Deep Learning Explainability for Breast Cancer Detection in Mammography

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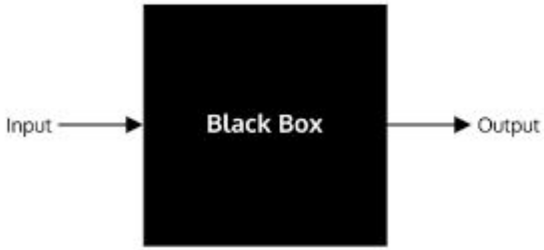
Universitat de Girona

Breast Cancer and Deep Learning

- One of the leading causes of mortality amongst women.
- Interest in improving detection methodologies.
- CAD systems and DL to aid and alleviate radiologists’ workload.
- CNN models have been researched for this task.
- Good results and comparable performance to radiologists.

The black-box paradigm

- Growing concerns when using DL models for medical tasks.
- DL models are black boxes.
- Difficult to understand their decision-making processes.
- Compliance with regulations: GDPR
- **Possible answer: Explainable AI (XAI)**



Goals

To visualize and evaluate the performance of a trained network for breast cancer detection with different XAI algorithms:

1. Patch-based XAI.
2. Whole mammogram XAI.
3. Evaluation of XAI methods (qualitative and quantitative).

XAI methods

Gradient-based

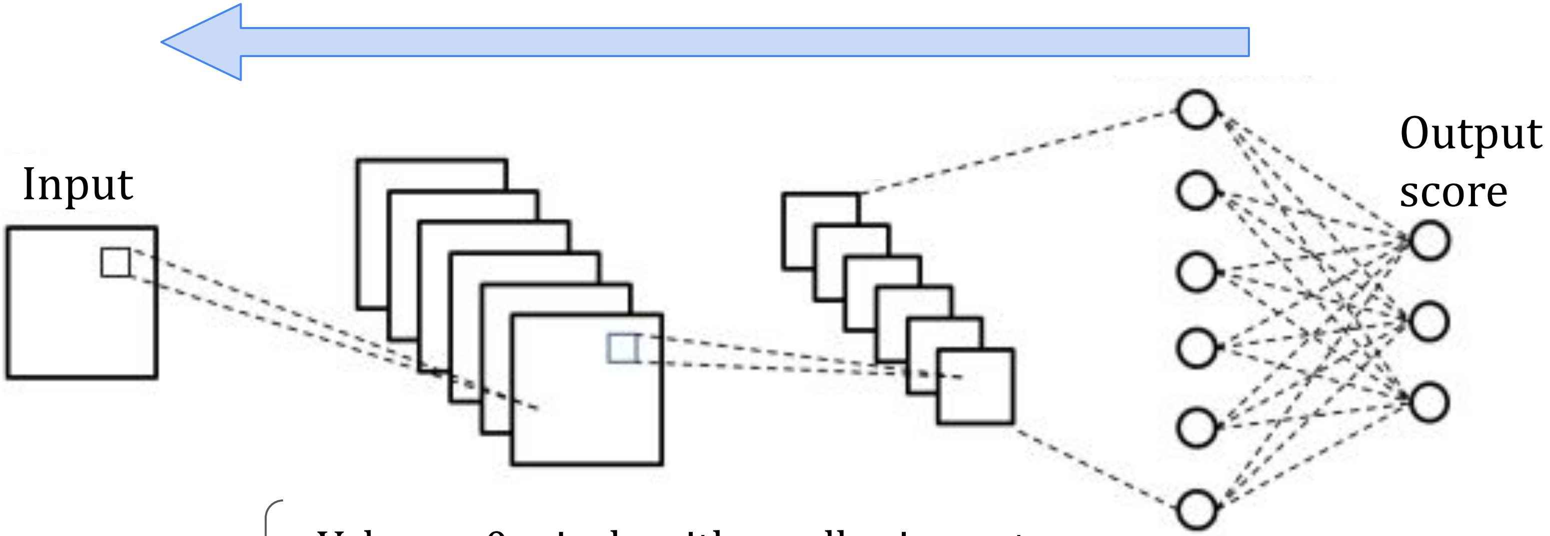
- Saliency maps
- Guided Grad-CAM
- Integrated Gradients (IG)
- DeepLIFT

Perturbation-based

- Occlusion
- LIME
- SHAP

Gradient-based approaches

Compute the attribution scores for the features by obtaining the gradients.

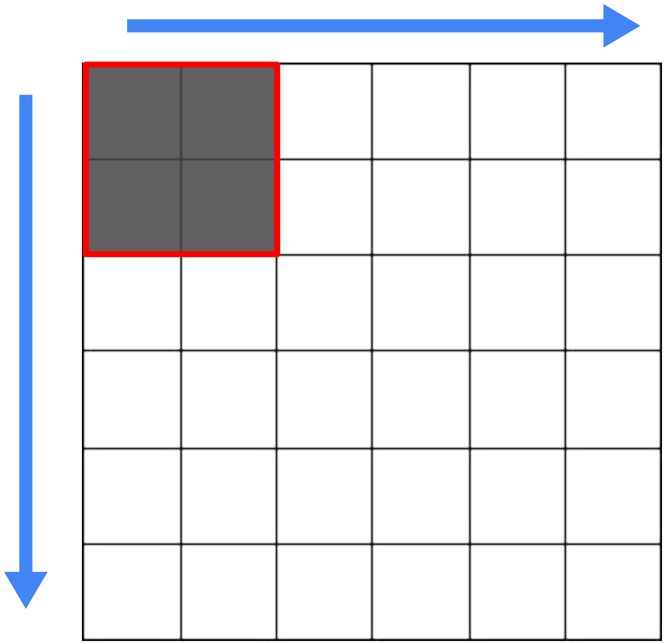


Saliency maps
- Values ≈ 0: pixels with smaller impact
- Large values: pixels which majorly affect the output score

