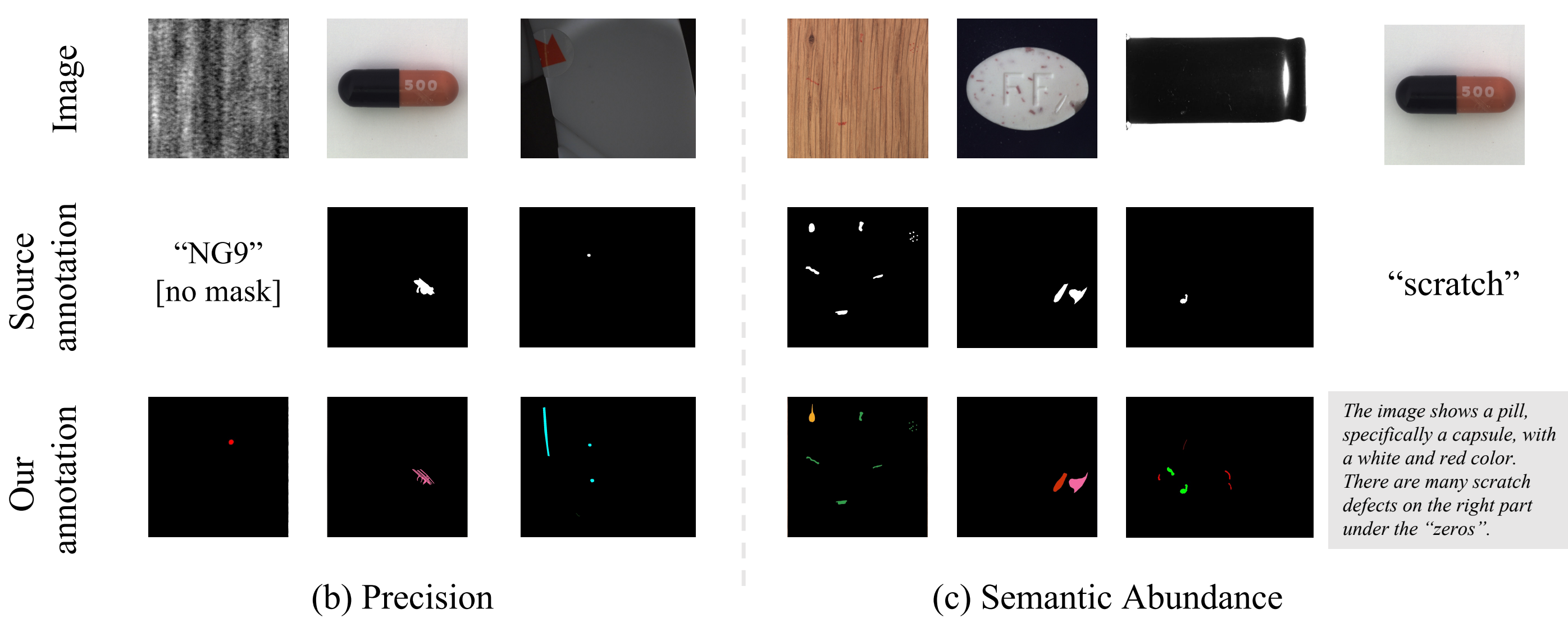
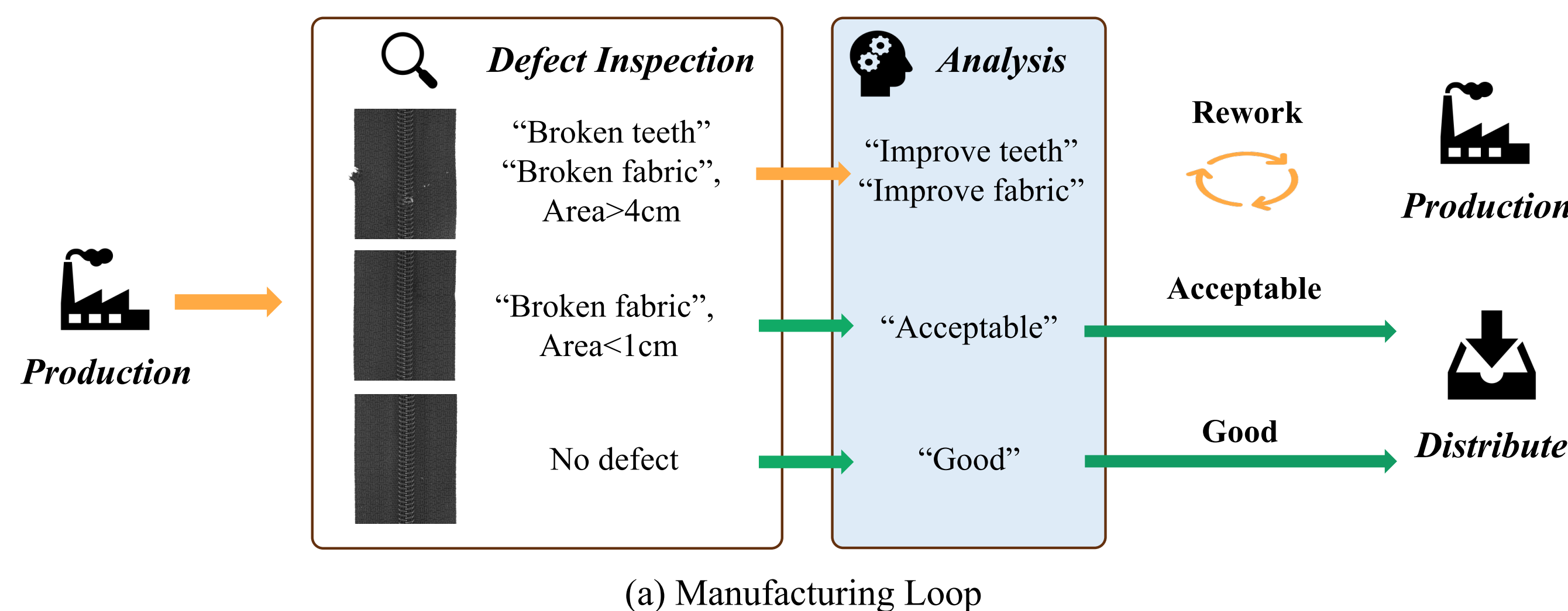




