

DETECTION AND DIAGNOSIS OF BREAST TUMORS USING DEEP CONVOLUTIONAL NEURAL NETWORKS

FINAL PRESENTATION

J.D. Gallego-Posada[†] D.A. Montoya-Zapata^{}*

O.L. Quintero-Montoya[‡]

{[†]jgalle29, ^{}dmonto39, [‡]oquinte1} (at) eafit (dot) edu (dot) co*



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INTRODUCTION

Breast Cancer Overview



Breast Cancer Overview



**Breast
cancer**

Most common
cancer in women

Breast Cancer Overview

**Breast
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Most common
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50%

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Of the cases occur in
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508k

Breast Cancer Overview

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Women are estimated
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worldwide due to BC

Breast Cancer Overview

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WHO

Breast Cancer Overview

Breast cancer

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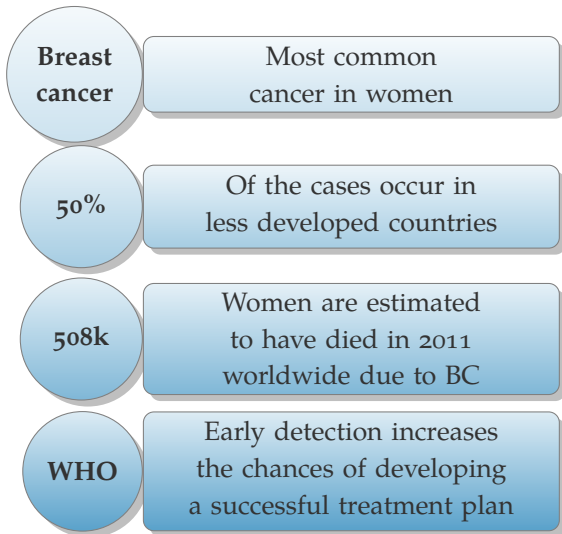
508k

Women are estimated to have died in 2011 worldwide due to BC

WHO

Early detection increases the chances of developing a successful treatment plan

Breast Cancer Overview



Computer-Aided Diagnosis System

To develop a computer system which can assist medical personnel with the early detection of tumors based on mammography images.

RELATED WORK



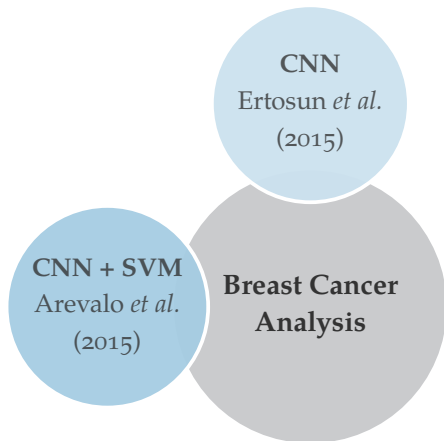
**Breast Cancer
Analysis**

Related Work

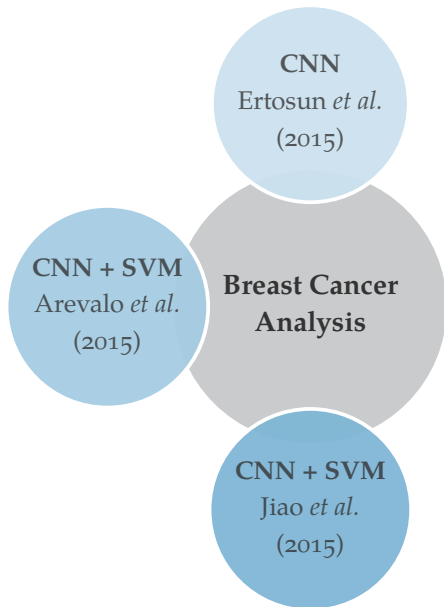
CNN
Ertosun *et al.*
(2015)

