Sparse Activations for Interpretable Disease Grading

Presented by DJOUMESSI Kerol

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July 12, 2023

Motivation

What is interpretability?

Interpretability is the degree to which a human can understand the cause of a decision (Miller 2019).

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Interpretability is the degree to which a human can understand the cause of a decision (Miller 2019).

Why do we need interpretable models?

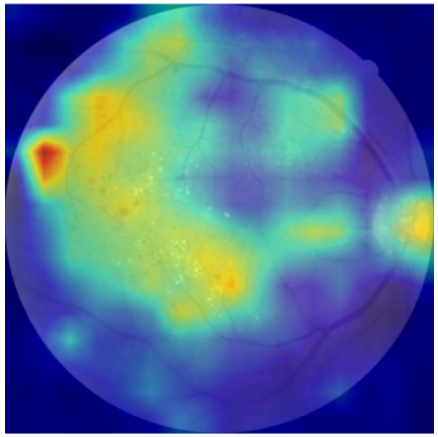
- Trust AI
- Bias detection
- Learning tools
- Policy/legal considerations

Interpretability methods

Why did a model make a specific prediction?

- Attribution maps: where a model looks

Post-hoc explanation



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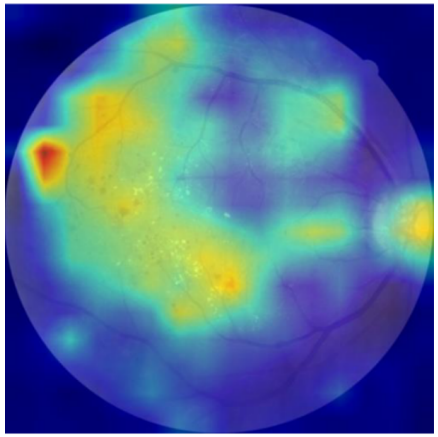

Interpretable-by-design models

- **Linear models**
- Prototypes-based models

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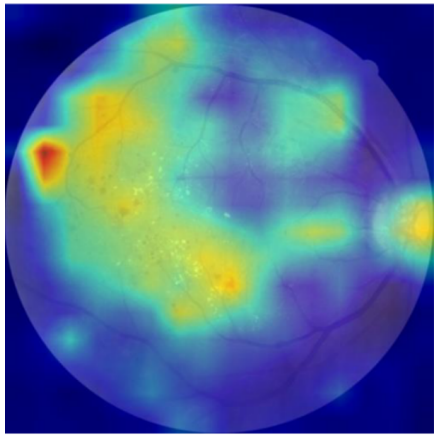

Interpretable-by-design models

- **Linear models**
- Prototypes-based models

The explanation may look different depending on reason for the explainability.

Attribution maps for medical images: drawbacks

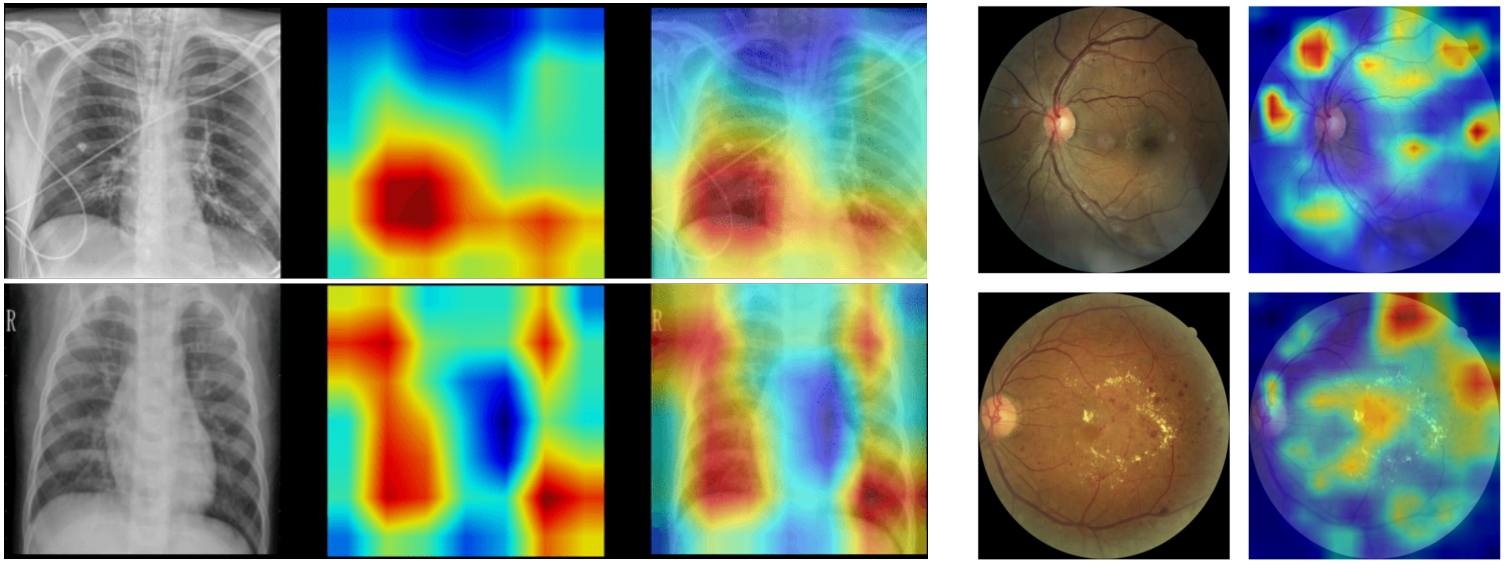

Figure reproduced from Bhowal et al. (2021)

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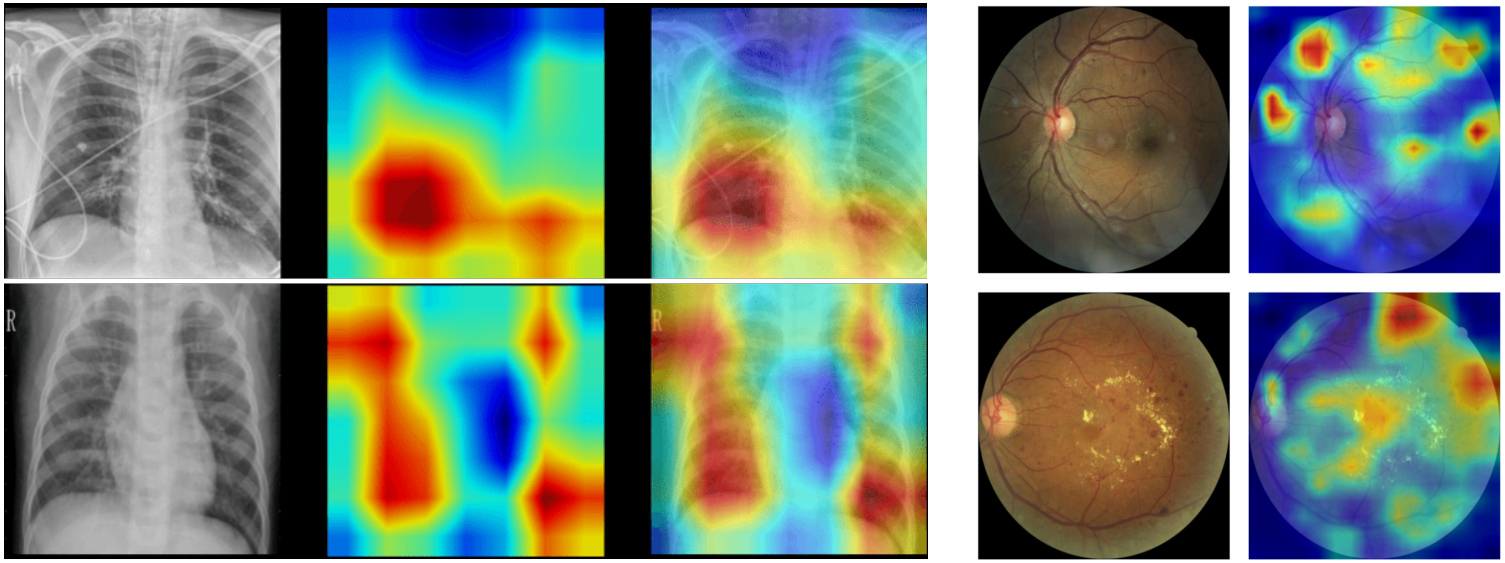