### Introduction

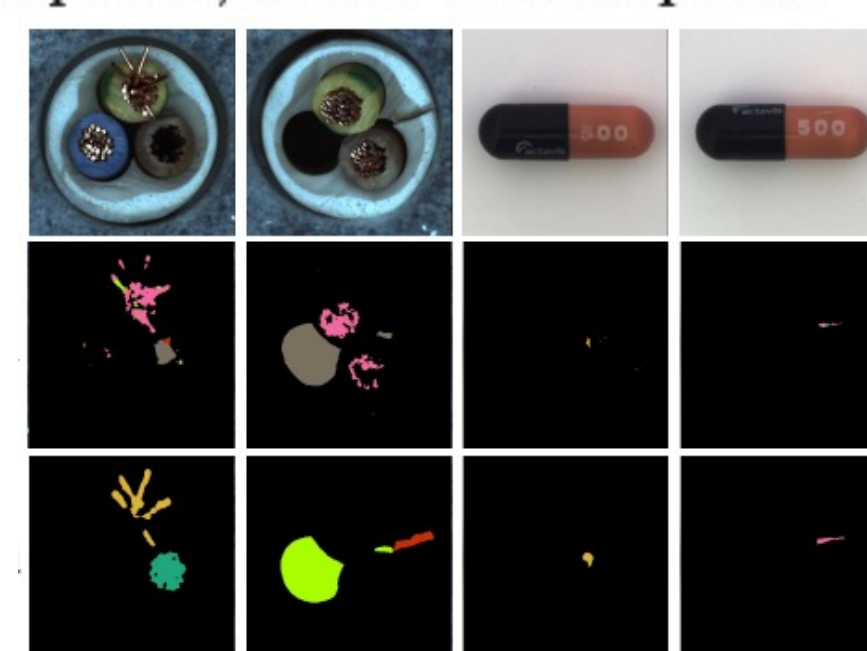
- Current datasets fall short in meeting the complex practical requirements of industrial defect inspection. They suffer from **poor quality annotations** and **insufficient sample diversity**.
- We introduce the **Defect Spectrum**, a comprehensive industrial defects benchmark offering **precise, semantic-rich, and large-scale** annotations.
- We introduce **Defect-Gen**, a two-stage diffusion-based generator for creating **high-quality** synthetic images from **limited** data.