Gradient-based approaches

Approach	Characteristic
Saliency	Baseline approach
DeepLIFT	Requires a reference value (e.g. a black image) and **compares** the activations with the **reference value** and the **input image**.
Integrated Gradients	Considers a **straight path between a baseline and an input image**, and computes gradients for each step, which are then accumulated.
Guided Grad-CAM	Computes the gradients w.r.t. the feature maps of the **last convolutional layer**. The feature maps' gradients are averaged and passed through a **ReLU**. Multiplication with **Guided Backpropagation**.

Perturbation-based approaches



- Occlusion: Sliding window.
- LIME: **Simple interpretable model** for the relationship between the changes to the image and the outputs.
- SHAP: Uses **Shapley values** and considers all **subsets**.

XAI in mammography

- Analyzing the impact via **SHAP** of each of the data's features in an ML-DL model that combined mammograms and clinical data for breast cancer detection (Akserlod-Ballin et al., 2019).
- Visualizing the network's process with **Grad-CAM** when predicting for view, laterality, or breast density (Yi et al., 2019).
- Confirming the correct performance of a proposed hybrid neural network with **CAM** (Huang et al, 2020).
- Gaining insight into CNNs' and Visual Transformers' inner processes for breast cancer detection with **Grad-CAM** and bounding boxes (Prodan et al., 2023).

Dataset

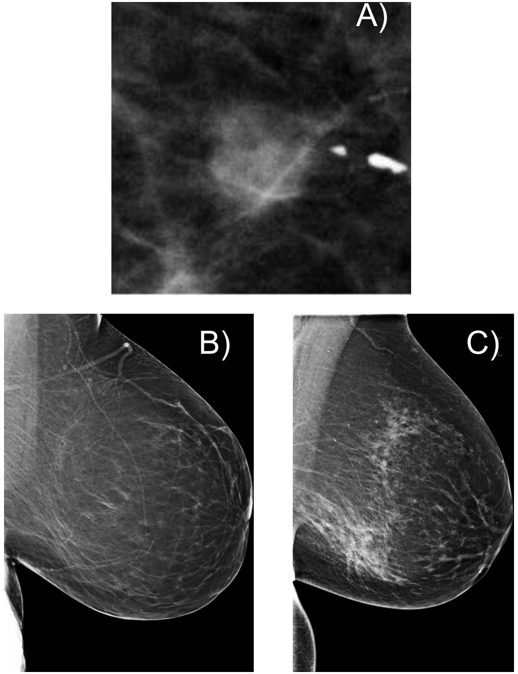
Iceberg selection
- OPTIMAM subset.
- Patches of mammograms with masses.
- 3808 mammograms, 7616 total patches.

RSNA22 subset
- 2767 mammograms.
- 2058 non-malignant, 709 malignant

OPTIMAM Hologic subset
- 7229 mammograms
- 3615 non-malignant, 3614 malignant

1° Task

2° Task



A) Iceberg selection example.
B) RSNA22 subset example.
C) OPTIMAM Hologic subset example.

Classification

Patch-based classification

- MobileNetV2 and ResNet-50
- Transformations: Horizontal flip, vertical flip and random 30° rotation 224x224 resizing, and normalization.
- CE Loss
- Adam
- Reduce LR on plateau scheduler