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- Approximate CNNs
- No actionable insights
- Often coarse-grained evidence

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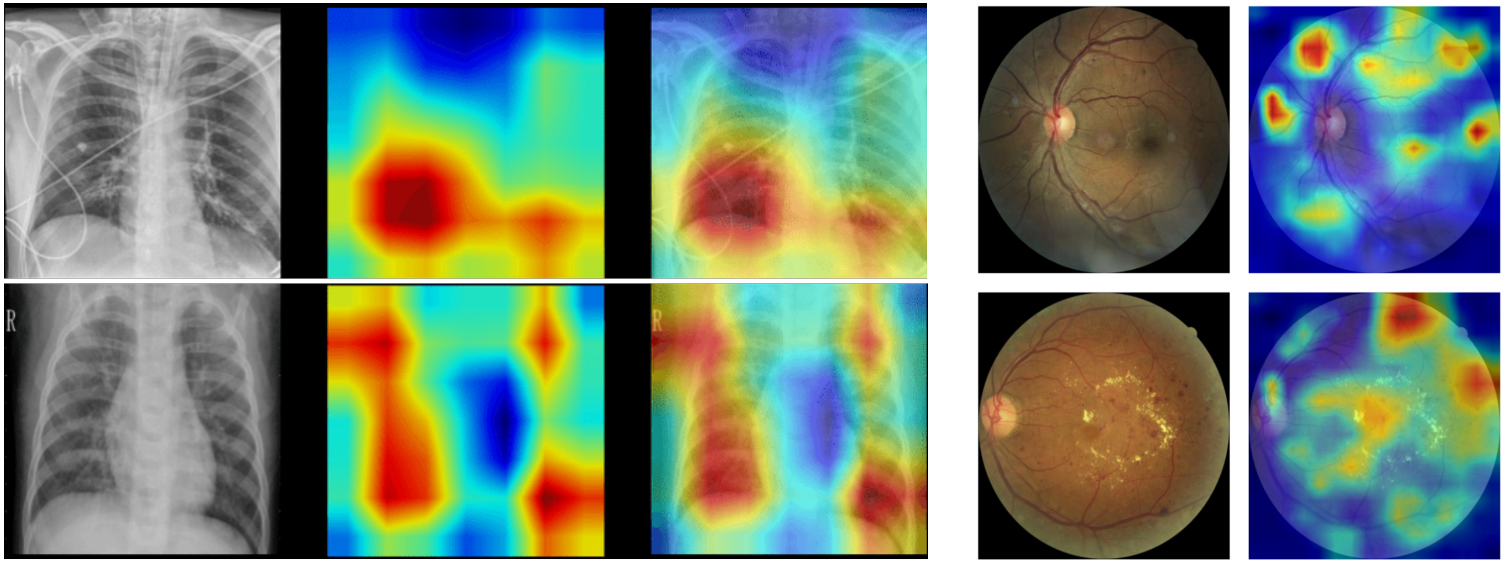

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- Highly variable
- Approximate CNNs
- No actionable insights
- Often coarse-grained evidence

- Not inherently interpretable
- Poor performance in Med. data
  - Reproducibility
  - Lesion localizations

Contribution: sparse BagNet

We propose an inherently interpretable model that combines the feature extraction capabilities of DNNs with the advantages of sparse linear models in interpretability.

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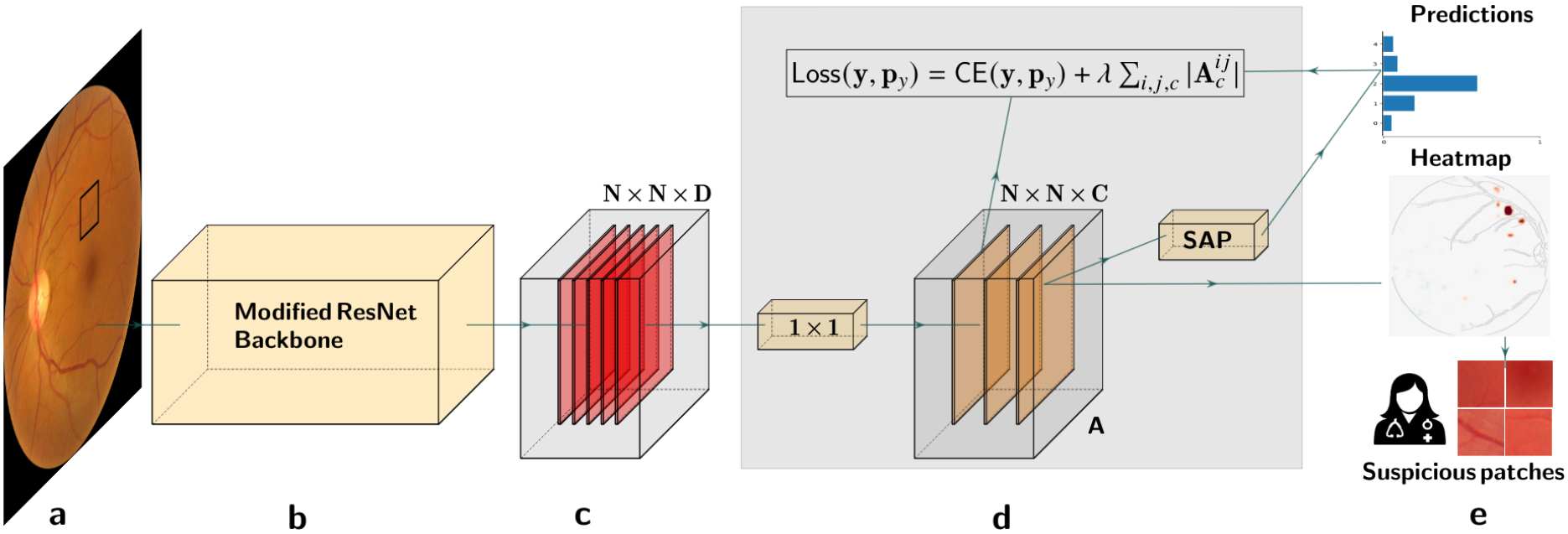

