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AI IN BRAIN HEALTH

A hybrid Fully Convolutional CNN-Transformer Model for Inherently Interpretable Disease Detection from Retinal Images

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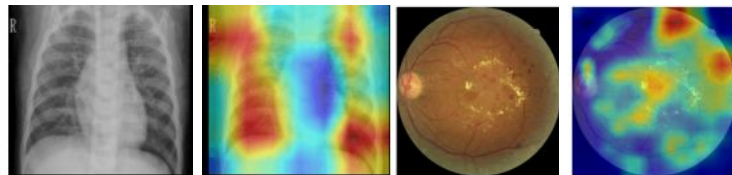
What is interpretability?

The degree to which a human can understand the cause of a decision (Miller, 2019)[1].

Why interpretable models?

- Learning tools
- Improve user trust
- Discover harmful biases
- Policy/legal considerations

Why did the model predict this?



Attribution maps: highlight relevant regions
~ *Post-hoc explanation*

Limitations of attribution maps

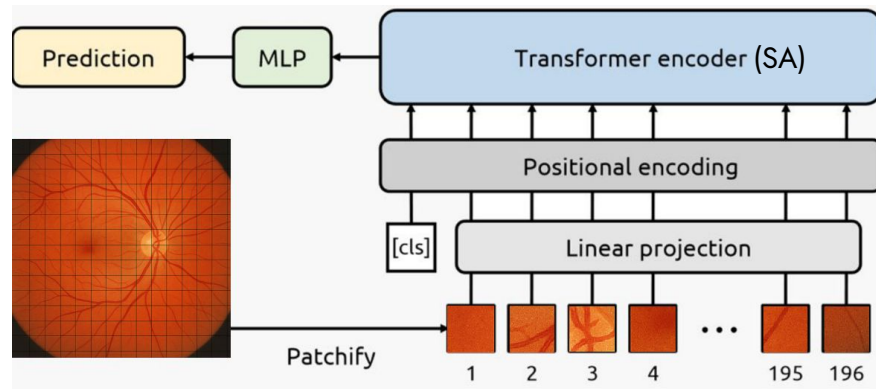
- Coarse-grained explanation
- Not inherently interpretable
- Poor performance on medical data
- *Mostly developed for CNN-based models*

Vision transformers

- Revolutionized computer vision
- Competitive alternative to CNNs
- Self attention long-range dependencies
- **Computational intensive** [2]

Hybrid CNN-Transformers

- Balance computational cost
- CNNs + Transformer module
- Locality + global dependencies
- **Interpretability remains challenging** [2]



