

Predicting Malignancy from Mammography Findings and Image Guided Core Biopsies

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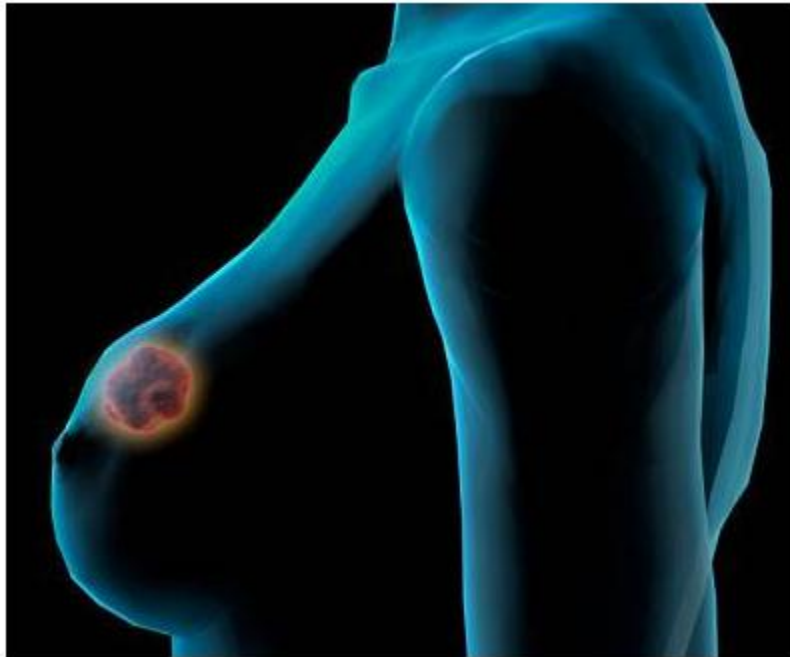
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Outline

- Breast Cancer
- Objectives
- Dataset
- Methodology
- Results and Analysis
- *MammoClass* (online tool)
- Conclusions

Breast Cancer



- USA:

- About 1 in 8 women ($\approx 12\%$) will develop invasive breast cancer during lifetime
- In 2014:
 - 232.670 invasive cancers
 - 40.000 ($\approx 17\%$) expected to die

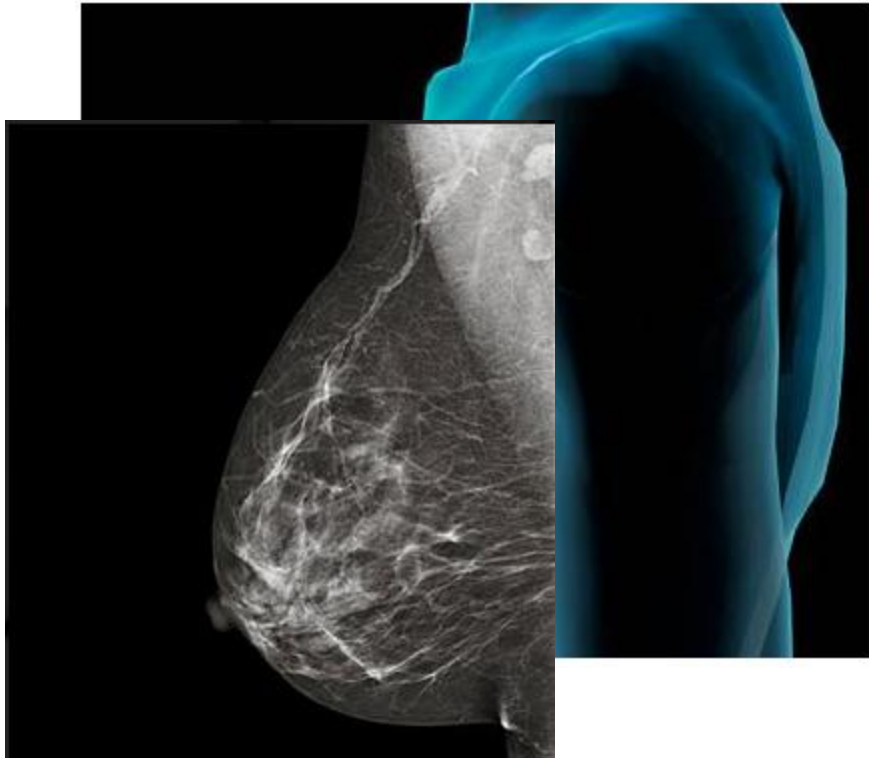
Source: *U. S. Breast Cancer Stats.* – accessed April 2015

