CONTRASTIVE LEARNING: AN EFFICIENT DOMAIN ADAPTATION STRATEGY FOR 2D MAMMOGRAPHY IMAGE CLASSIFICATION

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INTRODUCTION

- We seek to train a 2D mmammography image classifier that is invariant to image post-processing differences.
- In the ***Domain Adaptation*** literature, feature-based methods are usually used to learn a domain-invariant feature representation. The two main approaches are:
  - ***Discriminative Adversarial Neural Network (DANN):*** jointly train three networks (encoder, classifier, domain discriminator) to minimize the classifier loss and maximize the discriminator loss. The encoder tries to provide features that fool the discriminator but are useful for the discriminator [3].
    - Need of an additional network, which increases training time and resource consumption.
    - The gradients of the classifier and discriminator losses usually have different directions, making DANNs, as GANs, hard to train.
  - ***Mean Maximum Discrepancy (MMD):*** minimize the MMD, a dissimilarity measure between features from different domains [4], to attain domain-invariant features.
    - Can reduce feature-label correlation, decreasing class-separability and negatively impacting downstream task performance.
- ***Contrastive Learning***, widely used in Self-supervised Learning, learns a representation where semantically similar features are close to one another, and distant to semantically different ones.
  - ***Supervised Contrastive Learning*** is an efficient Domain Adaptation strategy for Domain Adaptation.

MATERIALS AND METHODS

Contrastive Learning-based Domain Adaptation

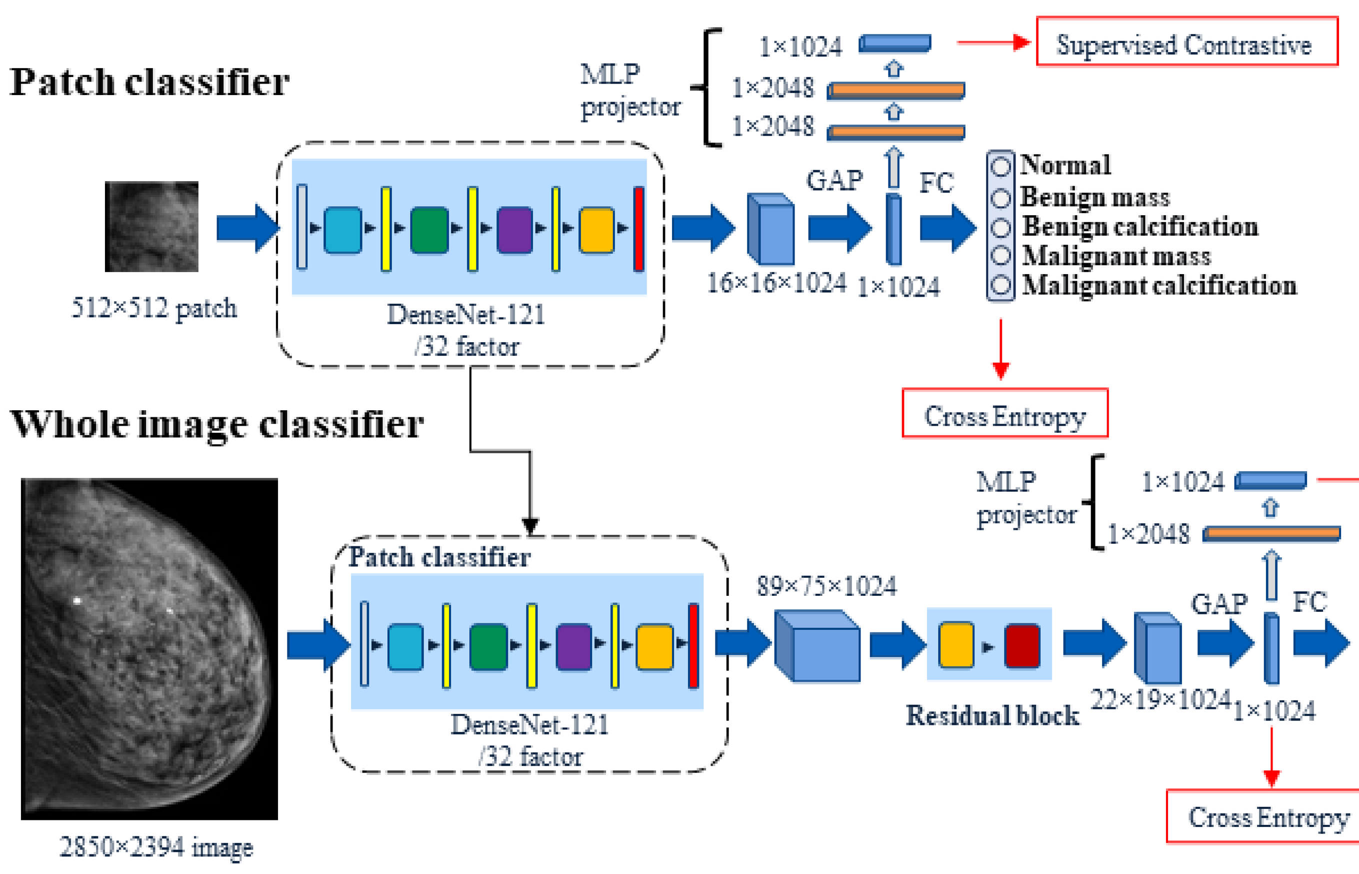
$$\mathcal{L}_B = \sum_{i=1}^{|B|} \frac{-1}{|\mathcal{P}_i|} \sum_{j \in \mathcal{P}_i} \log \frac{e^{z_i^T \cdot z_j/\tau}}{\sum_{l \in \mathcal{A}_i} e^{z_i^T \cdot z_l/\tau}}$$