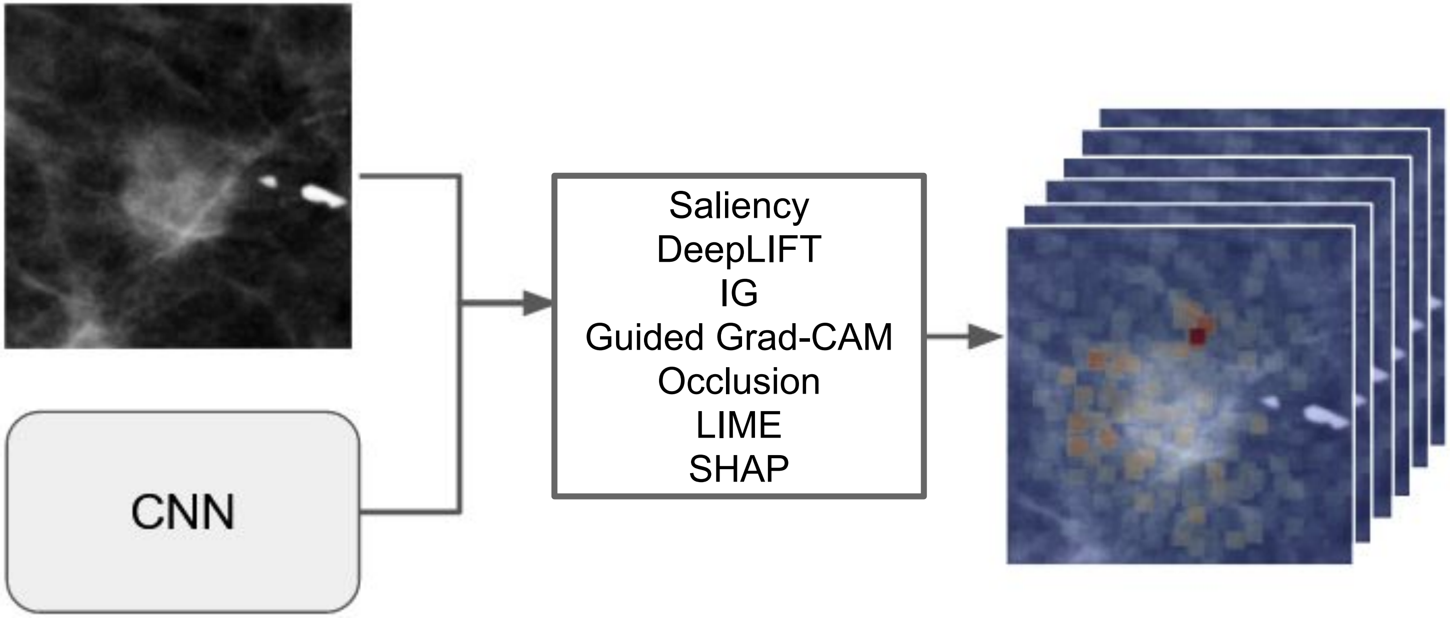
ResNet-50 selected

Whole mammogram classification

- ResNet-50 attempted first, but did not yield satisfactory results.
- EfficientNetB0 with:
  - SGD with momentum = 0.9
  - Cosine Annealing scheduler with warm restart
  - Input size = 1024 x 512

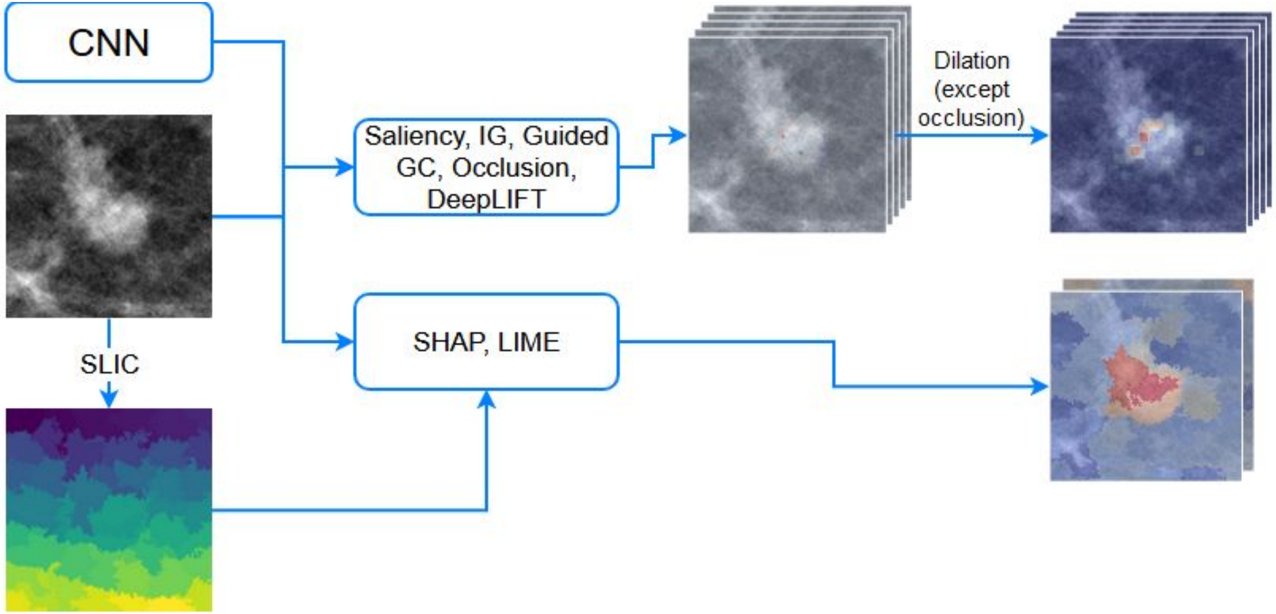
EfficientNetB0 selected

Attribution map generation



Attribution map generation

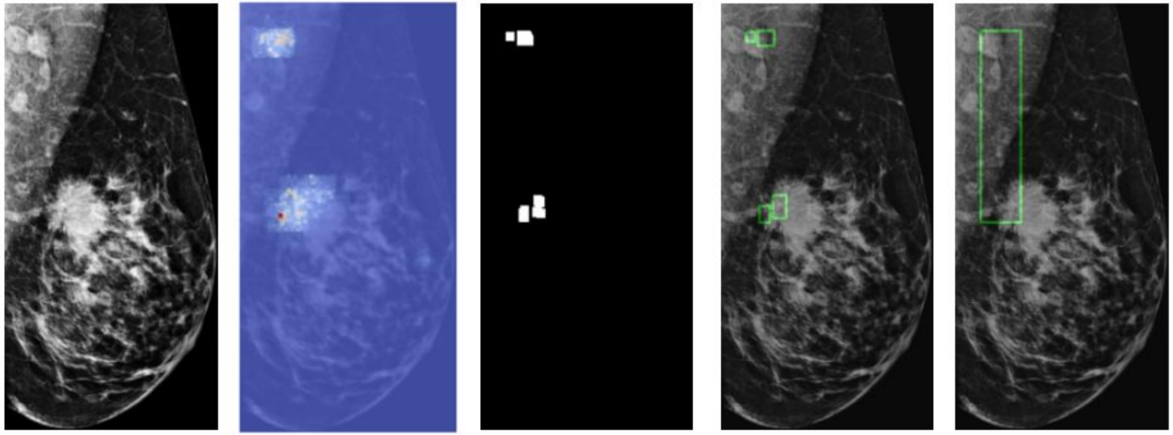
- **Guided Grad-CAM:** Requires layer.
- **Occlusion**
  - Sliding window shape (3,15,15) & (3,60,60).
  - Stride (3,8,8) & (3,30,30).
- **SHAP & LIME:** Segmentation mask provided.