- Portugal:

- About 1 in 11 women ($\approx 9\%$) will develop invasive breast cancer during lifetime
- Per year:
 - 5600 new cases
 - 1500 deaths (27%)

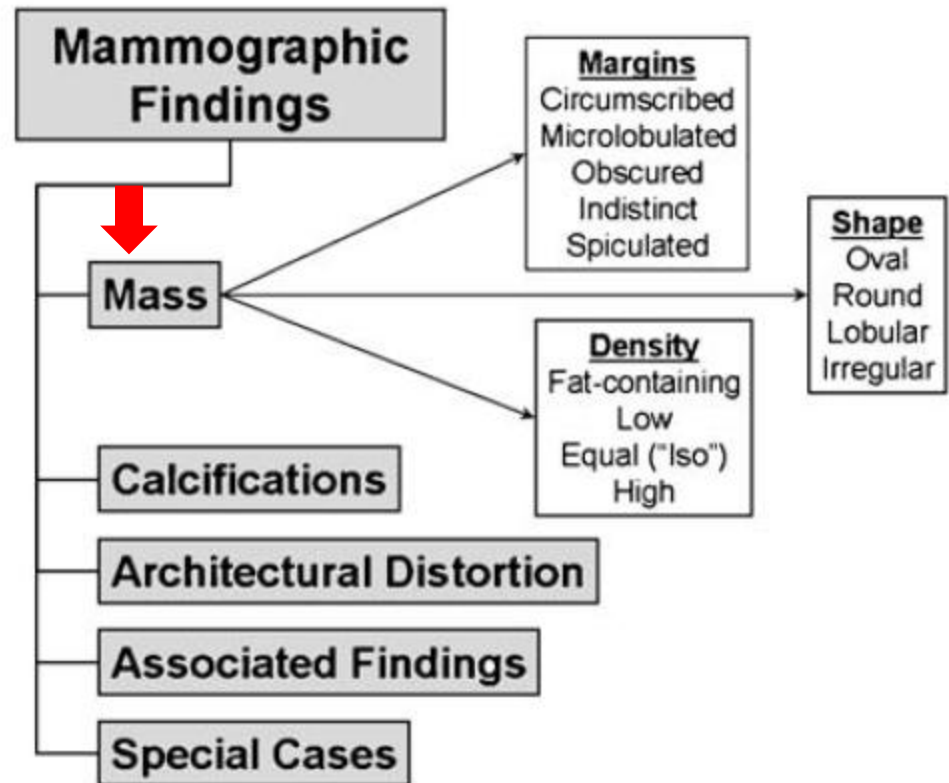
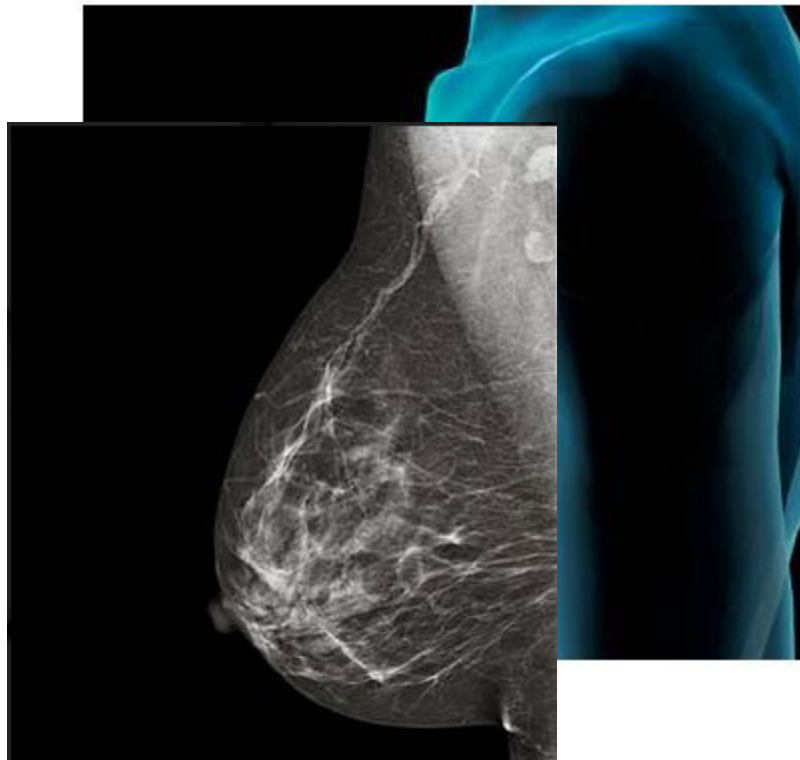
Source: *Laço Association* – accessed April 2015