**Breast Cancer
Analysis**

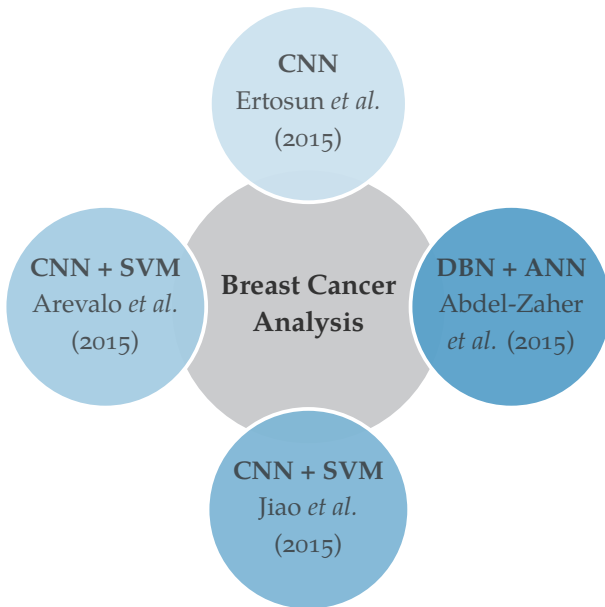
Related Work



Related Work

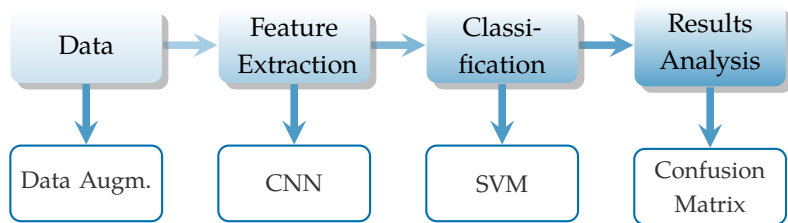


Related Work



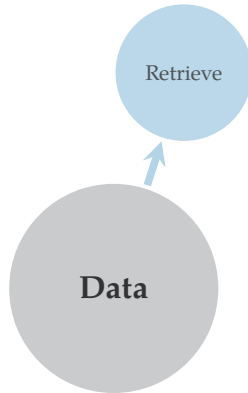
METHODOLOGY

Methodology

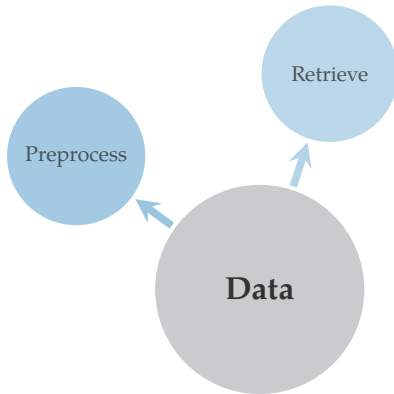




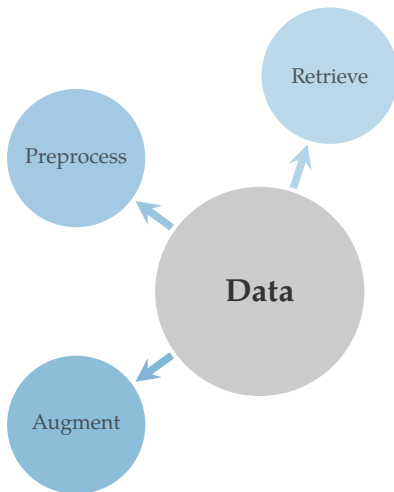
Data



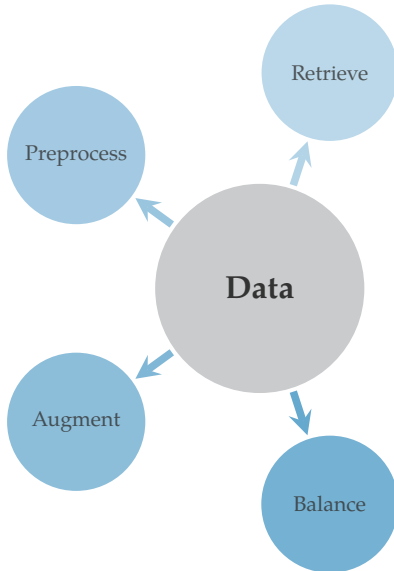
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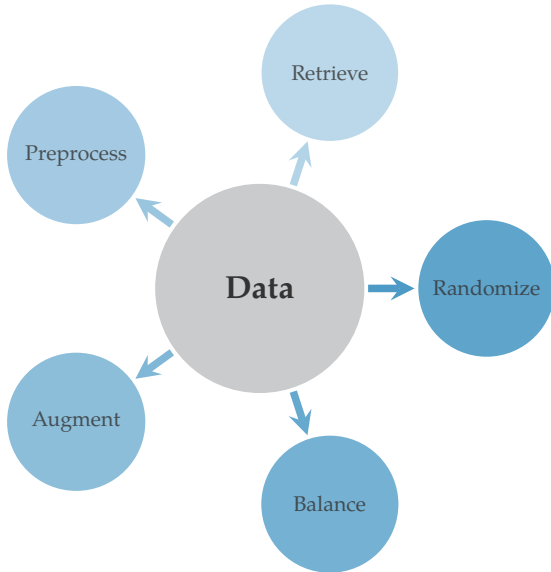