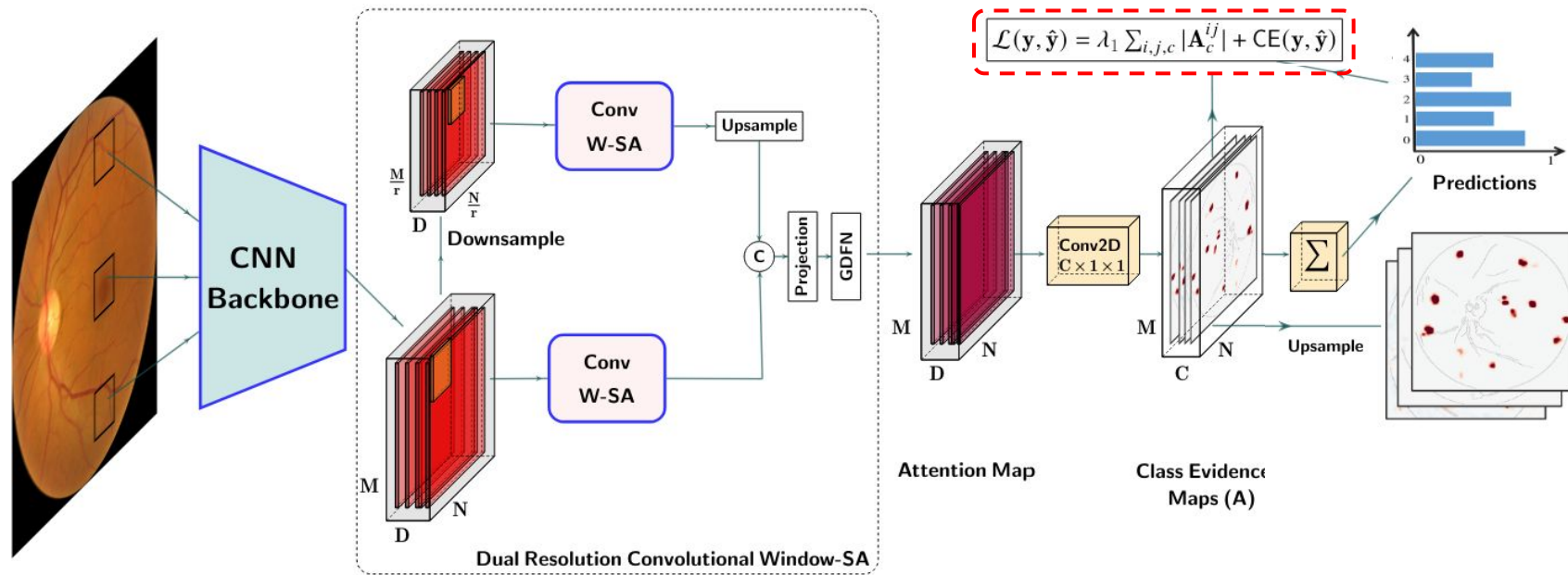
Explaining hybrid CNN-transformers

- Post-hoc for CNNs: GradCAM [3], LRP [4],
- Specialized techniques tailored for ViTs
 - Attention maps [5], Rollout [6], ...
- **Post-hoc vs self-explainable methods**
 - Prototypes-based for ViTs [7]

Contribution: Self-explainable CNN-Transformer



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W-SA: Window Self Attention

DRSA: Ilyas et al., MICCAI (2024); **Sparse Activations:** Djoumessi et al., MIDL (2023)

About DR and AMD

- Microvascular abnormalities
 - DR: Microaneurysms, Hard Exudates
 - AMD: Drusen
- Can lead to vision loss
- Well-defined grading systems

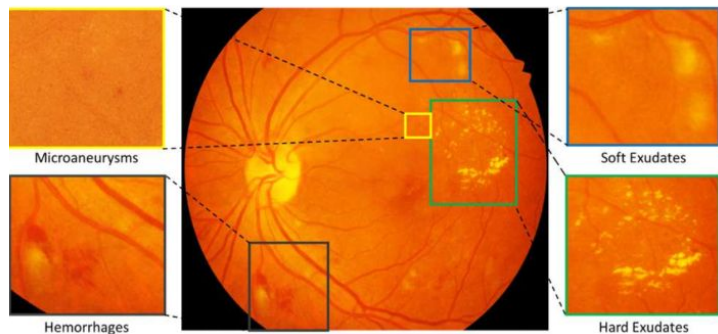
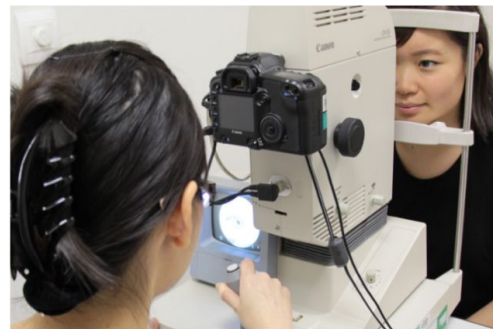


Figure reproduced from Powal et al. (2018)

Managing DR and AMD

- AI-based retinal image analysis
- Predict disease stage from lesions
- Early diagnosis improves treatment
- Progression: regular follow-ups