Quantitative Evaluation

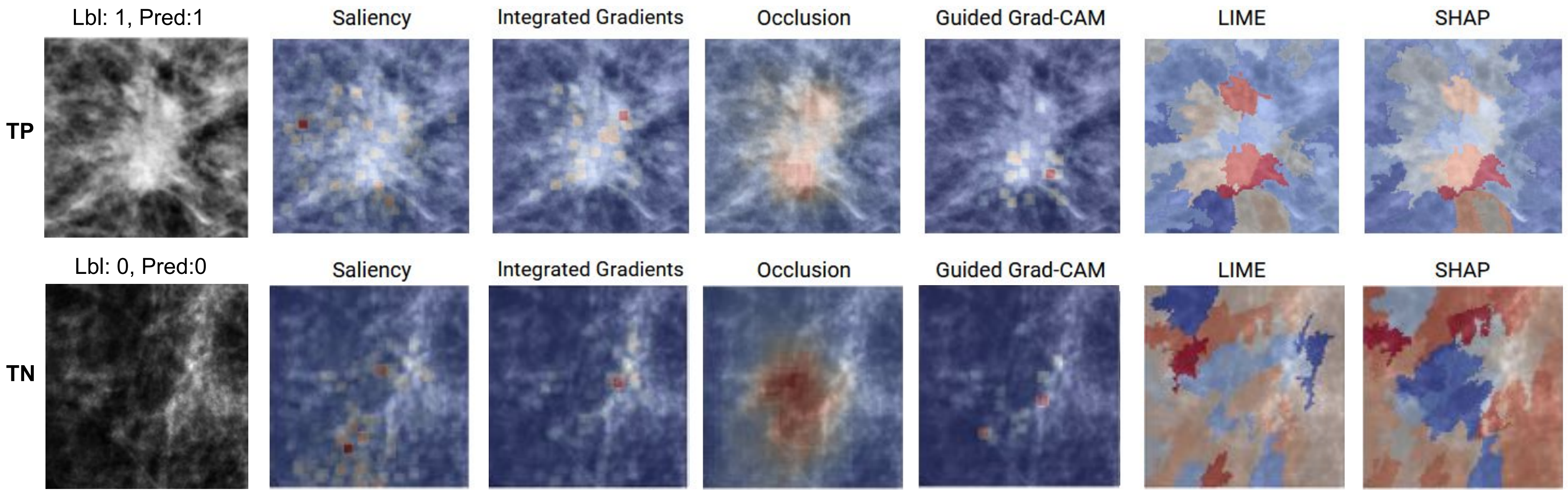
Quantitative Evaluation - IOU scores

- **Hypothesis**: the explainability results for the whole mammogram problem should show a relationship with the position of the lesions.
- Intersection over union (IOU) were computed w.r.t. the ground-truth bounding boxes for the malignant whole mammograms from the OPTIMAM Hologic subset.
- Bounding boxes were generated for this.