- $|B|$:batch size
- z_i : feature vector of the i^th input
- $\mathcal{P}_i$: set of all features that form positive pairs with z_i
- $\mathcal{A}_i$: set of all the other features (positive and negatives), excluding z_i
- τ : temperature parameter

- Use the ***Supervised Contrastive loss*** [2] to achieve Domain Adaptation
- Pull together features of images with the same class (positive pairs) for all domains.
  - Achieve ***Domain Adaptation***
- Push apart features of images with different class (negative pairs) for all domains.
  - Induce class-separability.
- We compare three training strategies:
  - End-to-end training with Cross Entropy, denoted as ***CE***.
  - Train with Supervised Contrastive + fine tune linear layer with Cross Entropy, denoted as ***SupContr***.
  - Train with Supervised Contrastive + fine tune the entire model with Cross Entropy, denoted as ***SupContr+CE***.

Patch-based classifier

- Train a ***DenseNet-121*** to classify ***512 × 512 pixels patches*** into five categories based on lesion type and pathology: normal, benign calcification, malignant calcification, benign mass, and malignant mass.
- Extend the patch-classifier into a ***whole image classifier*** by appending a residual block and re-training on full mammography images. More details on the model can be found in [1].
- For training with the Supervised Contrastive loss, a Multi Layer Perceptron (MLP) projector is added. The projector avoids achieving perfect invariance, which can lower downstream task performance and hurt generalization.