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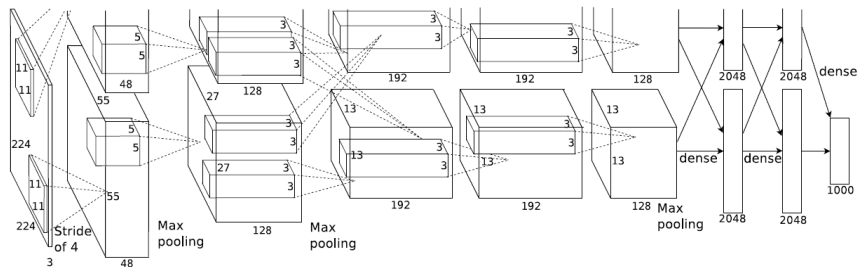
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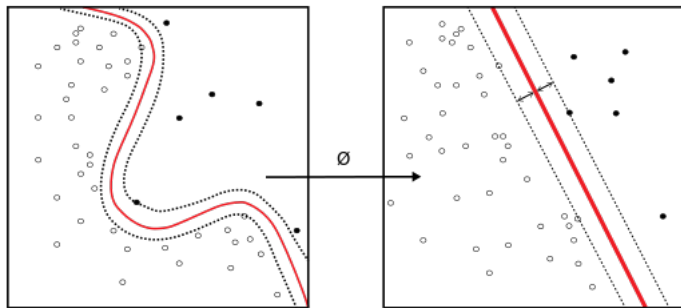


Data



Feature Extraction - AlexNet

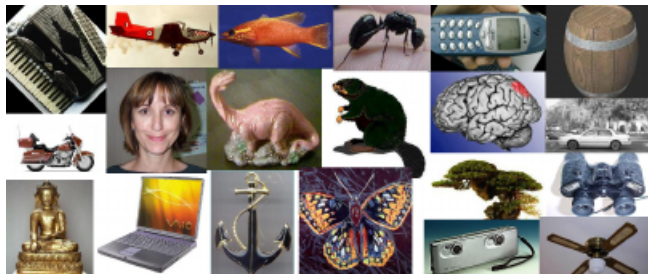




*"Kernel machines are used to transform **NON-LINEARLY** separable sets into a **HIGHER DIMENSION** space in which they are linearly separable."*

CALTECH-101

Data



- Compiled by California Institute of Technology
- RGB and B&W pictures
- 101 different categories