To assess our dataset's superiority, we design a simulation experiment that mirrors real-world manufacturing processes. We reduce the FPR while improving the recall rate.

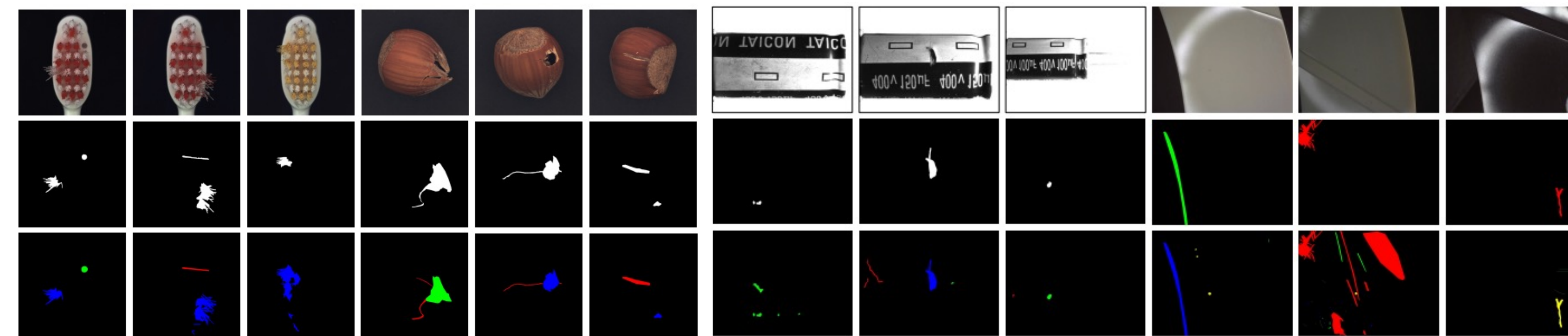
Example classes	Standard For Benign Products	
Zipper	No defect on teeth; Fabric defect < 4800 pixels	
Pill	No cracks; Contamination < 4000 pixels; Color stains < 300 pixels	
Wood	No scratch; No dent; Impurities < 250 pixels; Stain < 1000 pixels	

Method	↑ Recall (%) ↓ FPR (%)
Original	85.33 49.60
Defect Spectrum (DS)	<b>96.07 16.50</b>