Datasets and post-processing

Image w/o LUT

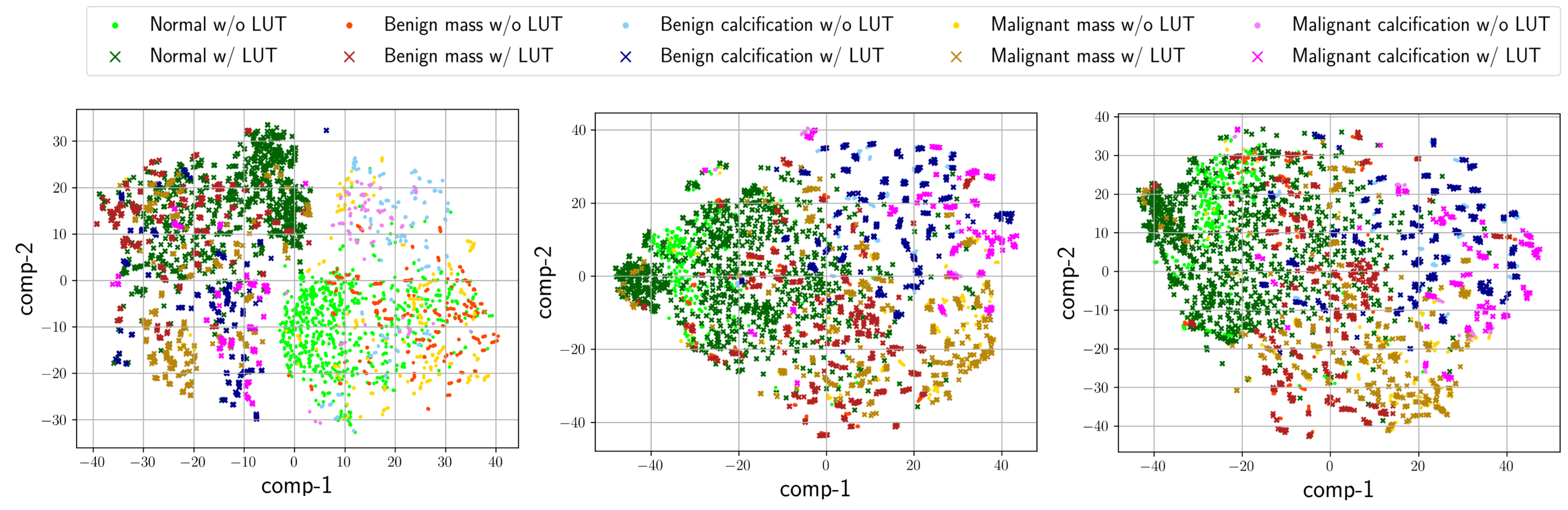
Image w/ LUT

- Domains are defined by image post-processing differences. Particular case: ***sigmoid Look-Up-Table (LUT).***
- From the GEHC internal dataset (1 539 cases), three distinct dataset types were created for training (1 237 cases) and validation (201 cases):
  - An ***augmented dataset***, which includes two versions of each image (w/ and w/o LUT applied).
  - ***Mixed datasets***, formed by randomly dividing the GEHC dataset into two groups. One group had images w/ LUT applied, while the other did not.
  - ***Mixed down sampled datasets***, generated by initially randomly excluding some images from the GEHC dataset using four keep ratios (0.6, 0.7, 0.8, and 0.9), followed by the creation of mixed datasets as described above.
- Unique test set (101 cases) containing the two versions of each image, w/ and w/o LUT applied.
- Patches are extracted from images with lesion-level annotations, as described in [1].

