Towards Explainable Defect Image Classification in Semiconductor Front-End Production

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Human Resources

Bridging Academia & Industry

University of Sarajevo

- Leading academic institution in Southeast Europe
- Strong expertise in engineering and technology research
- Global collaborator

KAI

- Industrial research center
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- Strong bridge between industry and academia

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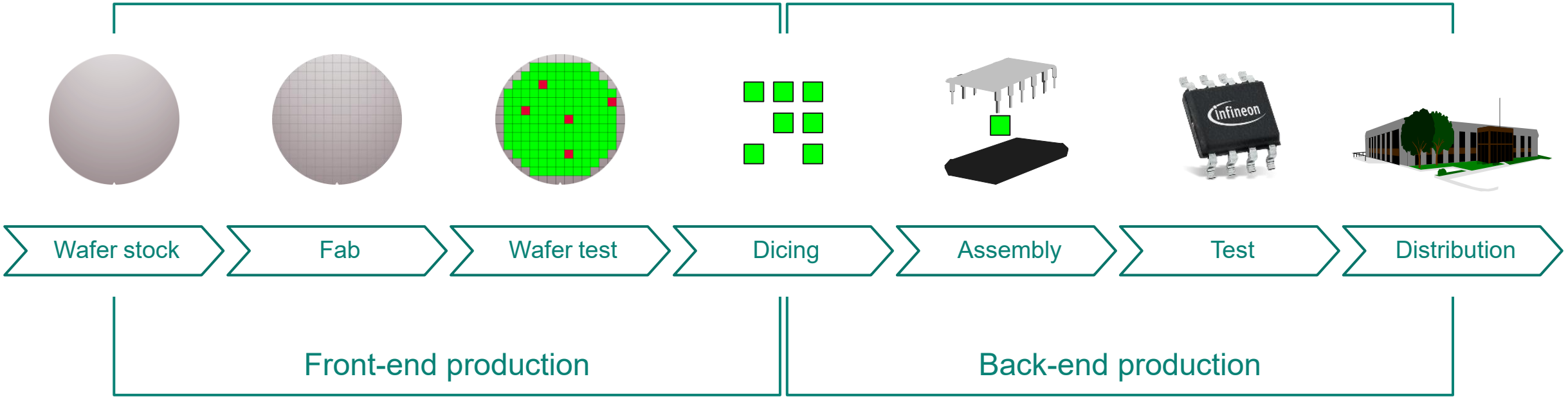
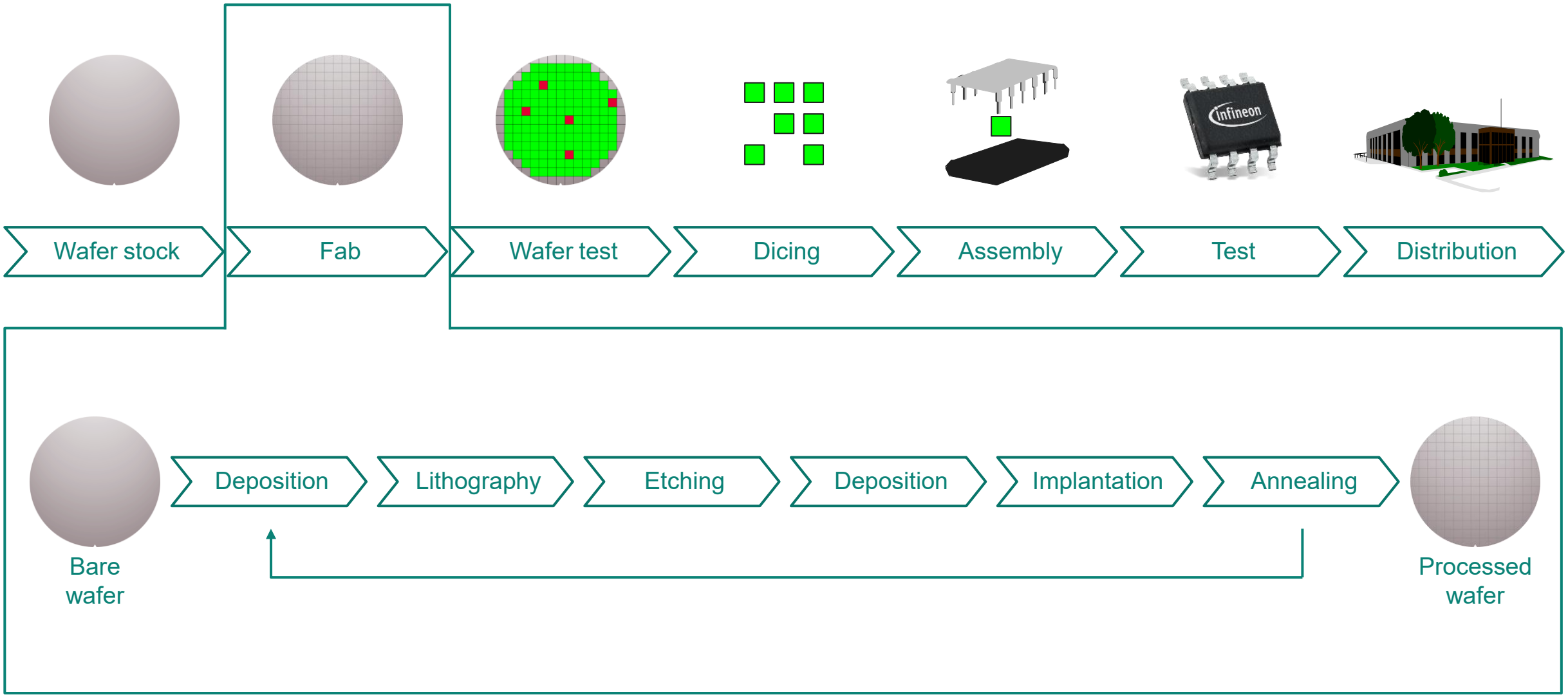
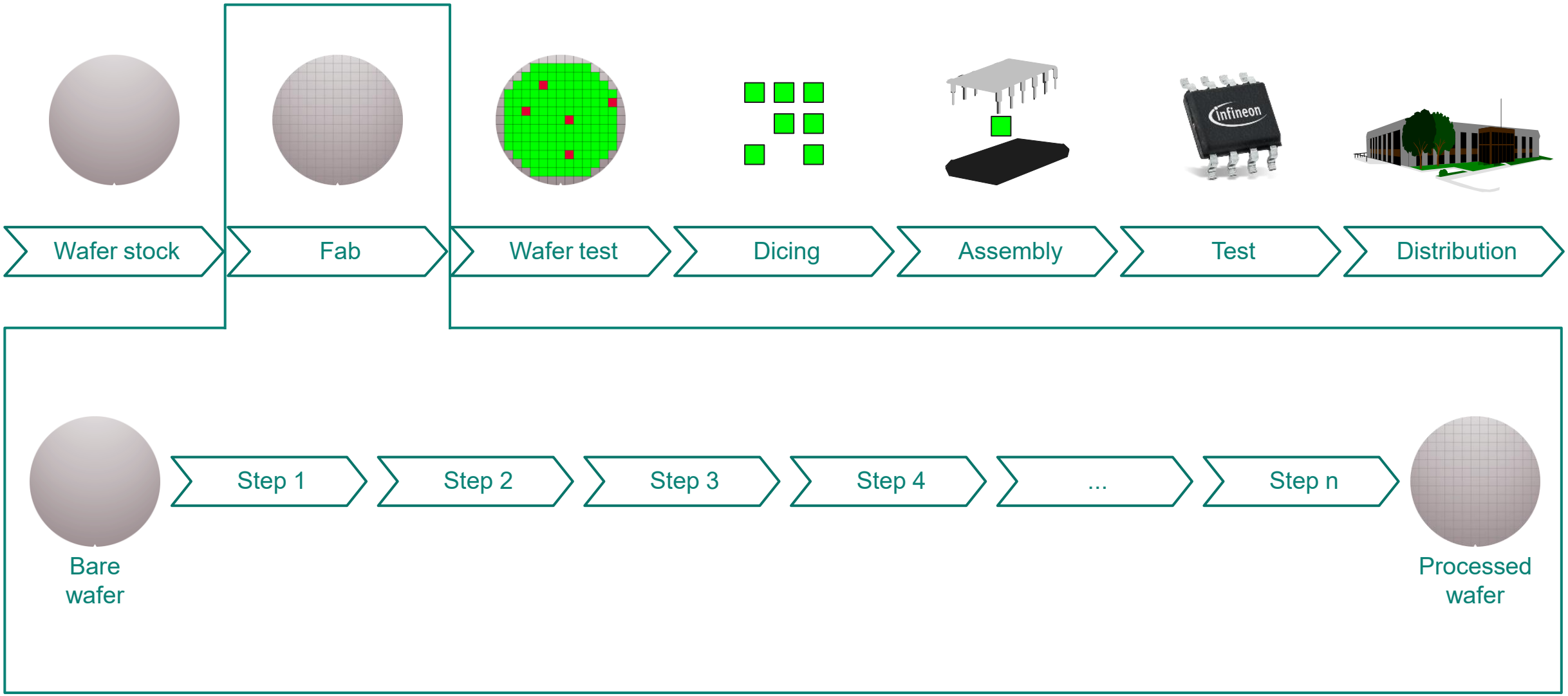
Semiconductor Production Processes



