A Deep Learning Classifier Using Sliding Patches for Detection of Mammographical Findings

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- Worldwide, has an average mortality rate of 13.6 per 100 000 women in 2020 [1]
- In Chile, has an average mortality rate of 11.8 per 100 000 women, as of 2018 [2]
- Early screening is effective but dependant on multiple social, healthcare and economic factors.
- Early diagnosis and survival rate in Chile has increased due to the implementation of screening programs [3]

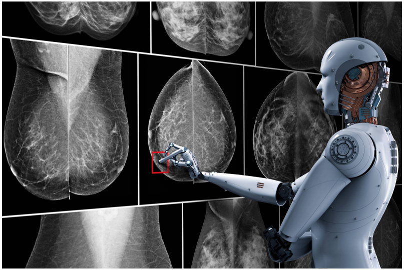
Figure: Mortality rate and number of potential lost years of life due to breast cancer of Chilean Women per region (2009-2018)

[1] *Breast Cancer Statistics | World Cancer Research Fund International*. WCRF International. URL: https://www.wcrf.org/cancer-trends/breast-cancer-statistics/ (visited on 11/09/2023)

[2] Ministerio de Salud. *Informe de Vigilancia de Cáncer. Análisis de Mortalidad Prematura y AVPP Por Cáncer. Década 2009-2018*. Chile: Departamento de Epidemiologia, 2021. URL: https://www.minsal.cl/wp-content/uploads/2022/01/Informe-Mortalidad-Prematura-y-AVPP-por-C%C3%A1ncer-2009-2018.pdf (visited on 11/09/2023)

[3] César del SM Castillo, M. Elena C. Cabrera, Lea Derio P., et al. “Resultados Del Tratamiento Del Cáncer de Mama, Programa Nacional de Cáncer Del Adulto”. In: *Revista médica de Chile* 145.12 (Dec. 2017), pp. 1507–1513. ISSN: 0034-9887. DOI: 10.4067/s0034-98872017001201507. URL: https://scielo.conicyt.cl/scielo.php?script=sci_abstract&pid=S0034-98872017001201507&lng=es&nrm=iso&tlng=en (visited on 04/21/2021)

- Machine Learning and Deep Learning models have been implemented for the detection of breast cancer in mammograms. [4]
- Current Challenges:
  - Detection of breast lesion location in mammograms [5]
  - Visualisation tools for interpretation of prediction models.
  - Breast Density Estimation
  - Breast image classification beyond malignity.



[4] Alejandro Rodríguez-Ruiz, Elizabeth Krupinski, Jan-Jurre Mordang, et al. "Detection of Breast Cancer with Mammography: Effect of an Artificial Intelligence Support System". In: *Radiology* 290.2 (Nov. 20, 2018), pp. 305–314. ISSN: 0033-8419. DOI: 10.1148/radiol.2018181371. URL: https://pubs.rsna.org/doi/10.1148/radiol.2018181371 (visited on 05/12/2021)

[5] O. Díaz, A. Rodríguez-Ruiz, A. Gubern-Mérida, et al. "¿Son los sistemas de inteligencia artificial una herramienta útil para los programas de cribado de cáncer de mama?" In: *Radiología* 63.3 (May 2021), pp. 236–244. ISSN: 00338338. DOI: 10.1016/j.rx.2020.11.006. URL: https://linkinghub.elsevier.com/retrieve/pii/S0033833820301752 (visited on 03/30/2023)

Ertosun and Rubin proposed a Deep Learning model for visual search in mammograms using a regional probabilistic approach. [6]

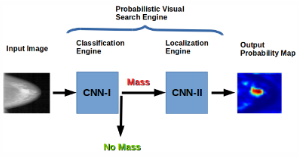


Figure: Probabilistic Visual Search Engine proposed by Ertosun and Rubin

[6] Mehmet Gunhan Ertosun and Daniel L. Rubin. "Probabilistic Visual Search for Masses within Mammography Images Using Deep Learning". In: *2015 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*. 2015 IEEE International Conference on Bioinformatics and Biomedicine (BIBM). Washington, DC, USA: IEEE, Nov. 2015, pp. 1310–1315. ISBN: 978-1-4673-6799-8. DOI: 10.1109/BIBM.2015.7359868. URL: http://ieeexplore.ieee.org/document/7359868/ (visited on 11/09/2023)