RESULTS

Patch-classifier - Transfer Learning (TL) from ImageNet

t-SNE feature visualization



CE **SupContr** **SupContr+CE**

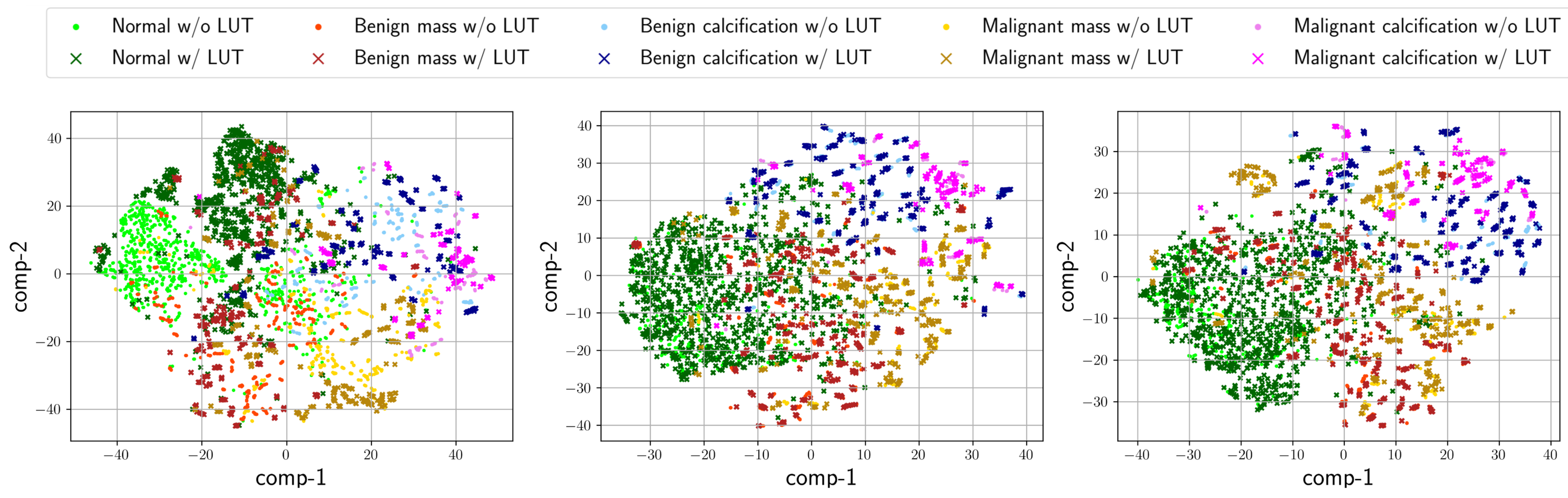
One-vs-one AUC *1

	CE	SupContr	SupContr + CE
mixed dataset 1	0.737 ± 0.008 (n.a.)	0.836 ± 0.006 (< 0.001)	**0.840 ± 0.006 (< 0.001)**
mixed dataset 2	0.692 ± 0.008 (n.a.)	0.820 ± 0.007 (< 0.001)	**0.833 ± 0.006 (< 0.001)**
mixed dataset 3	0.750 ± 0.008 (n.a.)	**0.850 ± 0.006 (< 0.001)**	0.842 ± 0.006 (< 0.001)
mixed dataset 4	0.745 ± 0.007 (n.a.)	**0.846 ± 0.005 (< 0.001)**	**0.846 ± 0.006 (< 0.001)**
augmented dataset	0.871 ± 0.006 (n.a.)	0.878 ± 0.005 (< 0.001)	**0.887 ± 0.005 (< 0.001)**

- In the t-SNE plot, features of CE are more separated by domain than by class. ***SupContr & SupContr+CE are domain-invariant.***
- ***SupContr & SupContr+CE outperform CE*** in all considered datasets.