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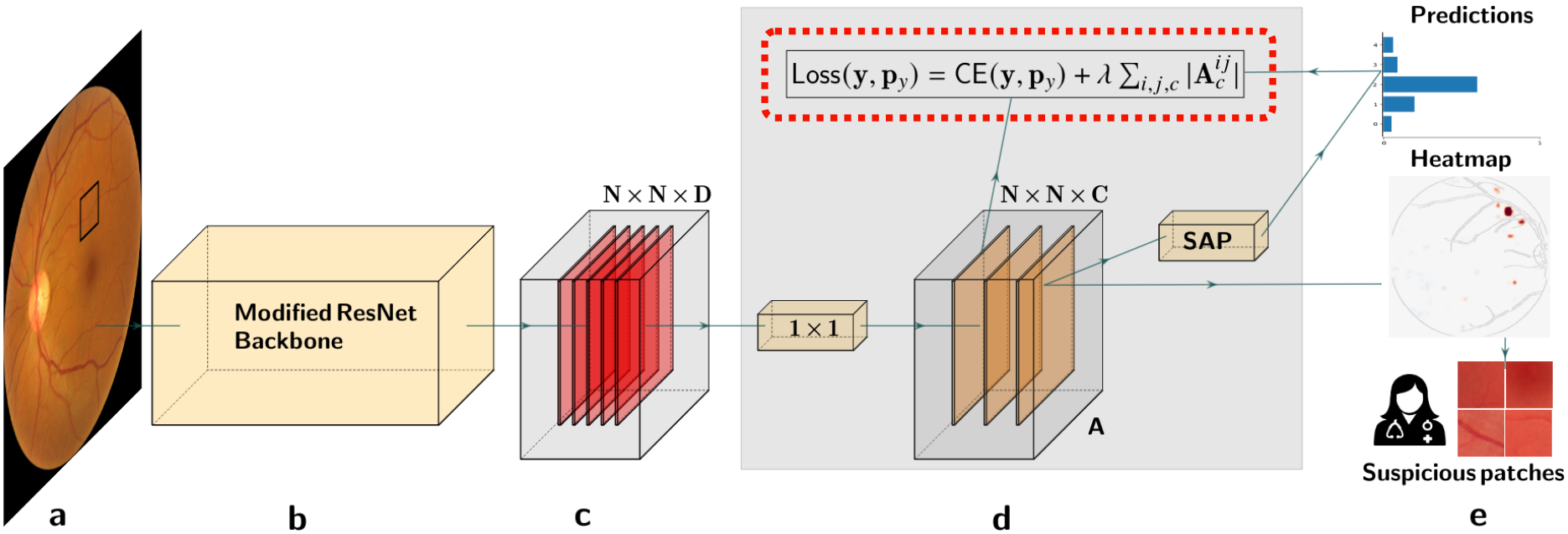
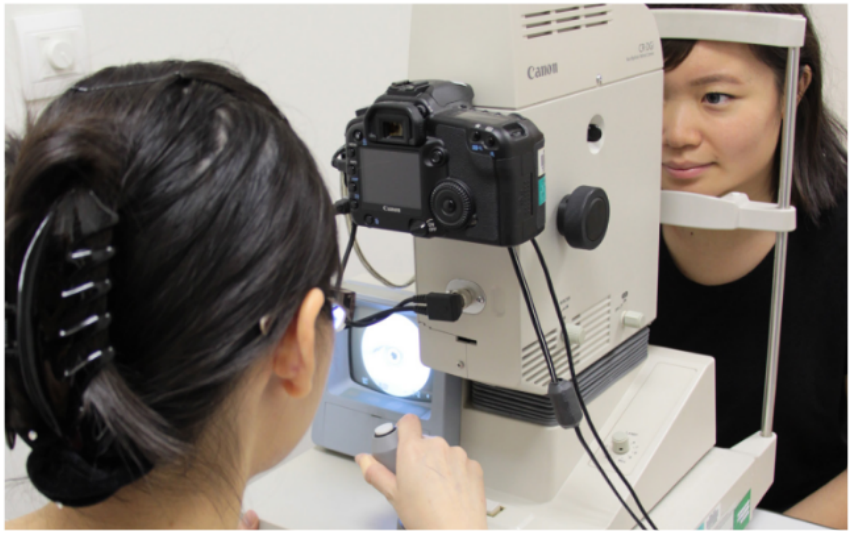
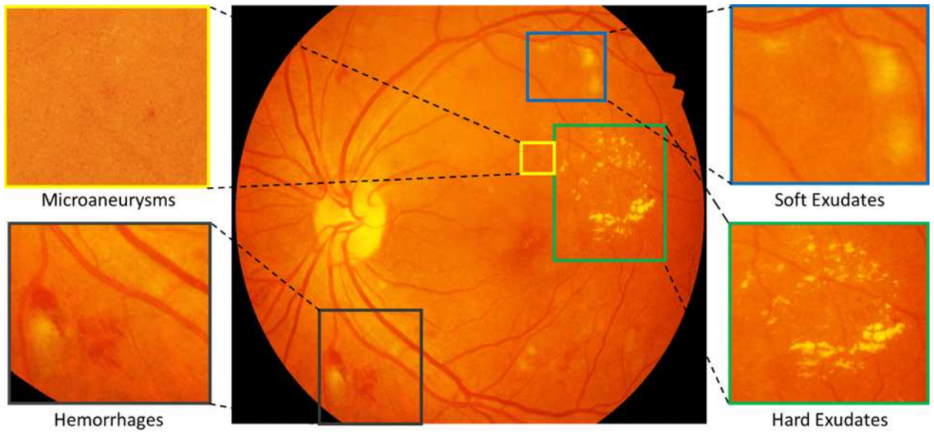


Application: Diabetic Retinopathy (DR) detection

About DR

- Microvascular complications
- Leading cause of blindness
- Affects 1 in 3 diabetes patients





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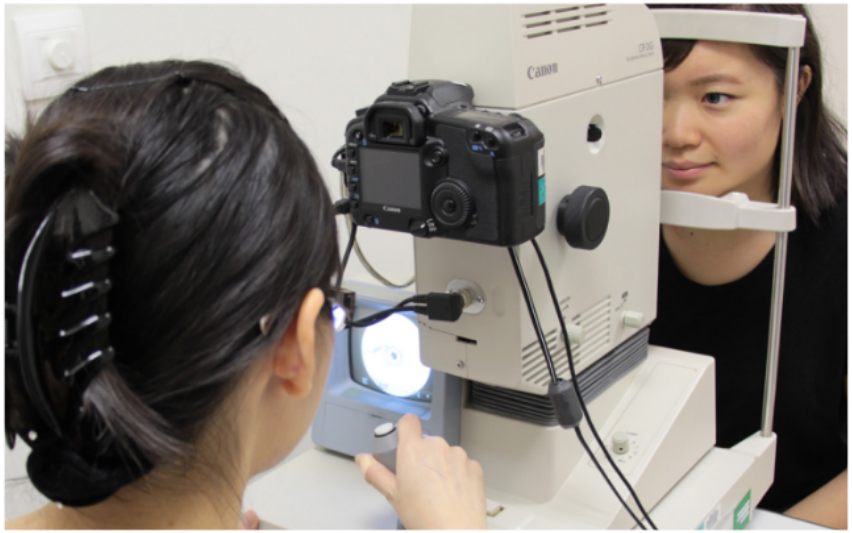
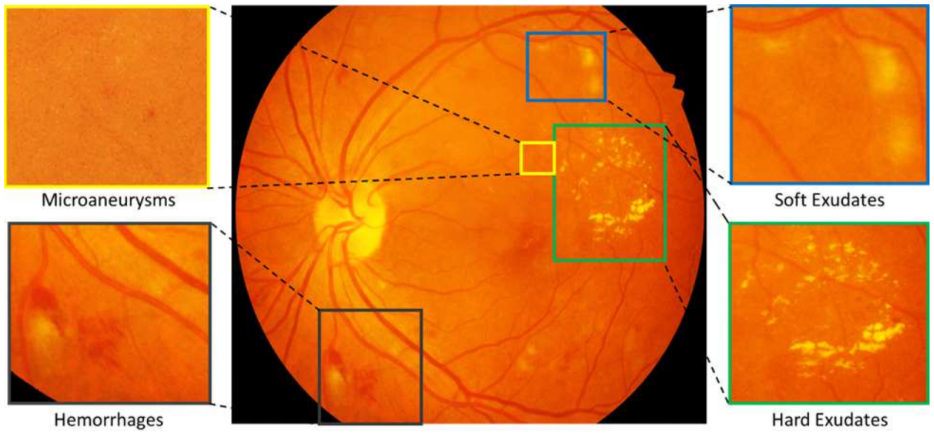


