



Towards Explaining SEM Defect Image Classification

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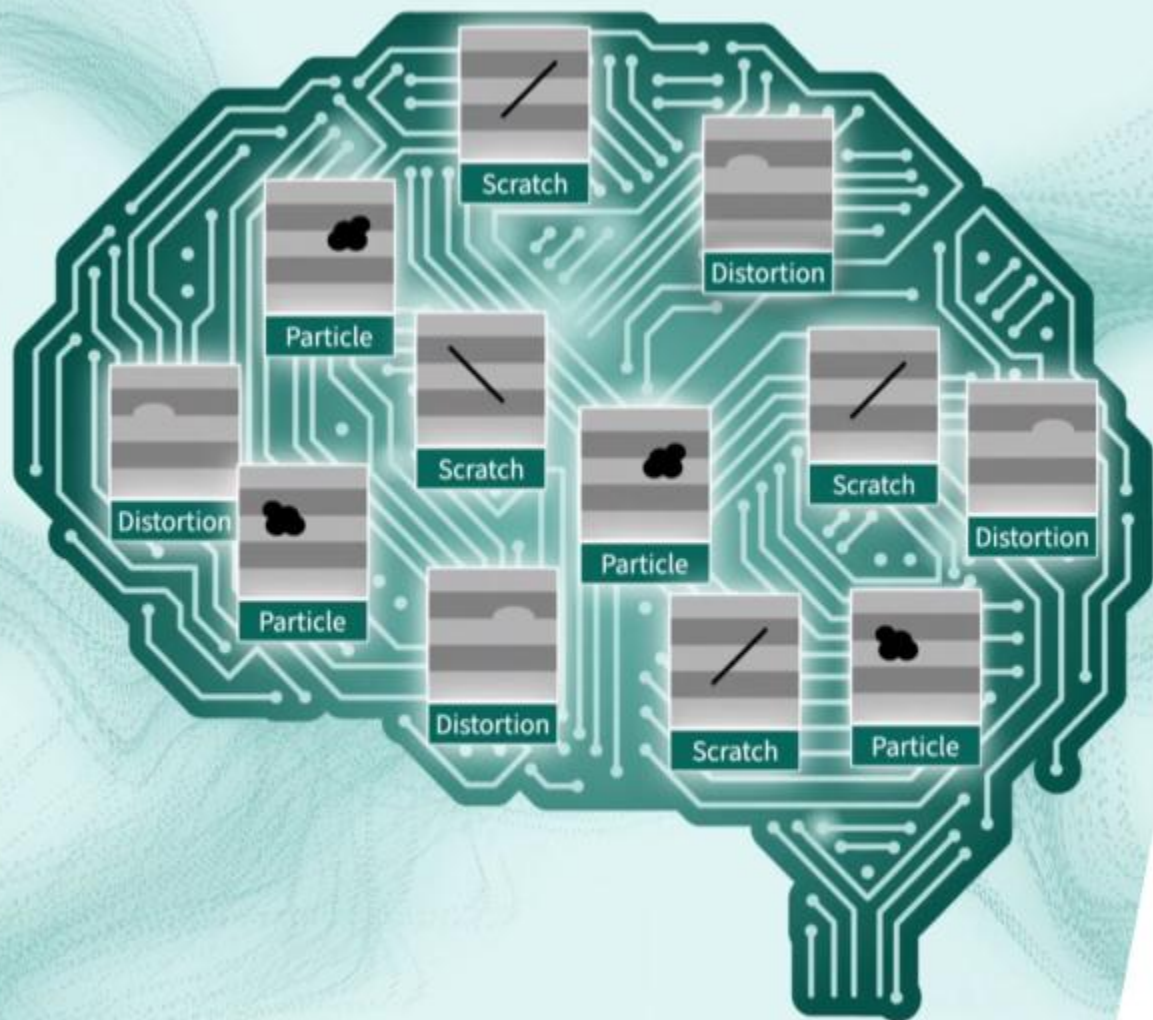
KAI GmbH

Data Science, Computer Vision



Olivia Pfeiler

Head of KAI Data Science



CoDIAC: AI-Powered Defect Image Classification



Objective classification



Time efficiency



Resource optimization



Motivation

Why explainable AI?



