

# SsaA: A Self-supervised auto-Annotation System for Online Visual Inspection and Manufacturing Automation

Jiawei Li<sup>1</sup>, Bolin Jiang<sup>2</sup>, Yan Liu<sup>1</sup>, Chengxiao Luo<sup>2</sup>, Naiqi Li<sup>2</sup>, Bin Chen<sup>3</sup>

<sup>1</sup>Manufacturing Department, Huawei Technologies, Dongguan, China

<sup>2</sup>Tsinghua Shenzhen International Graduate School, Shenzhen, China

<sup>3</sup>Harbin Institute of Technology, Shenzhen, China

li-jw15@tsinghua.org.cn, liuyan227@huawei.com, chenbin2021@hit.edu.cn

## Abstract

Recent trends in cloud computing technology effectively boosted the application of visual inspection. However, most of the available systems work in a human-in-the-loop manner and can not provide long-term support to the online application. To make a step forward, this paper outlines an automatic annotation system called SsaA, working in a self-supervised learning manner, for continuously making the online visual inspection in the manufacturing automation scenarios. Benefit from the self-supervised learning, SsaA is effective to establish a visual inspection application for the whole life-cycle of manufacturing. In the early stage, with only the anomaly-free data, the unsupervised algorithms are adopted to process the pretext task and generate coarse labels for the following data. Then supervised algorithms are trained for the downstream task. With user-friendly web-based interfaces, SsaA is very convenient to integrate and deploy both of the unsupervised and supervised algorithms. So far, the SsaA system has been adopted for some real-life industrial applications.

## 1 Introduction

Manufacturing automation has rapidly advanced with the process of cloud computing and online visual inspection systems [Amazon, 2020; Baidu, 2018; Huawei, 2020; Google, 2021]. By providing data labeling, GPU management, algorithm development, and cloud-to-edge deployment tools, current online systems follow canonical supervised learning manner and help to engage the human ability into the pipeline. However, since the online application continuously generates plenty of data, the manual operation is time-consuming and becomes a performance bottleneck. Therefore, there is a need to develop a less human involved long-term support system for the life-cycle of online applications [Li *et al.*, 2018b].

On the one hand, from the perspective of annotation, current supervised visual inspection relies on human expertise to make high-quality labels for the model training. However, with a human-in-the-loop manner, labeling image data by hand is a subjective task and inevitably to induce noise. Although some techniques about learning from noise labels

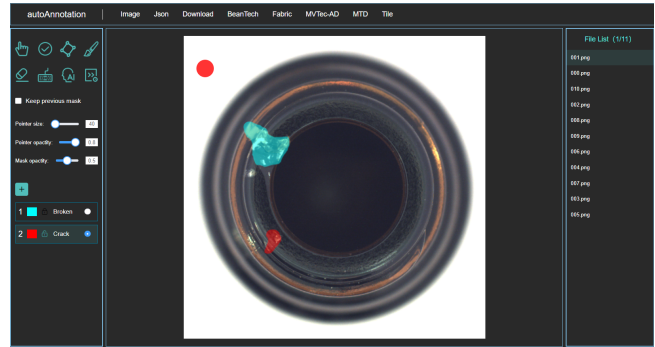


Figure 1: The web interface of our proposed SsaA system.

[Li *et al.*, 2018a] are developed to relieve this problem, the performance is still limited by the generalization ability of the models. Another way is to directly simplify human operations. In the medical image diagnosis scenario, some automatic systems are developed to assist the annotation and diagnosis of CT&MRI images. For example, the web-based tool Medseg [Medseg, 2020] and cross-platform software Pair [Pair, 2020] provide painting brush, eraser, zoom-in, zoom-out, and other AI-driven auxiliary operations for the pixel-level modification, which requires less effort for introducing human knowledge than typical annotation tools (e.g., Labelme [Russell *et al.*, 2008]).

On the other hand, from an online learning perspective, current supervised visual inspection methods (e.g., YOLOv4 [Bochkovskiy *et al.*, 2020], Faster-RCNN [Ren *et al.*, 2015]) need to be trained with typical defect samples in advance. Because the real-world manufacture defects (such as scratch, stain, foreign material) usually have variable shapes and patterns, the few-shot learning and AutoML methods are adopted for tackling this kind of long-tailed detection problem [Liu *et al.*, 2019]. Although the few-shot learning does not require extensive training data and is useful for the tail defect classes, it is hard to tackle the open-set defects, which are never seen before [Liu *et al.*, 2020]. Besides, current AutoML techniques focus on algorithm selection and neural architecture search [He *et al.*, 2021]. They can continue to learn good models from consistent data, but still have a gap to provide long-term support for online applications, especially when the incoming material and production are changed.

