Cross-Database Mammographic Image Analysis through Unsupervised Domain Adaptation

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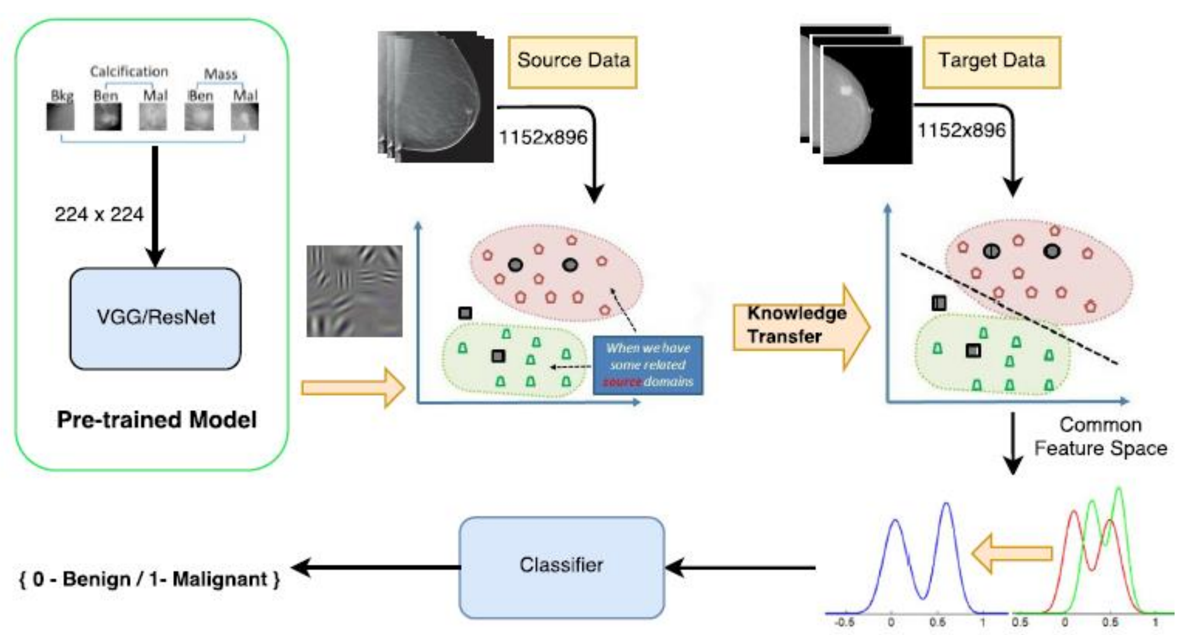
Introduction



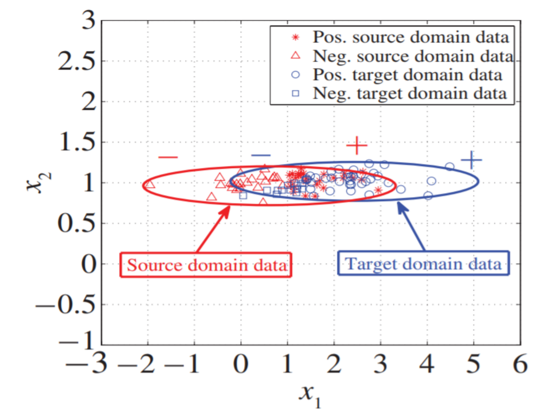
- Breast Cancer is common health issue
- 1.7 million cases were found and total 14.71% deaths occurred world wide
- Mammography is the best option available to diagnose breast cancer at early stage
- Radiologists expertise are required for interpolation of mammograms
- Computer Assisted Diagnosis (CAD) have caught the attention to automate the process of medical image classification
- CAD completely rely on the pre segmented portion of mammograms know as Region of Interest (ROI)
- These system rely on the assumption that training and future data has the same feature space and follows the same distribution
- It is expensive to acquire the sufficient new labeled data to rebuild the model
- Pre-trained End-to-End training models are used for feature extraction from publicly available databases
  - CBIS-DDSM
  - InBreast
  - MIAS
- Data has been transformed into same feature space using the following transfer learning methods:
  - TCA (Transfer Component Analysis)
  - BDA (Balance Distribution Adaption)
  - CoRAL (Correlation Alignment)

