Efficient Anomaly Detection in Industrial Images using Transformers with Dynamic Tanh

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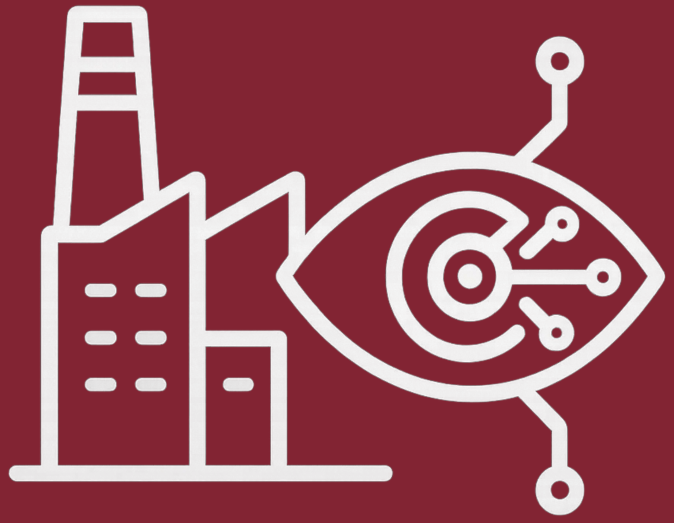
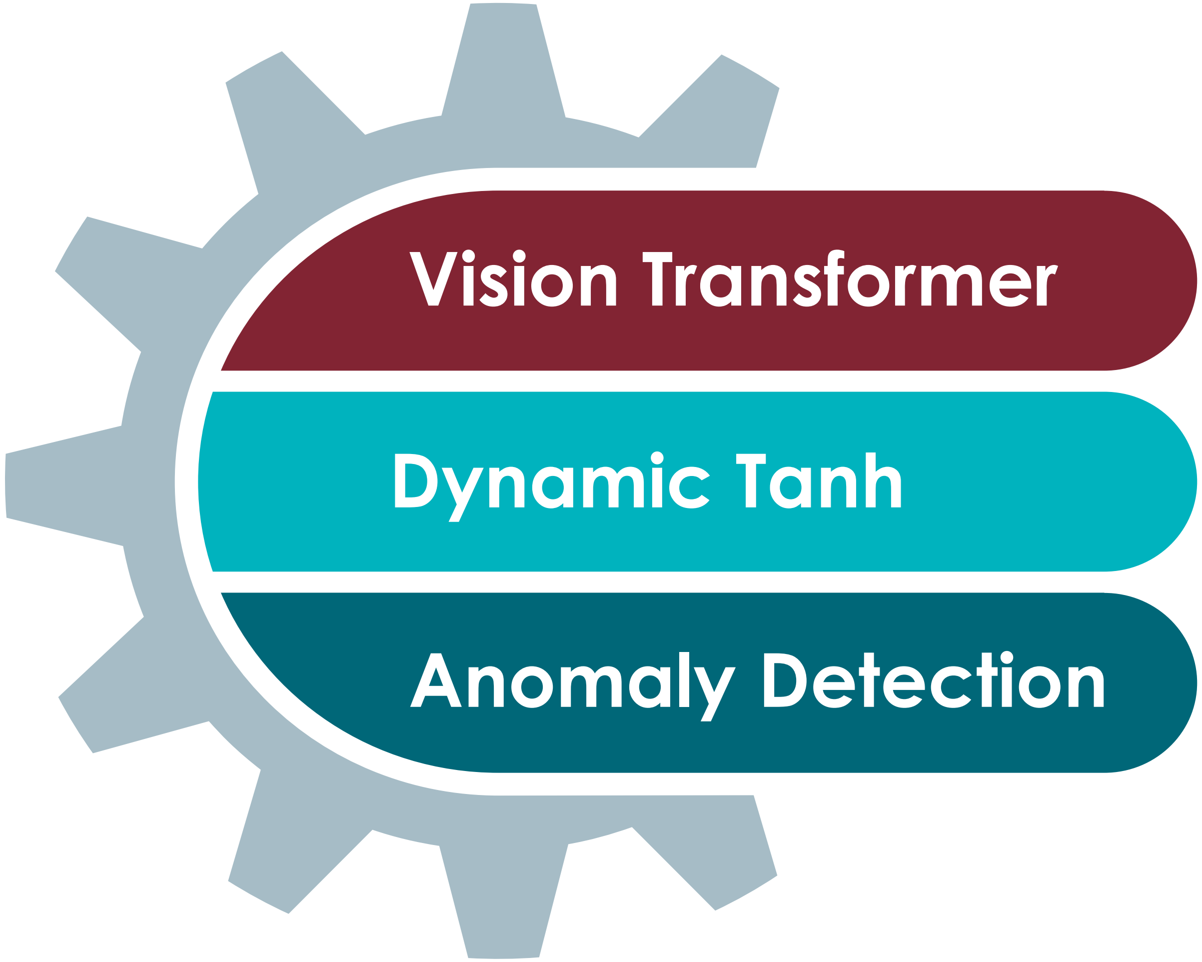