Classification performance

Dataset:

Kaggle DR detection (45,923; 5 classes), **AREDS AMD** (34,079; 6 classes)

	AREDS AMD		Kaggle DR		Computational Cost		
	Acc.	κ	Acc.	κ	Par.	Mem.	Time
ViT	.76 $\pm$.03	.90 $\pm$.02	.81 $\pm$.02	.71 $\pm$.04	86,094	341	09.5 $\pm$ 0.1
Swin	.78 $\pm$ 0.2	.92 $\pm$.02	.85 $\pm$.02	.81 $\pm$.03	86,883	358	15.5 $\pm$ 1.1
ResNet	.78 $\pm$.03	.89 $\pm$.02	.85 $\pm$.02	.81 $\pm$.03	23,518	101	04.2 $\pm$ 0.5
BagNet	.75 $\pm$.03	.88 $\pm$.02	.86 $\pm$.02	.83 $\pm$.03	16,271	193	15.1 $\pm$ 0.1
ResNet-FCL-SA	.78 $\pm$.03	.90 $\pm$.02	.86 $\pm$.02	.82 $\pm$.03	69,732	281	06.2 $\pm$ 0.2
BagNet-FCL-SA	.77 $\pm$.03	.89 $\pm$.02	.85 $\pm$.02	.83 $\pm$.03	62,501	306	27.3 $\pm$ 0.2
ResNet-Conv-SA	.78 $\pm$.03	.91 $\pm$.02	.85 $\pm$.02	.83 $\pm$.03	69,735	285	06.3 $\pm$ 0.6
BagNet-Conv-SA	.77 $\pm$.03	.90 $\pm$.02	.87 $\pm$.02	.84 $\pm$.02	62,913	310	27.3 $\pm$ 0.3
sResNet-Conv-SA	.79 $\pm$.02	.90 $\pm$.02	.85 $\pm$.02	.80 $\pm$.03	69,735	285	06.3 $\pm$ 0.6
sBagNet-Conv-SA	.77 $\pm$.03	.91 $\pm$.02	.85 $\pm$.02	.81 $\pm$.03	62,913	310	27.3 $\pm$ 0.3