Breast Screening Programs



- Reduction of death rate in 30%
- **Mammography:**
The cheapest and most efficient method to detect cancer in a preclinical stage

Mamography - BI-RADS® Descriptors



Outline

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- in P. Ferreira, et al., “**Studying the relevance of Breast Imaging Features**”, in Proc. International Conference on Health Informatics (HEALTHINF), 2011.

Objectives



- Build classifiers capable of predicting **mass density** and **malignancy** from a reduced set of mammography findings



- Reduce the number of unnecessary biopsies

Outline

- Breast Cancer
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Dataset



- Source:



- 348 cases
- Each case refers to a breast nodule **retrospectively** classified according to BI-RADS® system
- From mammographies results
- Collected between October 2005 and December 2007

Attributes

13 attributes

age_at_mammo

CLOCKFACE_LOCATION_OR_REGION

MASS_SHAPE

MASS_MARGINS

SIDE

DEPTH

MASS_MARGINS_worst

QUADRANT_LOCATION_def

SIZE

OVERALL_BREAST_COMPOSITION

Density_num

retro_density

outcome_num

118 (33.9%)
malignant (+)

230 (66.1%)
benign (-)

Masses classification

Prospective

- **Classification** of feature **mass density** just by **one radiologist**:
 - low density;
 - iso-dense;
 - high density;
- **Brief** and superficial medical **report** (at the time of imaging);
- **Classification under stress**.



mass density

density_num

Retrospective

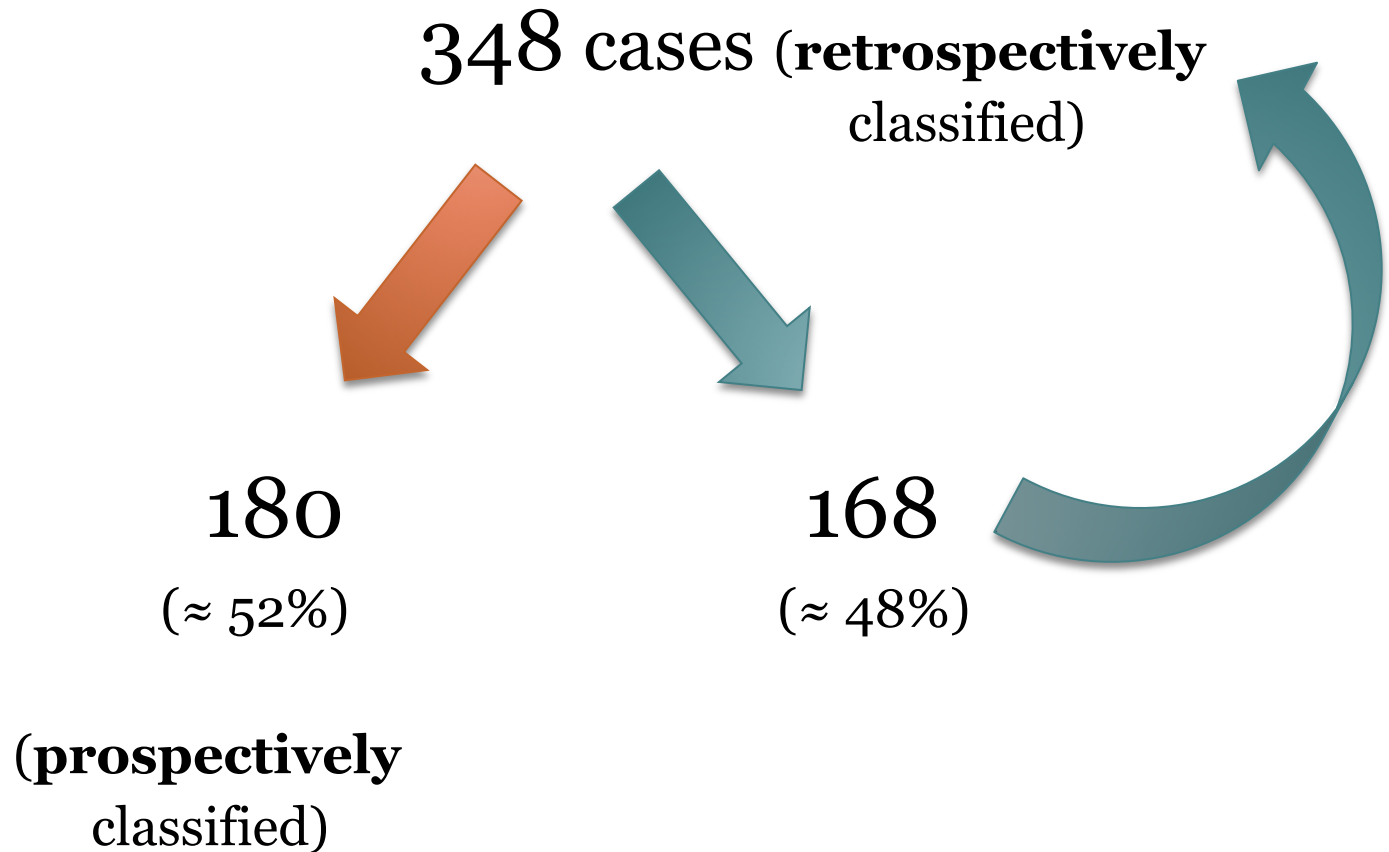
- **Classification** by a **group of experienced physicians** that **re-assess** all exams;
- **Review of mass density classification** made by radiologist (prospective study);
- **Classification without stress**;
- **Reference standard** for mass density.