Outline

- What's the problem?
- S.O.T.A
- Our approach
- Datasets
- The setup
- Evaluations
- Conclusions
- References

What’s the problem?

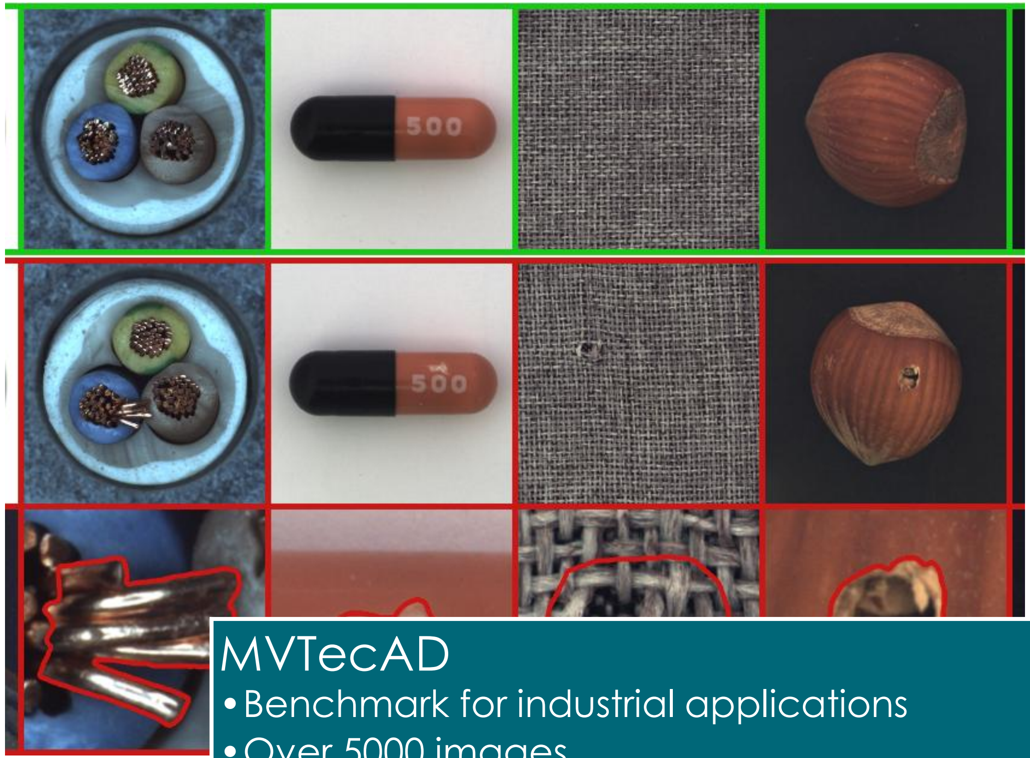


Our Task

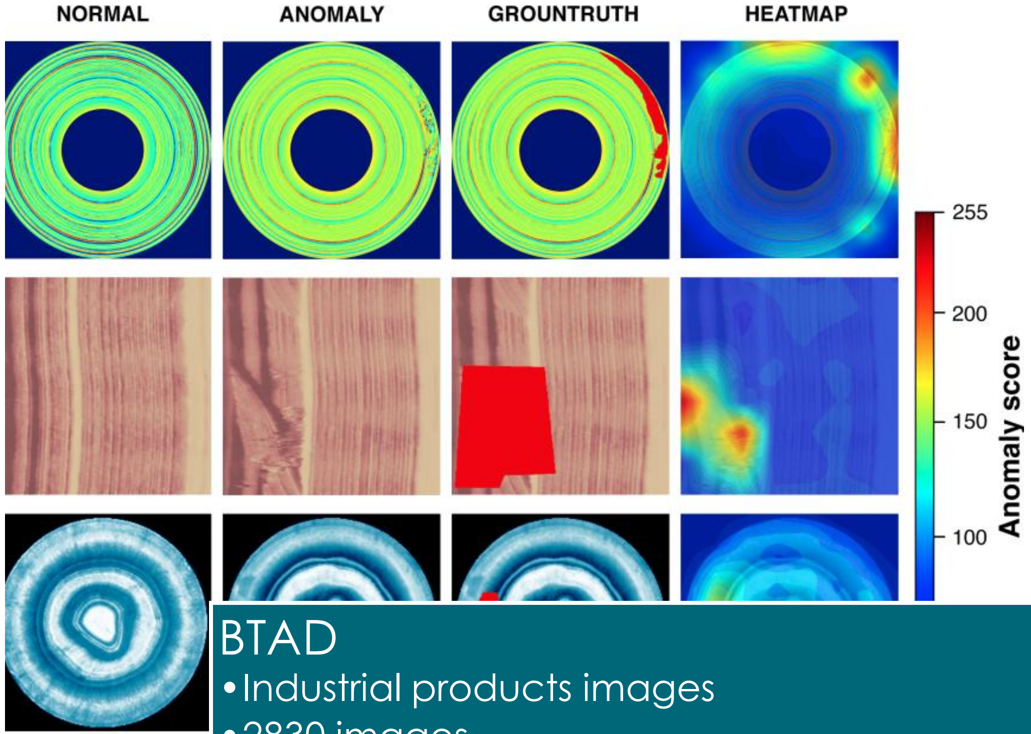
Vision Transformers (ViTs) and Dynamic Tanh (DyT) together should enhance industrial anomaly detection by combining powerful feature extraction with efficient processing, improving quality control, safety, and scalability in complex visual data environments.

We try to create a pipeline to demonstrate this.

Datasets



MVTecAD
- Benchmark for industrial applications
- Over 5000 images
- 15 classes, multiple kinds of defects per class