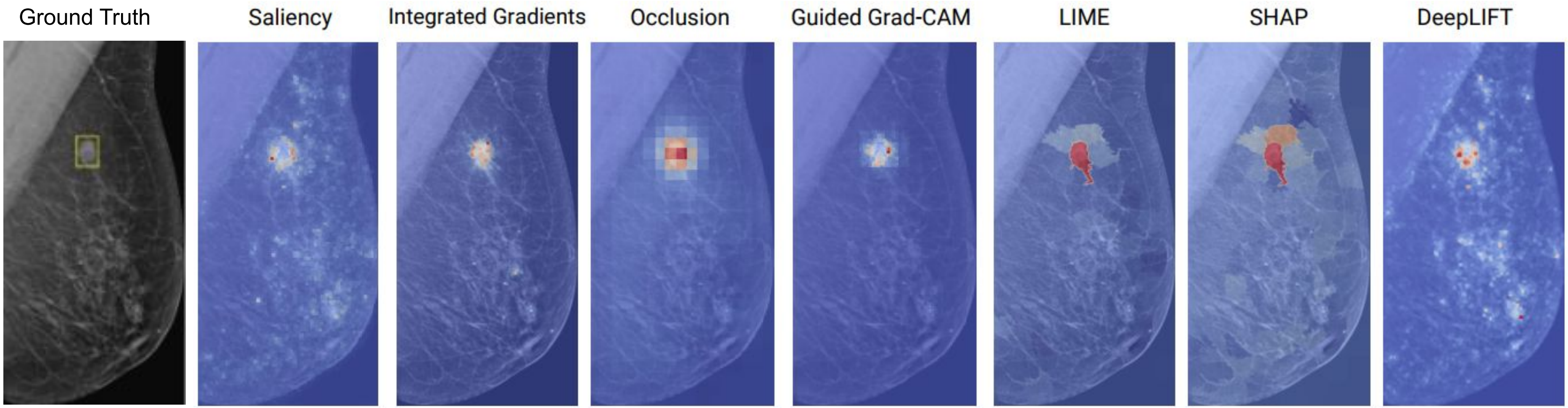


Original image Attribution map Binarized map Bounding Boxes Merged Boxes

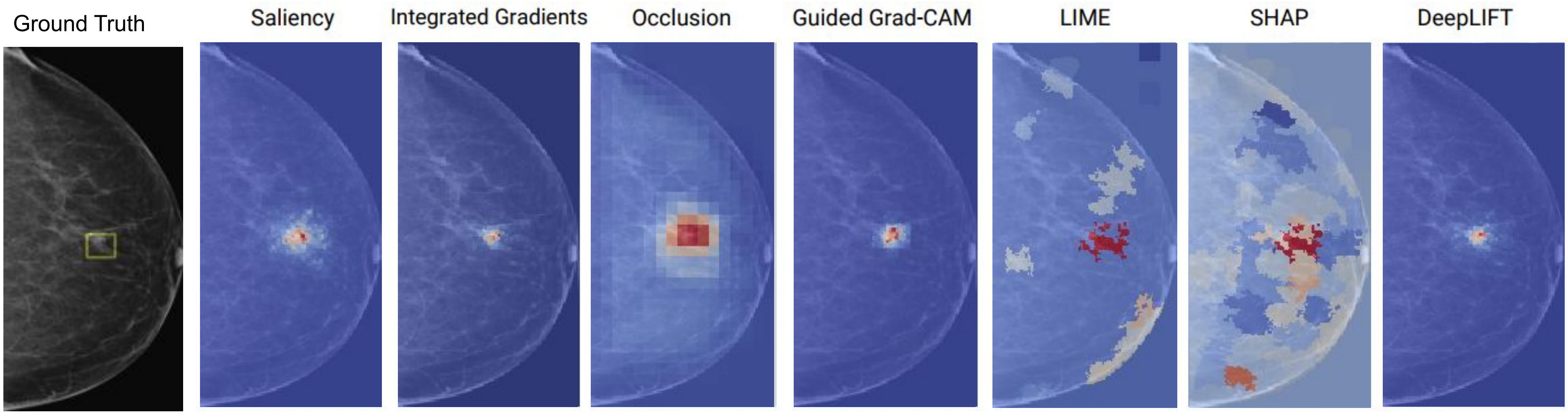
Patch-based classification



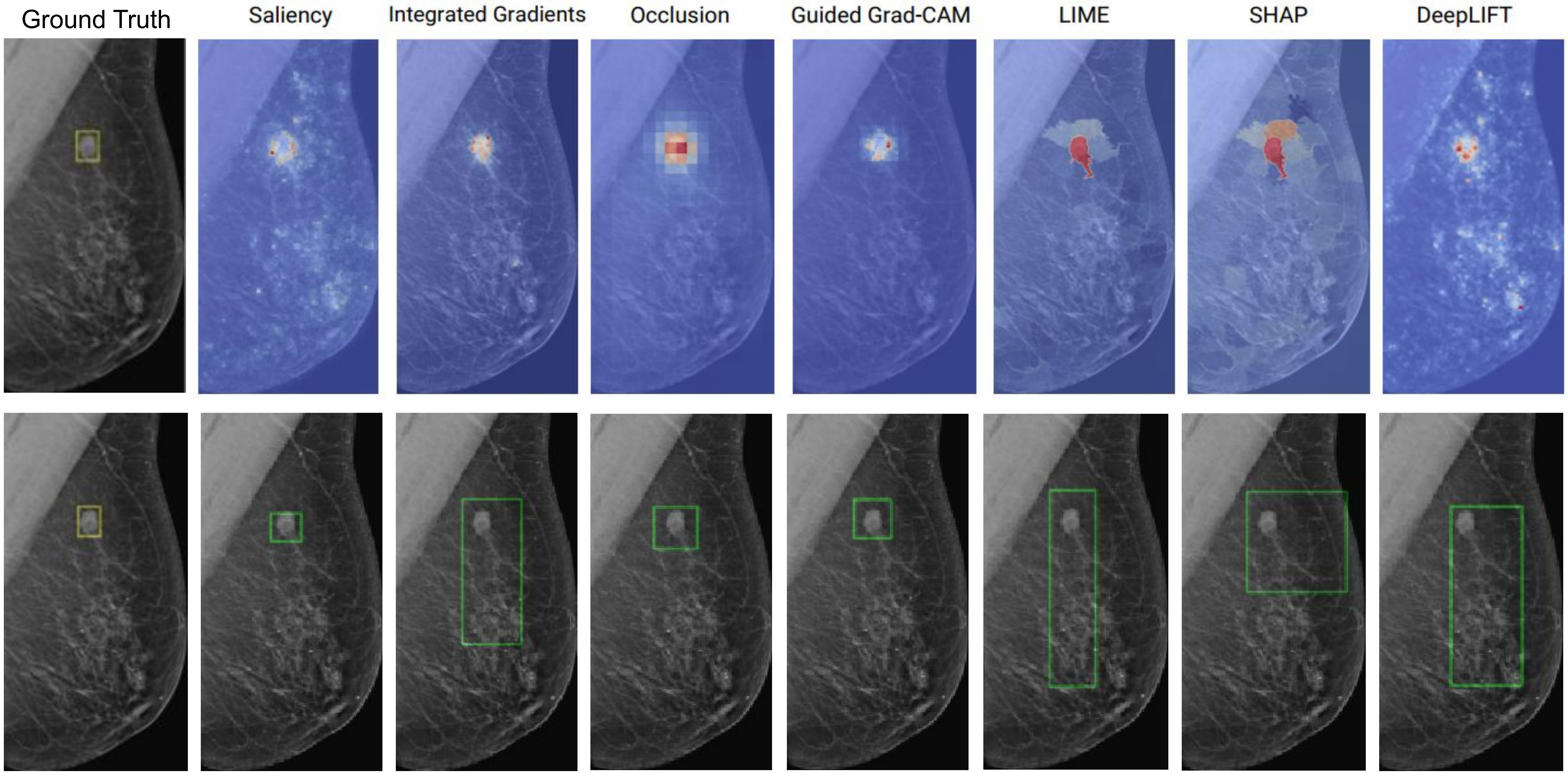
Whole mammogram classification: TP high probability



