Improved anomaly detection by training an autoencoder with skip connections on images corrupted with Stain-shaped noise

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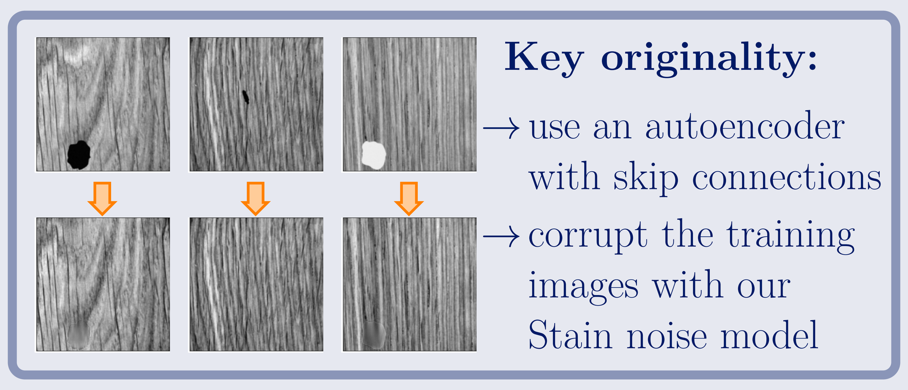
Overview: Our anomaly detection framework

We train an **AutoEncoder with Skip connections (AESc)** to reconstruct a clean version of an arbitrary input image.

Step 1 - Train an AESc to reconstruct a clean image (Dataset = clean images only!)



Step 2 - Detect anomalies on new images (Dataset = arbitrary image, i.e. with or without defects)

Anomalies are detected based on the reconstruction residual or uncertainty. Validation of the framework has been conducted over the MVTec AD dataset [1].

Keep in touch!

We would be happy to share additional knowledge/experiments with you. Do not hesitate to contact us!

Our implementation is available on Github.

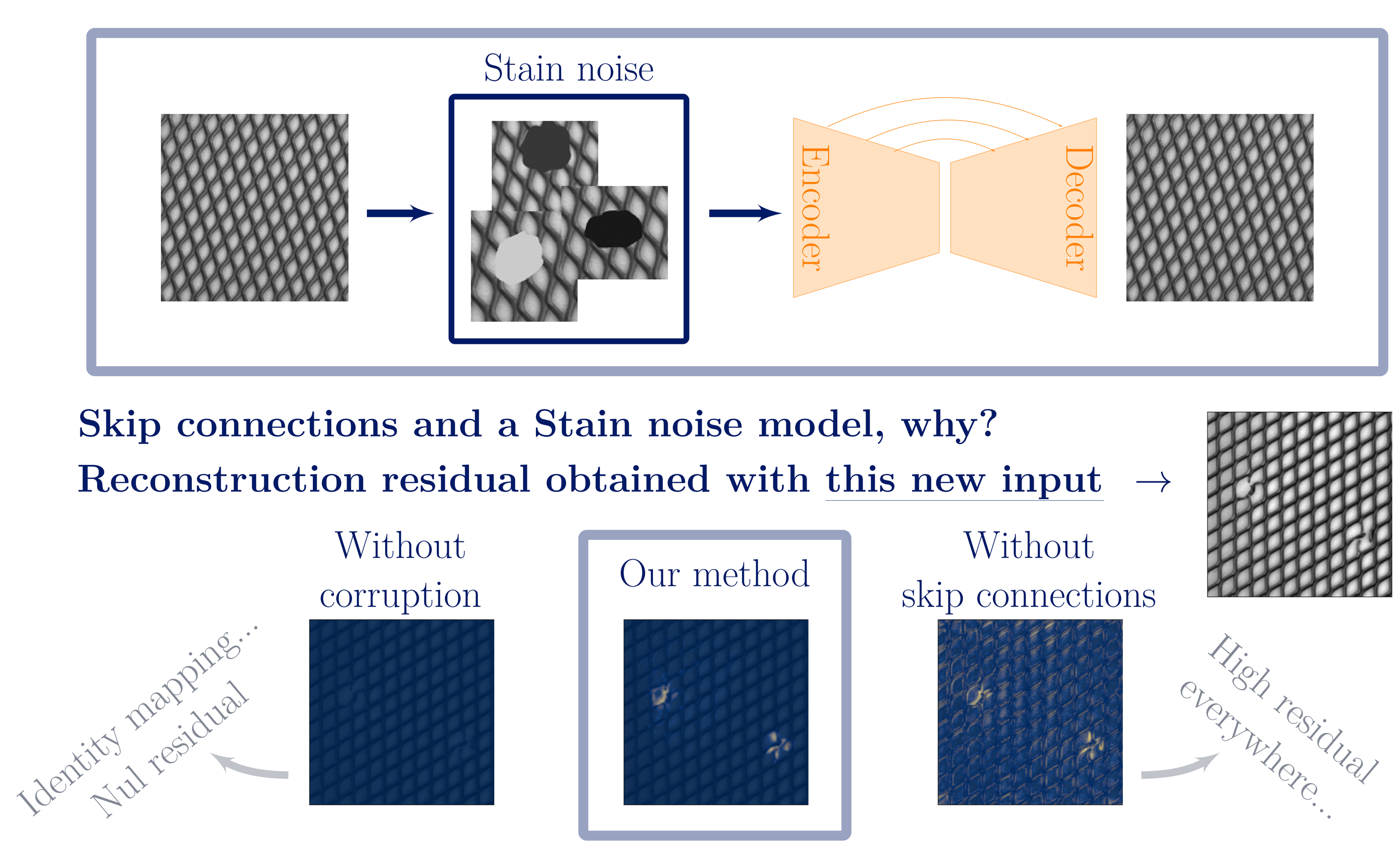
`https://github.com/anncollin/AnomalyDetection-Keras`