Increased trust in AI models



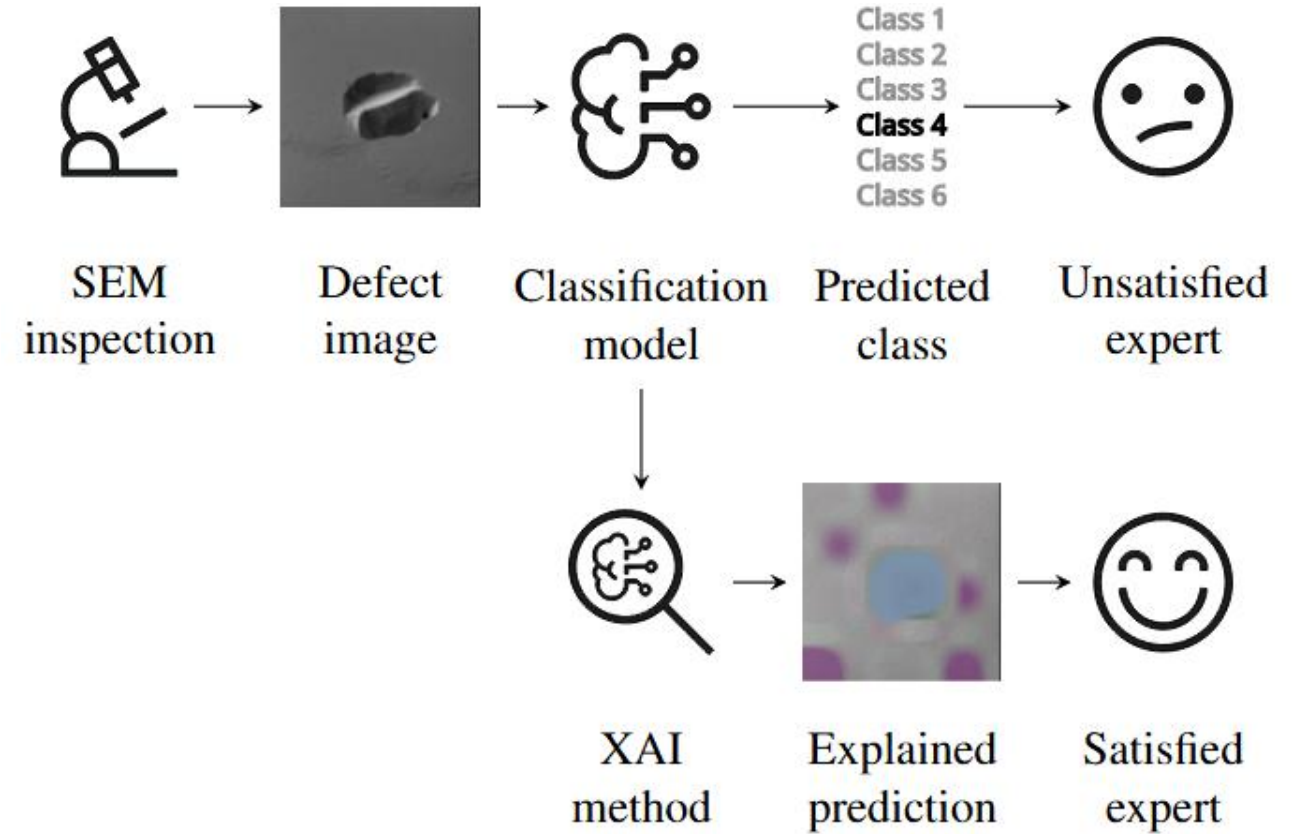
Improved debugging of AI models



Increased transparency of AI models



Regulatory and ethical concerns



Application paper under review at the European Conference on Artificial Intelligence (ECAI 2025)