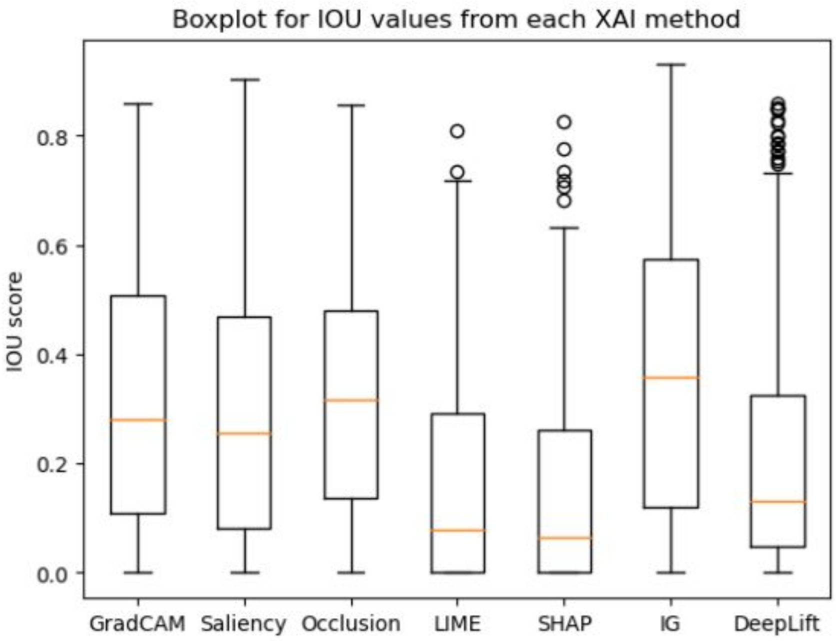
Whole mammogram classification: TP low probability



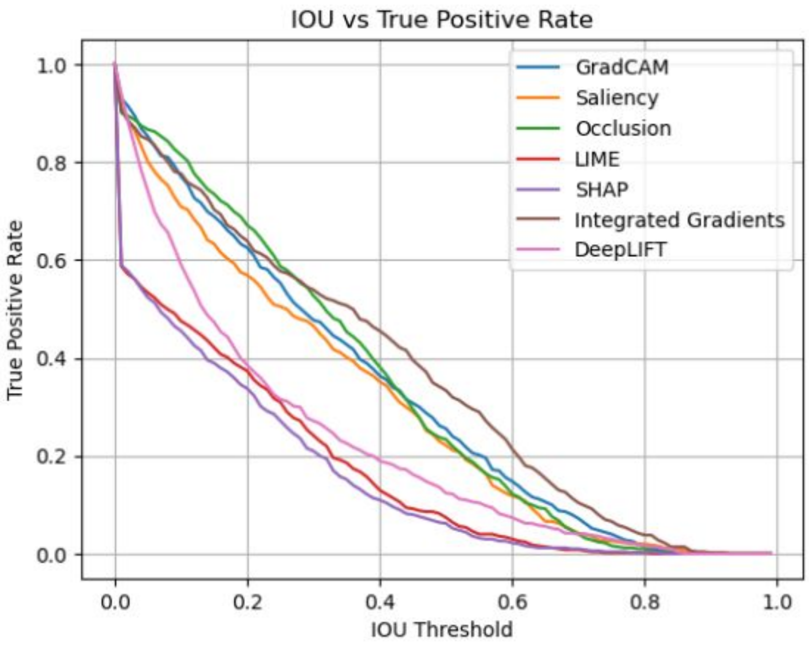
Bounding Boxes



IOU Scores



Boxplot for IOU values from each XAI method
IOU score
0.0
0.2
0.4
0.6
0.8
GradCAM
Saliency
Occlusion
LIME
SHAP
IG
DeepLift



