Although visual anomaly detection is very valuable, it is also quite challenging. One challenge common to all anomaly detection methods is the unexpectedness of anomalies. Typically in supervised classification, test classes come from the a similar distribution to the train data. In most anomaly detection settings, the distribution of anomalies is not observed during training time. Different anomaly detection methods differ by the way the anomalies are observed at training time. In this paper, we deal with the setting where at training time only normal data (but no anomalies) are observed. This is a practically useful setting, as obtaining normal data (e.g. products that contain no faults) is usually easy. This setting is sometimes called semi-supervised ([7]). As this notation is ambiguous, we shall refer to this setting as the normal-only training setting. An easier scenario is fully supervised i.e. both normal and anomalous examples are presented with labels during training. As this training setting is similar to standard supervised classification, a mature task with effective solutions, it will not be dealt with in this work.

Another challenge particular to visual anomaly detection (rather than non-image anomaly detection methods) is the localization of anomalies i.e. segmenting the parts of the image which the algorithm deems anomalous. This is very important for the explainability of the decision made by the algorithm as well as for building trust between operators and novel AI systems. It is particularly important for anomaly detection, as the objective is to detect novel changes not seen before which humans might not be familiar with. In this case, the computer may teach the human operator of the existence of new anomalies or alternatively the human may decide that an anomaly is not of interest thus not rejecting the product, resulting in cost-saving

We present a new method for solving the task of sub-image anomaly detection and segmentation. Our method does not require an extended training stage, it is fast, robust and achieves state of the art performance. Out methods consists of several stages: i) image feature extraction using a pre-trained deep neural network (e.g. an ImageNet trained ResNet) ii) nearest neighbor retrieval of the nearest K normal images to the target iii) finding dense pixel-level correspondence between the target and the normal images, target image regions that do not have near matches in the retrieved normal images are labeled as anomalous. Our method is extensively evaluated on an industrial product dataset (MVTech) as well as a surveillance dataset in a campus setting (Shanghai Tech Campus). Our method achieves state-of-the-art performance both on image-level and pixel-level anomaly detection.

2 Previous Work

Anomaly detection has attracted a large body of work over the last several decades. We present an overview of image-level and sub-image anomaly detection methods.

Image-level methods: We review methods that detect if an image is anomalous that are not particularly designed for segmenting the anomaly within the image.