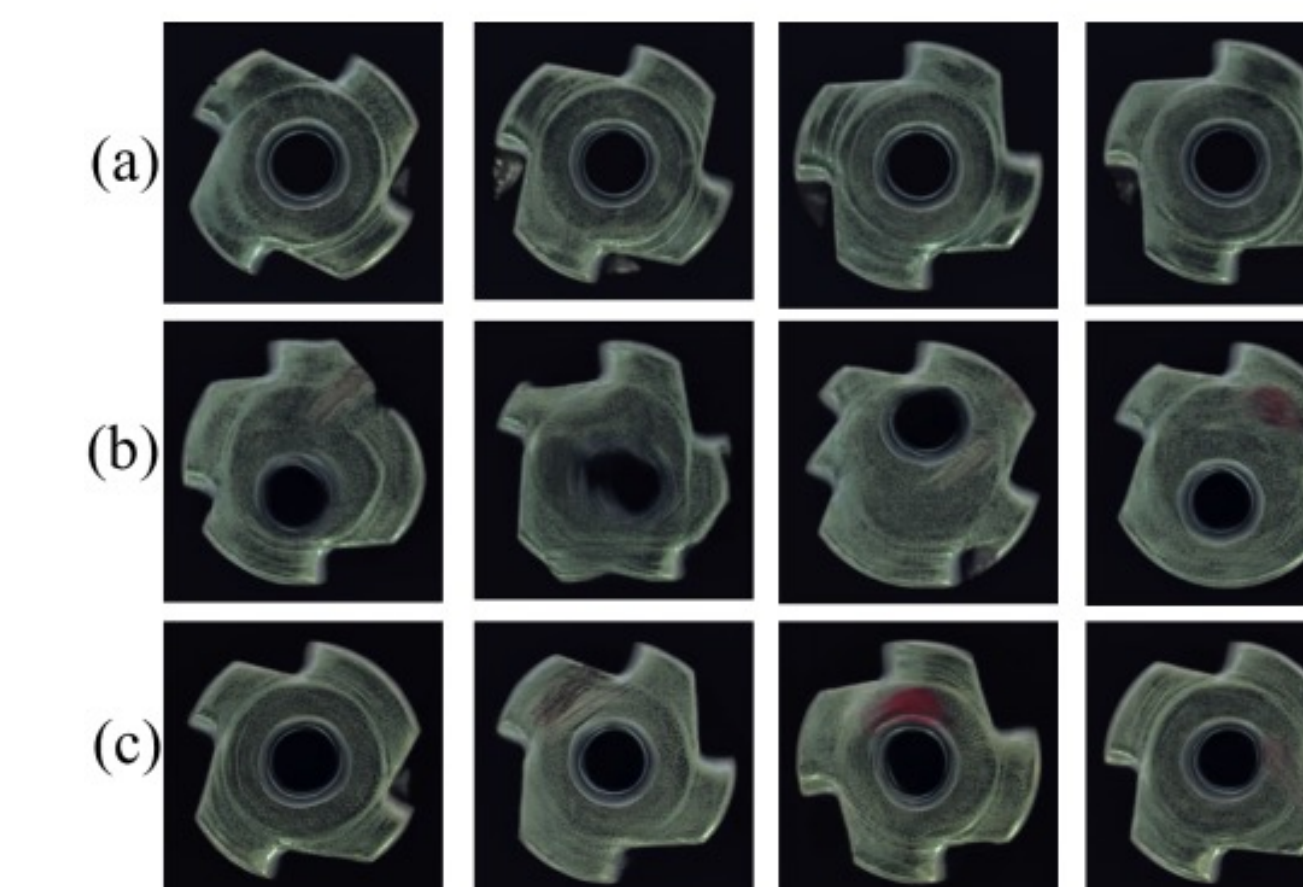
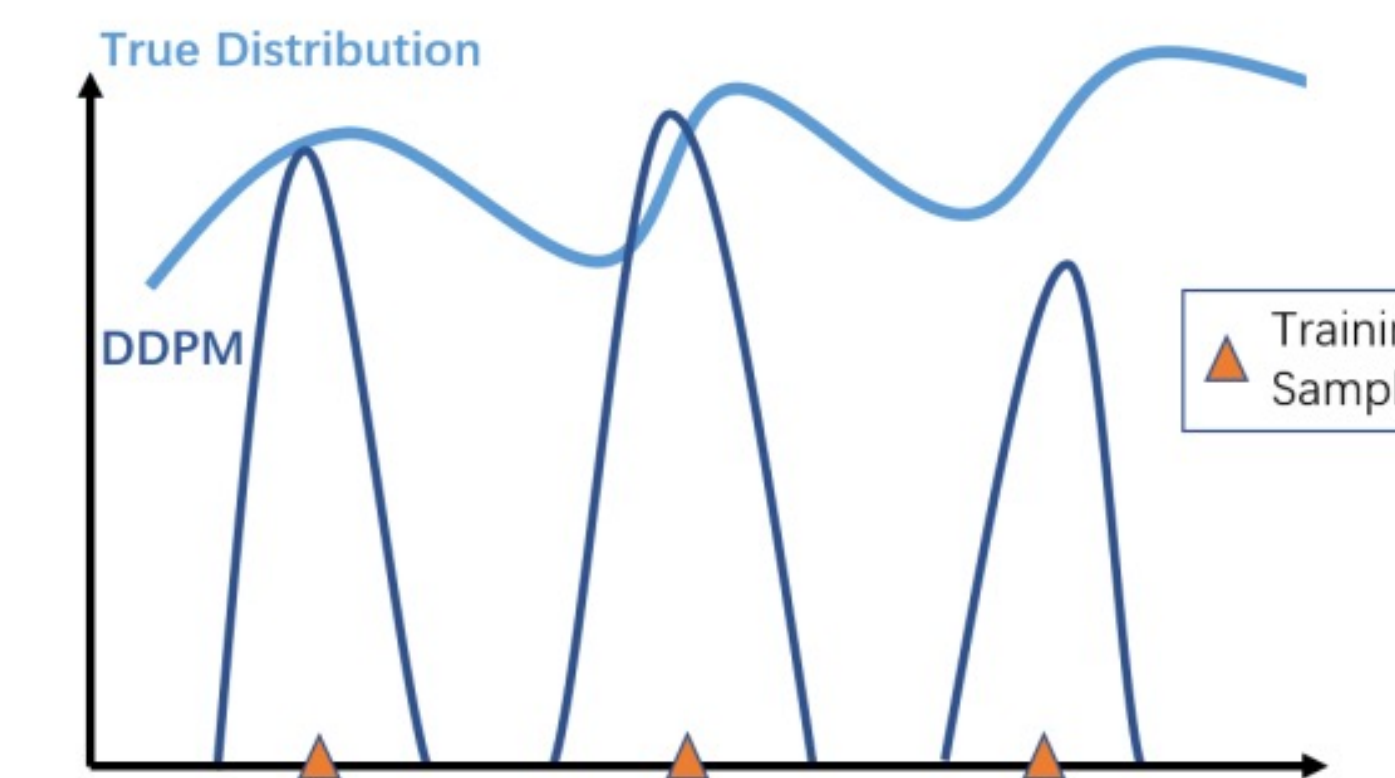