IOU vs True Positive Rate
True Positive Rate
IOU Threshold
0.0
0.2
0.4
0.6
0.8
1.0
GradCAM
Saliency
Occlusion
LIME
SHAP
Integrated Gradients
DeepLIFT

Computation Costs

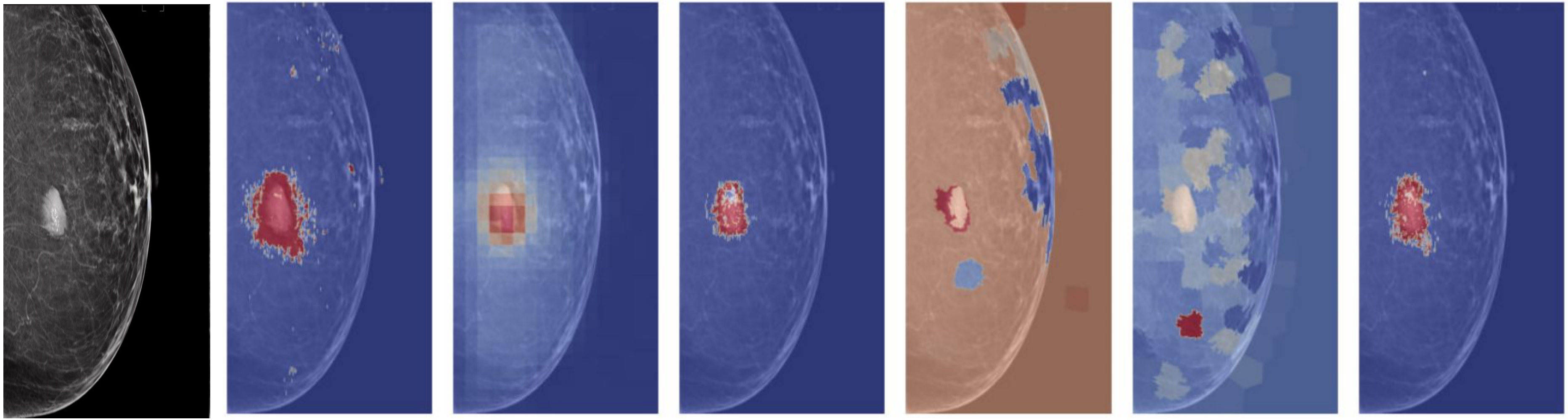
Less costly

More costly

Guided Grad-CAM, Saliency & DeepLIFT
LIME
Occlusion
SHAP
Integrated Gradients

Synthetic Lesions with Stable Diffusion

Original image Saliency Occlusion Guided Grad-CAM LIME SHAP DeepLIFT



Montoya, R. MAIA, 2023.

Summary

- XAI methods were applied on models trained on patch-based breast cancer classification and whole-mammogram classification.
- Highlighted regions mostly coincided with the mass regions in whole mammograms.
- Overall, IG performed best, and SHAP & LIME the worst.
- IG is very computationally costly, so Guided Grad-CAM might be better.

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Future Work

- XAI on state-of-the-art models.
- More refined bounding box generation method for improved IOU scores.
- XAI for breast cancer subtype classification.

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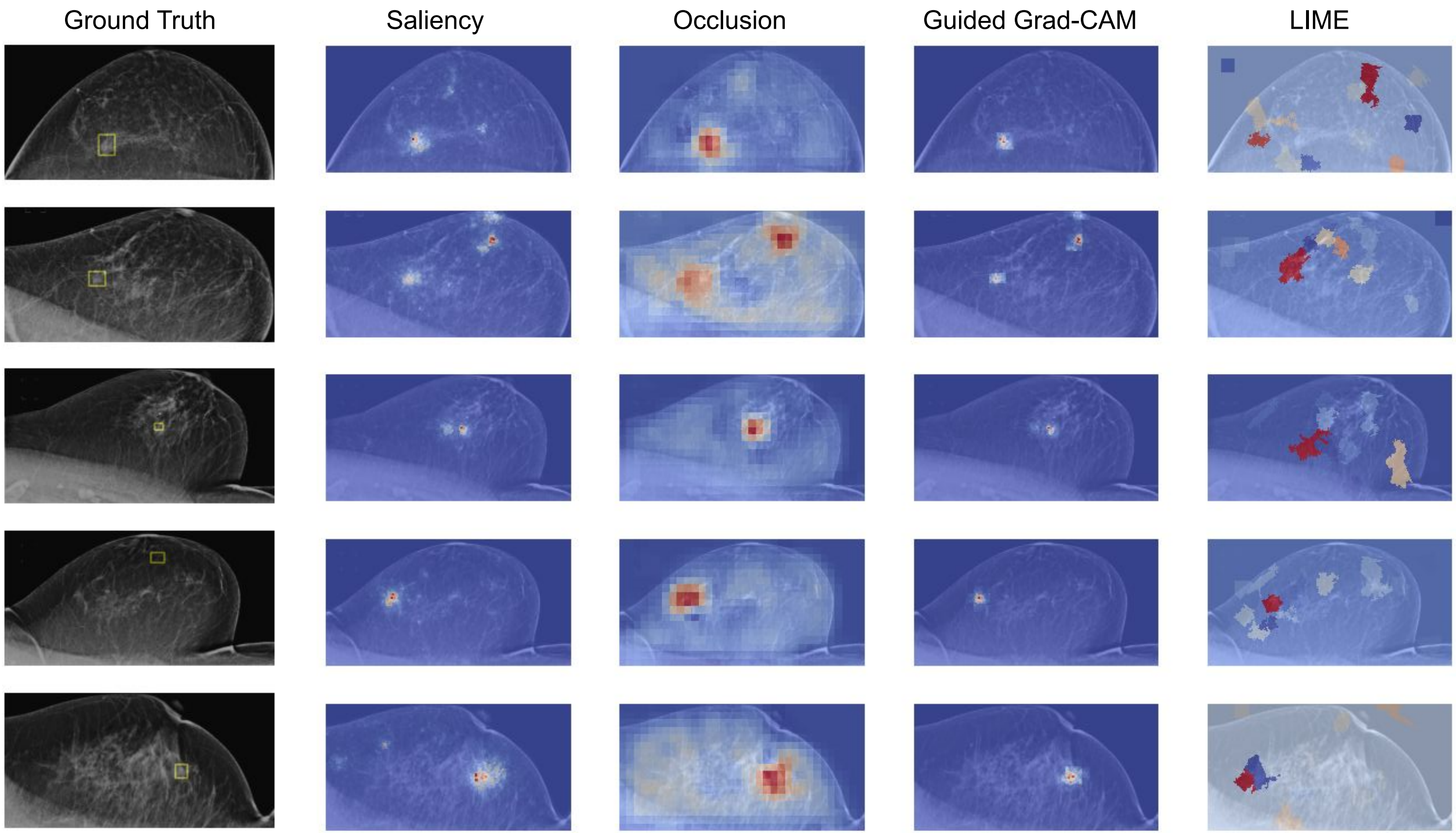
FN: Attribution maps