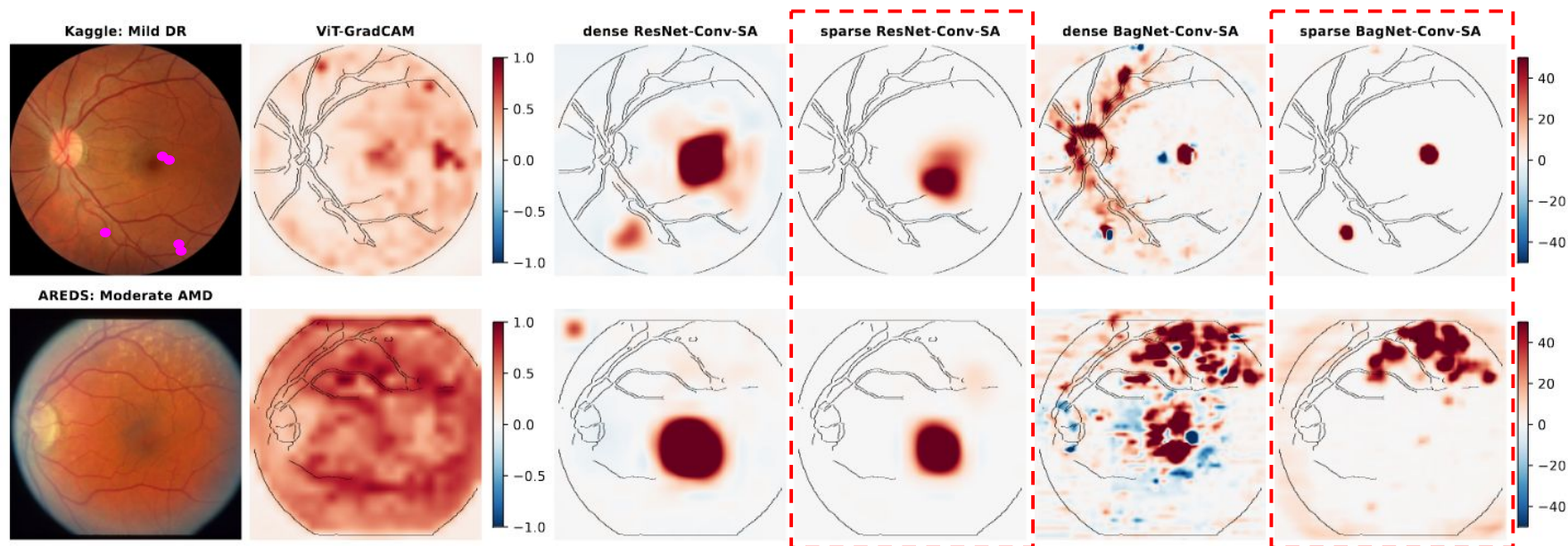
Sparsity

AREDS AMD. ResNet: 1e-04, BagNet: 7e-06

Kaggle DR. ResNet: 2e-4, BagNet: 3e-05

