Deep generative networks for anomaly detection from ultrasound images of materials

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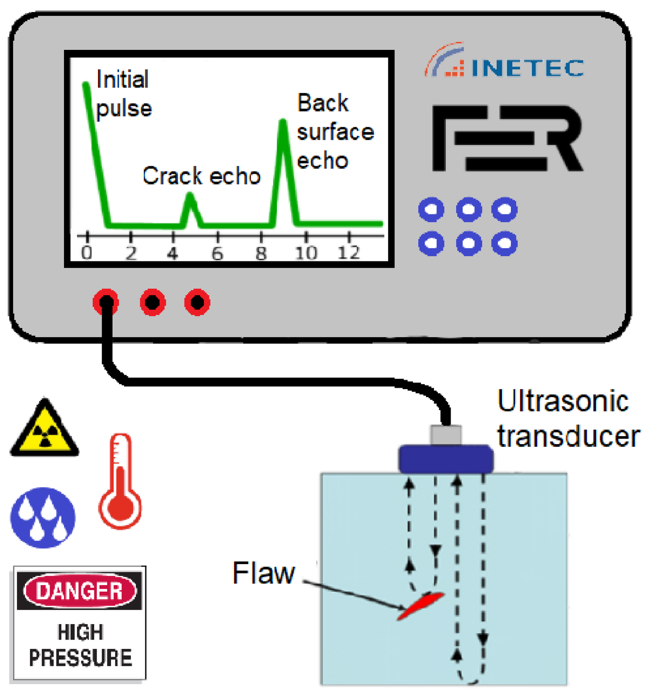
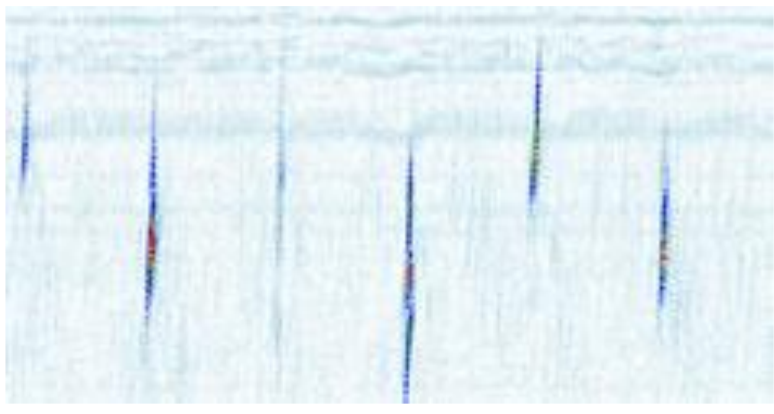
1. Introduction

Ultrasonic testing (UT)

- Type of non-destructive evaluation
- Advantages: simplicity, efficiency, reliability, precision
- Main drawback: **vast amounts of generated data**
- "SmartUTX" project:
  - "Smart" – artificial intelligence and advanced image processing techniques
  - "UT" – ultrasonic testing
  - "X" – extreme conditions





2. Problem Description

Defects

- Hard to distinguish from noise and geometry signals
- Very rare, vary in size and intensity → **traits of anomalies**