[7] Steven J. Frank. "A Deep Learning Architecture with an Object-Detection Algorithm and a Convolutional Neural Network for Breast Mass Detection and Visualization". In: *Healthcare Analytics* 3 (Nov. 1, 2023), p. 100186. ISSN: 2772-4425. DOI: 10.1016/j.health.2023.100186. URL:

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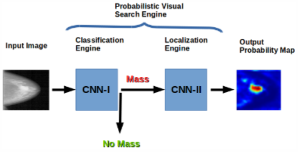

Figure: Probabilistic Visual Search Engine proposed by Ertosun and Rubin

Frank proposed using YOLO V5 for detection of breast lesions, combined with EfficientNet for classification of masses and microcalcifications. [7]

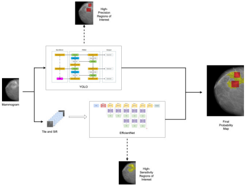

Figure: Combined detection model and classifier for breast cancer proposed by Frank

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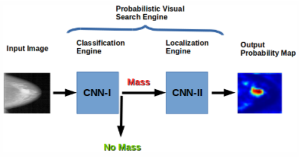

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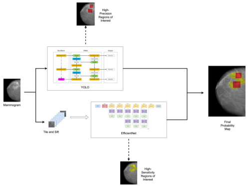

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Yi, Sawyer, Cohn III, et al. proposed a model for visualization of shared features between views of the breast for classification of benign and malignant breast tumours. [8]

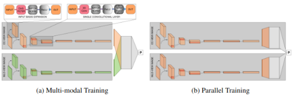

Figure: Multimodal architecture proposed by Yi, Sawyer, Cohn III, et al. for visualization of shared features between views of the breast.

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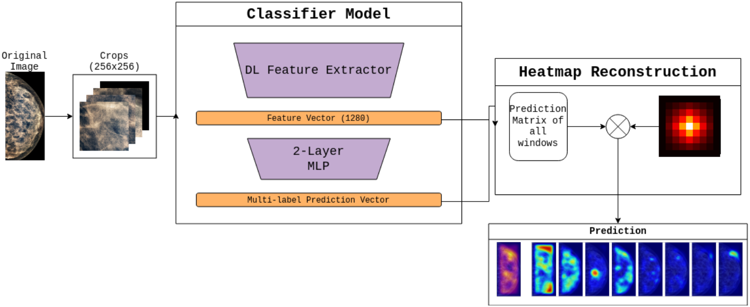
Our study proposes a Deep Learning Classifier trained on cropped segments of mammograms for multi-label classification of pathological findings.
General Inspection of the complete image using local patches to identify the probability of the presence of a pathological finding.



Dataset

- **Vindr-mammo** Dataset [9]
- 5000 digital mammogram examinations containing for each view:
  - BIRADs
  - Breast density
  - Bounding box of each finding present on the image
- 10 classes of pathological findings.
- Bounding boxes can have multiple labels.

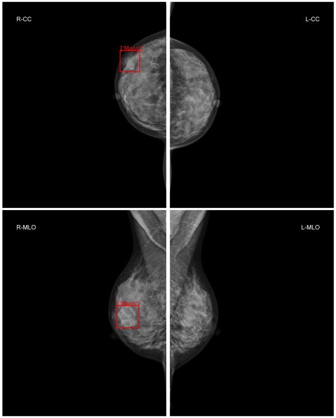


Figure: Example of a mammogram from the Vindr-mammo dataset.

[9] Hieu Huy Pham, Hieu Nguyen Trung, and Ha Quy Nguyen. *VinDr-Mammo: A Large-Scale Benchmark Dataset for Computer-Aided Detection and Diagnosis in Full-Field Digital Mammography*. Version 1.0.0. PhysioNet. DOI: 10.13026/BR2V-7517. URL: https://physionet.org/content/vindr-mammo/1.0.0/ (visited on 11/08/2022)

Table: Findings statistics of Vindr-Mammo Dataset

	Finding	Training	Test	Total
	Mass	989	237	1226
	Suspicious Calcification	428	115	543
Assymetries	General	77	20	97
	Focal	216	53	269
	Global	20	6	26
	Architectural Distortion	95	24	119
	Skin Thickening	45	12	57
Retractions	Skin	15	3	18
	Nipple	30	7	37
	Suspicious Lymph Node	46	11	57

- Each DICOM Image is normalised to a range of $[0, 1]$
- Apply CLAHE algorithm [10] for histogram equalization at 2 different scales
- Fuse the equalized images with the original, channel-wise
- Image is cropped to the bounding box of the breast using Otsu's thresholding.

