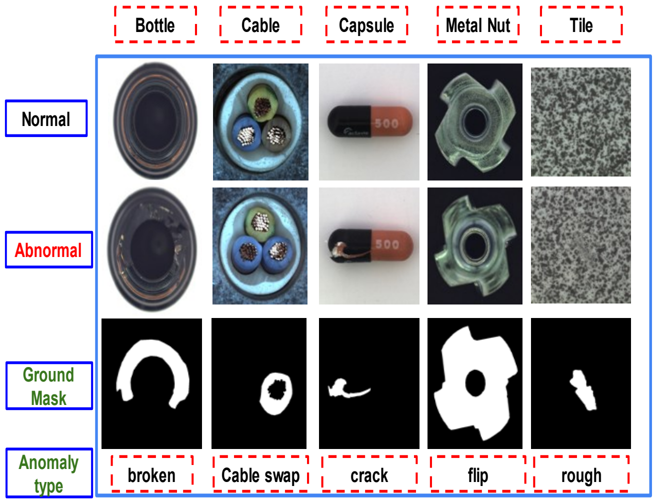

Fig. 3: Example images from MVTec: bottle, cable, capsule, metal-nut and tile class (from left) along with normal images (first row) and anomalous images (second row). The last two rows showing the ground-truth mask and the anomaly type within each class.

The loss is calculated as a combination of norm (L2) or lease square error (LSE) loss and structural similarity index (SSIM) loss to train both deep learning models as defined below. In equation (1), $\boldsymbol{x}$ represents the input image, while $\boldsymbol{y}$ represents the output predicted image by each model.

$$LSE_{loss} = \sum_{i=1}^{n}\left(y_i - f(x_i)\right)^2 \quad (1)$$

$$SSIM_{loss} = 1 - SSIM(y) \quad (2)$$

Here,

$$SSIM(y) = \frac{2\mu_x\mu_y + C1}{\mu_x^2\mu_y^2 + C1} \cdot \frac{2\sigma_{xy} + C_2}{\sigma_{x^2} + \sigma_{y^2} + C_2} \quad (3)$$

Overall loss function (L) is defined by Equation (4).

$$L = LSE_{loss} + SSIM_{loss} \quad (4)$$

The advantage of using a two-stage model is to substantially decrease the number of parameters while enhancing the classification and localization performance. We implemented the proposed approach and evaluated its performance using MVTec dataset [11].

Fig. 3 illustrates anomaly detection results for a few example images from MVTec. Table 1 demonstrates that the proposed model reduces the number of parameters of the model by 4 times compared with a previous work DREAM

[10] at the cost of negligible sacrifice of accuracy performance in mAUC%.

TABLE I. PERFORMACE AND PARAMETERS COMPARSION OF PRESENTED MODEL WITH THE STATE OF THE ART DREAM MODEL[10]

Method	***DREAM***	***Ours***
mAUC%	97.3	96.1
Paramters (*Million*)	97.4	23.9

The Fig. 4 shows the anomaly segmentation results compared with ground-truth for three categories i.e., cable, metal-nut and capsule. It can be seen that we get the cleaner images for anomaly free input image, while for anomalous image the more focus is on anomalous part.

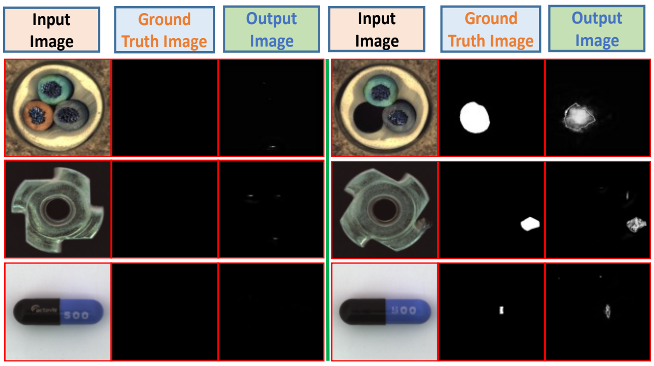

Fig. 4: The first images in each set of three categories indicate query images. The second images show the respective ground-truth. The third images depict the predicted result by our proposed model. Left side shows normal examples (no anomalies are detected), while the right side shows anomalous examples (anomalies are highlighted by while pixels).

III. CONCLUSION

In this work, we presented a two-stage anomaly detection model, which can detect anomalies precisely with a compact model size. It can improve the performance by applying new pseudo-anomaly insertion and segmentation method. By introducing a novel superpixel-based anomaly insertion method, the first stage model can effectively improve the training accuracy by increasing data augmentation for pseudo-anomalies. The second stage model can further improve the anomaly detection accuracy by recovering the missing anomalous patches. The proposed method shows the accuracy performance comparable to the state-of-art anomaly detector DREAM [10], while reducing the number of parameters consequently the inference speed by four times.

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