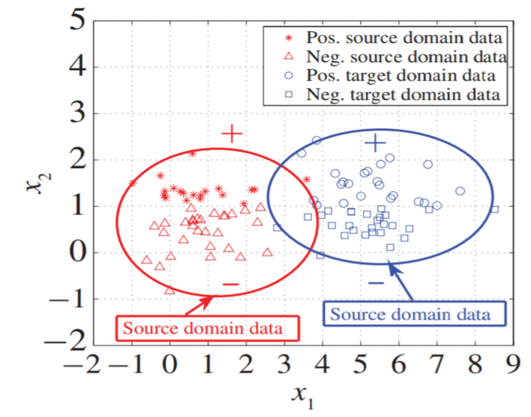
Transfer Learning

- Traditional machine learning methods learn models based on:
- Pre collected label data to predict new data
- New data should be in same distributed space
- It is difficult to get rich labeled data
- Transfer learning facilitates
- Different distribution for training and future data
- Transfer learning can be promising
  - › Characteristics of different sub domain are mapped into wide common domain

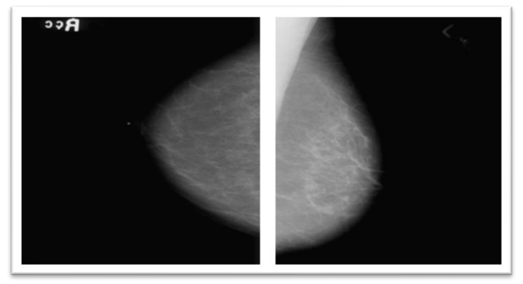
Methodology

- End-to-End training algorithm for whole-image breast cancer diagnosis is based on mammograms without the need of the ROI annotations.
  - In End-to-End three different convolutional network are used but first they trained on the patch classifier by changing the learning rate by freezing and unfreezing the layers.
  - They fixed the mammogram patch image size to 224 x 224 and whole image size 1152 x 896.
- Domain Adaption
  - TCA (Transfer Component Analysis)
    - › Learn the common Components
    - › Reduce the differences between source and target distribution by projecting on common subspace
  - BDA (Balance Distribution Adaption)
    - › Balance the marginal and conditional distribution adaption
      - For different data Marginal distribution is important
      - For similar data Conditional distribution is important
    - › Handles the data class imbalanced by adjusting each class weight
  - CoRAL (Correlation Alignment)
    - › CoRAL works on unsupervised domain adaption
    - › Map source domain distribution by recoloring the whitened features with second order statistics of target domain