Dataset

We used the public Carinthia dataset for our research

Images

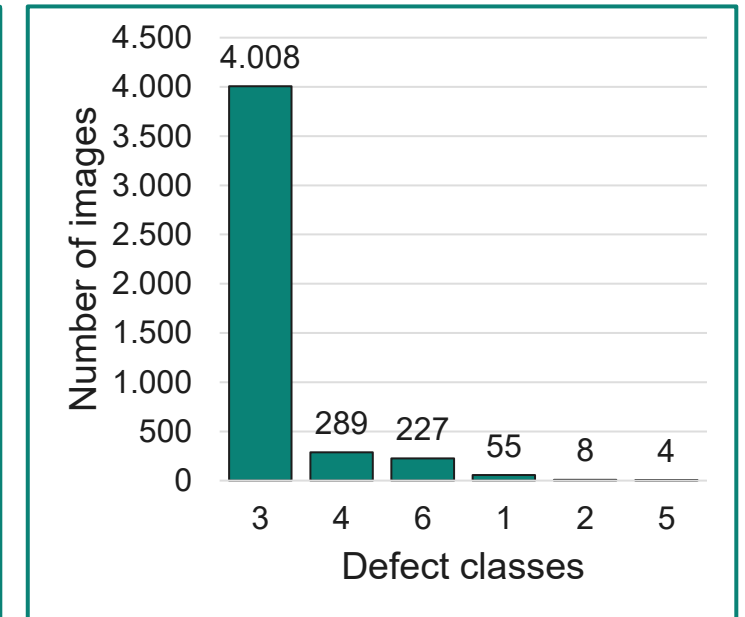
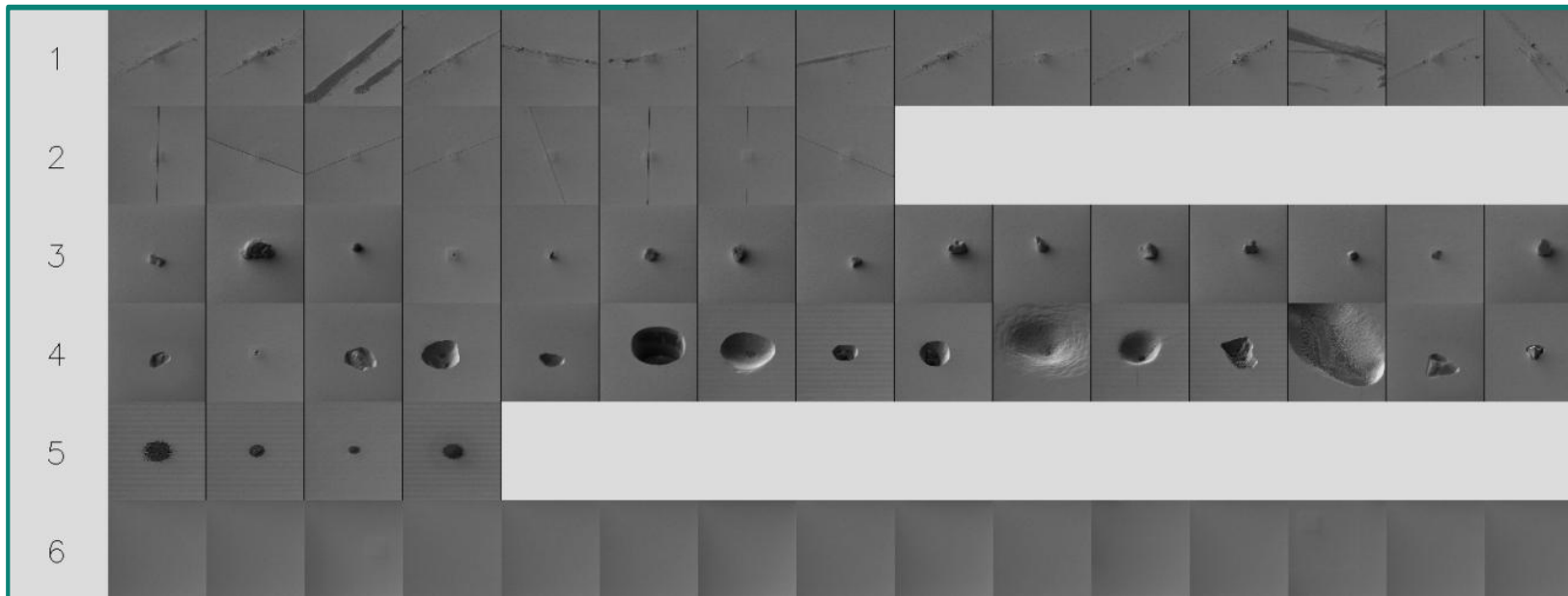
- Historical images from the production database

Labeling

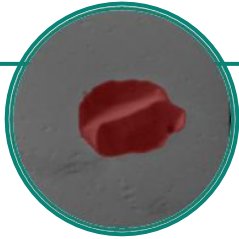
- Defined 6 expert defect classes
- Expert labeled ~4.600 images

Published

- [Carinthia dataset publicly available on Zenodo](#)



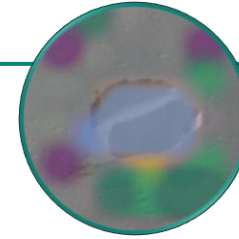
Automatic mask generation



SAM2¹

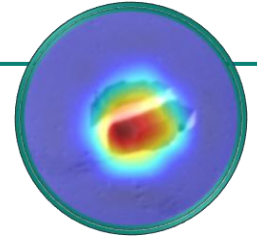
- Automatic mask generation using SAM2
- Expert validation of ground truth masks
- Carinthia-S dataset with ground truth segmentation masks