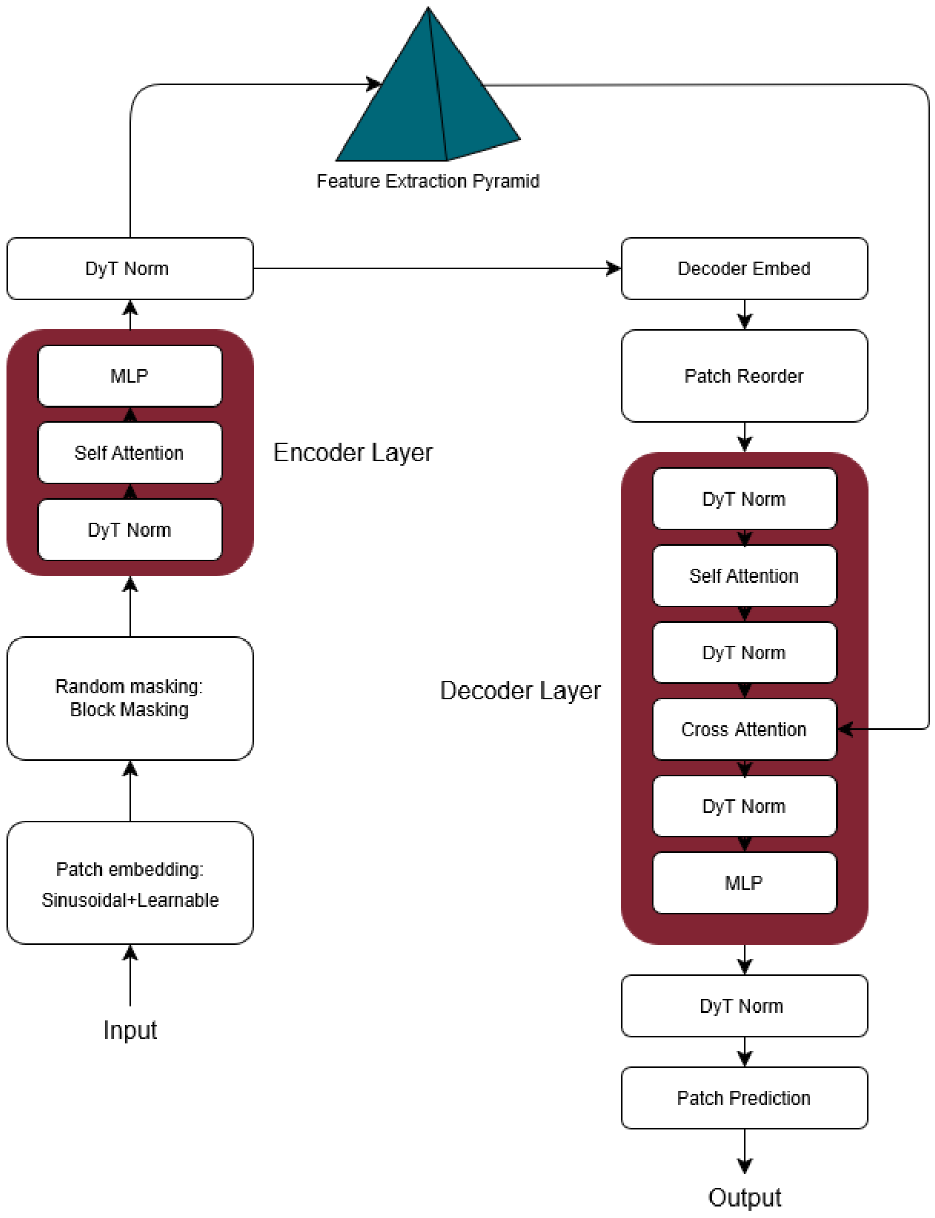
BTAD
- Industrial products images
- 2830 images
- 3 classes, every class has different size

S.O.T.A

Model / Method	Year	Datasets	Strengths	Limitations
VT-ADL (Vision Transformer ADL)	2021	MvTec AD, BTAD	Early ViT-based AD method; combines transformer with GMM for anomaly localization	Moderate localization accuracy; lower BTAD performance
ViT-AE + Memory (Sensors)	2024	MvTec AD, BTAD	Autoencoder + memory + coordinate attention; good detection + localization	Struggles with very fine-grained defects
MSTAD (Masked Subspace Transformer)	2023–24	MvTec AD, BTAD	Masking + subspace embedding improves both detection and localization	Higher model complexity; sensitive to hyperparameters

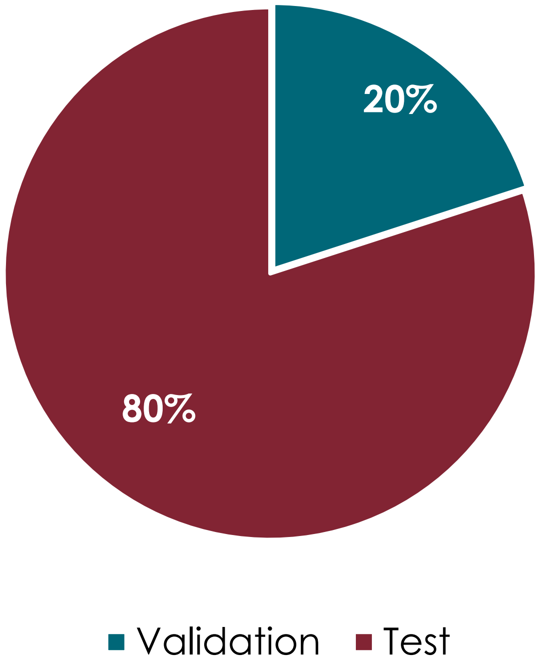
Our approach

- Masked Auto Encoder
- Sinusoidal patch embedding
- Block masking only in training!
- Asymmetric Encoder-Decoder design
- Cross Attention with Feature Pyramid