In this paper, we propose a self-supervised automatic annotation (SsaA) system to provide long-term support for on-line visual inspection and manufacturing automation. A user-friendly prototype system is developed<sup>1</sup> and shown in Figure 1. Powered by the object-oriented web front-end technologies [Fabric.js, 2011], the generated annotations like geometrical shapes are regarded as separated canvas elements, thus easy to distinguish the semantic information of different defects. Due to the distinction and relationship of unsupervised proxy task and supervised down-stream task [Pathak *et al.*, 2016; Grill, 2020], self-supervised learning has advantages for on-line learning. In our demo video<sup>2</sup>, an unsupervised anomaly detection model is trained on the image data of qualified products (do not need any label to indicate the defect), then predicts defects or generates pixel-level fine-graded labels for sustainable manufacturing.

## 2 The Prototype System

### 2.1 System Architecture

Recently, Amazon launched the Lookout for Vision tool [Amazon, 2020], an anomaly detection solution that uses supervised learning to spot defects and anomalies on thousands of manufacturing images. It roughly has a typical two-stage workflow: creating labels for collected data and training a supervised model, then inferring the online data. Google also launched a new Visual Inspection AI tool [Google, 2021] based on their cloud platform, which aims to help manufacturers to reduce defects. Due to the active learning and AutoML techniques, it achieves less labeling effort and higher training precision. However, it is still based on supervised learning and relies on human efforts for long-term support.

As shown in Figure 2, our proposed SsaA prototype is designed with self-supervised learning, and has a closed-loop architecture to process the continuous online data with a user-friendly auto-annotation interface.

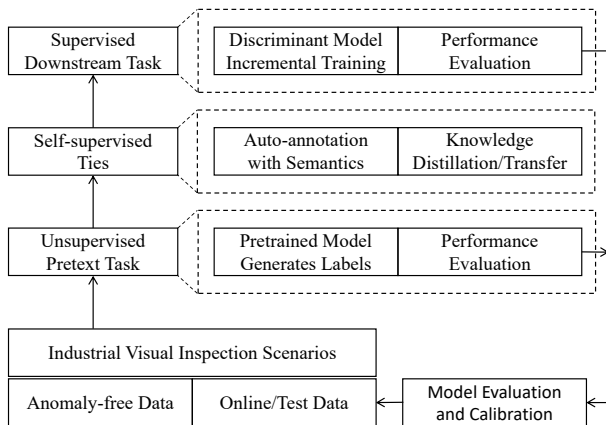


Figure 2: System architecture of self-supervised visual inspection.

<sup>1</sup>Link for trials: <http://121.37.246.245:8888/index.html>

<sup>2</sup>Demo video link: <http://121.37.246.245:8888/#/video>

### 2.2 Manufacturing Automation

Industrial visual inspection and medical imaging diagnosis have some common ground, while the former process manufacturing defects and the latter process visible diseases.

The pandemic of Covid-19 speeds up automatic diagnosis techniques to some extent, especially when the medical resources are insufficient, AI-based tools and algorithms are developed to ease the shortage [Suri *et al.*, 2021]. Medseg is an advanced web-based tool for computer-aided medical imaging diagnosis [Medseg, 2020]. It follows a typical client-server architecture and can diagnose a single case at a time. The front-end page is written in vanilla JavaScript Canvas to support the pixel-level annotation. The back-end server provides 25 pre-trained AI models for download and uses the local GPU to make the automatic diagnosis.

Because the industrial manufacture highly scheduled on time and being uninterrupted, our proposed SsaA system is powered with some different techniques. It has an upgraded front-end written in the object-oriented Fabric.js Canvas, thus not only supporting the pixel-level annotation, but also requiring less effort and being faster when changing the semantic information of automatically generated annotations. Besides, the back-end of SsaA is powered by cloud computing and encapsulates the interface of different computing frameworks (e.g., Mindspore, Tensorflow, Pytorch, Halcon), thus is compatible with various hardware resources and algorithms. When the production environment is changed, the SsaA system requires less development and deployment costs.

### 2.3 Self-supervised Learning

A typical self-supervised learning procedure has two stages. The pre-train stage has a pretext task to train the unsupervised model with unlabeled data. In the finetune stage, a downstream task is defined to train the supervised model with extracted features and labeled data. According to different pretext tasks and model architectures, the mainstream self-supervision can be summarized into contrastive, generative, or generative-contrastive based methods [Liu *et al.*, 2021].