Evaluation of XAI methods on the Carinthia-S dataset



CRAFT²

- Concept Recursive Activation FacTORIZATION
- Concept-based explanations
- Provide explanations in form of human-understandable concepts



GradCAM³

- Gradient-weighted class activation
- Feature-based explanations
- Provide explanations in form of saliency maps

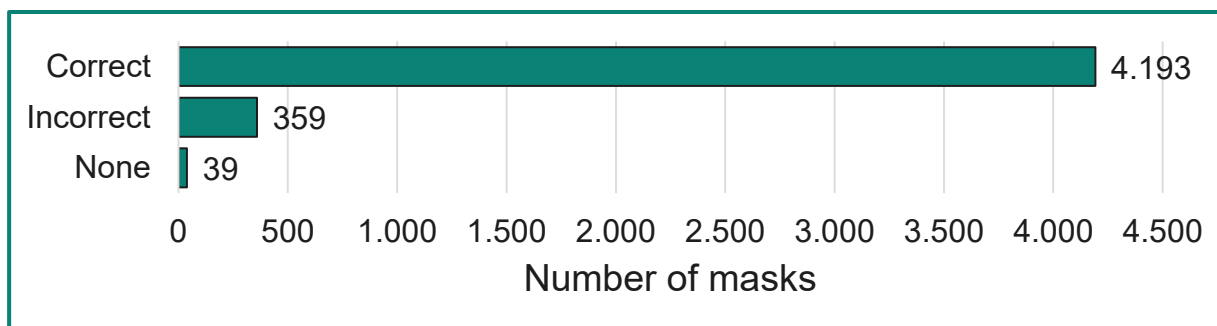
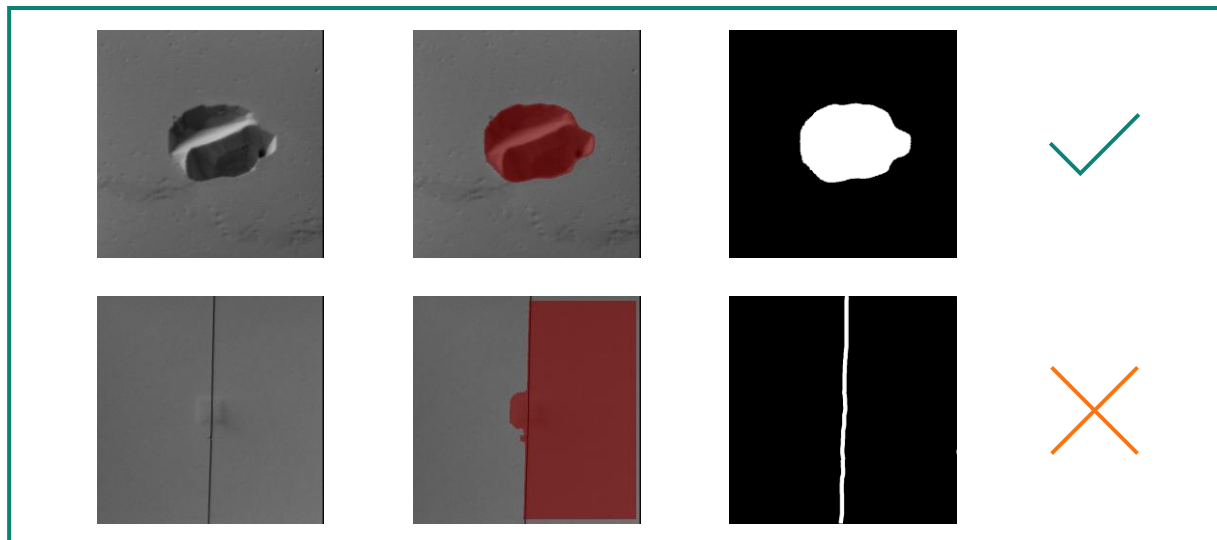
1. Ravi N, Gabeur V, Hu YT, Hu R, Ryali C, Ma T, Khedr H, Rädle R, Rolland C, Gustafson L, Mintun E. Sam 2: Segment anything in images and videos. arXiv preprint arXiv:2408.00714. 2024 Aug 1.

2. Fel, Thomas, et al. "Craft: Concept recursive activation factorization for explainability." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2023.

3. Selvaraju, Ramprasaath R., et al. "Grad-cam: Visual explanations from deep networks via gradient-based localization." Proceedings of the IEEE international conference on computer vision. 2017.