Front-End Production Processes

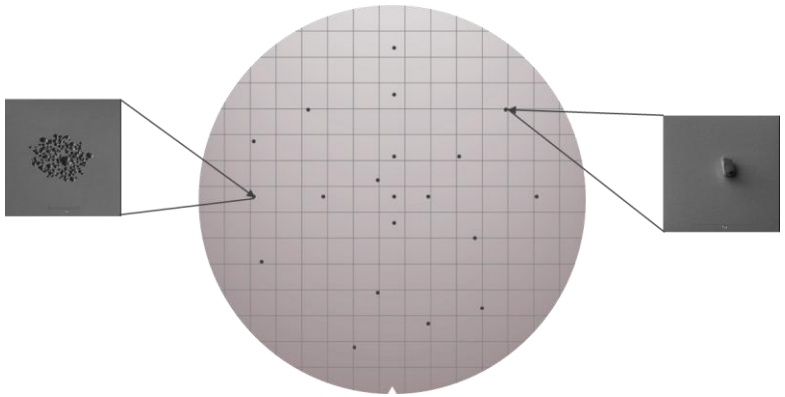


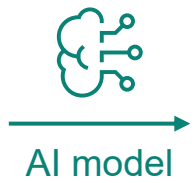
Front-End Production Processes

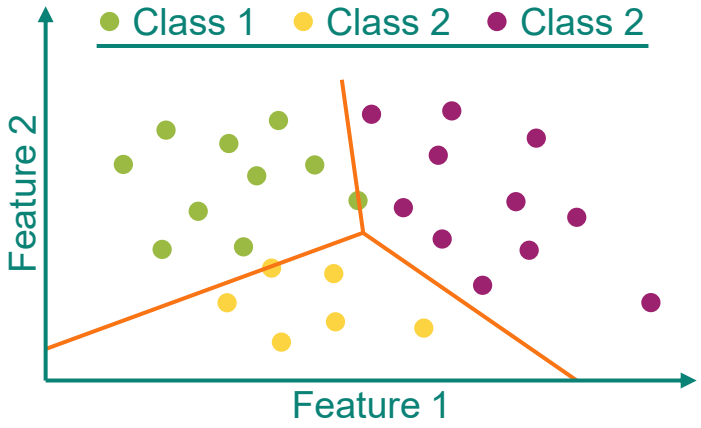


Quality Checks in Front-End Production

Defect Image Classification







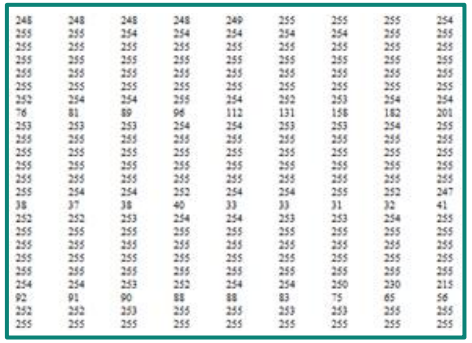
What is Computer Vision?

Automation of human visual tasks

Computer-enabled information extraction

Human vision vs. computer vision

What we see



What computers see

Some computer vision techniques

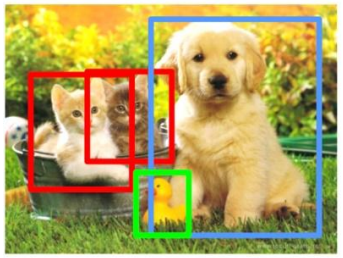
Classification

Cat

Classification + localization

Cat

Object detection



Cat, Dog, Duck

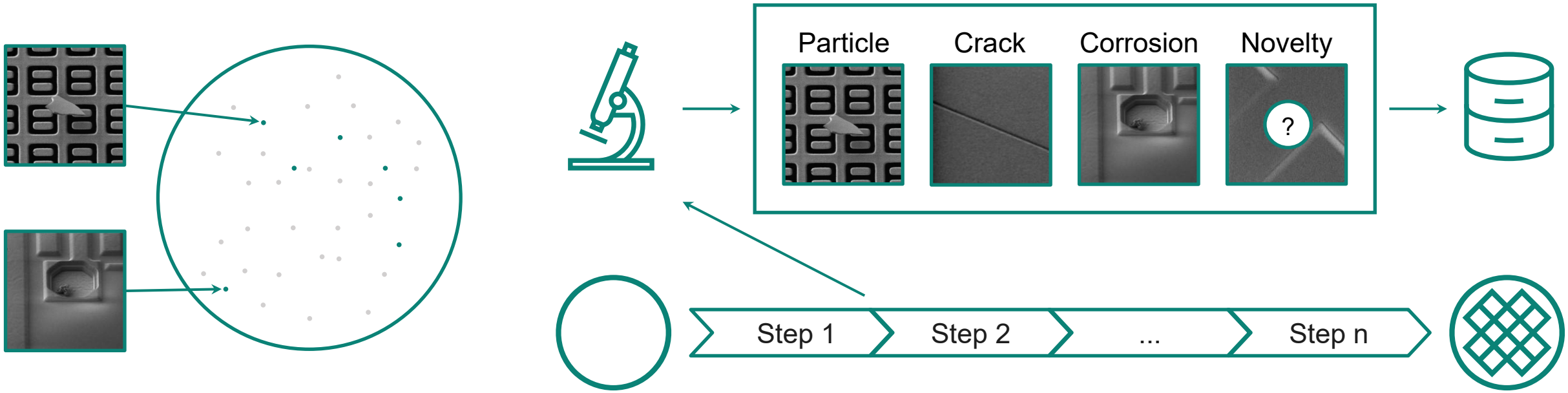
Instance segmentation

Cat, Dog, Duck

Source: https://www.augmentedstartups.com/blog/mastering-image-classification-techniques-enhancing-accuracy-and-efficiency

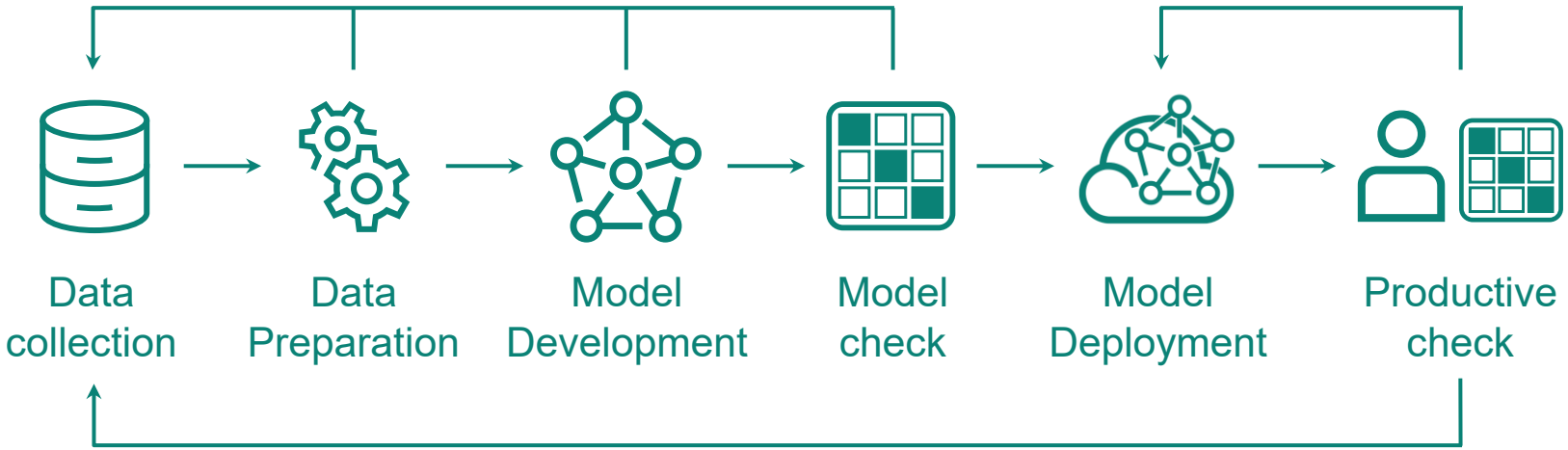
Enhancing Sustainability in Semiconductor Manufacturing Through AI-Powered Defect Image Classification

Defect Image Classification in Front-End Production



- Current state
  - Manual defect image classification by humans
- Goal
  - Automated defect image classification using AI models
- Challenges
  - Novelty detection, model monitoring & update
  - Scaling to other production sites & other use cases

Pipeline



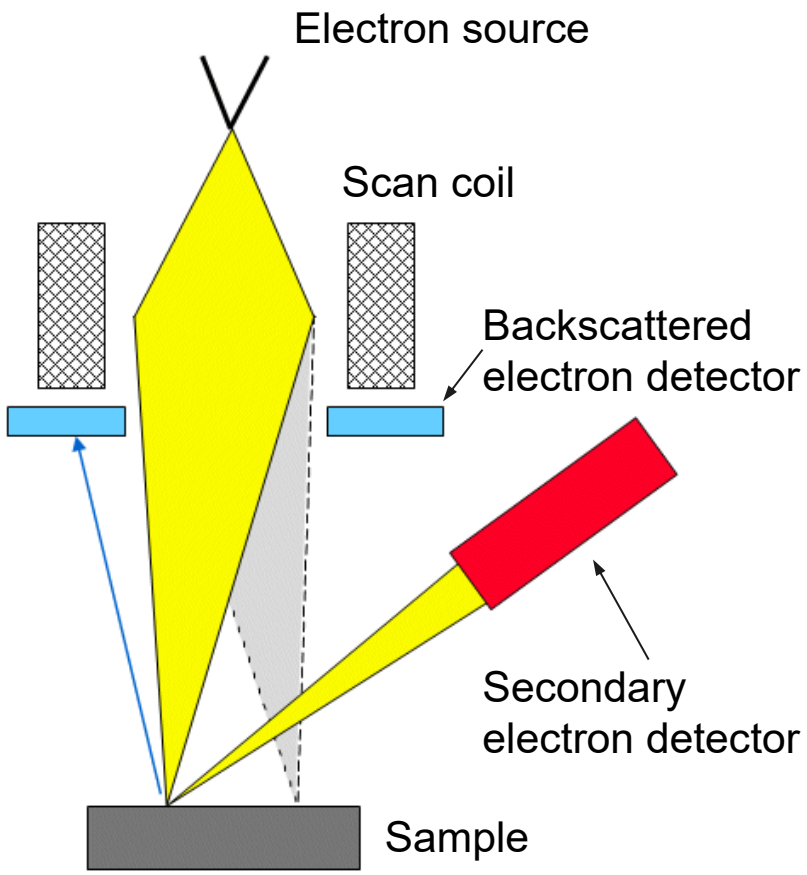
Model development

- Model-centric vs. data-centric approaches
- Training from scratch vs. transfer learning
- Model check on test dataset