The final setup

- Images resized to 256x256
- Encoder depth is 16
- Decoder depth is 2
- 16 x 16 patch size
- Different embedding dimensions
- 75% of the image masked



Our seed obiously is:

Two training is better than one

PRETRAINING

80 epochs

Weighted loss:
SSIM for context
+
MSE for reconstruction

+

FINETUNING

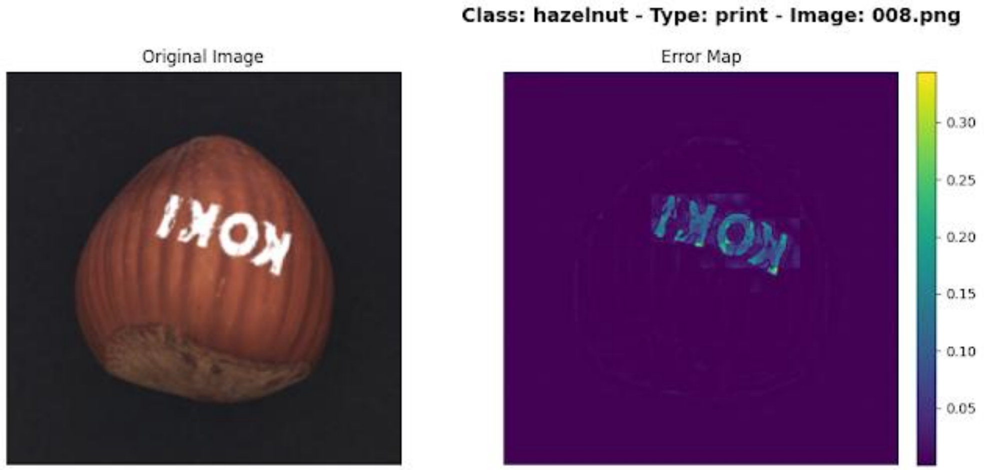
40 epochs

Only recon MSE loss

Dynamic threshold tuning
on Validation data

What did we accomplish?