[10] S.M. Pizer, R.E. Johnston, J.P. Ericksen, et al. "Contrast-Limited Adaptive Histogram Equalization: Speed and Effectiveness". In: *[1990] Proceedings of the First Conference on Visualization in Biomedical Computing*. [1990] Proceedings of the First Conference on Visualization in Biomedical Computing. May 1990, pp. 337–345. DOI: 10.1109/VBC.1990.109340. URL: https://ieeexplore.ieee.org/document/109340 (visited on 10/03/2023)

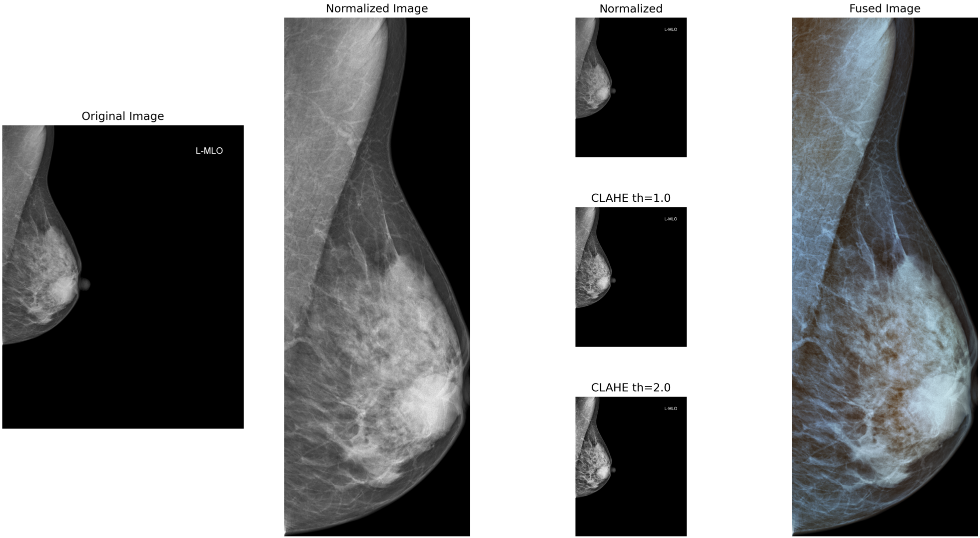


Figure: Image processing pipeline

We evaluated the following architectures as a backbone:

- ResNet50 [6]
- EfficientNetV2 [16]
- DenseNet121 [8]
- Swin Transformer [10]
- MobileNet [7]
- VGG19 [15]

- We use the backbone of the selected architecture as a feature extractor.
- Output is flattened and fed to the classifier.
- Dropout of 0.5 of each input before the Classifier (On training).
- Classifier using a 2-layer MLP with 512 hidden units and ReLU activation.
- Output layer with sigmoid activation.

- For each finding present on an image, we sampled a random area of the finding.
- Area and aspect ratio randomly sampled from an Uniform distribution.
  - Area: [.05, 5.] of the finding bounding box area.
  - Aspect ratio: [0.33, 1.66] of the finding bounding box aspect ratio.
  - The bounding box center is uniform sampled from 50 px around the original center.
- For normal images (*No Finding*), we sample a random area of the breast, with similar sampling parameters.
- Sampled image is resized to 256×256 pixels.
- **Image augmentation**: Contrast, brightness, saturation, flip and rotation are randomly modified.