Contributions

Generating ground truth masks with SAM2



Algorithm 1 Ground Truth Generation

Input: Image $x \in \mathbb{R}^{H \times W \times 3}$

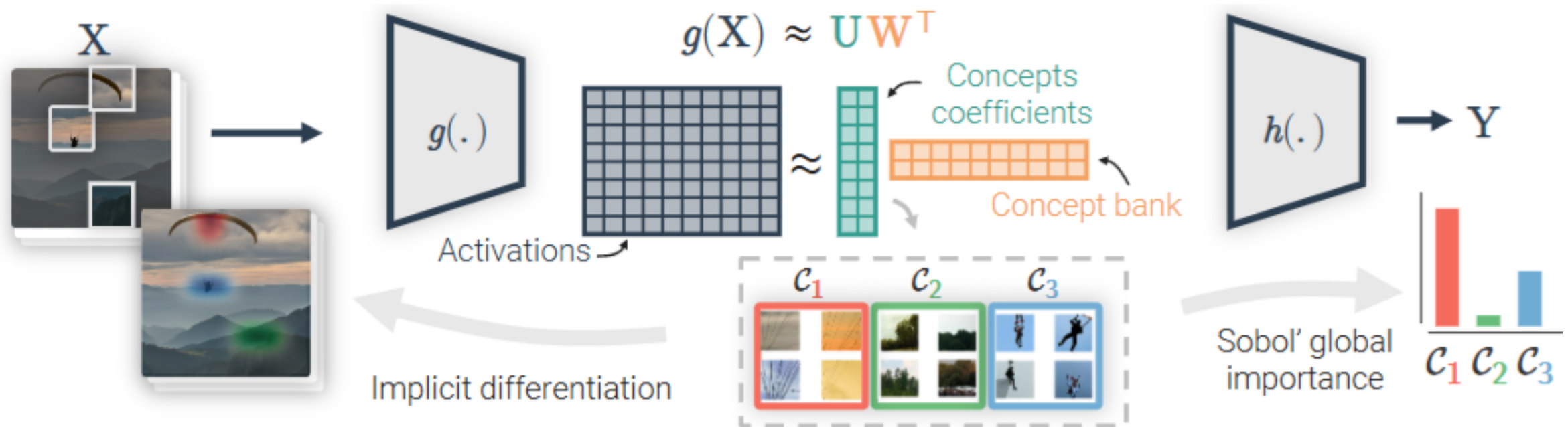
Output: Binary mask $M \in \{0, 1\}^{H \times W}$

- 1: **Stage 1:** $\mathcal{M} = \{M_1, M_2, \dots, M_n\} \leftarrow \text{SAM2}(x)$ {Generate candidate masks}
- 2: **for** $i = 1$ to n **do**
- 3: $A_i \leftarrow \sum_{p \in M_i} 1$ {Calculate area}
- 4: $C_i \leftarrow \frac{1}{A_i} \sum_{p \in M_i} p$ {Calculate centroid}
- 5: $d_i \leftarrow \frac{\|C_i - C_I\|}{\sqrt{H^2 + W^2}}$ {Normalized distance to image center}
- 6: $S_i \leftarrow A_i \cdot (1 - d_i)^\alpha$ { α : center bias parameter}
- 7: **end for**
- 8: $M_k \leftarrow \arg \max_i S_i$ s.t. $A_i > \beta \cdot H \cdot W$ { β : min area ratio}
- 9: **Stage 2:** $M' \leftarrow 1 - M_k$ {Invert mask}
- 10: $\{C_1, C_2, \dots, C_m\} \leftarrow \text{ConnectedComponents}(M')$
- 11: $j \leftarrow \arg \max_i |C_i|$ {Find largest component}
- 12: $M[p] \leftarrow \begin{cases} 1, & \text{if } p \in C_j \\ 0, & \text{otherwise} \end{cases}$ {Final binary mask}
- 13: **return** M
- 14: **Stage 3:** Experts manual validation of generated masks.

Ravi N, Gabeur V, Hu YT, Hu R, Ryali C, Ma T, Khedr H, Rädle R, Rolland C, Gustafson L, Mintun E. Sam 2: Segment anything in images and videos. arXiv preprint arXiv:2408.00714. 2024 Aug 1.