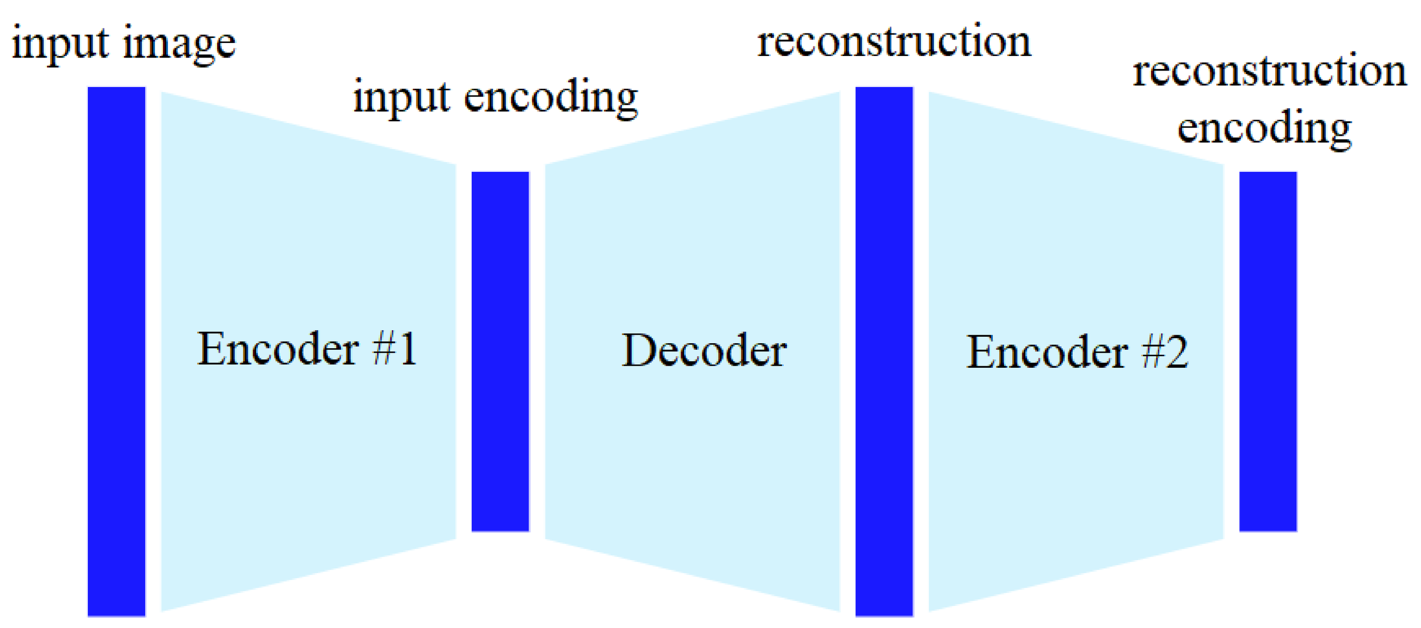
Anomaly (defect) detection (AD)

- Unsupervised or semi-supervised – **using only normal images**, i.e., the ones without defects
- Creating **representations of „normality"** to detect anomalies → generative networks

3. Methodology

Variational autoencoder (VAE)

- Trained to reconstruct the input
- Also learns a latent representation of the input based on a set of normal (Gaussian) distributions → μ_z and σ_z
- AD criteria – reconstruction quality and deviations from ideal distributions → anomalies should stand out
- Adding **another encoder at the VAE output** and training it to give the same representation as the first encoder creates new criteria [1]
  - **Differences between input and reconstruction encodings**