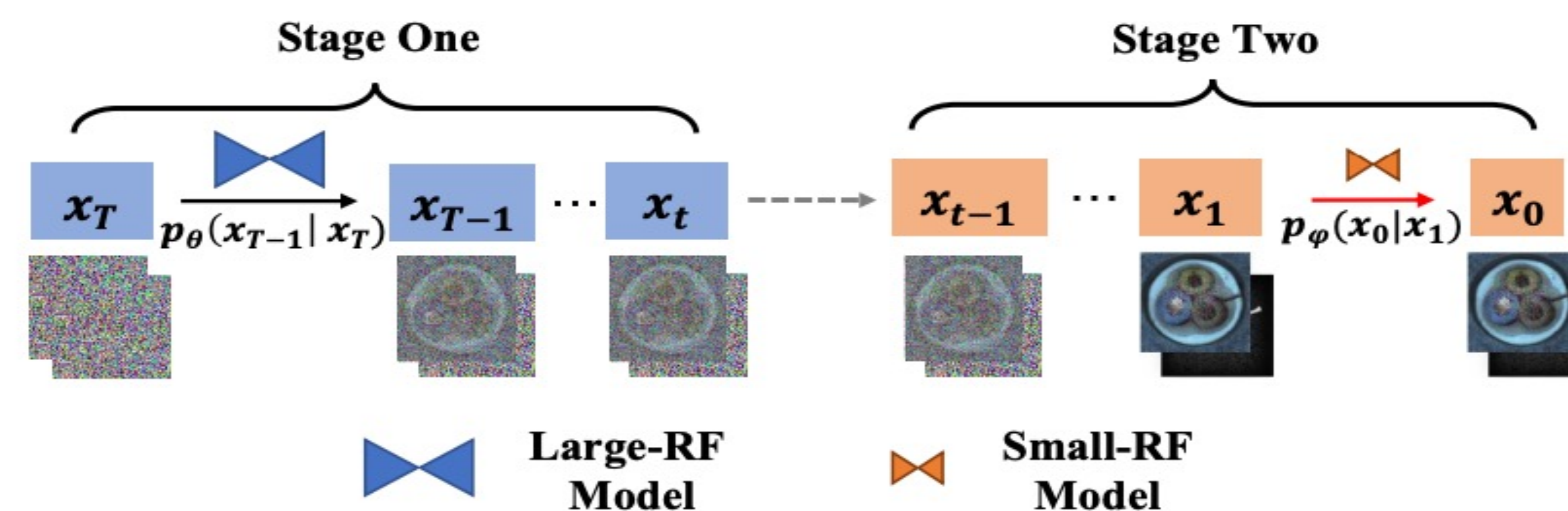
### Defect Spectrum Dataset