Managing DR

- Diagnosis and grading based on retinal fundus images
- Early diagnosis and treatment
- Regular monitoring + screening



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Referable DR detection: classification performances

Dataset description:

- Kaggle fundus data set for DR detection
- Referable DR classification task: $\{0,1\}$ vs $\{2,3,4\}$

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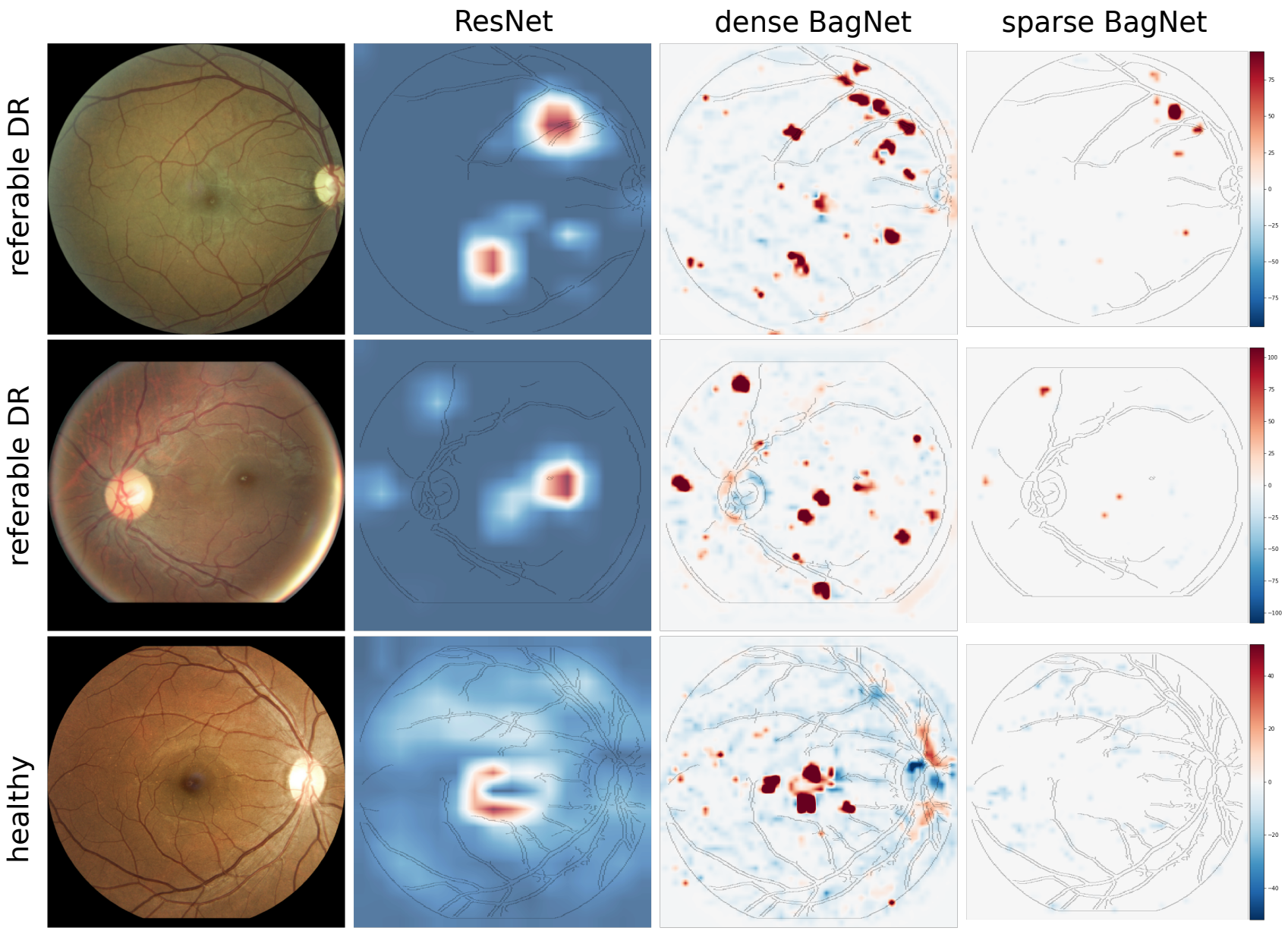
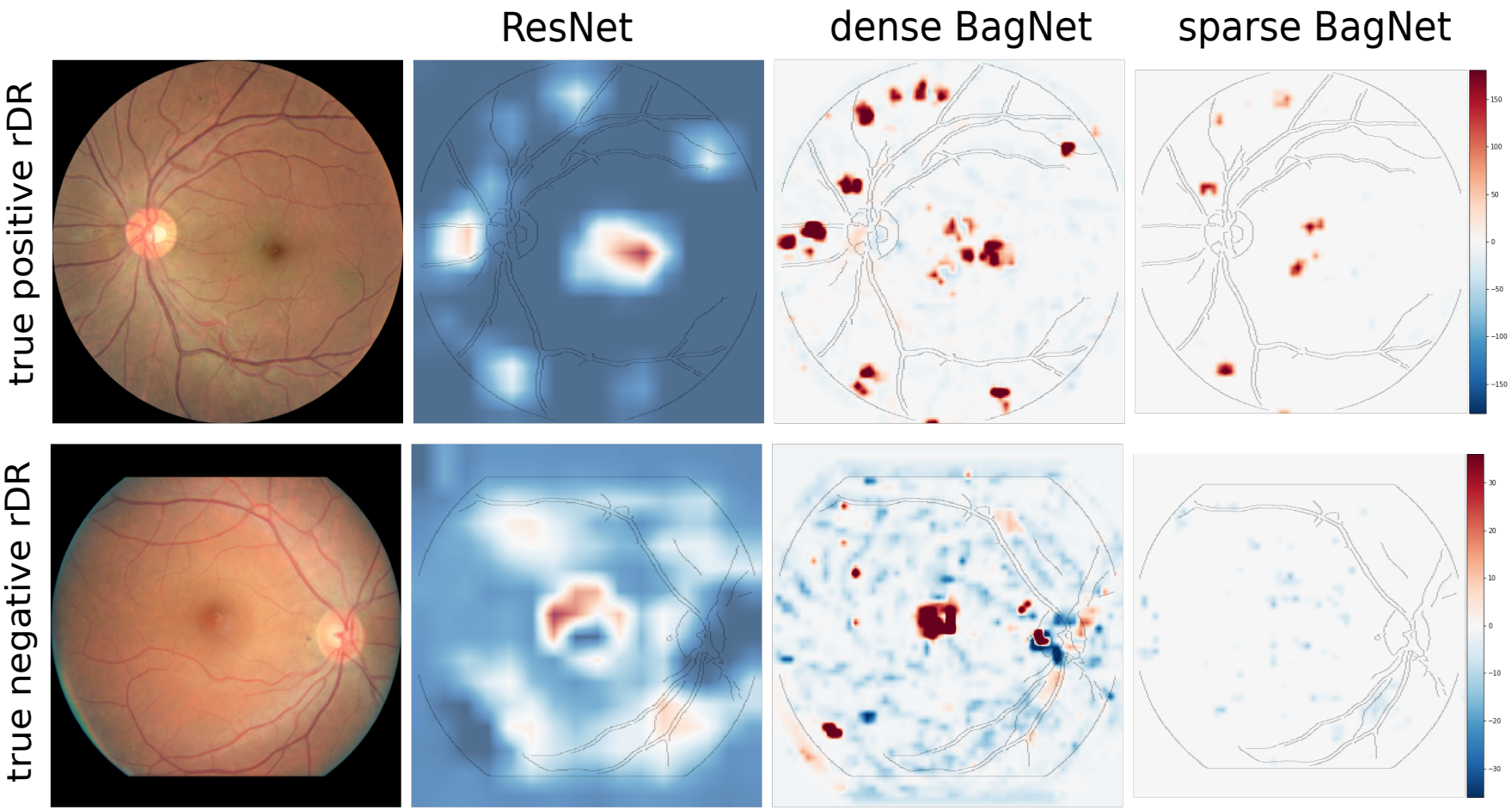
	Accuracy	**AUC**
ResNet-50	0.942	0.960
Dense BagNet	0.936	0.957
Sparse BagNet	0.928	0.937