mass density

retro_density

Masses classification



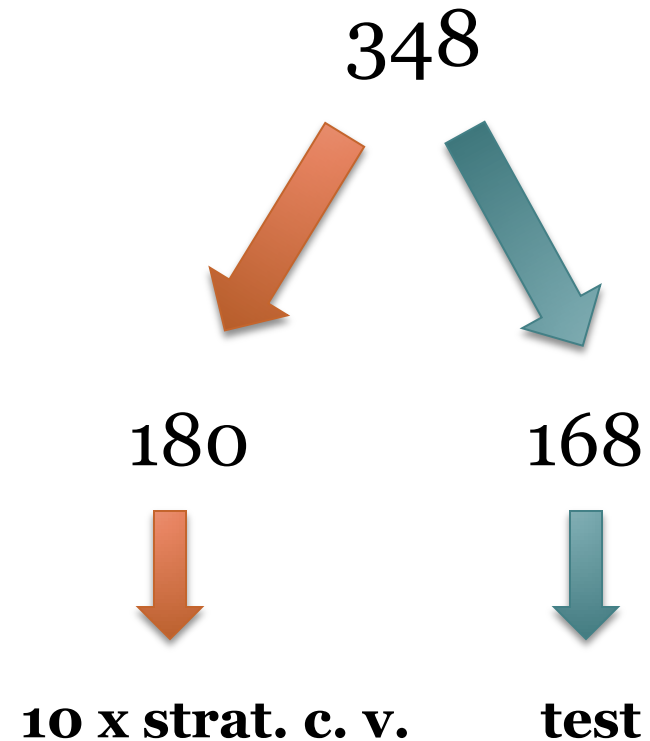
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Methodology



- WEKA
- Paired Corrected T-Tester
 - **Significance level: 0.05**



Methodology - Experiments

10 x stratified. c. v.

180

- E_1 – Predicting malignancy with *retro_density*
- E_2 – Predicting malignancy with *density_num*
- E_3 – Predicting malignancy without mass density