Contributions

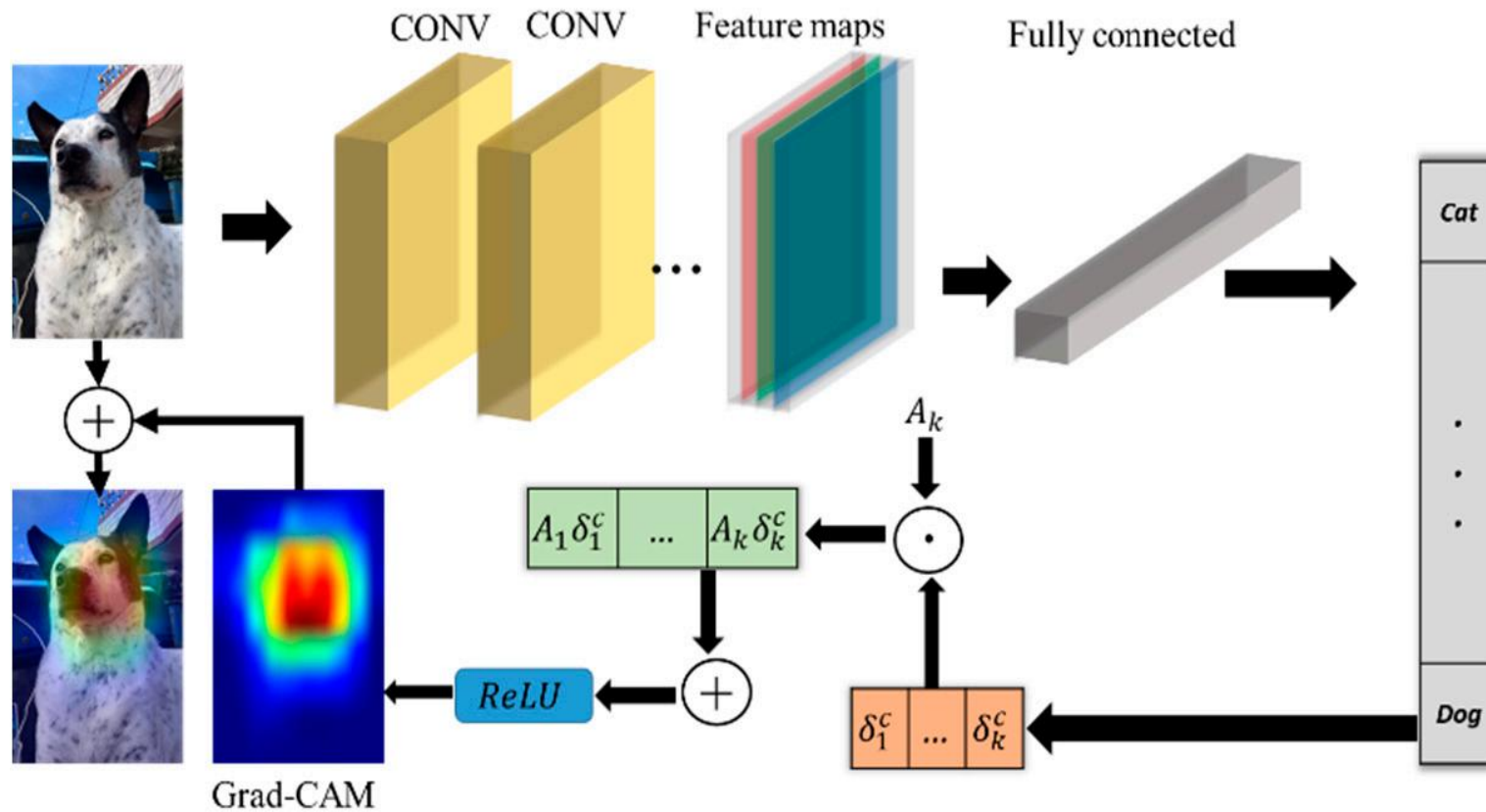
Explaining image classifications with CRAFT



Fel, Thomas, et al. "Craft: Concept recursive activation factorization for explainability." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2023.