Parameter (M), Memory (Mb): Time (s)

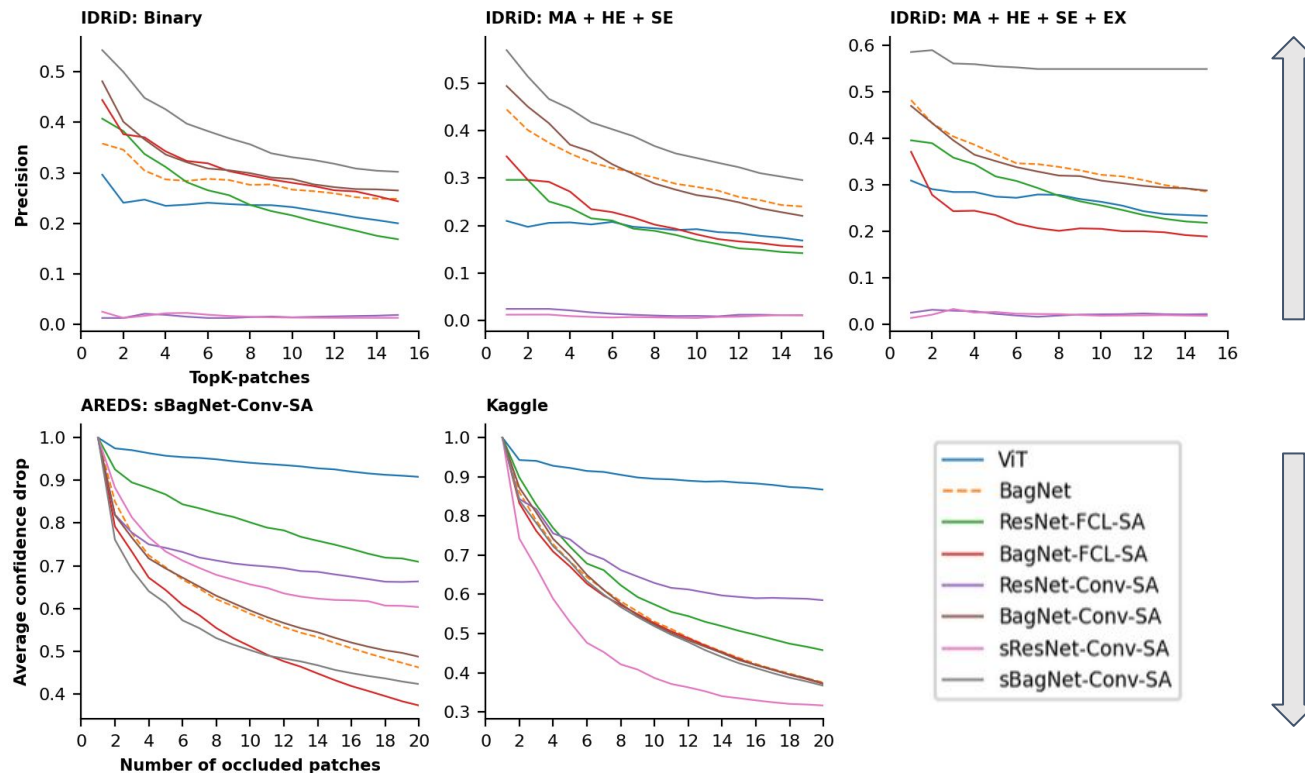
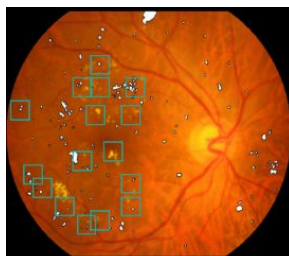
Qualitative heatmap evaluation