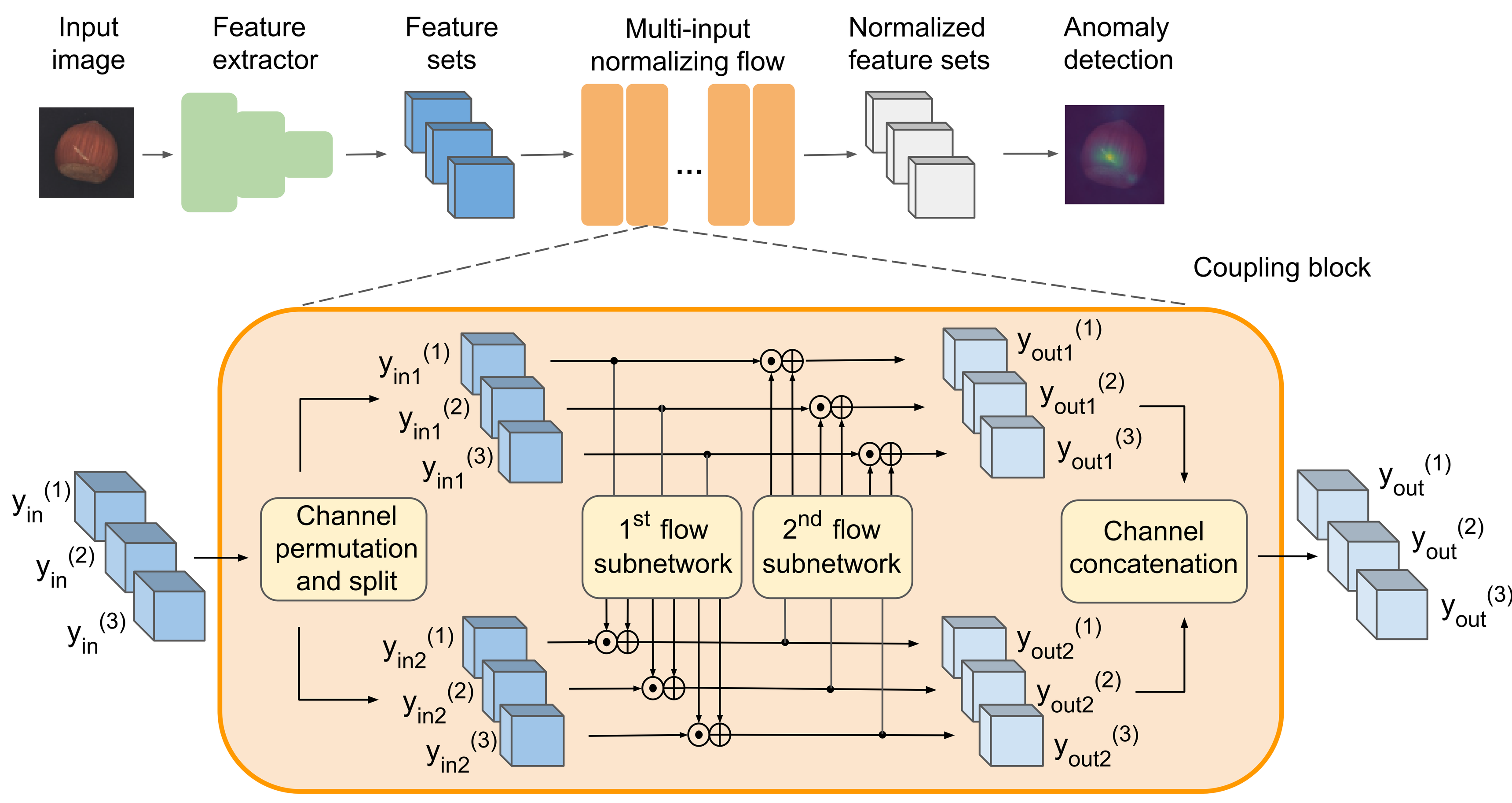
Architecture of the VAE with an additional encoder

Normalizing flow (NF)

- Performs density estimation → used for AD
- Uses bijective transformations (e.g., '+' and '·') to reduce input distributions to normal distributions in the output
- Trained by maximizing log-likelihood

$$p_X(\boldsymbol{x}) = p_Z(\boldsymbol{z}) \left|\det \frac{\partial \boldsymbol{z}}{\partial \boldsymbol{x}}\right| \qquad \log p_X(\boldsymbol{x}) = \log p_Z(\boldsymbol{z}) + \log \left|\det \frac{\partial \boldsymbol{z}}{\partial \boldsymbol{x}}\right|$$

- Significant reduction in model size and using simpler feature extractors improve AD



NF's AD pipeline and architecture of one coupling block

4. Results

VAE

AUC-ROC values [%] for used AD criteria				
Reconstruction error	μ_z deviation	σ_z deviation	**μ_z difference**	σ_z difference
54.39	59.35	58.32	**69.37**	63.2

The additional encoder gives significantly better criteria because it makes excellent use of the information present in the reconstructions.

NF

AUC-ROC values [%] for state-of-the-art methods			
GANomaly	PaDiM	DifferNet	**Our NF**
73.0	81.9	74.8	**82.8**

The multi-input NF achieves higher results than state-of-the-art AD methods [2]. NFs have already proven to be good AD methods, but the simplifications we introduced gave a model adapted to the relatively simple structures seen in UT data.

5. Conclusion

Generative methods have previously already shown their applicability in AD. Anomalies in ultrasound images of materials pose a difficult problem, even for such methods. Our proposed modifications improve their results and reliability, as well as reduce computational requirements.

Acknowledgments

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References

[1] F. Milković et al., Ultrasound Anomaly Detection Based on Variational Autoencoders, 12th ISPA, Zagreb, Croatia, 2021, https://doi.org/ 10.1109/ISPA52656.2021.9552041.
[2] L. Posilović et al., Deep learning-based anomaly detection from ultrasonic images, Ultrasonics 124, 2022, https://doi.org/10.1016/j.ultras.2022.106737

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