Patch-classifier - Transfer Learning from CBIS-DDSM [6]*2

t-SNE feature visualization

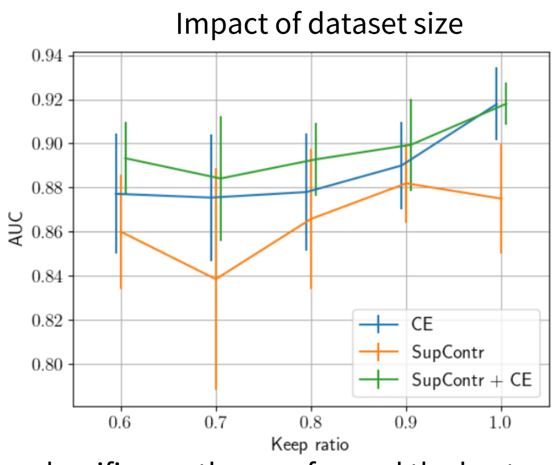


CE **SupContr** **SupContr+CE**

One-vs-one AUC *1

	CE	SupContr	SupContr + CE
mixed dataset 1	0.905 ± 0.005 (n.a.)	0.898 ± 0.005 (< 0.001)	**0.920 ± 0.005 (< 0.001)**
mixed dataset 2	**0.922 ± 0.004 (n.a.)**	0.889 ± 0.005 (< 0.001)	0.910 ± 0.005 (< 0.001)
mixed dataset 3	**0.926 ± 0.004 (n.a.)**	0.876 ± 0.005 (< 0.001)	0.922 ± 0.004 (< 0.001)
mixed dataset 4	**0.919 ± 0.004** (n.a.)	0.867 ± 0.005 (< 0.001)	**0.920 ± 0.004 (n.s.)**
augmented dataset	**0.927 ± 0.004 (n.a.)**	0.880 ± 0.005 (< 0.001)	0.919 ± 0.004 (< 0.001)

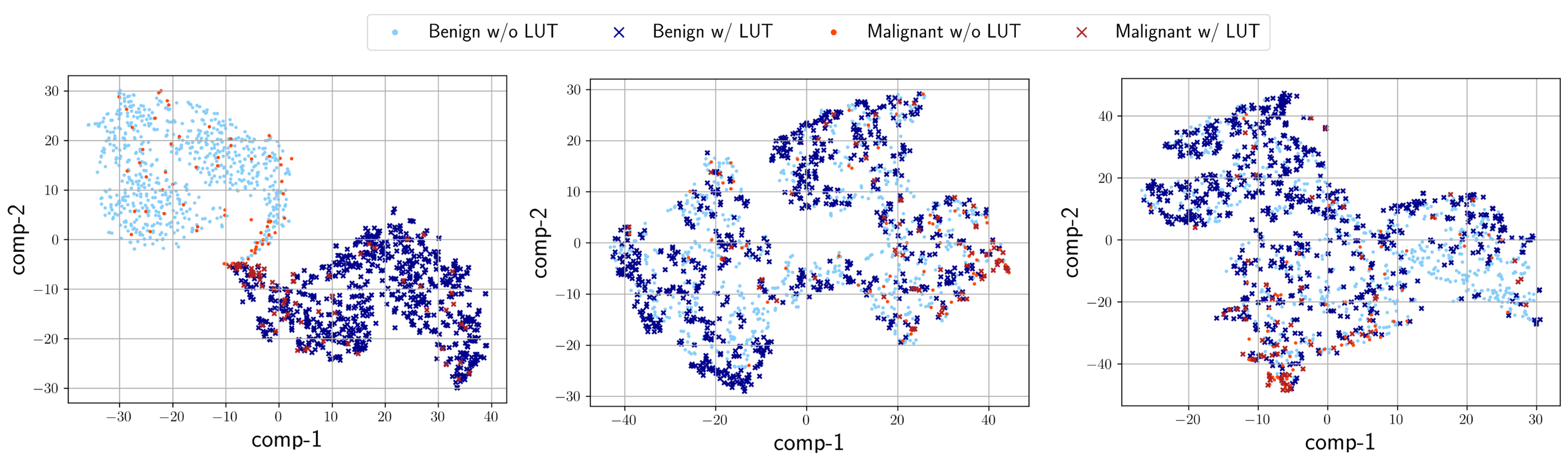
Impact of dataset size



- Features from ***CE are more domain-invariant*** that when using TL from CBIS-DDSM (except for the normal patches), decreasing the impact of Domain Adaptation.
- ***SupContr & SupContr+CE fail to outperform CE.***
- Only patch-classifiers pre-trained on CBIS-DDSM were used for the whole image classifier, as they performed the best.
- When training in downs-sampled datasets, ***SupContr+CE outperforms CE for decreasing dataset sizes.***