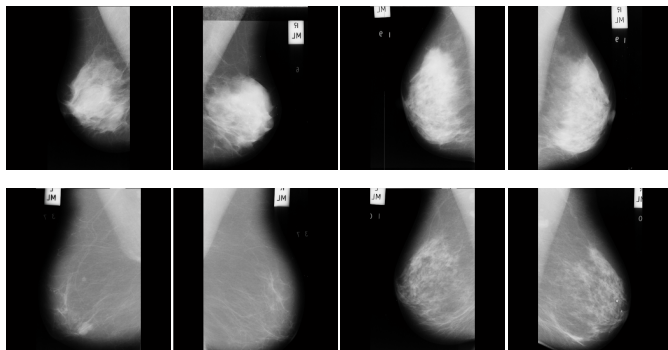
Results - Caltech + VGG

		<i>Target</i>				Total
		Airplanes	Faces	Bikes	Watches	
<i>Output</i>	Airplanes	97.5	0	0	2.5	97.5
	Faces	0	97.5	0	2.5	97.5
	Bikes	0	0	100	0	100
	Watches	0	0	0	100	100
	Total	100	100	100	95.24	98.75

Results - Caltech + AlexNet

		<i>Target</i>				Total
		Airplanes	Faces	Bikes	Watches	
<i>Output</i>	Airplanes	97.5	0	0	2.5	97.5
	Faces	0	100	0	0	100
	Bikes	0	0	100	0	100
	Watches	0	0	0	100	100
	Total	100	100	100	97.56	99.38

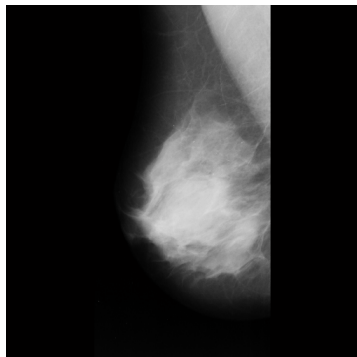
MINI-MIAS



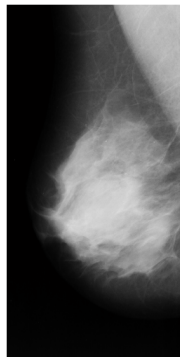
- United Kingdom National Breast Screening Programme [6]
- 322 mammograms - 3 categories
- 1024×1024 pixels

Source: Suckling *et al.* (1994)