Referable DR detection: qualitative heatmap evaluation



Referable DR detection: quantitative heatmap evaluation



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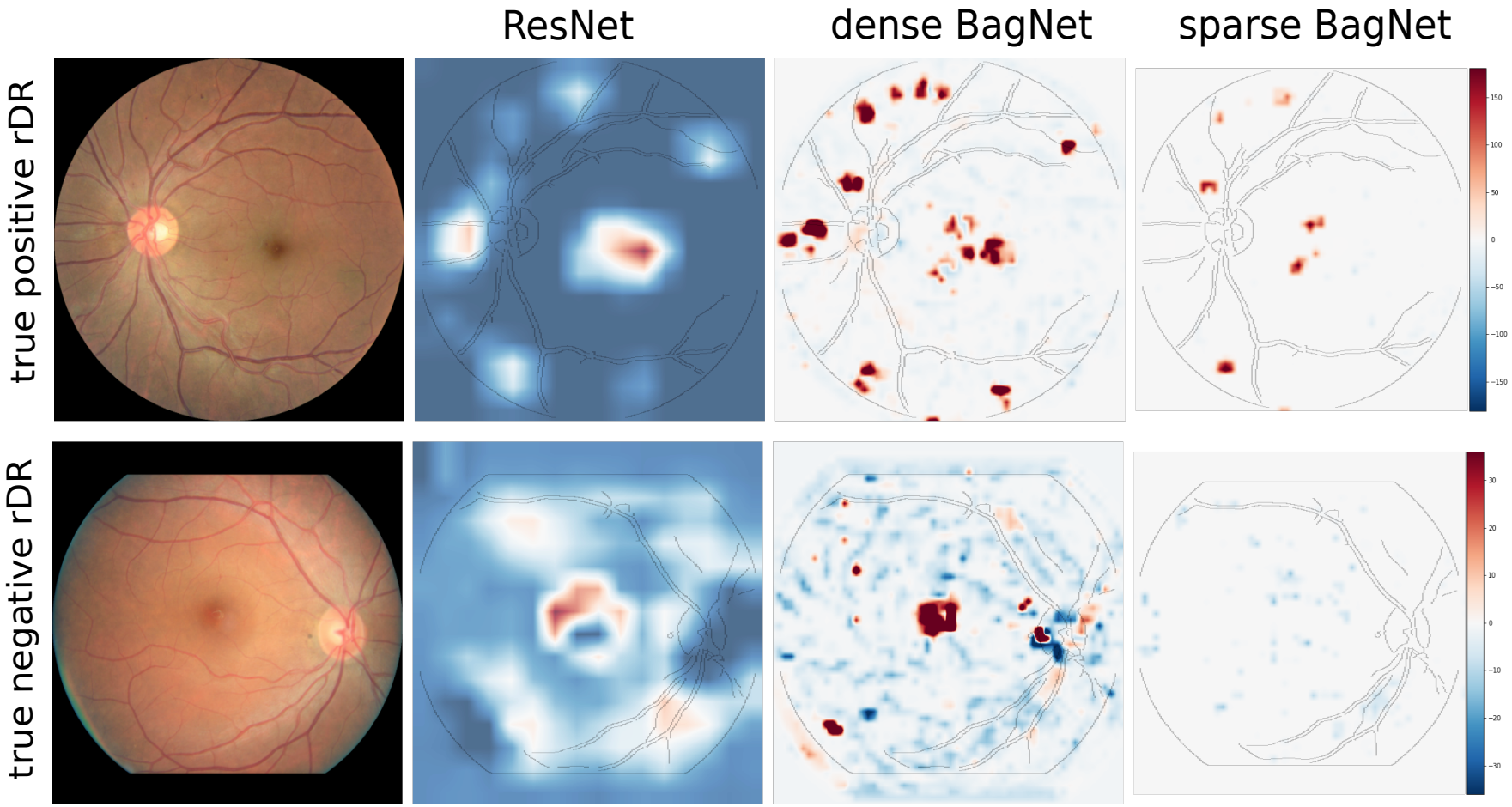
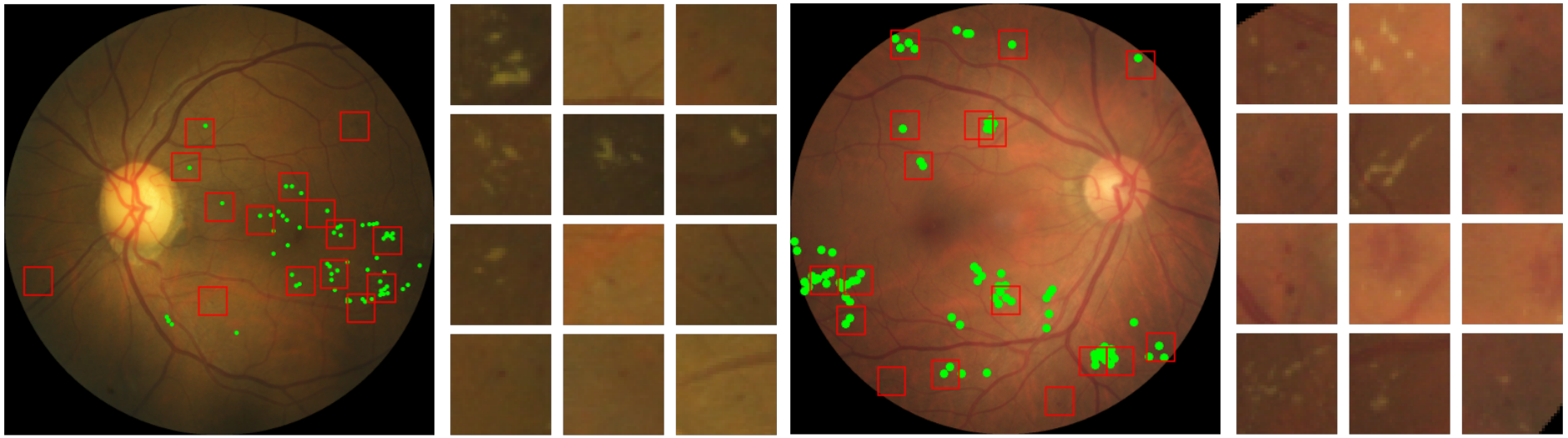


	$\uparrow \mathbf{r}^{-}_{\mathbf{LG}}$	$\uparrow \mathbf{r}^{+}_{\mathbf{LG}}$
Dense BagNet	0.922 ± 0.03	0.145 ± 0.06
Sparse BagNet	0.991 ± 0.04	0.374 ± 0.33

Referable DR detection: quantitative heatmap evaluation

- Lesion annotations (15 images)