	Annotated Defective Images	Defect Type	Pixel-wise Label	Multiple Defective Label	Detailed Caption
AITEX [36]	105	12	✓		
AeBAD [51]	346	4	✓		
BeanTech [27]	290	3	✓		
Cotton-Fabric [20]	89	1			
DAGM2007 [46]	900	6			
KolektorSDD2 [39]	356	1	✓		
MVTec [3]	1258	69	✓		
VISION V1 [1]	4165	44	✓	✓	
VisA [56]	1200	75	✓		
Defect Spectrum	<b>3518+1920*</b>	<b>125</b>	✓	✓	✓



### Defect-Gen

By using the limited available data, we propose a two-staged diffusion-based generator, called the "Defect-Gen" to generate both defective images and masks.



#### I. Few-shot Challenge

Due to the scarcity of defect images, models trained on few samples often memorize the training set and fail to capture the true data distribution.

#### II. Modeling Patch-Level Distribution

To alleviate the above-mentioned problem, we propose to model the patch-level distribution instead of the image-level distribution.

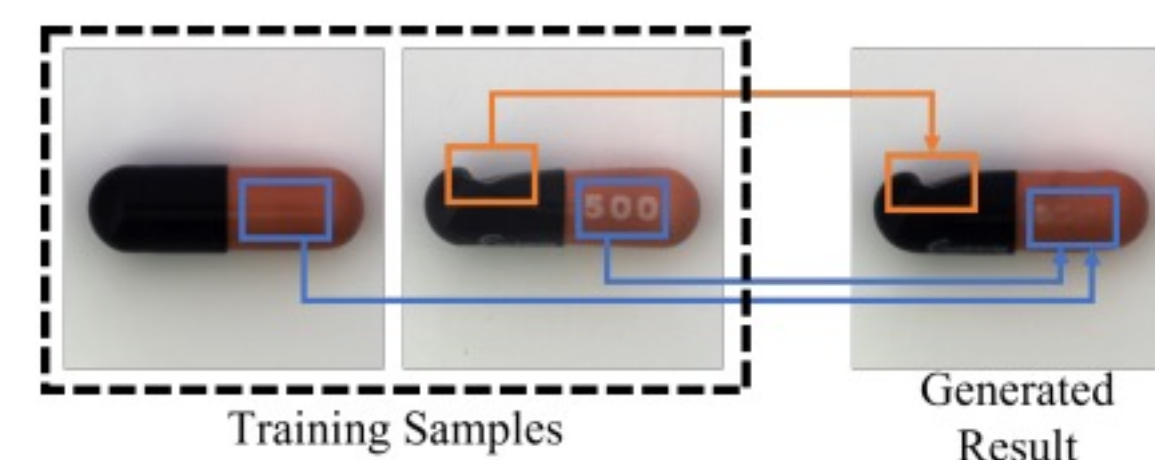
#### III. Restraining the Receptive Fields

We can naively crop image into patches to achieve patch-level modeling. However, it is hard to use learned patches to reconstruct into a whole image during inference. Alternatively, we reduced number of down-sampling layers to constrain the output receptive fields. This allows the model to only be visible to small patches on the original images.

#### IV. Handling the Global Distortion

Patch-level modeling is effective in overcoming overfitting, it falls short of representing the global structure of the entire image. Thus, we trained a two-staged diffusion model, one with large RFs and one with small RFs. During inference, we use the large-RF model to capture the geometry structure in the early steps, and then switch to the small-RF model to generate diverse local patches in the remaining steps.

### Evaluation of Defect-Gen



	DS-MVTec	DS-VISION	DS-Cotton
DeepLabV3+	51.58/55.55	52.33/53.46	48.73/58.58
Mask2Former	45.70/50.16	54.12/55.47	64.09/65.39
MiT-B0	46.45/56.21	49.62/50.75	50.52/55.86