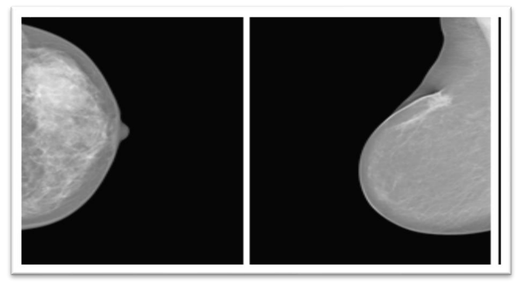




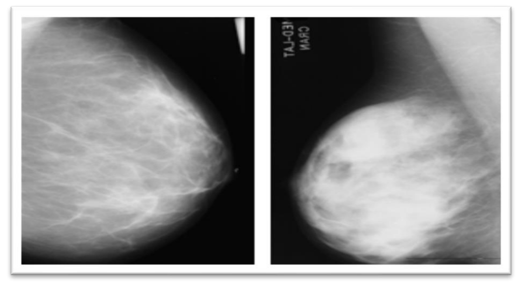
Datasets



CBIS- DDSM



InBreast

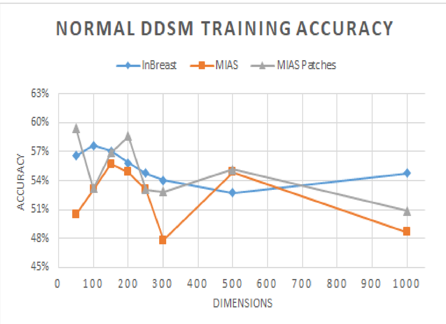


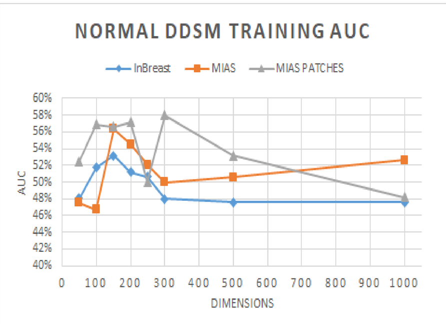
MIAS

- Three publicly available dataset are used
  - CBIS-DDSM
    - › 3103 scanned mammograms
    - › Data contain Benign and Malignant images
    - › Dataset contains Cranial Cardo (CC) and Media later oblique (MLO) views
  - InBreast
    - › Full field digital images contain different color profiles
    - › The dataset contains 410 mammograms from 115 patients including Cranial Cardo (CC) and Media Later Oblique (MLO) views
    - › Data contains BI-RAIDS readings
    - › Sample was divided in Benign and Malignant based on BI-RAIDS reading

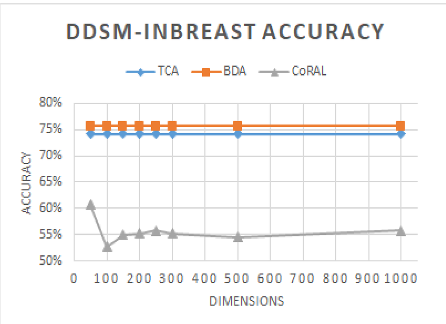
- MIAS
  - Dataset contains 322 MLO view mammograms
  - MIAS images are scanned copies of films
  - Only 109 images are labeled

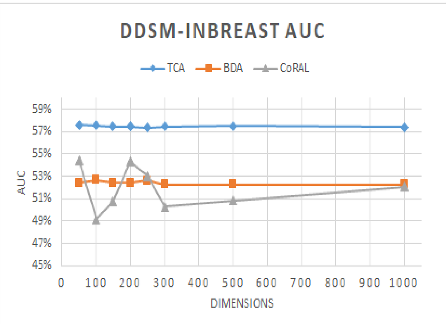
Experimental Results



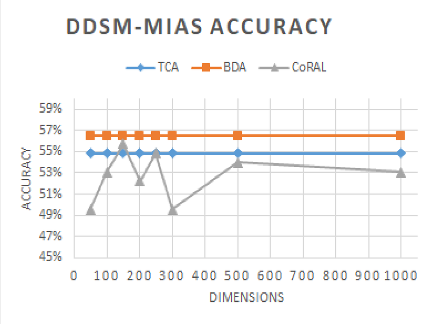


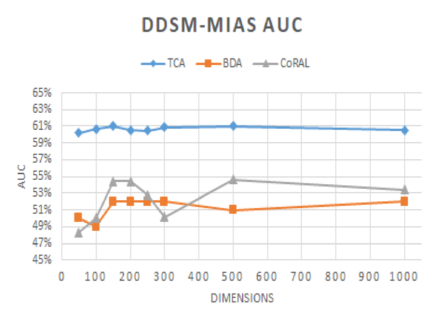
Dimension	InBreast		MIAS		MIAS PATCHES	
	Accuracy	AUC	Accuracy	AUC	Accuracy	AUC
50	56.58%	48.08%	50.44%	47.5%	59.48%	52.49%
100	57.62%	51.7%	53.09%	46.68%	53.15%	56.89%
150	57.1%	53.16%	55.75%	56.33%	56.89%	56.62%
200	55.81%	51.19%	54.86%	54.49%	58.62%	57.19%
250	54.78%	50.67%	53.09%	52.09%	53.09%	50%
300	54%	47.98%	47.78%	49.97%	52.58%	57.98%
500	52.71%	47.6%	54.86%	50.6%	55.17%	53.14%
100	54.78%	47.6%	48.67%	52.62%	50.86%	48.17%