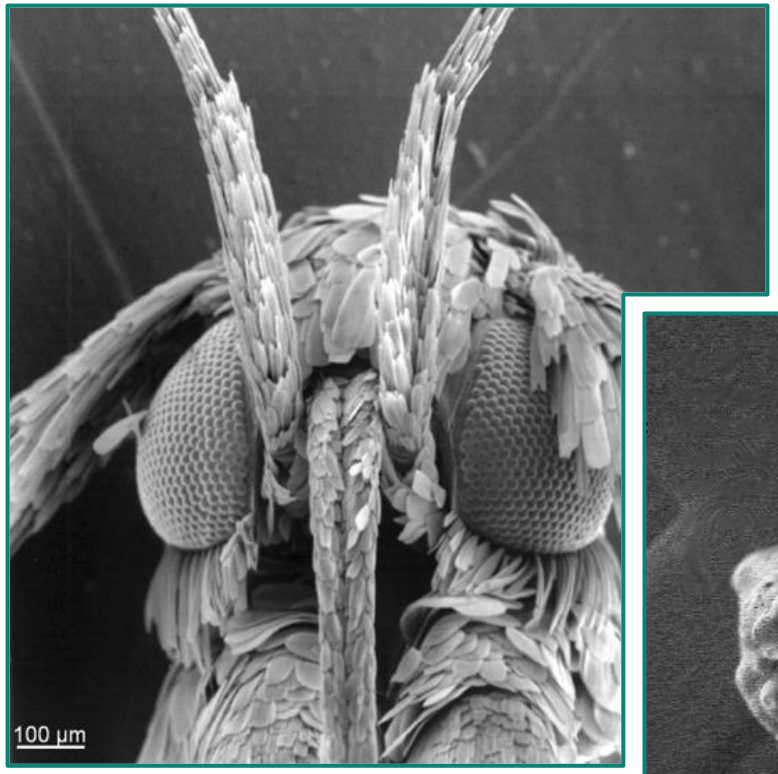
Model deployment

- Model hosted on Infineon internal cloud platform
- Mission critical A → 24/7 support by ML engineers
- Productive checks via model monitoring → model updates

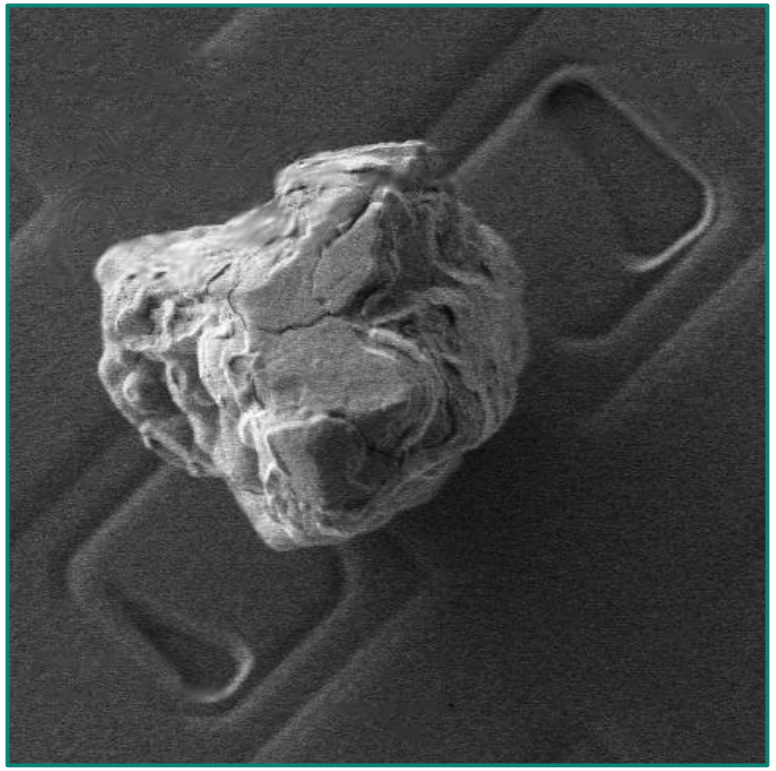
Data Source are Scanning Electron Microscopy Images



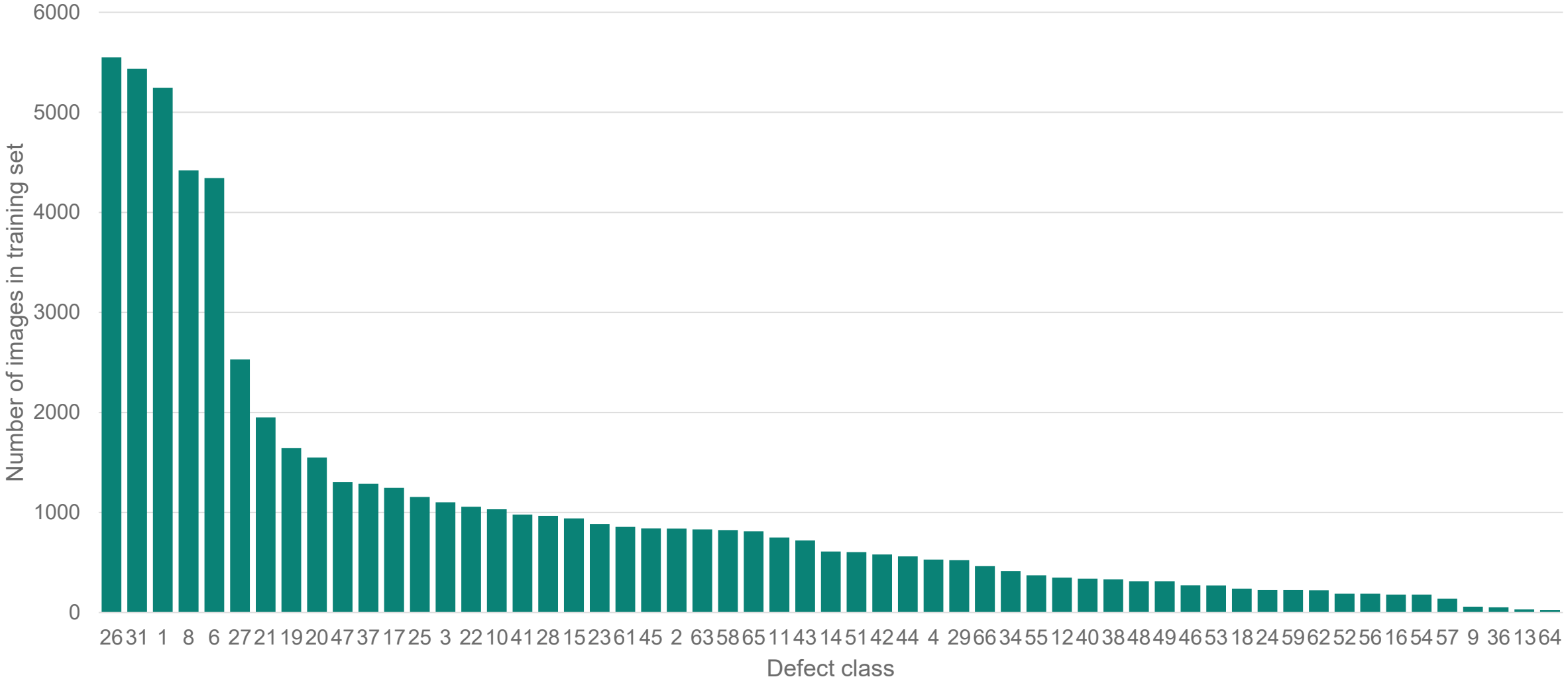
https://de.wikipedia.org/wiki/Rasterelektronenmikroskop