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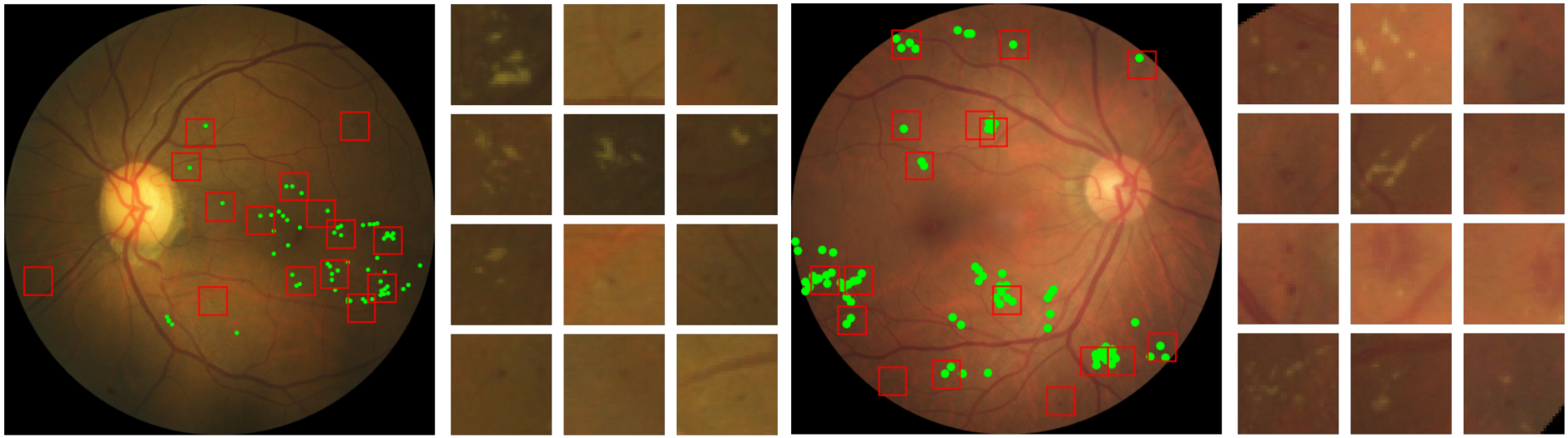

	Precision
Dense BagNet	0.219 ± 0.1
Sparse BagNet	0.791 ± 0.1

Multiclass DR detection: classification performances

- Multiclass task
- $\{0\}$ vs $\{1\}$ vs $\{2\}$ vs $\{3\}$ vs $\{4\}$

	Acc.
ResNet-50	0.862
Dense BagNet	0.864
Sparse BagNet	0.850

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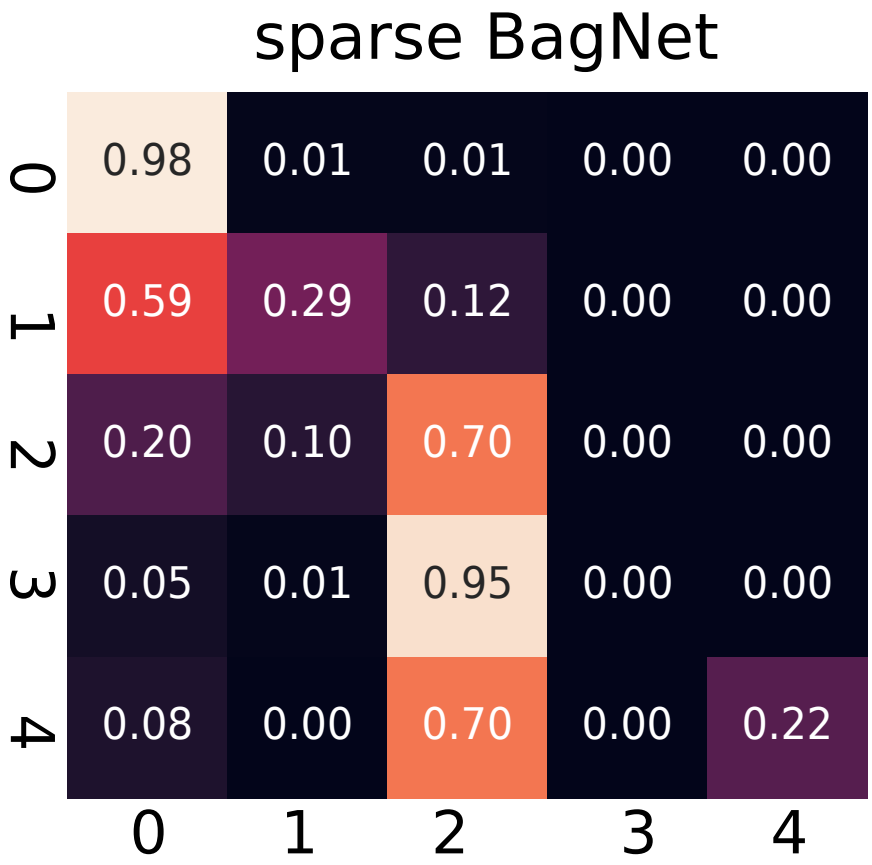
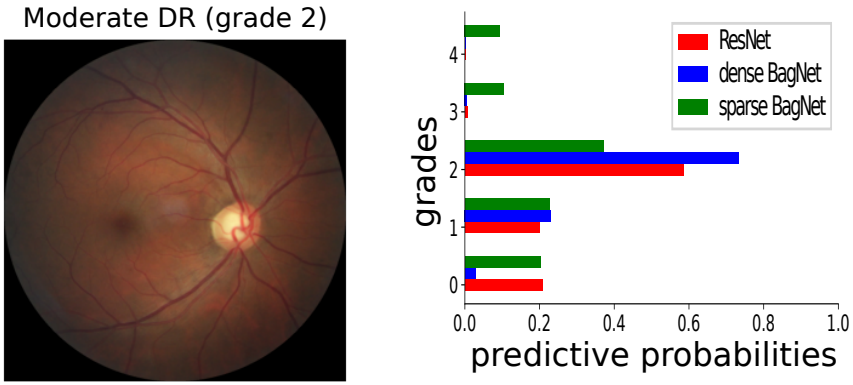
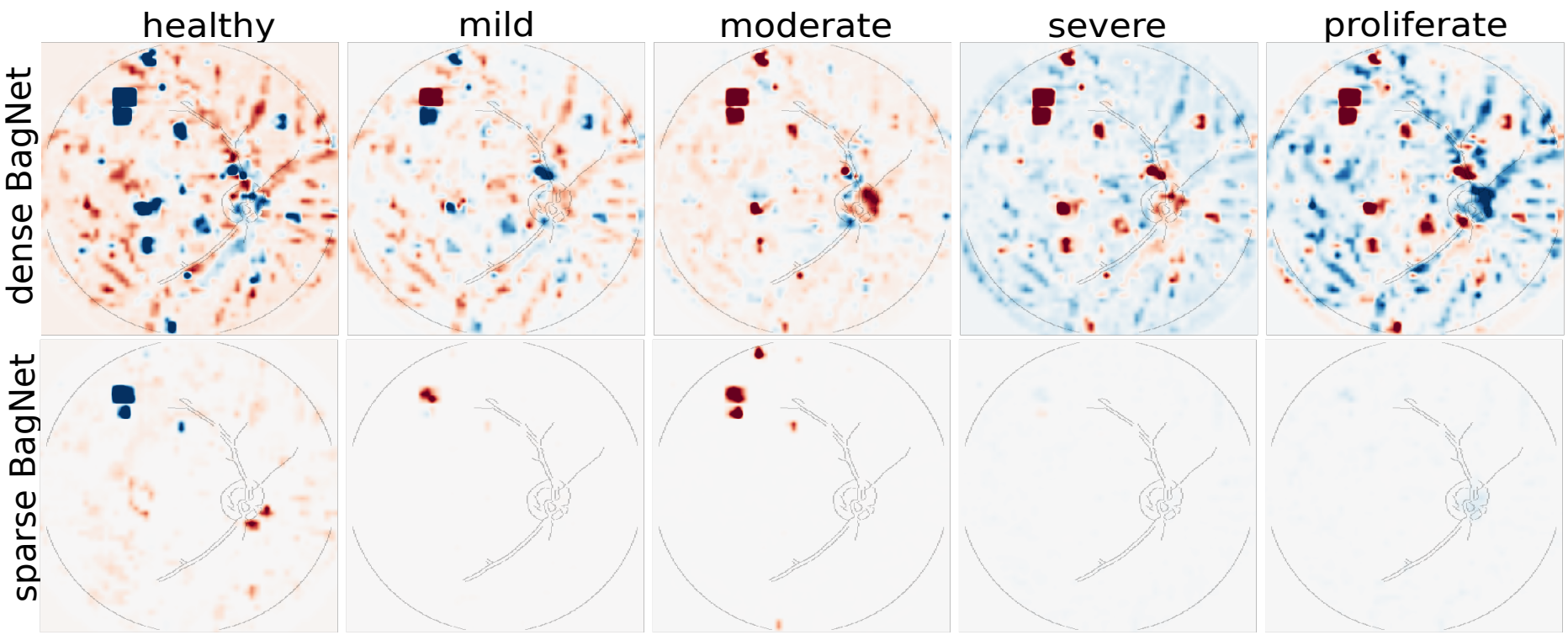