Due to highly explainable diagnosis results, the AutoEncoder and UNet models family are widely used in medical imaging and industrial manufacturing applications [Baur *et al.*, 2021; Isensee *et al.*, 2021; Niu *et al.*, 2021]. To discriminate the open-set defects, a recent study tries to simultaneously perform the unsupervised image reconstruction and supervised anomaly detection tasks [Zavrtanik *et al.*, 2021]. It utilizes a Perlin noise generator to capture a variety of anomaly shapes, then joint train the AutoEncoder and UNet models on the augmented dataset. Different from relying on a noise prior, another approach trains a model to propagate the initial annotation in the pretext task and generates annotations for the downstream task [Yeung *et al.*, 2021].

To design a prototype for online visual inspection, we leverage the incremental data for the self-supervised learning of open-set defects. The unsupervised image reconstruction and supervised image segmentation are defined as the pretext task and downstream task, respectively. A generative model is trained on the anomaly-free image and generates pixel-level labels for online data. Then train the discriminant model with the incremental data for sustainable defect detection.

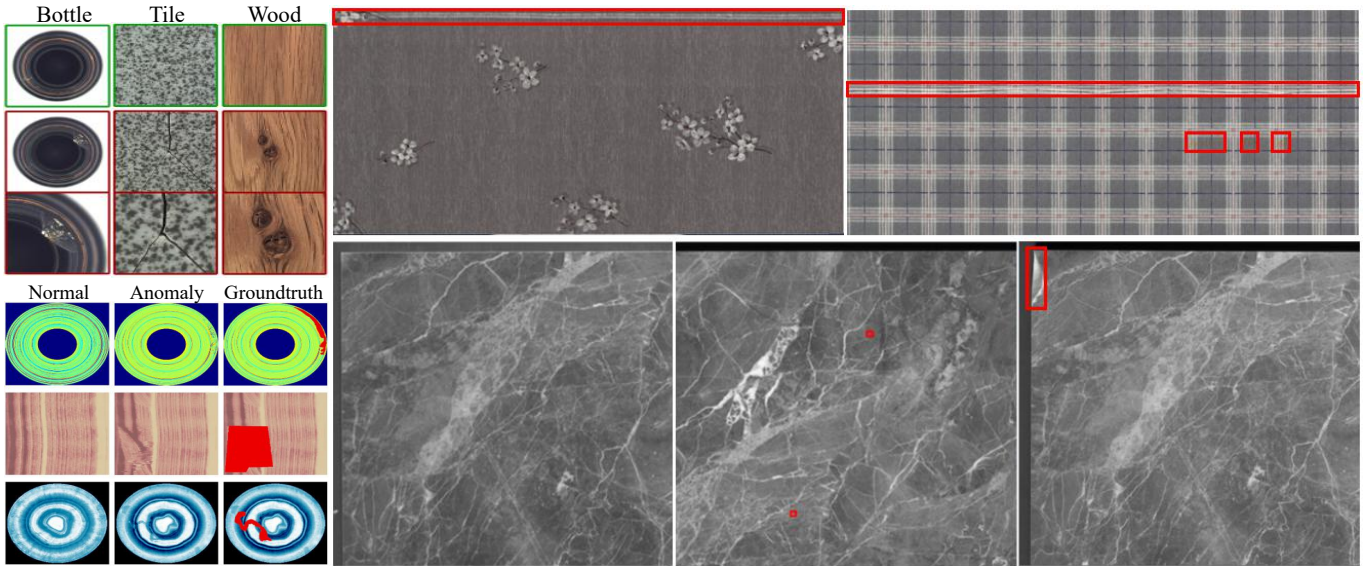


Figure 3: Four public available datasets for industrial visual inspection: MVTec-AD, BeanTech, TianChi-Fabric, and TianChi-Tile.

### 3 Online Visual Inspection

#### 3.1 Anomaly Detection Datasets

MVTec-AD dataset [Bergmann *et al.*, 2019] contains 15 different textures or products. We design the demo routine with the *Bottle* class, which is representative and usually used for the unsupervised anomaly detection task. It has a high-quality image with  $900 \times 900$  resolution. The training set of the *Bottle* contains 209 variable anomaly-free samples, while the testing set has 20 normal samples, 42 samples with broken defects, and 21 samples with contamination defects.