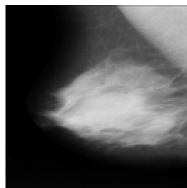
Data Preprocessing



Original



Cropped

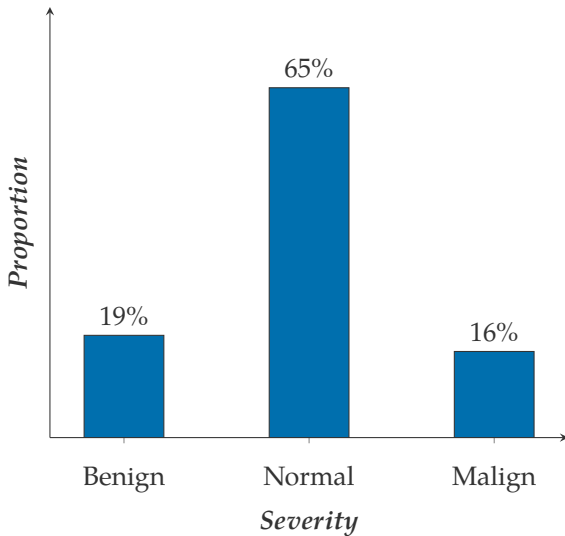


Resized

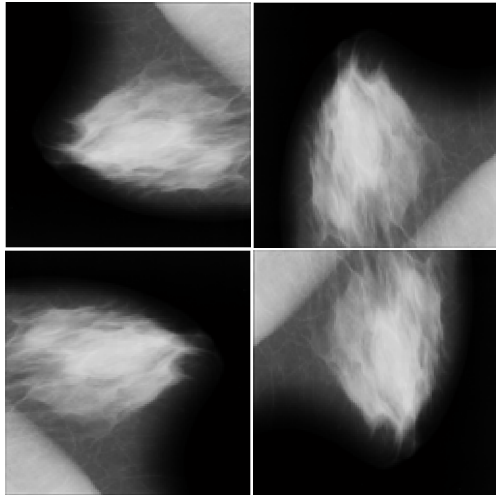
Results - mini-MIAS + AlexNet

		<i>Target</i>			
		Benign	Malign	Normal	Total
<i>Output</i>	Benign	36.53	48.12	15.35	36.53
	Malign	27.39	56.12	16.49	56.12
	Normal	31.34	56.29	12.36	12.36
	Total	38.35	34.96	27.97	35.01

Unbalanced Data



Data Augmentation



Source: Suckling *et al.* (1994)


Results - Augmented mini-MIAS + AlexNet

		<i>Target</i>			Total
		Benign	Malign	Normal	
<i>Output</i>	Benign	61.79	20.33	17.87	61.79
	Malign	18.79	61.75	19.46	61.75
	Normal	22.88	20.67	56.46	56.46
	Total	59.73	60.10	60.20	60.01

Results - Augmented mini-MIAS + VGG

		<i>Target</i>			
		Benign	Malign	Normal	Total
<i>Output</i>	Benign	63.63	18.45	17.92	63.63
	Malign	17.86	64.37	17.77	64.37
	Normal	16.91	17.54	65.55	65.55
	Total	64.66	64.14	64.75	64.52