Whole Image classifier - from Patch-classifier w/ TL from CBIS-DDSM

t-SNE feature visualization

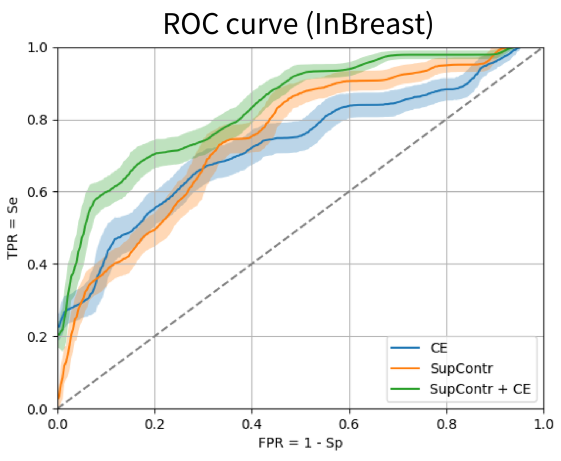


CE **SupContr** **SupContr+CE**

AUC *1

	CE	SupContr	SupContr + CE
mixed dataset 1	0.723 ± 0.056 (n.a.)	0.772 ± 0.053 (< 0.001)	**0.793 ± 0.049 (< 0.001)**
mixed dataset 2	0.747 ± 0.046 (n.a.)	0.801 ± 0.041 (< 0.001)	**0.811 ± 0.047 (< 0.001)**
mixed dataset 3	0.716 ± 0.062 (n.a.)	**0.786 ± 0.049 (< 0.001)**	**0.781 ± 0.054 (< 0.001)**
mixed dataset 4	0.714 ± 0.061 (n.a.)	0.762 ± 0.051 (< 0.001)	**0.794 ± 0.048 (< 0.001)**
augmented dataset	0.745 ± 0.050 (n.a.)	0.763 ± 0.058 (< 0.001)	**0.816 ± 0.042 (< 0.001)**
InBreast *3	0.733 ± 0.096 (n.a.)	0.746 ± 0.083 (n.s.)	**0.831 ± 0.071 (< 0.001)**

ROC curve (InBreast)



- Features of CE are more separated by domain than by class while ***SupContr & SupContr+CE are domain-invariant.***
- ***SupContr & SupContr+CE outperform CE***, despite that not being the case in the patches (see patch classifier w/ TL from CBIS-DDSM).
- SupContr & SupContr+CE trained on all the mixed datasets outperform CE trained on the augmented dataset (despite it having been trained on twice the amount of data).
- ***SupContr & SupContr+CE exhibit higher generalization than CE in InBreast.***

*1 Bootstrapping is used for calculating error bars and p-values.

*2 a public scanned film mammography image collection.

*3 only the linear layer was fine-tuned in InBreast, while freezing the feature extraction.

CONCLUSIONS & DISCUSSION

- ***Supervised Contrastive Learning*** enables to obtain a ***domain-invariant*** classifier.
- ***Patch-classifier***
  - In CE, domains are adapted when doing Transfer Learning (TL) from CBIS-DDSM (except for normal patches), but non-adapted when doing TL from ImageNet. ***SupContr increased Domain Adaptation.***
  - SupContr increased AUC when training with smaller sub-sets of the GEHC dataset, or when initializing weights from ImageNet.
  - No impact on AUC when initializing weights from a pre-trained model on CBIS-DDSM [6].
- ***Whole image classifier***
  - In CE, domains are not adapted despite using the patch-classifier with TL from CBIS-DDSM, possibly due to the maladaptation of normal patches.
  - ***SupContr attained Domain Adaptation.***
  - ***SupContr significantly increased AUC*** on the mixed & augmented datasets, and proved generalization in InBreast [5].
- The Contrastive-based Domain Adaptation can be easily extended to other imaging modalities and beyond medical imaging.

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