BeanTech dataset [Mishra *et al.*, 2021] is a real-world anomaly detection dataset. It contains three different industrial products. The appearance of BeanTech Product 1 and 3 are similar to the MVTec-AD *Bottle*. It is with  $1600 \times 1600$  pixels and the anomaly-free samples are more variable. The training set has 400 anomaly-free samples, while the testing set has 21 normal samples and 49 not-good samples.

TianChi-Fabric [TianChi, 2019] is an artificial fabric defect detection dataset. It contains more than 3,107 samples with object-level annotations for the supervised defect detection task. On the official annotation file, the dataset has a total of 16,457 defects that belong to 15 different types. Because the texture on different fabrics is quite different, this dataset also provides a standard anomaly-free template image for each kind of texture. Therefore, all the defect areas could be observed by a direct difference between the not-good samples and the corresponding template image.

TianChi-Tile [TianChi, 2021] is a real-world tile defect detection dataset and was photographed from a fixed camera of a tile factory production line. It contains more than 12,000 samples with object-level annotations for the supervised defect detection task. Because some defects are very small ( $< 3\%$  field of camera view), and there is no anomaly-free template image for some defective samples, this dataset is more difficult than the TianChi-Fabric dataset.

#### 3.2 Visual Inspection Routines

According to the system architecture in Figure 2, all the self-supervised visual inspection routines have three different stages. To simulate the data incoming of online applications, we independently and sequentially align the three stages to a train set, an online set, and a test set.

The first routine in our prototype is with the MVTec-AD *Bottle* and BeanTech datasets. We perform the unsupervised image reconstruction pretext task with a **training set**, which includes 10 anomaly-free samples. Then the pre-trained model is adopted to generate pixel-level labels for the **online set**, which includes 12 normal, broken, and contamination samples. After that, we perform a supervised image segmentation downstream task and evaluate the performance with a **test set**, which includes the other 12 defective samples. As shown in Figure 3, the appearance of BeanTech Product 1 and 3 are similar to the *Bottle*, thus we also have a routine to show the transfer learning ability in the prototype.

The second routine in our prototype is with the Tianchi-Fabric and Tianchi-Tile datasets. Following section 2.3 and not using the AutoEncoder and UNet, we further adopt a GAN inversion method [Pan *et al.*, 2021] to perform the downstream task, which has strong generalization ability and is capable for the productions with more variations.

### 4 Conclusion and Future Works

In this paper, we design the SsaA prototype system for online visual inspection. Benefiting from self-supervised learning and a well-designed front-end page, we achieve long-term support for manufacturing automation and demo that.

Now we can use the expert's experience on specific productions to make the auto-annotation with semantics. We plan to develop general automatic evaluation methods in the future, thus supporting some more real-life scenarios.