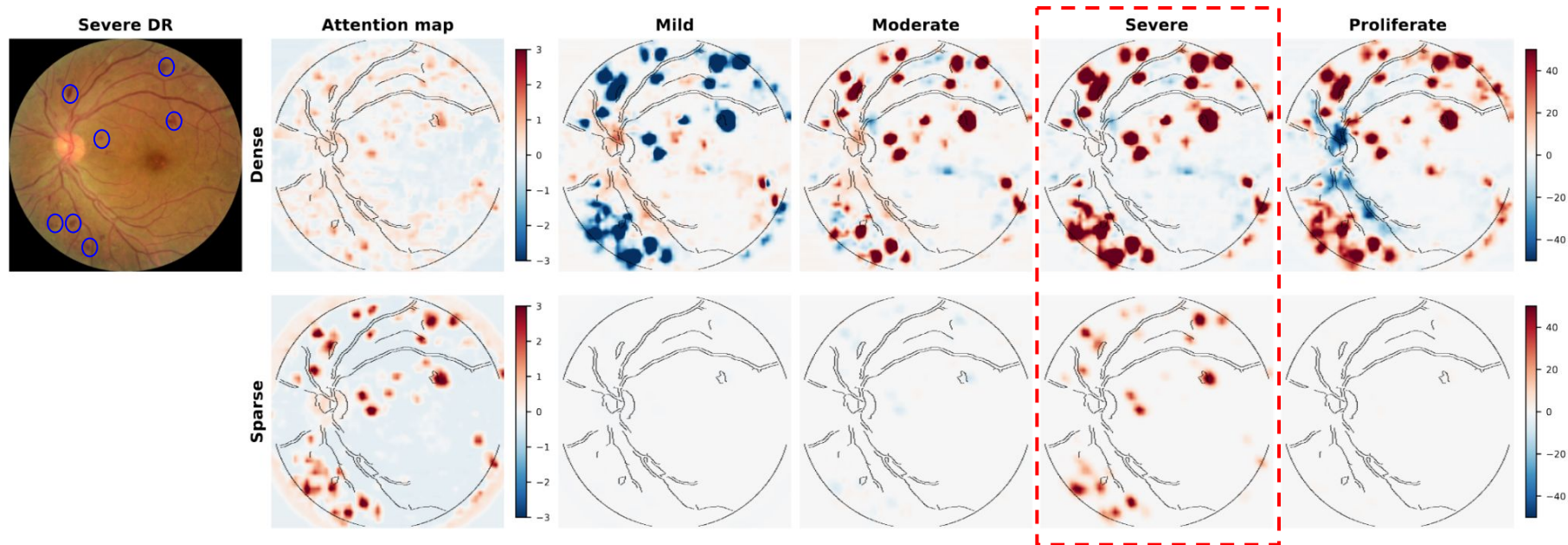
Quantitative Heatmap Evaluation

IDRiD dataset: 81 images

- Lesion annotations



Interpretability for Multi-class DR Detection



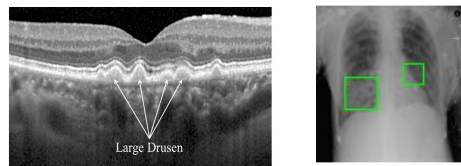
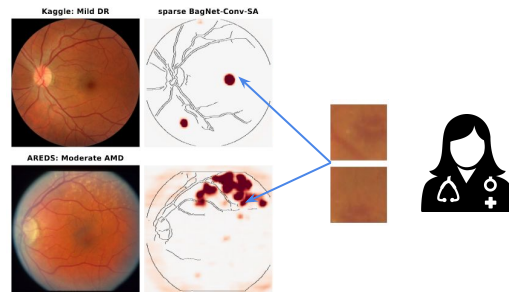
Conclusion

Summary

- Effectively combine prior work (DRSA, CvT, sparse explanation)
- Hybrid fully convolutional interpretable CNN-Transformer models
- CNNs: BagNet & ResNet
- Task: retinal disease detection (AMD, DR)
- Qualitative & quantitative metrics to assess the interpretability

Future work

- Clinical user validation
- Generalizability: extend to other modalities
- Improve model performance on data regime (late-stage DR)
- Aggregation techniques & extensive hyperparameters search



h. Kaggle: sBagNet-Conv-SA

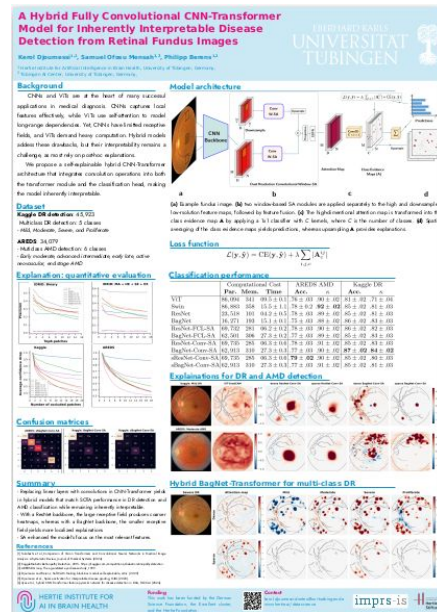
0	4828	177	110	3	0
1	212	237	88	0	0
2	124	92	782	53	0
3	6	1	79	87	0
4	10	0	36	31	0
	0	1	2	3	4

Acknowledgments



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Thank you for your attention!



Q & A

- [1] Miller Tim, *Explanation in artificial intelligence: Insights from the social sciences* (2019)
- [2] Kim et al., *Systematic review of hybrid vision transformer architectures for radiological image analysis* (2025)
- [3] Selvaraju et al., *GradCAM: Visual explanations from deep networks via gradient-based localization* (2017)
- [4] Bach et al., *On pixel-wise explanations for non-linear classifier decisions by layer-wise relevance propagation* (2015)
- [5] Dosovitskiy et al., *An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale* (2020)
- [6] Abnar et al., *Rollout: Quantifying attention flow in transformers* (2020)
- [7] Ashkan et al., *Protoformer: Embedding Prototypes for Transformers* (2022)
- [8] Ilyas et al., *A Hybrid CNN-Transformer Feature Pyramid Network for Granular Abdominal Aortic Calcification Detection from DXA Images* (2024)
- [9] Wu et al., *CvT: Introducing convolutions to vision transformers* (2021)
- [10] Djoumessi et al., *Sparse Activations for Interpretable Disease Grading* (2023)
- [11] Djoumessi et al., *Soft-CAM: Making black box models self-explainable for high-stakes decisions* (2025)