Contributions

Explaining image classifications with GradCAM

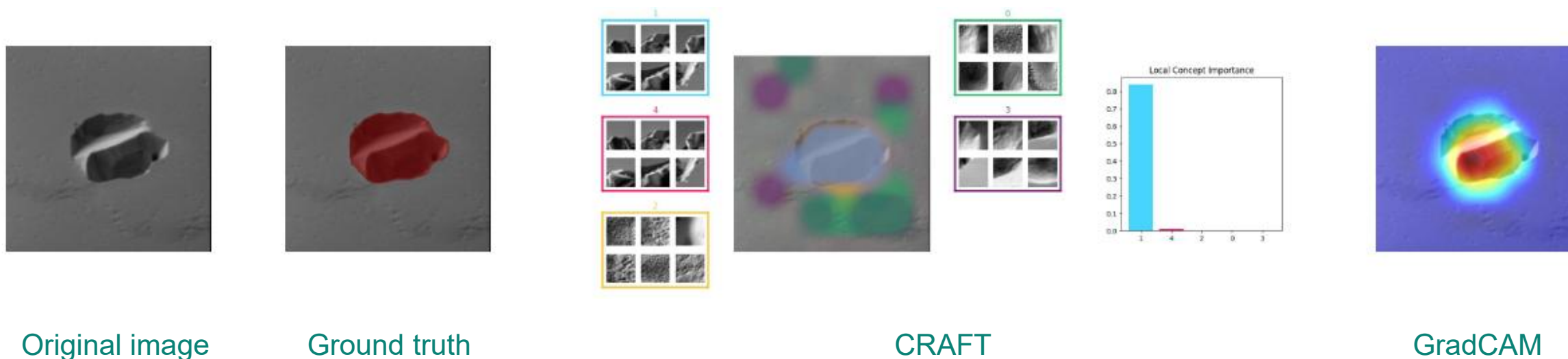


Selvaraju, Ramprasaath R., et al. "Grad-cam: Visual explanations from deep networks via gradient-based localization." Proceedings of the IEEE international conference on computer vision. 2017.

Results

Insights from qualitative evaluation of XAI methods

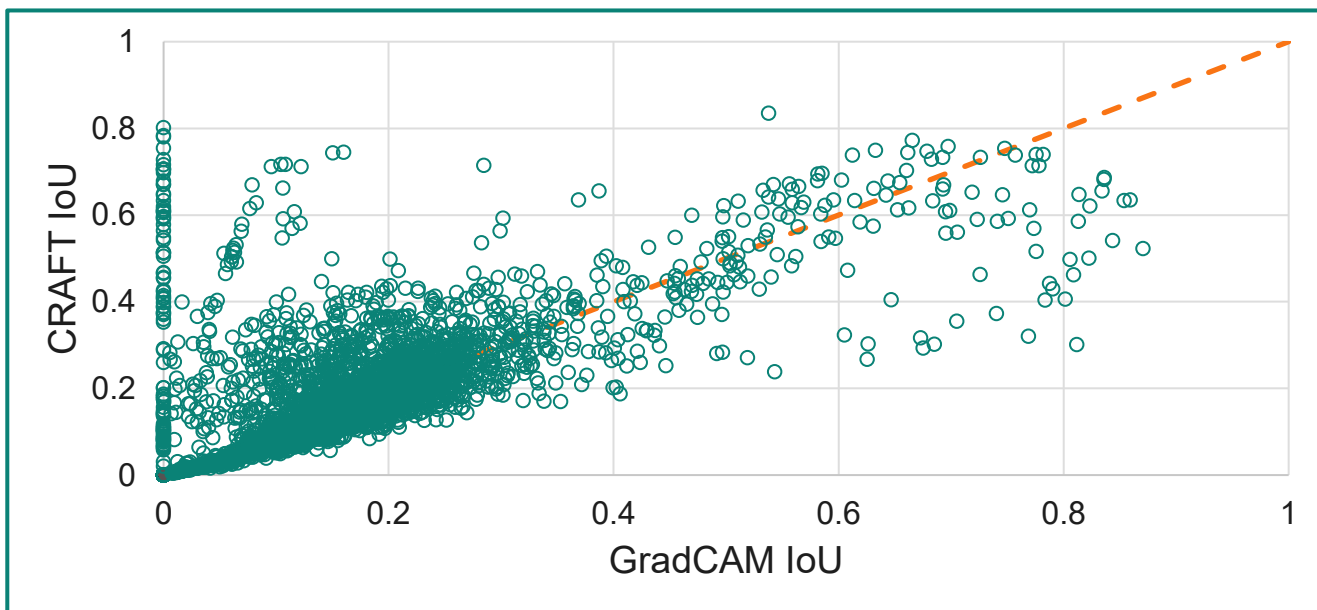
- GradCAM and CRAFT highlight critical regions relevant to the model's decision-making process
- CRAFT is resilient to imperceivable image changes
- CRAFT enhances interpretability by visualizing meaningful concepts that influence predictions



Results

Quantitative evaluation of XAI methods

Method	Accuracy	Precision	Recall	Dice	IoU
CRAFT	0.899 ± 0.028	0.179 ± 0.165	0.925 ± 0.232	0.269 ± 0.171	0.168 ± 0.132
GradCAM	0.907 ± 0.075	0.164 ± 0.138	0.851 ± 0.295	0.254 ± 0.154	0.156 ± 0.118



Algorithm 2 Binary Mask Extraction from GradCAM

Input: GradCAM explanation $e_{gc} \in \mathbb{R}^{H \times W \times 3}$, Threshold $\tau \in [0, 1]$