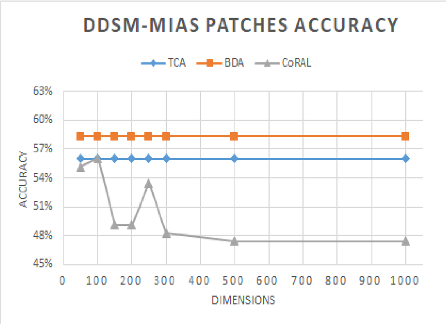


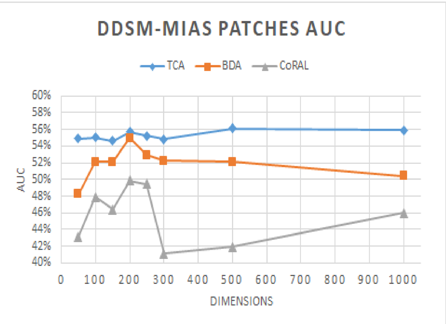
Dimension	TCA		BDA		CoRAL	
	Accuracy	AUC	Accuracy	AUC	Accuracy	AUC
50	74.16%	57.6%	75.64%	52.43%	60.72%	54.48%
100	74.16%	57.55%	75.64%	52.68%	52.71%	49.18%
150	74.16%	57.45%	75.64%	52.4%	55.03%	50.78%
200	74.16%	57.48%	75.64%	52.4%	55.29%	54.31%
250	74.16%	57.36%	75.64%	52.6%	55.81%	53.01%
300	74.16%	57.46%	75.64%	52.28%	55.29%	50.29%
500	74.16%	57.52%	75.64%	52.28%	54.52%	50.85%
1000	74.16%	57.43%	75.64%	52.28%	55.81%	52.08%





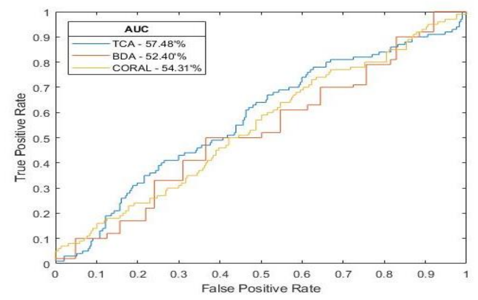
Dimension	TCA		BDA		CoRAL	
	Accuracy	AUC	Accuracy	AUC	Accuracy	AUC
50	56.03%	54.93%	58.33%	48.24%	55.17%	43.14%
100	56.03%	55.05%	58.33%	52.1%	56.03%	47.9%
150	56.03%	54.6%	58.33%	52.1%	49.13%	46.4%
200	56.03%	55.72%	58.33%	54.96%	49.13%	49.89%
250	56.03%	55.26%	58.33%	52.94%	53.44%	49.47%
300	56.03%	54.81%	58.33%	52.25%	48.27%	41.09%
500	56.03%	56.14%	58.33%	52.1%	47.41%	41.9%
1000	56.03%	55.93%	58.33%	50.44%	47.41%	45.97%



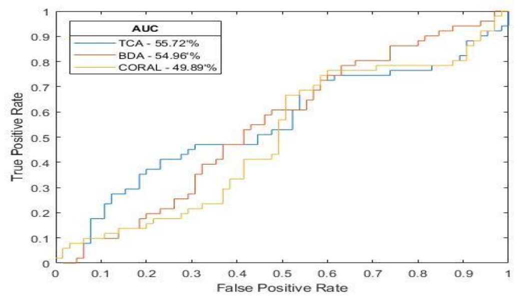


Dimension	TCA		BDA		CoRAL	
	Accuracy	AUC	Accuracy	AUC	Accuracy	AUC
50	54.86%	60.22%	56.52%	50.01%	49.55%	48.36%
100	54.86%	60.66%	56.52%	48.99%	53.1%	50.06%
150	54.86%	61.01%	56.52%	51.99%	55.75%	54.46%
200	54.86%	60.59%	56.52%	51.99%	52.21%	54.43%
250	54.86%	60.47%	56.52%	51.99%	54.86%	52.78%
300	54.86%	60.88%	56.52%	51.99%	49.55%	50.13%
500	54.86%	61.04%	56.52%	51.01%	53.98%	54.65%
1000	54.86%	60.53%	56.52%	51.99%	53.09%	53.45%

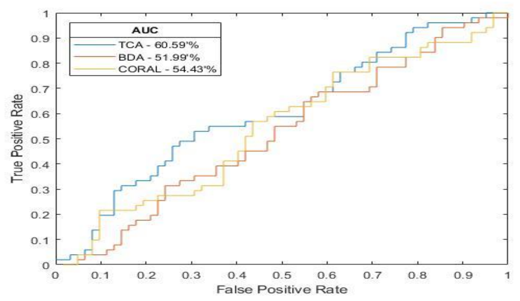
DDSM- INBREAST



DDSM- MIAS



DDSM- MIAS PATCHES



References

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