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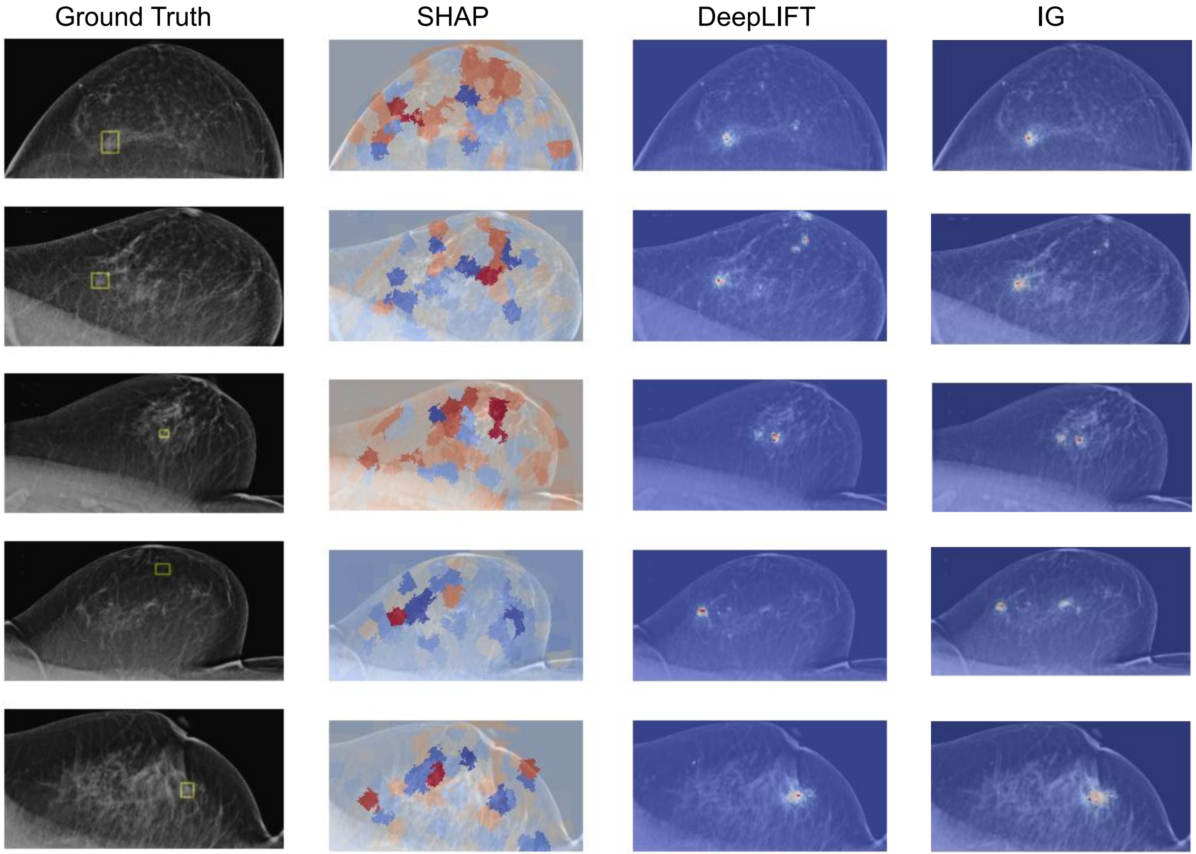

Computation Costs

Less costly

More costly

Method	Time for 10 imgs
Guided Grad-CAM, Saliency & DeepLIFT	~3.5 s
LIME	22.5 s
Occlusion	43.7 s
SHAP	3 min 43.3 s
Integrated Gradients	3 min 13.7 s