References

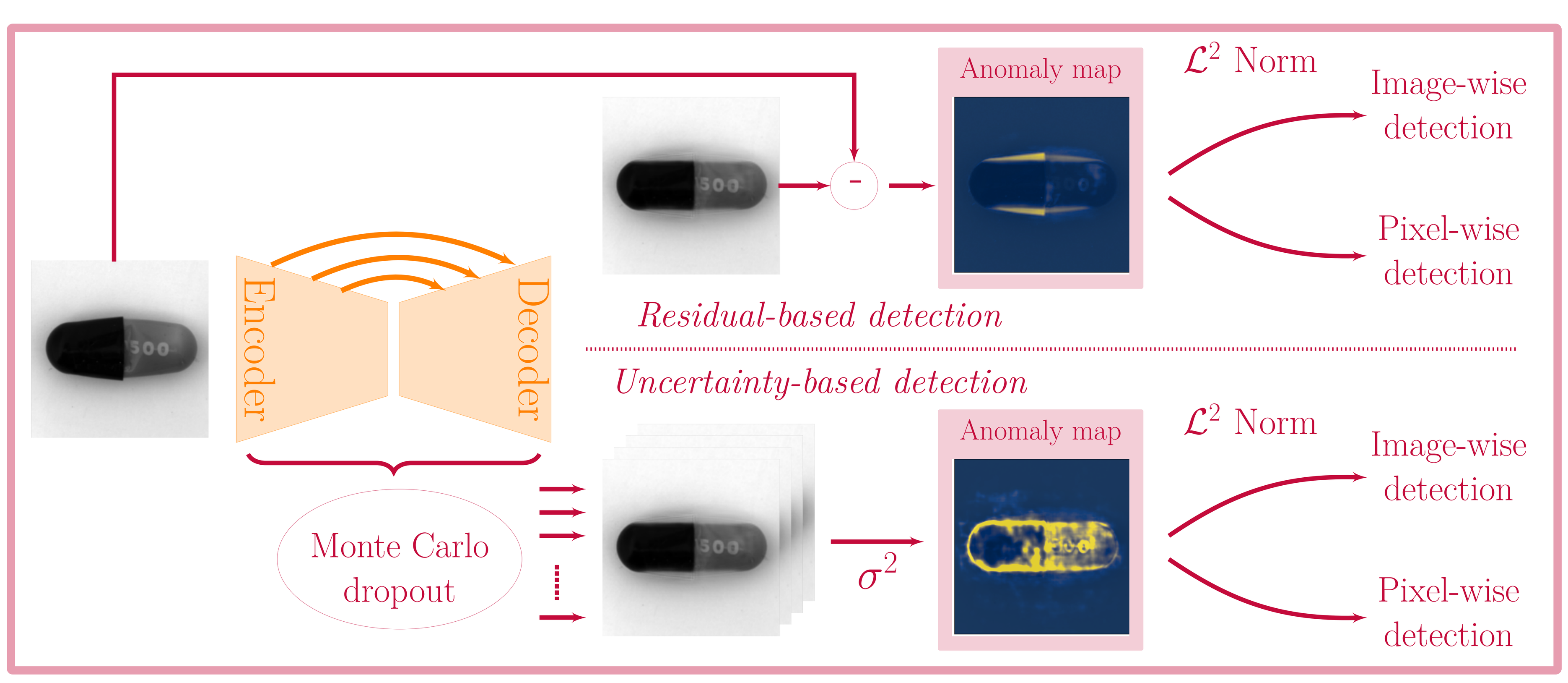
[1] Paul Bergmann, Michael Fauser, David Sattlegger, and Carsten Steger. MVTec AD - A Comprehensive Real-World Dataset for Unsupervised Anomaly Detection. *Cvpr 2019*, pages 9592–9600, 2019.