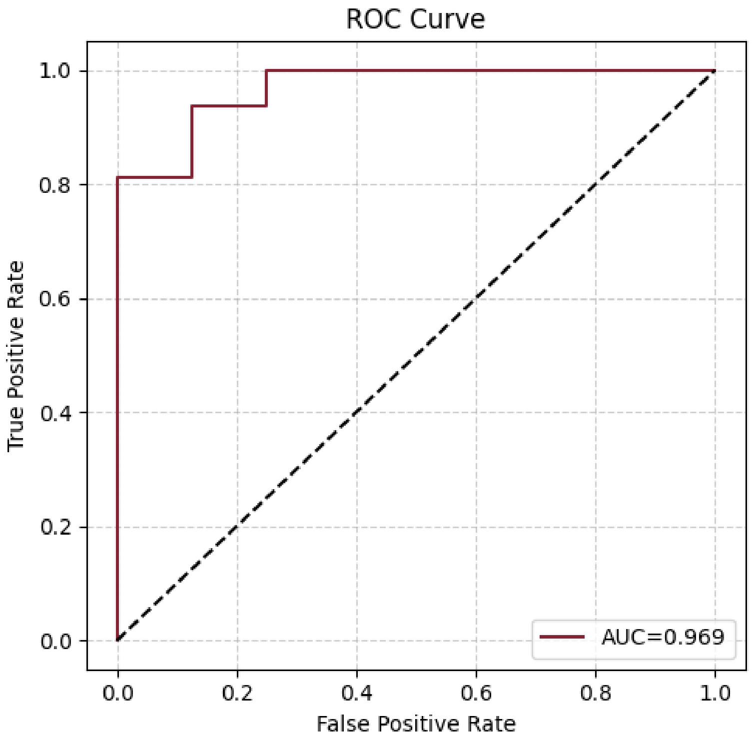
Just Pretraining

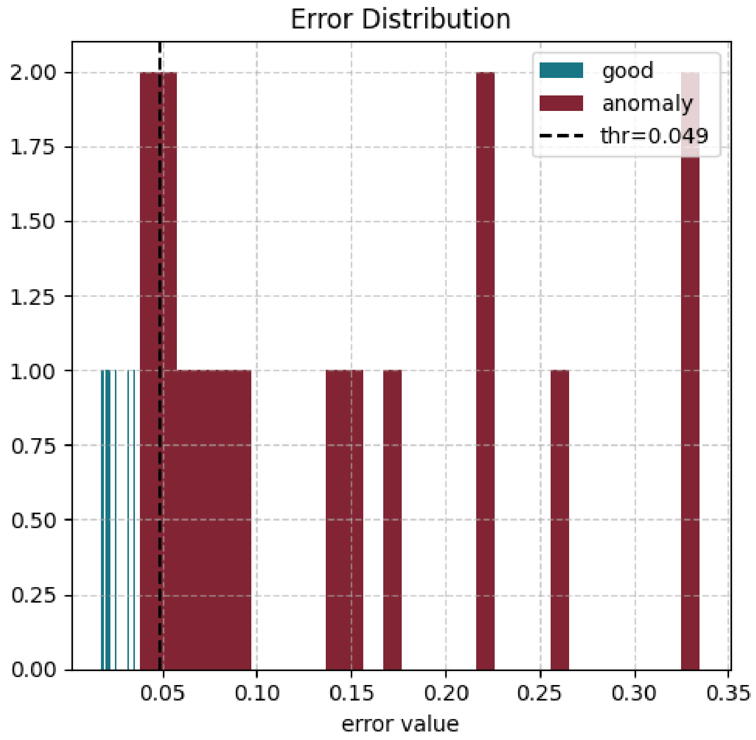


After Fine Tuning

Evaluation methods

- PRO: Per Region Overlap
- AUROC
- F1= $\frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$





What did we accomplish?

	AUC	F1 -Score	AUPRO
Bottle	0.48	0.86	0.33
Cable	0.51	0.75	0.3
Capsule	0.58	0.90	0.21
Carpet	0.38	0.86	0.47
Grid	0.82	0.84	0.41
Hazelzut	0.81	0.77	0.72
Leather	0.68	0.85	0.46
Metal Nut	0.34	0.9	0.70
Pill	0.67	0.92	0.76
Tile	0.72	0.83	0.46
ToothBrush	0.37	0.84	0.74
Transistor	0.38	0.57	0.39
Wood	0.85	0.86	0.46
Zipper	0.46	0.88	0.39
01	0.25	0.83	0.65
02	0.71	0.93	0.43
03	0.44	0.17	0.58

Category	1-NN	OC SVM	VT-ADL (Ours)
Carpet	0.512	0.355	**0.773**
Grid	0.228	0.125	**0.871**
Leather	0.446	0.306	0.728
Tile	0.822	0.722	0.796
Wood	0.502	0.336	**0.781**
Bottle	0.898	0.85	**0.949**
Cable	0.806	0.431	0.776
Capsule	0.631	0.554	0.672
Hazelnut	0.861	0.616	0.897
Metal Nut	0.705	0.319	0.726
Pill	0.725	0.544	0.705
Screw	0.604	0.644	**0.928**
Toothbrush	0.675	0.538	**0.901**
Transistor	0.68	0.496	**0.796**
Zipper	0.512	0.355	0.808
Means	0.64	0.479	0.807

Prdt	**PRO Score ours**	**PR AUC ours**	AE MSE	AE MSE+SSIM
0	*0.92*	0.99	0.49	0.53
1	*0.89*	0.94	0.92	0.96
2	*0.86*	0.77	0.95	0.89
Mean	*0.89*	**0.90**	0.78	0.79

TABLE IV

Some Baseline PRO Scores

Is DyT worth it?

	DyT	LayerNorm
FLOPs	2955149312	2936799232
GPU Inference Time [ms]	12.57	14.27
CPU Inference Time [ms]	141.25	127.83

Further developments…

More epochs!
We tried one class 200 epochs pre-training!

New per class specific tailored augmentation:
we have 3 and 4 transf. Based on class type, we could improve

Min-Max game:
Adversarial finetuning with CNN

What we did and what we learnt

- With great datasets come great challanges: started with one class, ended with 18, everyone has its own character!
- Start small and grow big: in a limited resources context a small ViT could be the best option
- Stay dynamic: from normalization to threshold definition, adaptive and tailored solutions works better
- Computer vision engineers have no time to sleep

References

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