Example of sampling

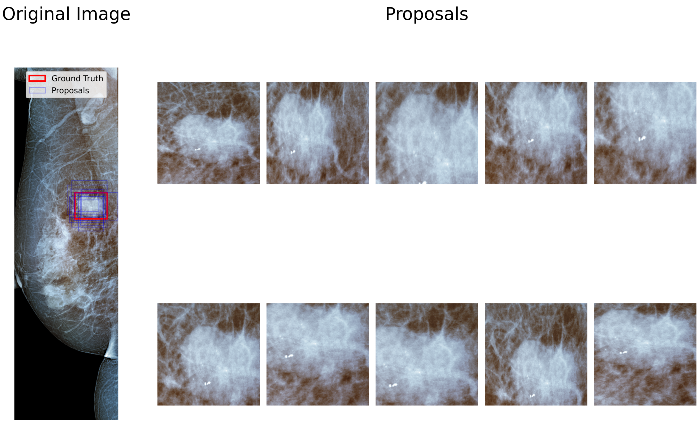


Figure: Example of sampling of ten positive proposals from a finding.

- Focal Loss Function [11]
  - $\mathcal{L}_{\text{Focal}} = -(1 - p_t)^{\gamma} \log(p_t)$
  - γ is a focusing parameter.
  - $\gamma = 0$ is equivalent to Cross Entropy Loss.
  - We used a γ of 2.
- Adam Optimizer with a starting learning rate of 1×10^{-4}
- Reduce on plateau with a patience of 5 epochs and a factor of 0.1
- Weighted Class Sampling of the dataset, in order to reduce imbalance.

[11] Tsung-Yi Lin, Priya Goyal, Ross Girshick, et al. *Focal Loss for Dense Object Detection*. Version 2. Feb. 7, 2018. DOI: 10.48550/arXiv.1708.02002. arXiv: 1708.02002 [cs]. URL: http://arxiv.org/abs/1708.02002 (visited on 07/13/2023). preprint

Our method

- Segmentation of the complete image into a set of overlapping windows of size 256×256 pixels and stride of 32 px.
- Reconstruction of prediction heatmap from the overlapping windows.
- Feature visualization by weighted sum of feature maps, based on most important features. Using a *Random Forest Classifier* trained on the features extracted from the training set.
- Random Forest achieves similar results as the MLP classifier, and used only to identify the most important features

Table: F1 Score for Pathological findings classification task with Vindr, comparing different Deep Learning Models.

	N	DenseNet	EfficientNet	ResNet50	SwinTransformer	VGG19	MobileNet
Mass	237	0.783	0.815	0.742	0.770	0.756	0.708
Suspicious Calcification	115	0.847	0.865	0.860	0.828	0.873	0.828
Assymetries	79	0.306	0.295	0.200	0.310	0.204	0.324
Suspicious Lymph Node	11	0.667	0.500	0.737	0.370	0.400	0.476
Weighted Average	442	0.712	**0.727**	0.675	0.693	0.679	0.665

EfficientNet has the best overall performance, with an F1 score of 0.727. We chose this model as the backbone for our classifier.

Table: Metrics of pathological findings classification task using Vindr

	Accuracy	Precision	Recall	F1	Support
No Finding	0.963	0.999	0.959	0.979	3643
Mass	0.973	0.746	0.819	**0.781**	237
Suspicious Calcification	0.991	0.855	0.817	**0.836**	115
Asymmetries	0.978	0.356	0.203	0.258	79
Architectural Distortion	0.994	0.533	0.333	0.410	24
Suspicious Lymph Node	0.998	0.571	0.364	0.444	11
Skin Thickening	0.998	0.778	0.583	0.667	12
Retractions	0.998	1.000	0.222	0.364	9

Our model achieves a weighted Accuracy of 92.49 % and a weighted F1 score of 0.9542

Prediction on local windows

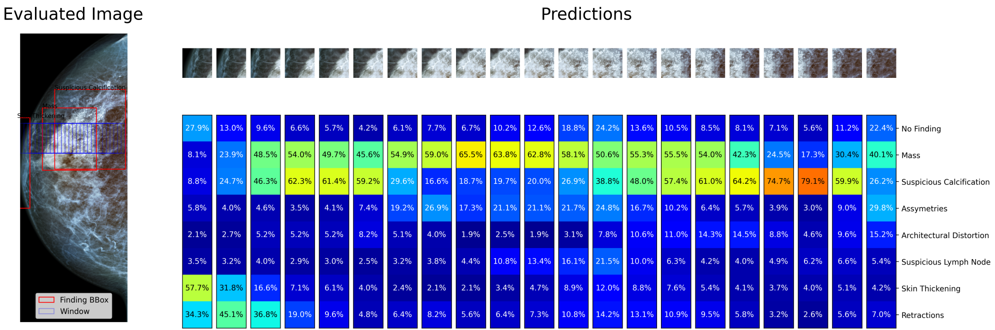


Figure: Image with bounding boxes of its findings and prediction of a row of local windows using our classifier.