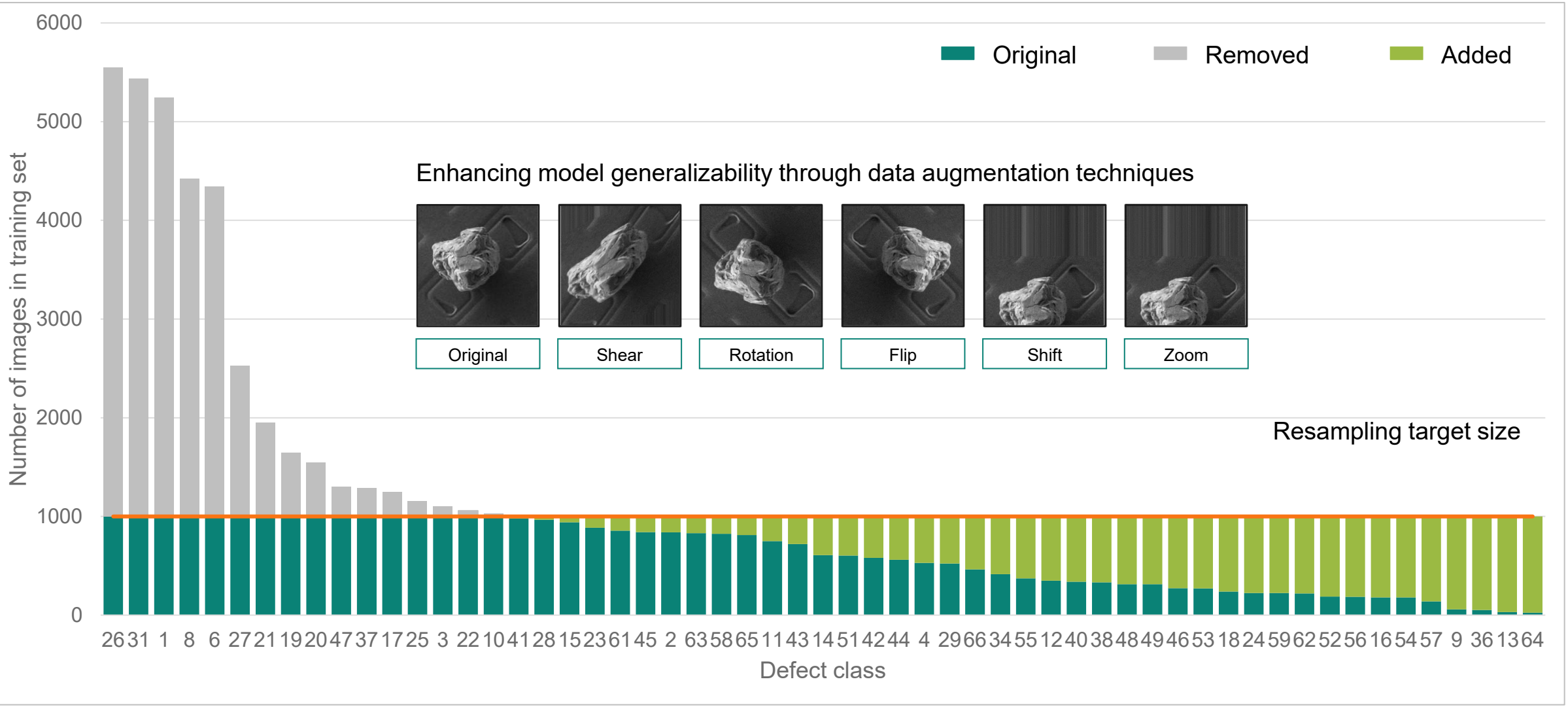
https://commons.wikimedia.org/wiki/File:Insect_SEM_gracilariidae.jpg



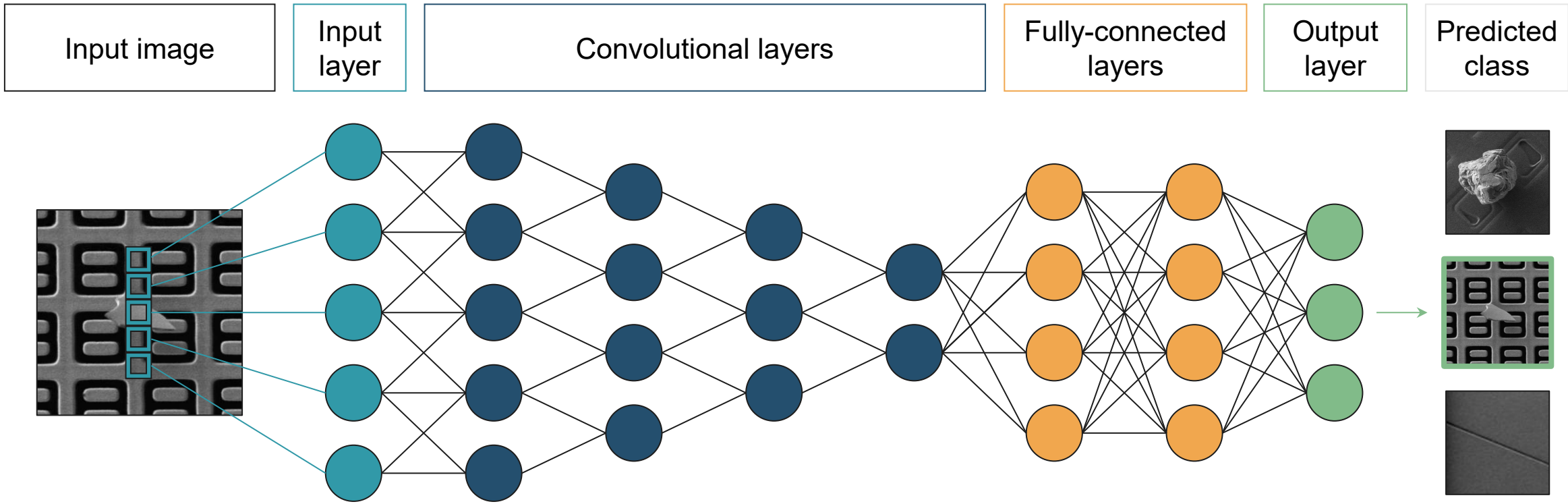
Dataset Distribution per Base Material



Data-Level Balancing



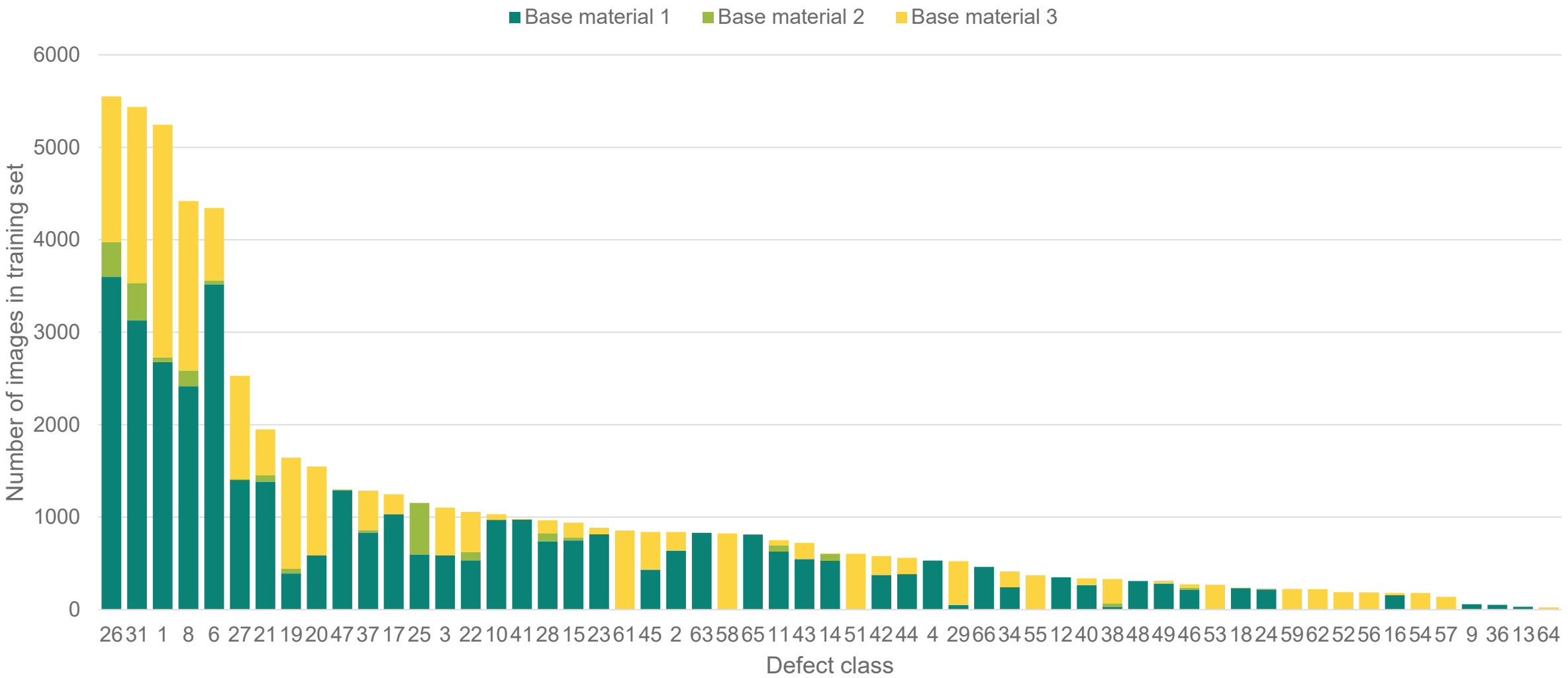
Model Training



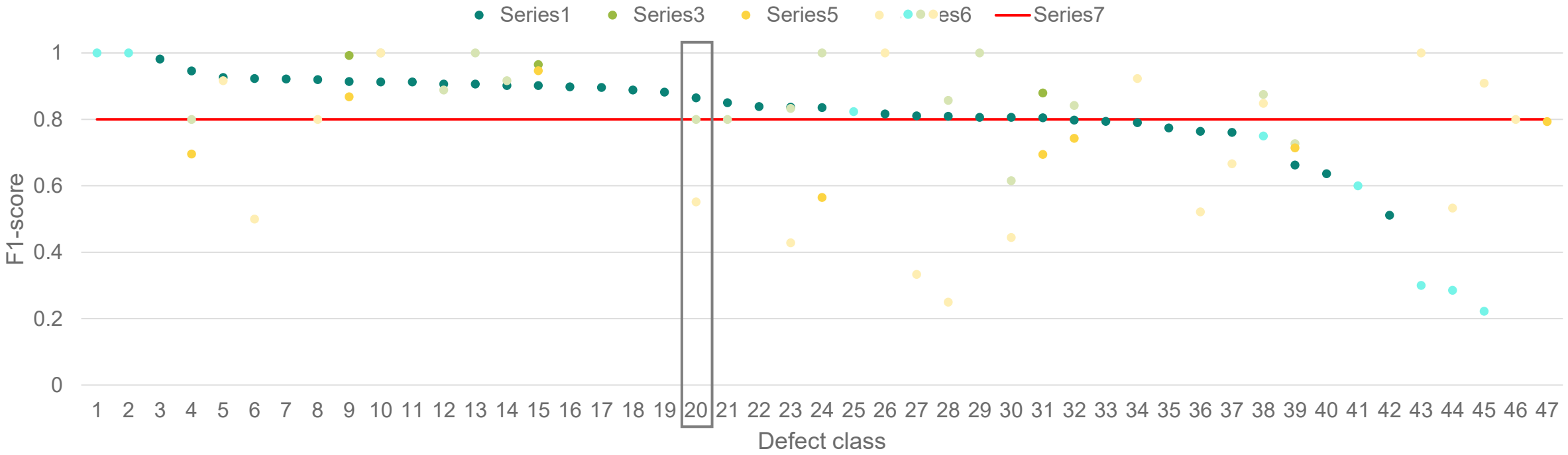
Dataset: SEM images of defect inspections from all manufacturing steps, 57 classes