Multiclass DR detection: qualitative heatmap evaluation





Conclusion

Key contributions

1. BagNet's modifications
2. Inherently interpretable attribution map
3. Quantitative metrics to access the interpretability

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2. Inherently interpretable attribution map
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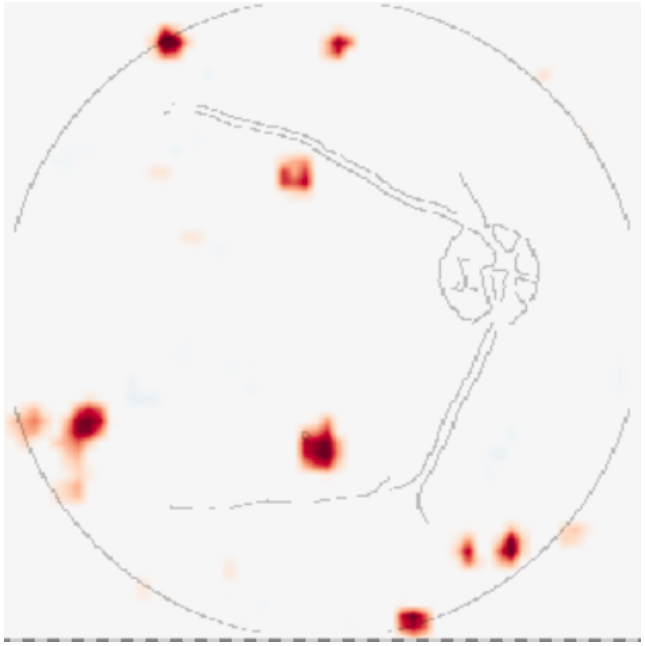
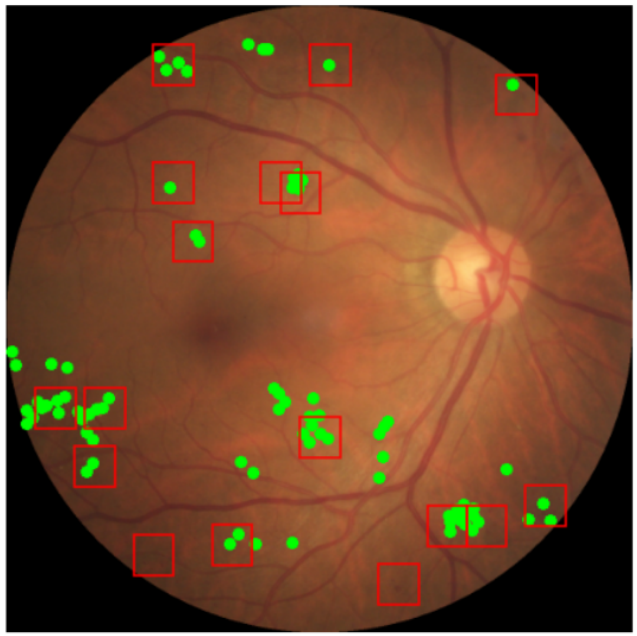
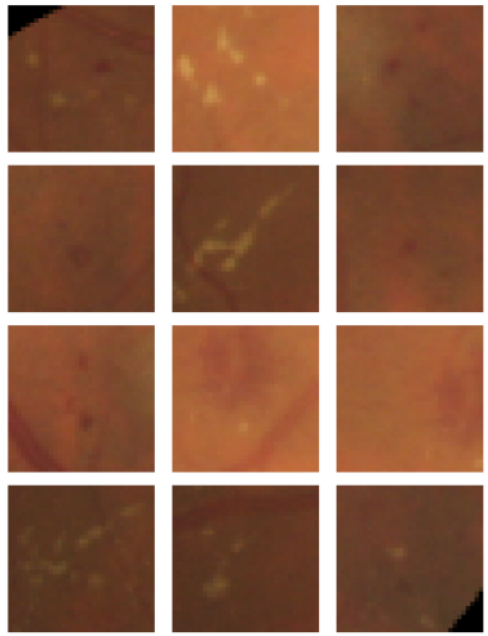
Summary

- Enforcing sparse heatmap improves the interpretability
- Suitable for small lesions distributed over the image
- Comparable SOTA performance on DR detection

Next step







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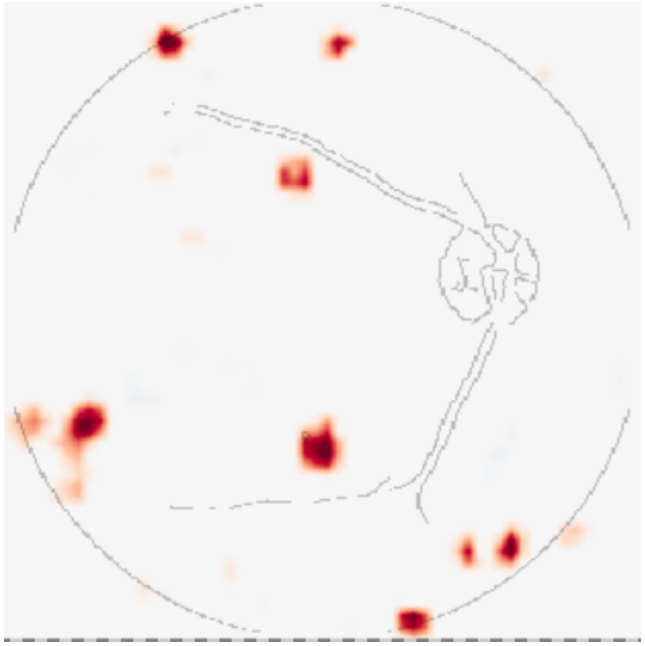
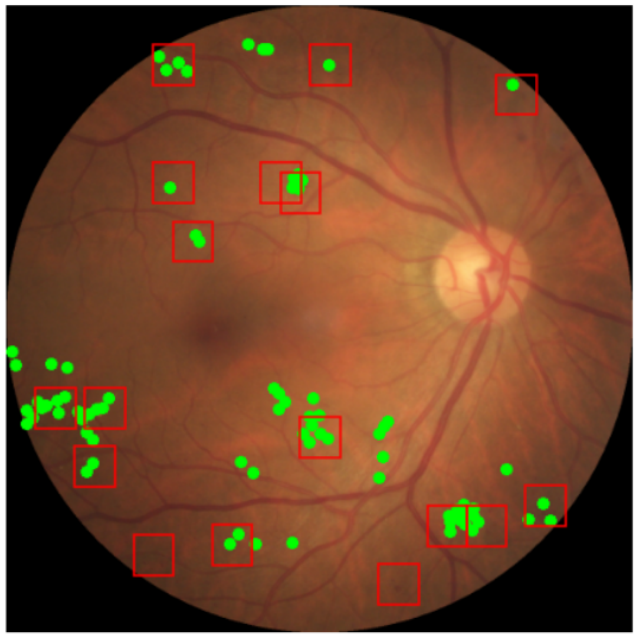
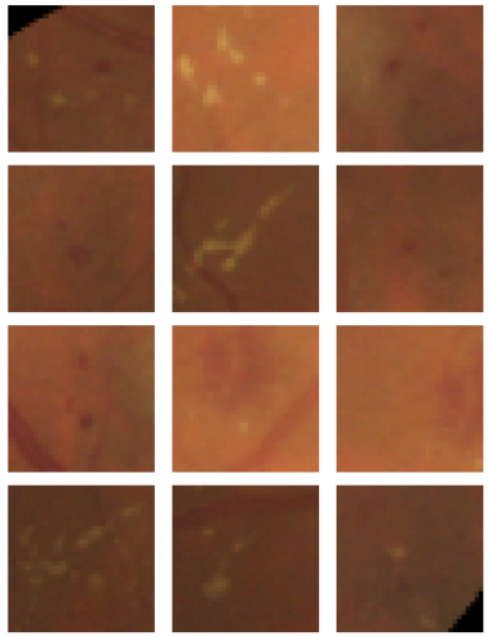