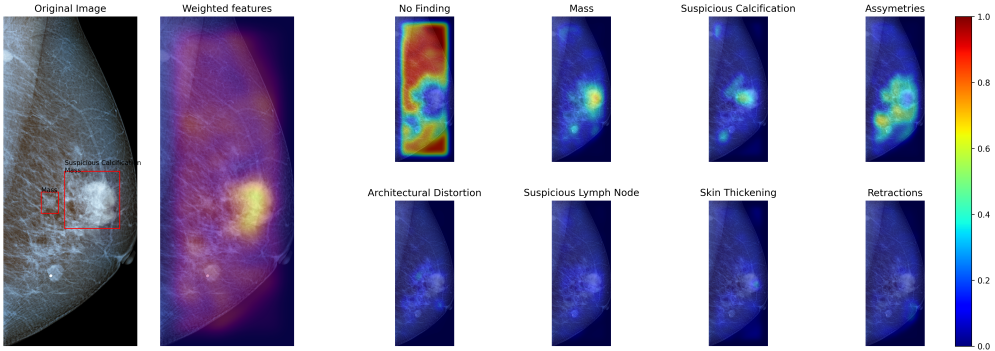


Figure: Cropped test image with bounding boxes of its findings, feature activation heatmap, and prediction of the classifier.

Effects of scale of window

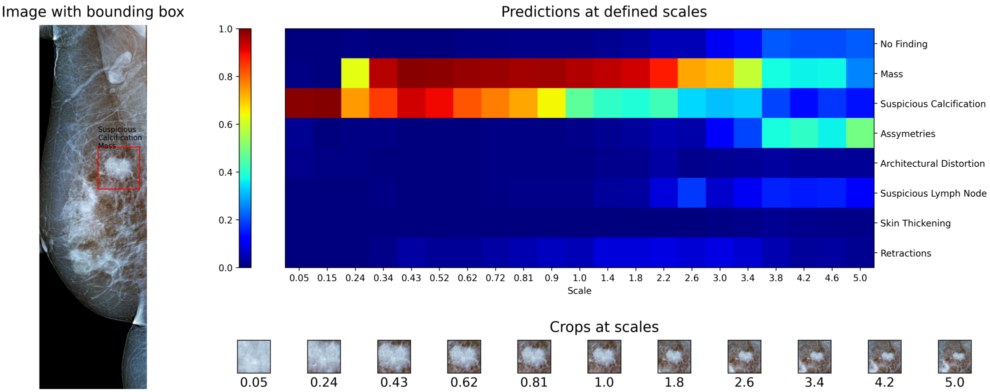


Figure: Prediction of classifier, using finding at different scales.

- Low availability of data for some classes impact performance on certain findings.
- High sensitivity of our model to less frequent findings. (e.g. Local Asymmetries)
- Our model is able to identify findings regardless of scale of windows.

Future Work

- Study of unknown-to-model images for measurement of performance with local population.

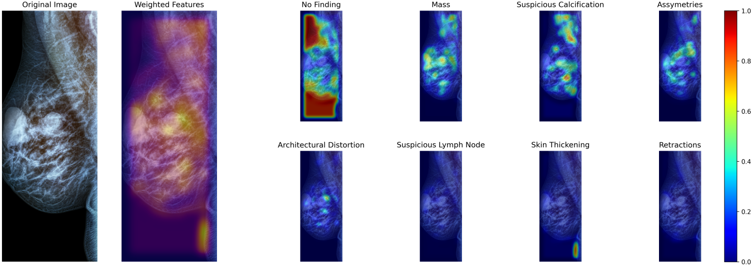


Figure: Right MLO image of Chilean patient

- Analysis of selected features and their relationship with findings, in order to identify possible biases and discard of low-performance predictions.

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