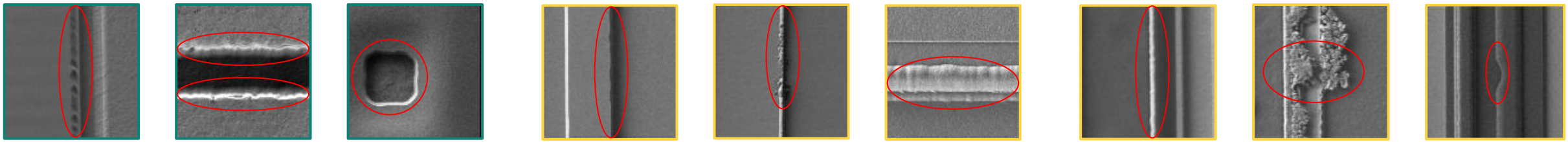
Model: CNN (EfficientNetV2S, initialized with the pretrained ImageNet weights) trained with data-centric approach

Dataset Distribution per Base Material



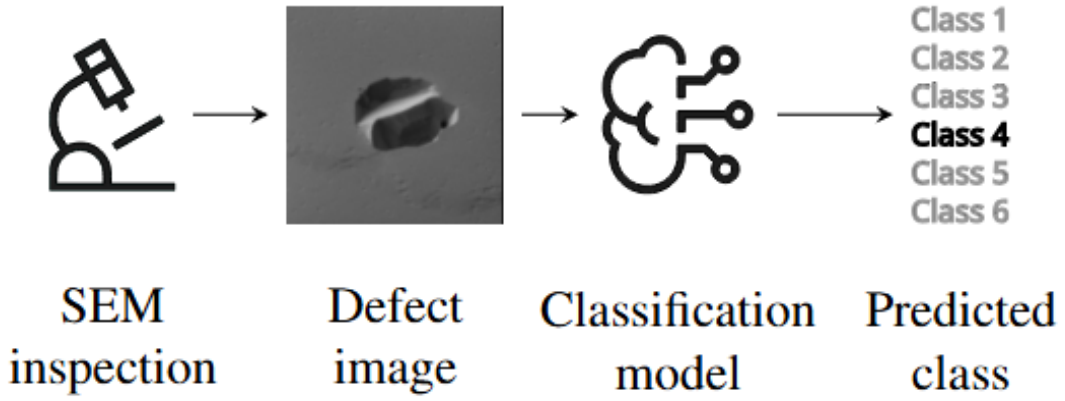
F1-Score Analysis on Validation Data





Motivation

Why explainable AI is essential for defect image classification?



Paper accepted at the European Conference on Artificial Intelligence (ECAI 2025)

Motivation for XAI Research

Why explainable AI?

§ Meet regulatory requirements

EU AI Act

Preamble (72)

*[…] **transparency** **should be required for high-risk AI systems** […]. High-risk AI systems should be designed in a manner to enable deployers to **understand** how the AI system works, […]*

Article 13

*1. **High-risk AI systems** shall be designed and developed in such a way as to ensure that their operation is **sufficiently transparent** to enable deployers **to interpret** a system's output and **use it appropriately**. […]*

https://artificialintelligenceact.eu/ai-act-explorer/

Motivation for XAI Research

Why explainable AI?

§ Meet regulatory requirements

Improved debugging of AI models

Wilhelm von Osten and Clever Hans

Clever Hans effect:

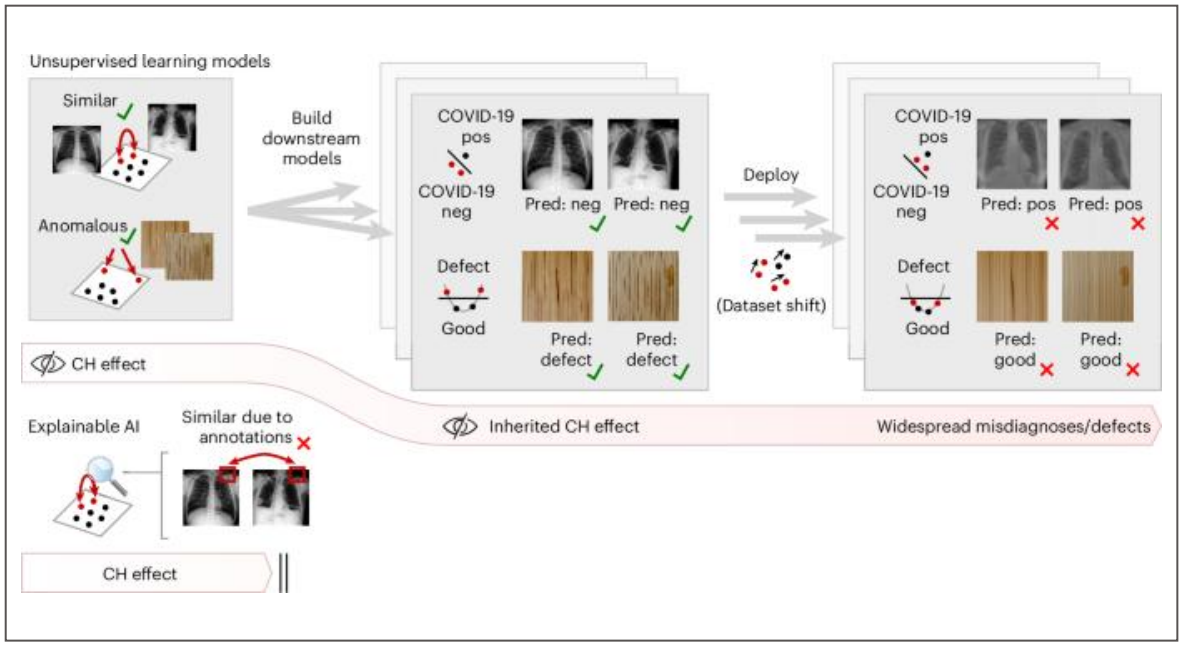
Not every "good" solution is the one you want!

https://en.wikipedia.org/wiki/Clever_Hans

Motivation for XAI Research

Why explainable AI?

- Meet regulatory requirements
- Improved debugging of AI models
- Increased transparency of AI models



Explainable AI:

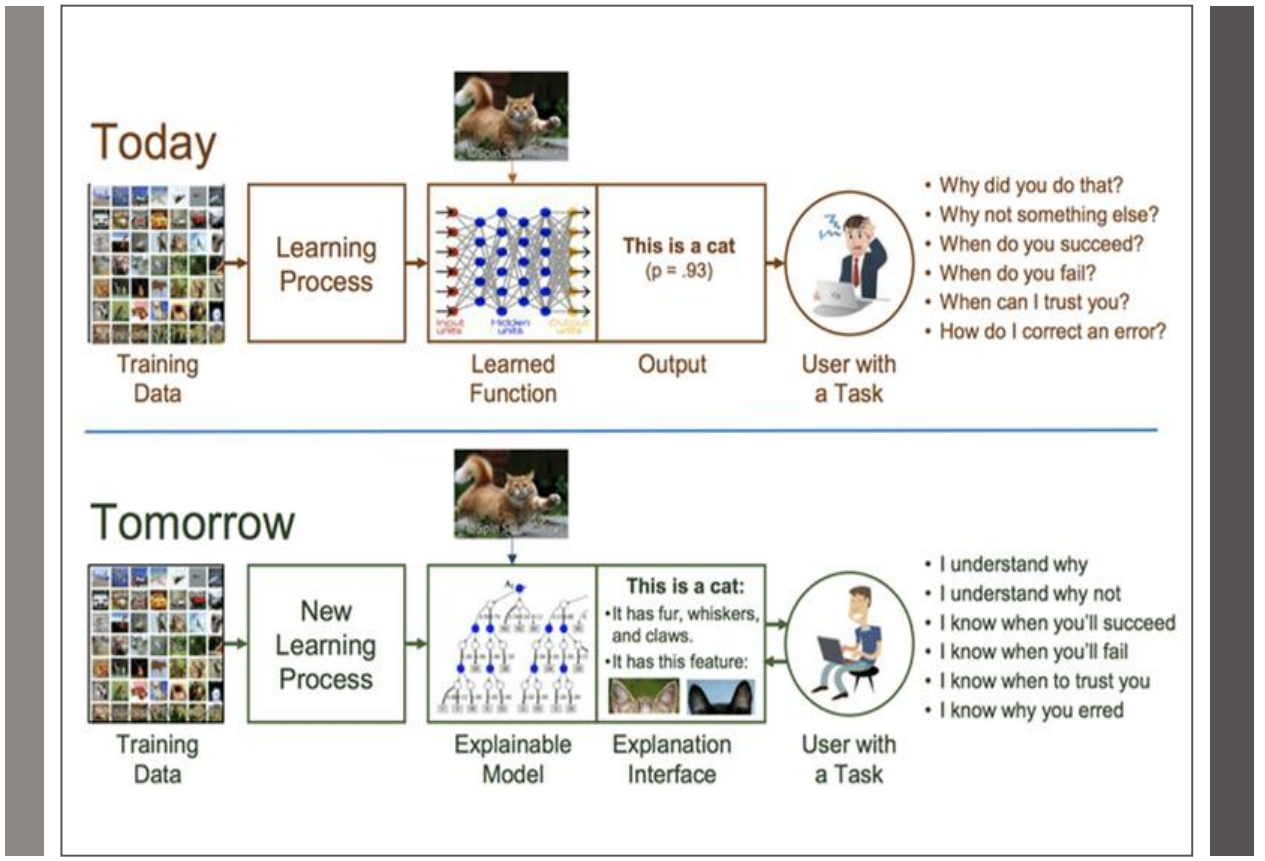
XAI reveals Clever Hans effects in unsupervised learning models

Kauffmann, Jacob, et al. "Explainable AI reveals Clever Hans effects in unsupervised learning models." Nature Machine Intelligence (2025): 1-11.