Output: Binary mask $M_{gc} \in \{0, 1\}^{H \times W}$

1: $e \leftarrow e_{gc}[:, :, 0]$ {Red activation}

2: $e_{\text{norm}} \leftarrow \frac{e}{\max(e)}$

3: $M \leftarrow \mathbf{1}_{e_{\text{norm}} > \tau}$

4: **return** M

Algorithm 3 Binary Masks Extraction from CRAFT

Input: CRAFT explanation $e_c \in \mathbb{R}^{H \times W \times 3}$, Concept colors $\mathcal{C} = \{c_1, c_2, \dots, c_k\}$, $c_i \in \mathbb{R}^3$, Color tolerance $\delta \in \mathbb{R}^+$

Output: Binary concept masks $M = \{M_1, M_2, \dots, M_k\}$, $M_i \in \{0, 1\}^{H \times W}$

1: $e \leftarrow \text{Crop}(e_c)$ {Crop to heatmap explanation}

2: **for** $i \in \{1, 2, \dots, k\}$ **do**

3: $D_i(x, y) \leftarrow \text{ExtractConceptMasks}(e_i, c_i)$ {Extract concept masks based on color distance}

4: $M_i \leftarrow \mathbf{1}_{D_i \leq \delta}$

5: **end for**

6: **return** M

Results

Key findings from expert user study



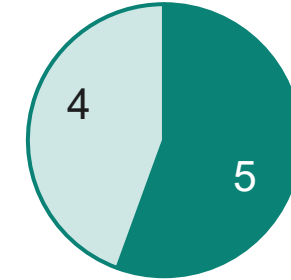
Participation of 9 experts



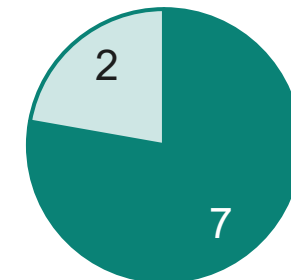
Evaluation using 5-point Likert explanation satisfaction

Questions

- Q1 From the explanation, I understand how the model works.
- Q2 This explanation of how the model works is satisfying.
- Q3 This explanation of how the model works has sufficient detail.
- Q4 This explanation of how the model works seems complete.
- Q5 This explanation of how the model works tells me how to use it.
- Q6 This explanation of how the model works is useful to my goals.
- Q7 This explanation of the model shows me how accurate the model is.
- Q8 This explanation lets me judge when I should trust and not trust the model



5/9 experts found the explanations understandable (3.6/5) and satisfying (3.4/5)



7/9 experts found explanation helped judging when to trust or distrust the model's prediction (3.8/5)

R. R. Hoffman, S. T. Mueller, G. Klein, and J. Litman. Metrics for explainable ai: Challenges and prospects. arXiv preprint arXiv:1812.04608, 2018.

Conclusion & outlook

Conclusion



Proposal of algorithm for automatic generation of ground truth masks for SEM defect images



Introduction of Carinthia-S dataset with expert validated ground truth segmentation masks



Novel application of CRAFT to enhance explainability in SEM defect image classification

Outlook



Application of methods on an internal more complex dataset



Enhancing robustness of automatic ground truth segmentation algorithm

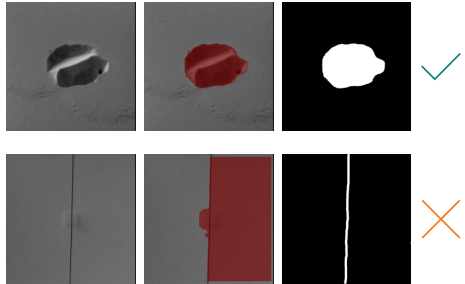


Dynamic hyperparameter tuning for CRAFT



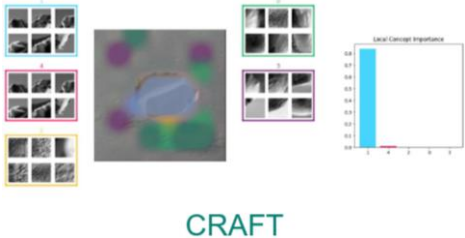
Improving CRAFT heatmap generation

Your input matters!



Automatic ground truth mask generation

- Who has experience with automatic ground truth mask generation?
- Are there recommendations for segmentation models with proven effectiveness?



XAI methods

- Who has experience with XAI methods for image classification?
- Are there recommendations for XAI methods with proven effectiveness?



Computer vision expertise

- Who among you is currently working on computer vision topics or knows someone who is?
- Collaboration and sharing insights on computer vision topics are always of great interest to us!

Thank you for your attention!



IPCEI Microelectronics and
Communication Technologies

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