CONCLUSIONS

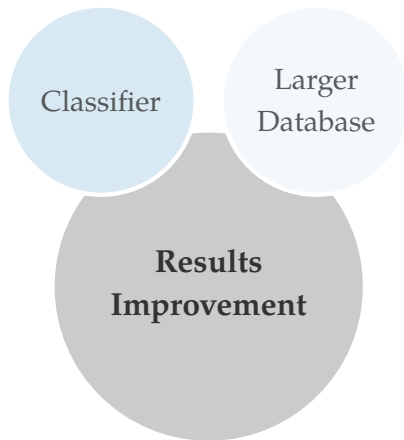


**Results
Improvement**

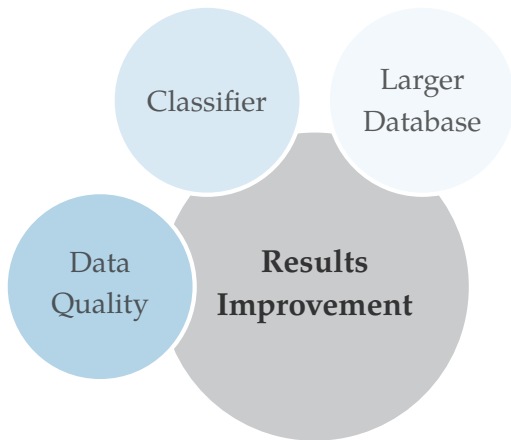
Conclusions + Future Work



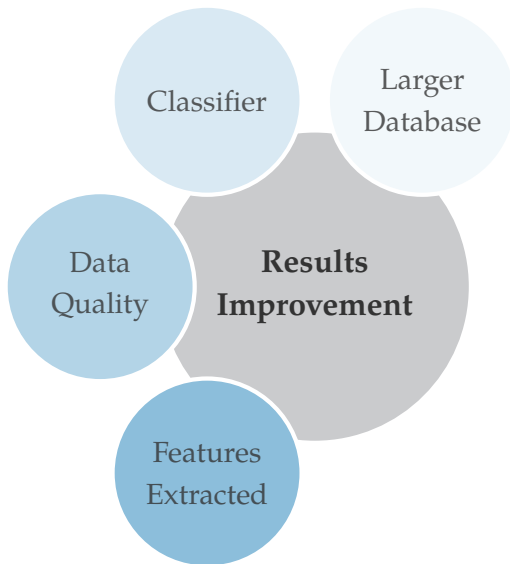
Conclusions + Future Work



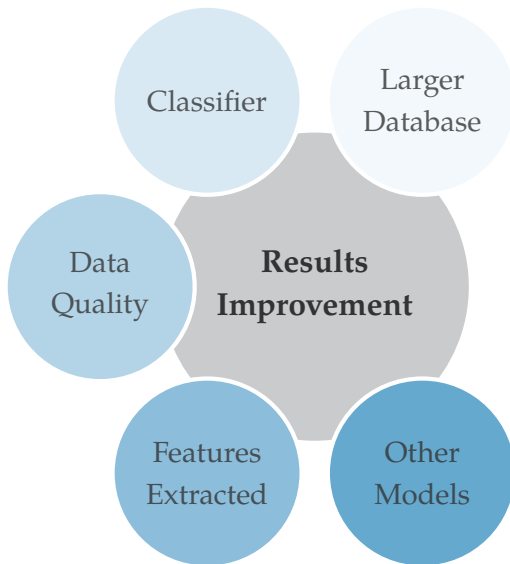
Conclusions + Future Work



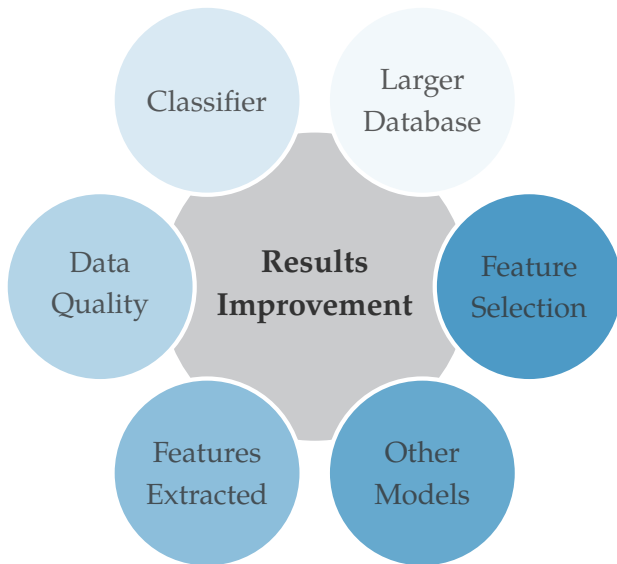
Conclusions + Future Work



Conclusions + Future Work



Conclusions + Future Work



REFERENCES

References I

- [1] World Health Organization, "Breast cancer: prevention and control," 2016, [Accessed: 19 - May - 2016]. [Online]. Available: <http://www.who.int/cancer/detection/breastcancer/en/>
- [2] M. G. Ertosun, and D. L. Rubin, "Probabilistic visual search for masses within mammography images using deep learning," in *Bioinformatics and Biomedicine (BIBM)*, 2015 *IEEE International Conference*, 2015, pp. 1310–1315.
- [3] J. Arevalo, F. A. González, R. Ramos-Pollán, J. L. Oliveira, and M. A. G. Lopez, "Convolutional neural networks for mammography mass lesion classification," in 2015 *37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2015, pp. 797–800.
- [4] Z. Jiao, X. Gao, Y. Wang, and J. Li, "A deep feature based framework for breast masses classification," in *Neurocomputing*, vol. 197, 2016, pp. 221–231.
- [5] A. M. Abdel-Zaher, and A. M. Eldeib, "Breast cancer classification using deep belief networks," in *Expert Systems with Applications*, vol. 46, 2016, pp. 139–144.

References II

- [6] J. Suckling, J. Parker, D. Dance, S. Astley, I. Hutt, C. Boggis, I. Rick-etts, E. Stamatakis, N. Cerneaz, S. Koket al., "The mammographic image analysis society digital mammogram database," in *Excerpta Medica. International Congress Series*, vol. 1069, 1994, pp. 375–378.
- [7] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet Classification with Deep Convolutional Neural Networks," *Advances In Neural Information Processing Systems*, 2012, pp. 1–9.

QUESTIONS