Motivation for XAI Research

Why explainable AI?

- Meet regulatory requirements
- Improved debugging of AI models
- Increased transparency of AI models
- Increased trust in AI models



Turek, M.: DARPA - Explainable Artificial Intelligence (XAI) Program (2017)
https://www.darpa.mil/program/explainable-artificial-intelligence

Motivation for XAI Research

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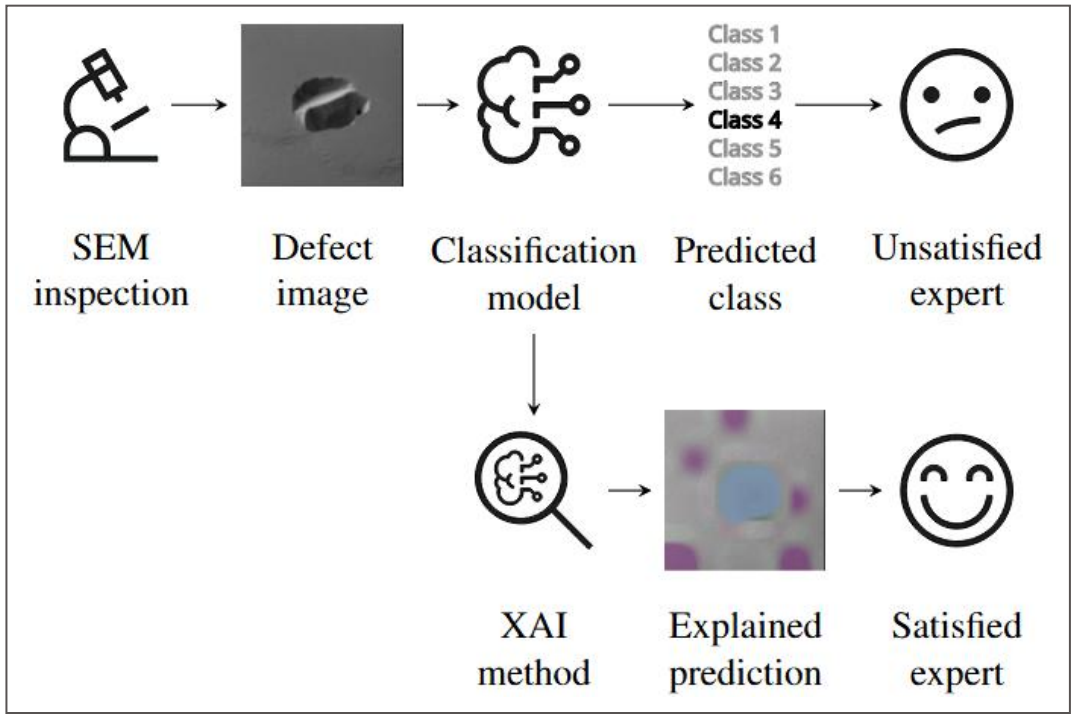


XAI in defect image classification:

Empowering experts to interpret model predictions!

Paper accepted at the European Conference on Artificial Intelligence (ECAI 2025)

Dataset for our XAI Research

We used the public Carinthia dataset for our research

Images

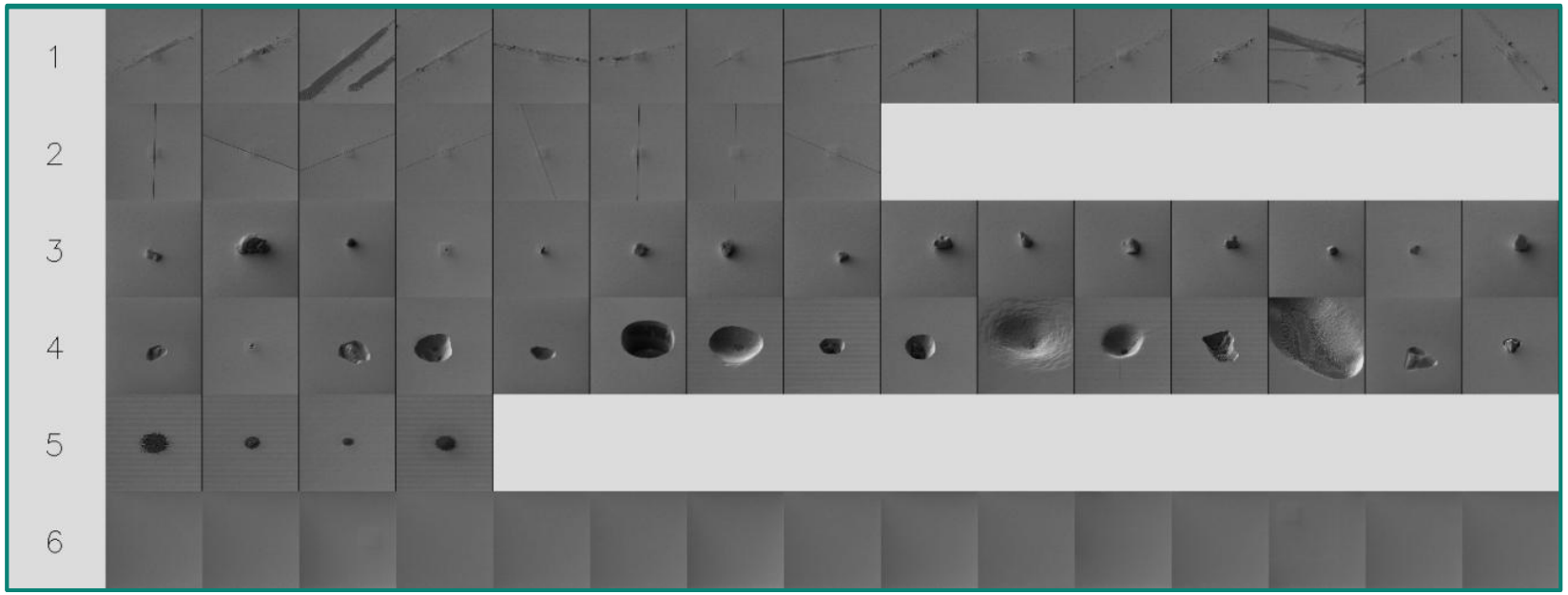
- Historical images from the production database

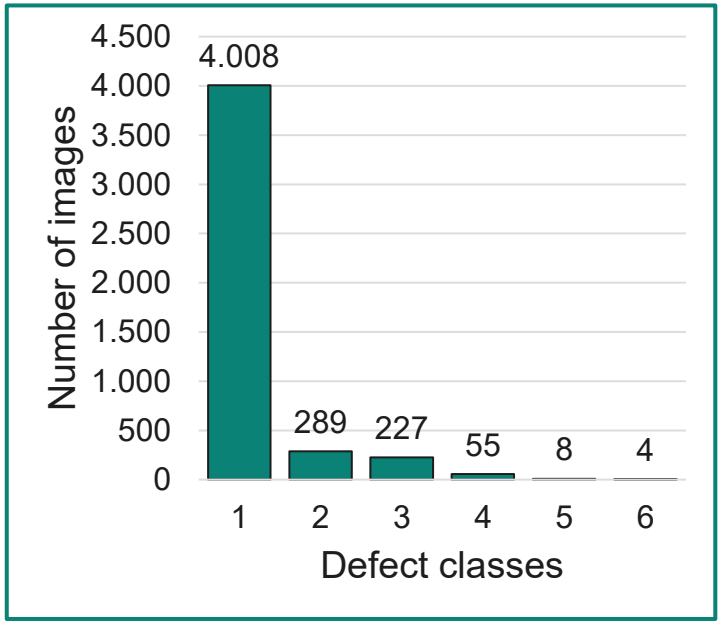
Labeling

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

Published

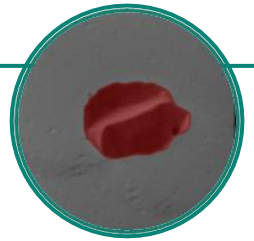
- Carinthia dataset publicly available on Zenodo





Contributions to XAI Research

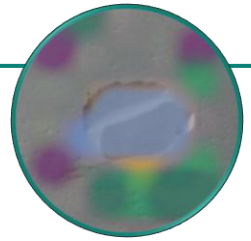
Automatic mask generation



SAM2[1]