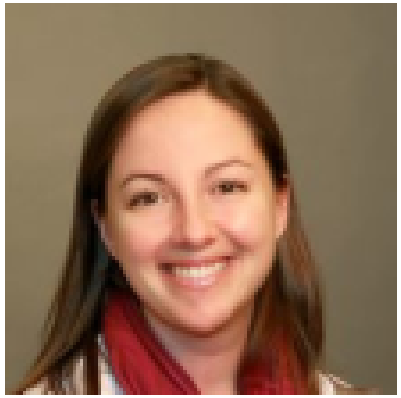
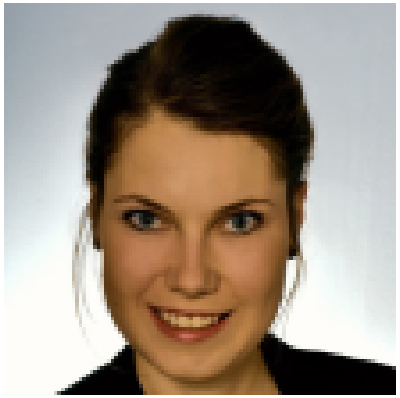




Clinical study

Does highlighting suspicious areas of the image improve diagnostic performance?

Acknowledgements



GitHub

Paper

Thank you for your attention!

Poster location: **W08**

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Dataset

Dataset Description:

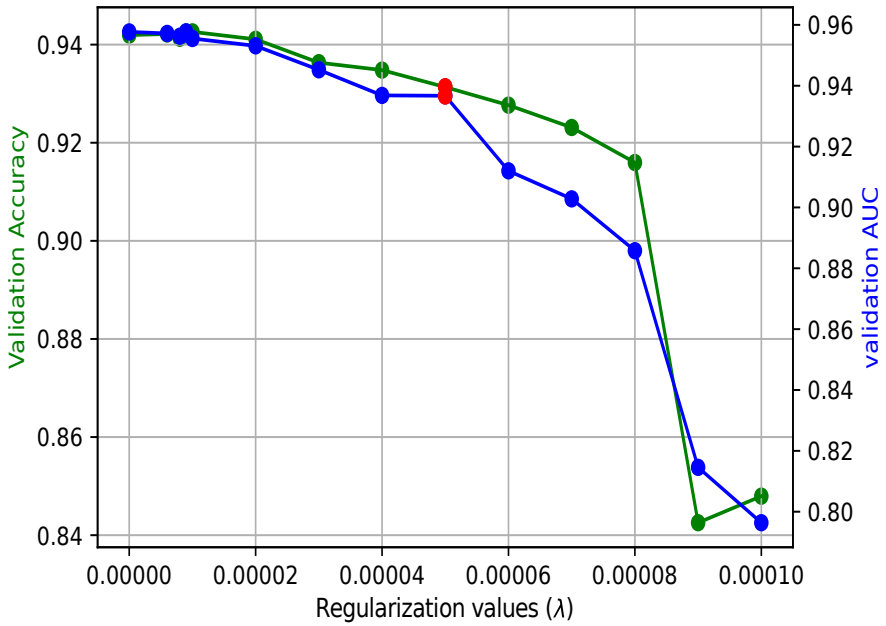
- Kaggle dataset: $88,702$
- Quality filtering: $45,923$
- Referable task: $\{0,1\}$ vs $\{2,3,4\}$
- Multiclass task: $\{0\}$ vs $\{1\}$ vs $\{2\}$ vs $\{3\}$ vs $\{4\}$

Method: Model's architecture

- BagNet encodes the input:
  - $f_{bag}(X) = A' \in R^{N \times N \times D}$
  - $A' \xrightarrow{C_{1\times1}} A \in R^{N \times N \times C}$
  - $\mathbf{A} \xrightarrow{\mathbf{SAP}} \mathbf{l_c} \in \mathbf{R^{1 \times C}}$
- Patch-based model

- Small receptive field
- Heatmap = evidence map
- λ controls the sparsity
- Suspicious patch visualization

Sparsity hyperparameter λ



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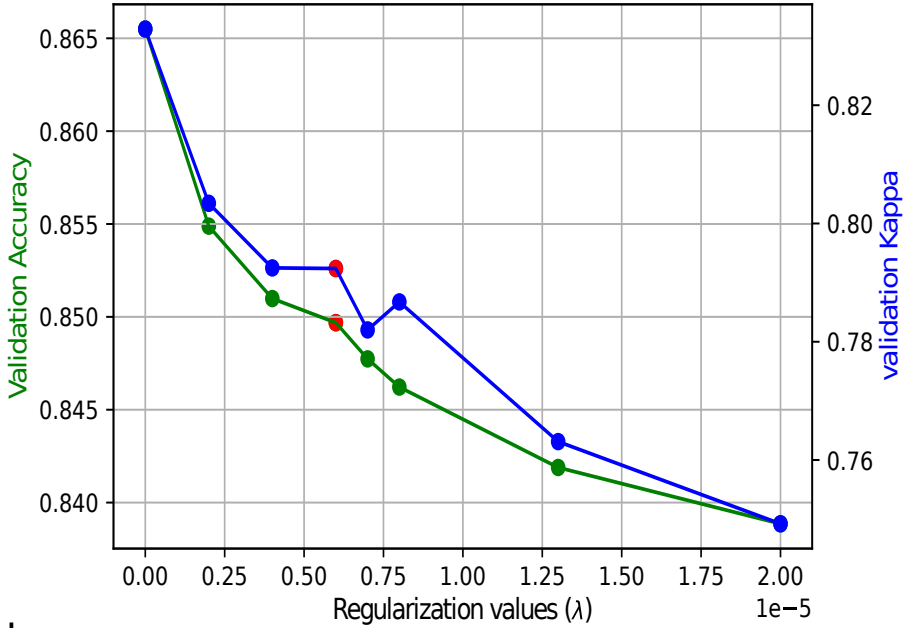

b

Sparse BagNet limitations