[2] Chaoqing Huang, Jinkun Cao, Fei Ye, Maosen Li, Ya Zhang, and Cewu Lu. Inverse-Transform AutoEncoder for Anomaly Detection. *arXiv preprint arXiv:1911.10676*, 2019.

Step 1 - Training



Step 2 - Detect anomalies



Quantitative Results

We compared our approach (Uncertainty- & Residual-based detection) with 2 SotA methods:

- ITAE [2] for Image-Wise detection
- AE_{L2} [1] for Pixel-Wise detection

		Image-Wise Detection			Pixel-Wise Detection		
		Unc.	**Res.**	**ITAE [2]**	**Unc.**	**Res.**	**AE_{L2} [1]**
Textures	Carpet	0.80	**0.89**	0.71	**0.91**	0.79	0.59
	Grid	**0.97**	**0.97**	0.88	**0.95**	0.89	0.90
	Leather	0.72	**0.89**	0.87	0.87	**0.95**	0.75
	Tile	0.95	**0.99**	0.74	**0.79**	0.74	0.51
	Wood	0.78	**0.95**	0.92	**0.84**	**0.84**	0.73
	Mean	0.84	**0.94**	0.82	**0.87**	0.84	0.70
Objects	Bottle	0.82	**0.98**	0.94	**0.88**	0.84	0.86
	Cable	0.87	**0.89**	0.83	0.84	0.85	**0.86**
	Capsule	0.71	**0.74**	0.68	**0.93**	0.83	0.88
	Hazelnut	0.90	**0.94**	0.86	0.89	0.88	**0.95**
	Metal Nut	0.62	**0.73**	0.67	0.62	0.57	**0.86**
	Pill	0.62	**0.84**	0.79	**0.85**	0.74	**0.85**
	Screw	0.80	0.74	**1.00**	0.95	0.86	**0.96**
	Toothbrush	0.99	**1.00**	**1.00**	**0.93**	**0.93**	**0.93**
	Transistor	0.90	**0.91**	0.84	0.78	0.80	**0.86**
	Zipper	0.93	**0.94**	0.80	**0.90**	0.78	0.77
	Mean	0.82	**0.87**	0.84	0.86	0.81	**0.88**
	Global mean	0.83	**0.89**	0.84	**0.86**	0.82	0.82

+12% +17%

+3% -2%

+5% +4%

Our method is extremely effective on textures!

Residual indicator works well for **Image-Wise detection**
Uncertainty indicator works well for **Pixel-Wise detection**

Qualitative Results

Residual & Uncertainty indicators handle low contrast defects differently