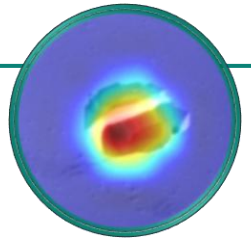
- Automatic mask generation using SAM2
- Expert validation of ground truth masks
- Carinthia-S dataset with ground truth segmentation masks

Evaluation of XAI methods on the Carinthia-S dataset



CRAFT[2]

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



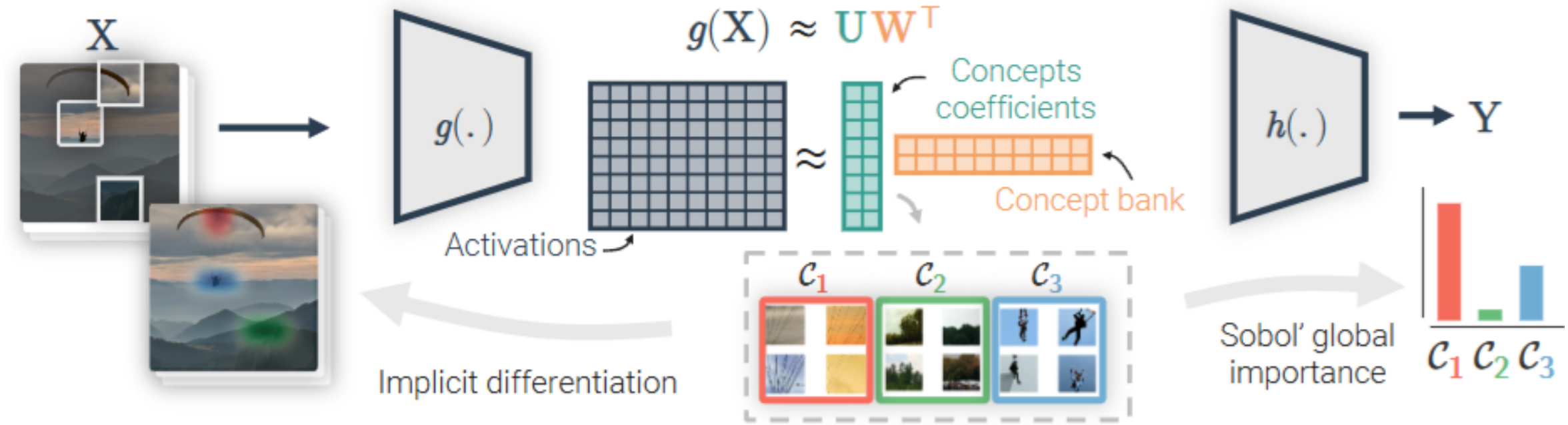
GradCAM[3]

- 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 to XAI Research

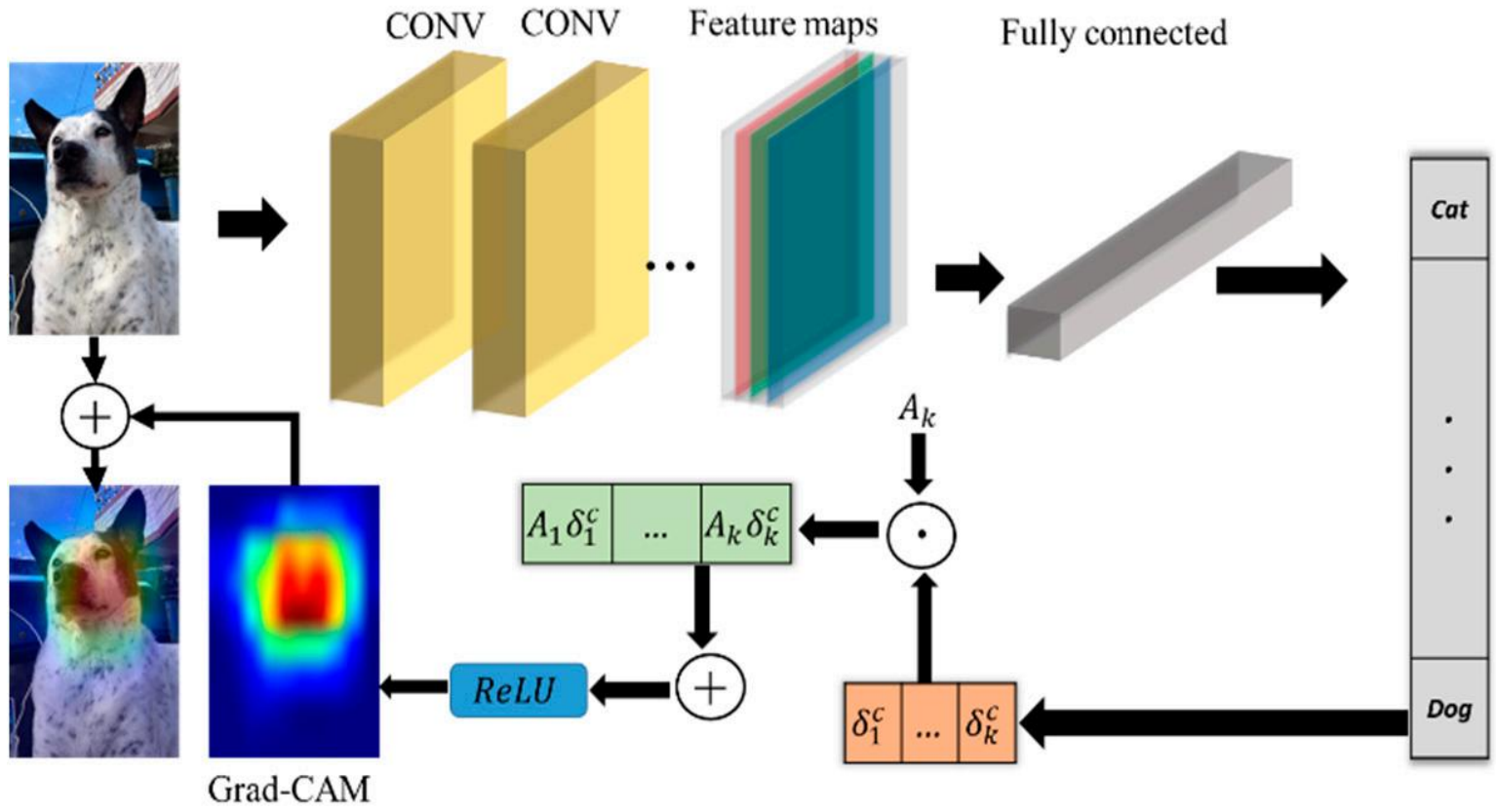
Explaining image classifications with CRAFT



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 to XAI Research

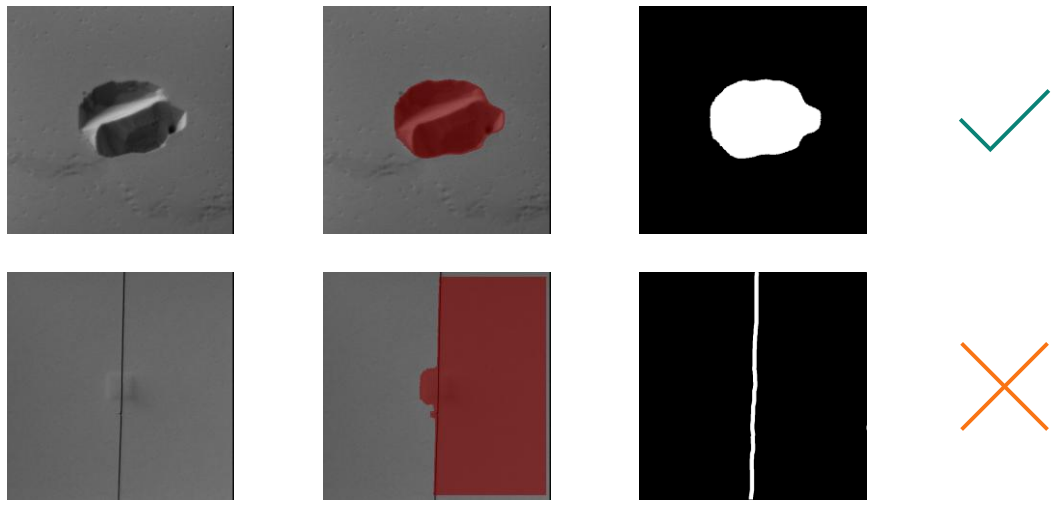
Explaining image classifications with GradCAM

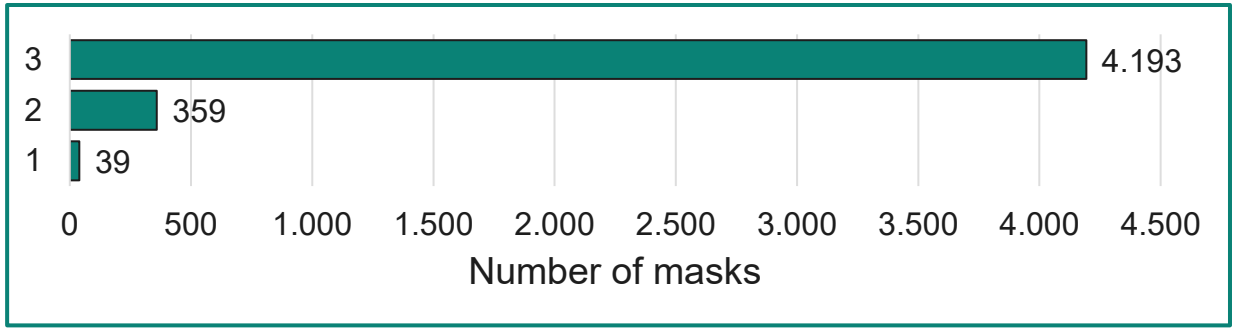


Selvaraju, Ramprasaath R., et al. "Grad-cam: Visual explanations from deep networks via gradient-based localization." Proceedings of the IEEE international conference on computer vision. 2017.