## References

- [Amazon, 2020] Amazon. Lookout for vision. [https://aws.amazon.com/lookout-for-vision/?nc1=h\\_ls](https://aws.amazon.com/lookout-for-vision/?nc1=h_ls), 2020.
- [Baidu, 2018] Baidu. Paddlepaddle easydl. <https://cloud.baidu.com/product/easydl>, 2018.
- [Baur *et al.*, 2021] Christoph Baur, Stefan Denner, Benedikt Wiestler, Nassir Navab, and Shadi Albarqouni. Autoencoders for unsupervised anomaly segmentation in brain mr images: A comparative study. *Medical Image Analysis*, 2021.
- [Bergmann *et al.*, 2019] Paul Bergmann, Michael Fauser, David Sattlegger, and Carsten Steger. Mvtec ad—a comprehensive real-world dataset for unsupervised anomaly detection. *IEEE/CVF conference on computer vision and pattern recognition*, 2019.
- [Bochkovskiy *et al.*, 2020] Alexey Bochkovskiy, Chien-Yao Wang, and Hong-Yuan Mark Liao. Yolov4: Optimal speed and accuracy of object detection. 2020.
- [Fabric.js, 2011] Fabric.js. Javascript html5 canvas library. <http://fabricjs.com>, 2011.
- [Google, 2021] Google. Visual inspection ai. <https://cloud.google.com/solutions/visual-inspection-ai>, 2021.
- [Grill, 2020] et al. Grill, Jean-Bastien. Bootstrap your own latent—a new approach to self-supervised learning. *Advances in Neural Information Processing Systems*, 2020.
- [He *et al.*, 2021] Xin He, Kaiyong Zhao, and Xiaowen Chu. Automl: A survey of the state-of-the-art. *Knowledge-Based Systems*, 2021.
- [Huawei, 2020] Huawei. Industrial intelligent. [https://www.huaweicloud.com/product/ei\\_industrial](https://www.huaweicloud.com/product/ei_industrial), 2020.
- [Isensee *et al.*, 2021] Fabian Isensee, Paul Jaeger, Simon Kohl, Jens Petersen, and Klaus Maier-Hein. nnu-net: a self-configuring method for deep learning-based biomedical image segmentation. *Nature methods*, 2021.
- [Li *et al.*, 2018a] Jiawei Li, Tao Dai, Qingtao Tang, Yeli Xing, and Shu-Tao Xia. Cyclic annealing training convolutional neural networks for image classification with noisy. *IEEE International Conference on Image Processing*, 2018.
- [Li *et al.*, 2018b] Liangzhi Li, Kaoru Ota, and Mianxiong Dong. Deep learning for smart industry: Efficient manufacture inspection system with fog computing. 2018.
- [Liu *et al.*, 2019] Ziwei Liu, Zhongqi Miao, Xiaohang Zhan, Jiayun Wang, Boqing Gong, and Stella Yu. Large-scale long-tailed recognition in open world. *IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2019.
- [Liu *et al.*, 2020] Bo Liu, Hao Kang, Haoxiang Li, Gang Hua, and Nuno Vasconcelos. Few-shot open-set recognition using meta-learning. *IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2020.
- [Liu *et al.*, 2021] Xiao Liu, Fanjin Zhang, Zhenyu Hou, Li Mian, Zhaoyu Wang, Jing Zhang, and Jie Tang. Self-supervised learning: Generative or contrastive. *IEEE Transactions on Knowledge and Data Engineering*, 2021.
- [Medseg, 2020] Medseg. Ai. <https://www.medseg.ai>, 2020.
- [Mishra *et al.*, 2021] Pankaj Mishra, Riccardo Verk, Daniele Fornasier, Claudio Piciarelli, and Gian Luca Foresti. Vt-adl: A vision transformer network for image anomaly detection and localization. *IEEE 30th International Symposium on Industrial Electronics*, 2021.
- [Niu *et al.*, 2021] Tongzhi Niu, Bin Li, Weifeng Li, Yuanhong Qiu, and Shuanlong Niu. Positive-sample-based surface defect detection using memory-augmented adversarial autoencoders. *IEEE/ASME Transactions on Mechatronics*, 2021.
- [Pair, 2020] Pair. Annotation. <https://aipair.com.cn>, 2020.
- [Pan *et al.*, 2021] Xingang Pan, Xiaohang Zhan, Bo Dai, Dahua Lin, Chen Change Loy, and Ping Luo. Exploiting deep generative prior for versatile image restoration and manipulation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2021.
- [Pathak *et al.*, 2016] Deepak Pathak, Philipp Krahenbuhl, Jeff Donahue, et al. Context encoders: Feature learning by inpainting. *IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2016.
- [Ren *et al.*, 2015] Shaoqing Ren, Kaiming He, Ross Girshick, and Jian Sun. Faster r-cnn: Towards real-time object detection with region proposal networks. *Advances in Neural Information Processing Systems*, 2015.
- [Russell *et al.*, 2008] Bryan C Russell, Antonio Torralba, Kevin P Murphy, and William T Freeman. Labelme: a database and web-based tool for image annotation. *International journal of computer vision*, 2008.
- [Suri *et al.*, 2021] Jasjit Suri, Sushant Agarwal, Alessandro Carriero, et al. Covlias 1.0 vs. medseg: Artificial intelligence-based comparative study for automated covid-19 computed tomography lung segmentation in italian and croatian cohorts. *Diagnostics*, 2021.
- [TianChi, 2019] Alibaba TianChi. A fabric defects dataset. <https://tianchi.aliyun.com/competition/entrance/231748/information>, 2019.
- [TianChi, 2021] Alibaba TianChi. A tile defects dataset. <https://tianchi.aliyun.com/competition/entrance/531846/information>, 2021.
- [Yeung *et al.*, 2021] Pak-Hei Yeung, Ana IL Namburete, and Weidi Xie. Sli2vol: Annotate a 3d volume from a single slice with self-supervised learning. *International Conference on Medical Image Computing and Computer-Assisted Intervention*, 2021.
- [Zavrtanik *et al.*, 2021] Vitjan Zavrtanik, Matej Kristan, and Danijel Skočaj. Draem—a discriminatively trained reconstruction embedding for surface anomaly detection. *IEEE/CVF International Conference on Computer Vision*, 2021.