Contributions to XAI Research

Automatic ground truth masks generation





Algorithm 1

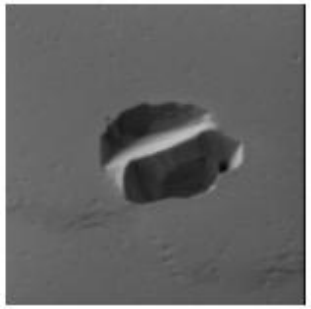
- Automated candidate mask generation using SAM2
- Filtering masks based on prior knowledge
- Expert validation and refinement

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.

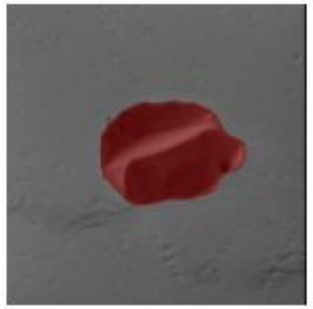
Results of our XAI Research

Insights from qualitative evaluation of XAI methods

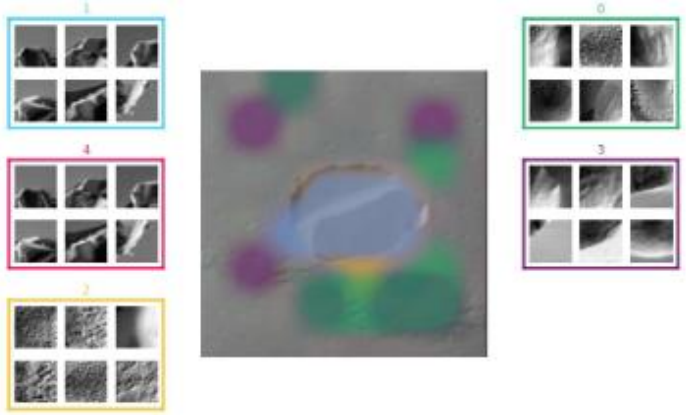
- GradCAM and CRAFT highlight critical regions relevant to the model's decision-making process
- CRAFT is resilient to imperceivable image changes
- CRAFT enhances interpretability by visualizing meaningful concepts that influence predictions



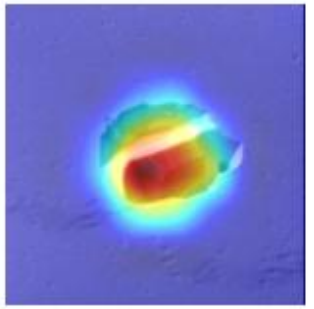
Original image



Ground truth



CRAFT

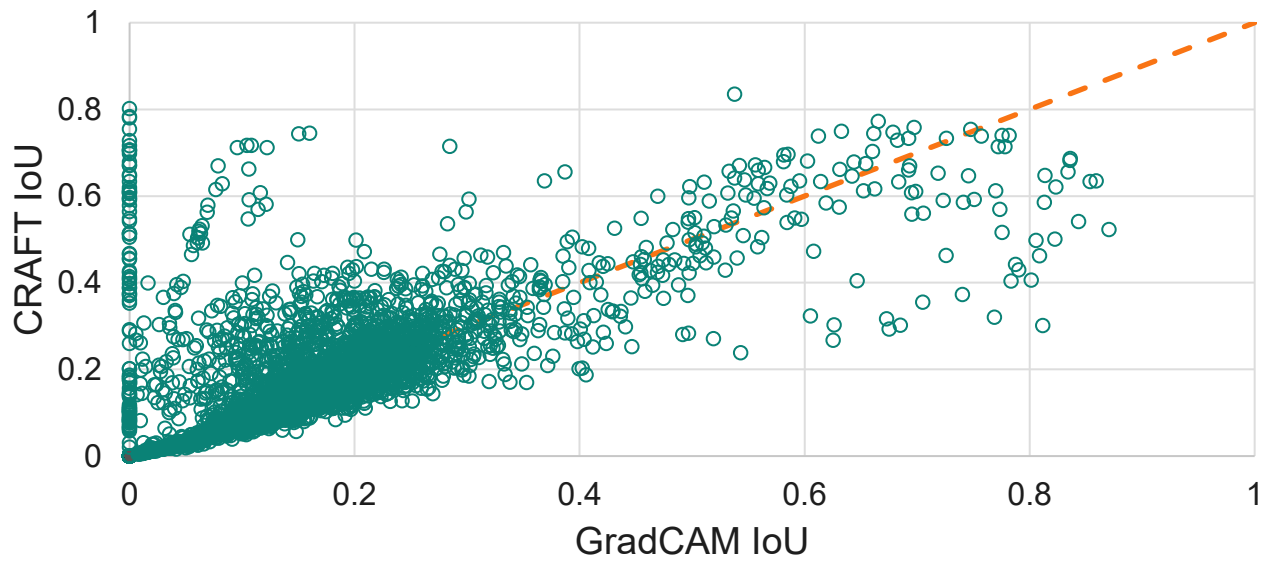


GradCAM

Results of our XAI Research

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

Thresholding the activation maps

Algorithm 3

Pixel-wise color matching

Thresholding with a tolerance

Results of our XAI Research

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.

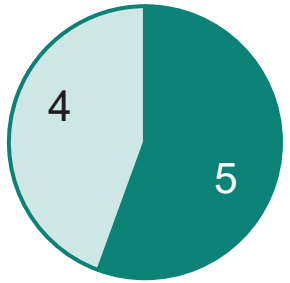
Q4 This explanation of how the model works seems complete.

Q5 This explanation of how the model works tells me how to use it.

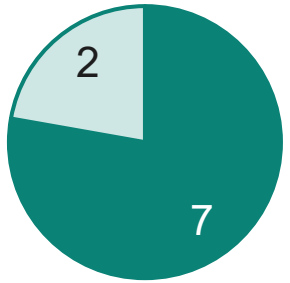
Q6 This explanation of how the model works is useful to my goals.

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 preprintarXiv:1812.04608, 2018.

Conclusion & Outlook for our XAI Research

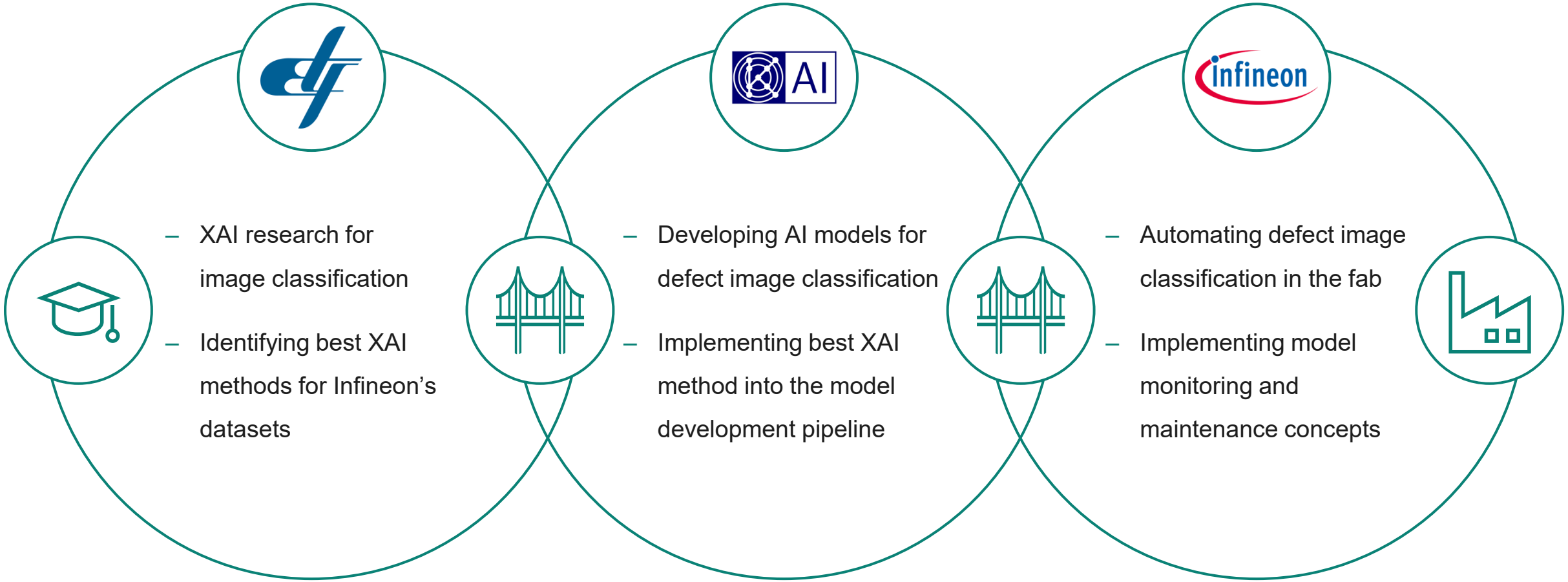
Conclusion

- 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

Overall Conclusion



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Where?
In the hall

When?
During the breaks

Why?
To connect with us 🎁

Thank you for your attention!

IPCEI Microelectronics and Communication Technologies

This work is funded by the Austrian Federal Ministry of Climate Action, Environment, Energy, Mobility, Innovation and Technology, the Austrian Federal Ministry of Digital and Economic Affairs, and implemented by Austria Wirtschaftsservice (AWS) and the Austrian Research Promotion Agency (FFG) in the frame of the Important Project of Common European Interest (IPCEI) on Microelectronics and Communication Technologies (ME/CT).

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