- E_4 – Predicting *retro_density**
- E_5 – Predicting *density_num**

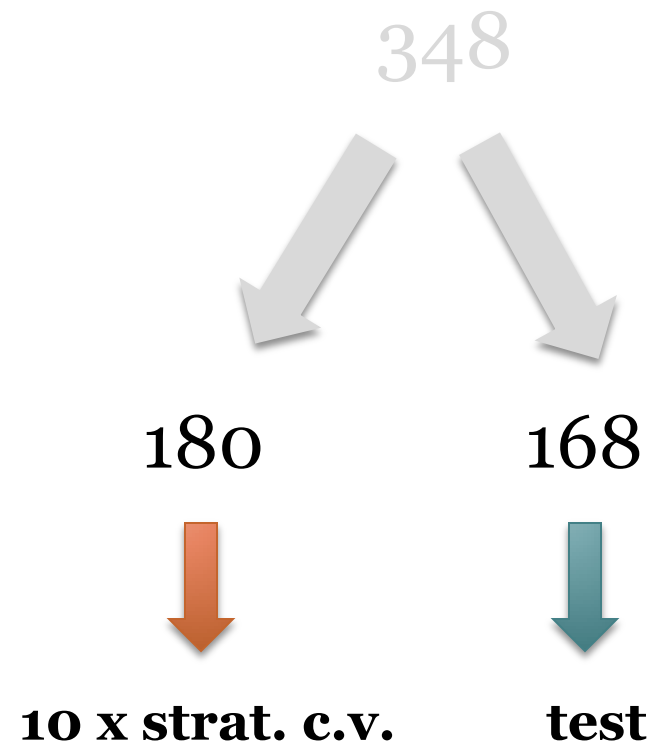
* in all experiments the *low* and *iso* densities were merged into a single class

Methodology - Algorithms applied

- ZeroR (baseline classifier)
 - OneR
 - DTNB
 - PART
- rules*
- J48
 - DecisionStump
 - RandomForest
 - SimpleCart
 - NBTree
- trees*
- NaiveBayes
 - BayesNet (TAN)
- bayes*
- SMO
- functions*

internal parameter variation

Results



Results - Experiments

10 x stratified. c. v.

180

*Predicting malignancy
with retro_density*

Exp	Algorithm	CCI	K	F	AUROC
E1	SMO	85.6 \pm 7.3	0.69 \pm 0.16	0.80 \pm 0.11	0.84 \pm 0.08
E1	DTNB	81.6 \pm 8.2	0.60 \pm 0.18	0.74 \pm 0.13	0.88 \pm 0.07
E1	NaiveBayes	81.3 \pm 9.5	0.61 \pm 0.20	0.76 \pm 0.12	0.88 \pm 0.08
E1	J48	80.7 \pm 9.3	0.59 \pm 0.20	0.75 \pm 0.13	0.79 \pm 0.11
E2	SMO	83.9 \pm 7.7	0.66 \pm 0.17	0.78 \pm 0.11	0.82 \pm 0.08
E2	NaiveBayes	80.3 \pm 9.3	0.59 \pm 0.19	0.75 \pm 0.12	0.87 \pm 0.09
E2	DTNB	79.8 \pm 9.5	0.56 \pm 0.21	0.72 \pm 0.15	0.86 \pm 0.09
E2	J48	75.4 \pm 9.5	0.47 \pm 0.21	0.65 \pm 0.15	0.73 \pm 0.12
E3	SMO	83.8 \pm 7.7	0.65 \pm 0.17	0.78 \pm 0.11	0.82 \pm 0.09
E3	J48	76.3 \pm 9.9	0.49 \pm 0.22	0.67 \pm 0.15	0.76 \pm 0.13
E3	NaiveBayes	76.2 \pm 9.9	0.51 \pm 0.20	0.71 \pm 0.13	0.85 \pm 0.09
E3	DTNB	75.7 \pm 9.0	0.48 \pm 0.19	0.67 \pm 0.13	0.81 \pm 0.10
E4	SMO	81.3 \pm 8.2	0.52 \pm 0.21	0.64 \pm 0.17	0.75 \pm 0.11
E4	J48	74.4 \pm 8.8	0.32 \pm 0.24	0.47 \pm 0.21	0.67 \pm 0.15
E4	DTNB	73.5 \pm 10.0	0.34 \pm 0.24	0.51 \pm 0.19	0.76 \pm 0.12
E4	NaiveBayes	72.8 \pm 9.9	0.37 \pm 0.23	0.56 \pm 0.18	0.77 \pm 0.11
E5	NaiveBayes	67.2 \pm 12.1	0.33 \pm 0.25	0.62 \pm 0.15	0.72 \pm 0.14
E5	SMO	66.8 \pm 10.7	0.31 \pm 0.22	0.55 \pm 0.16	0.65 \pm 0.11
E5	J48	63.6 \pm 10.1	0.26 \pm 0.21	0.56 \pm 0.15	0.62 \pm 0.13
E5	DTNB	62.1 \pm 11.9	0.22 \pm 0.24	0.54 \pm 0.16	0.64 \pm 0.14

*Predicting
retro_density*

Results - Experiments

Predicting density

180

Results - Experiments

10 x stratified. c. v.

- E_4 – Predicting *retro_density*

SVM's

CCI: 81.3% (+/-8.2)

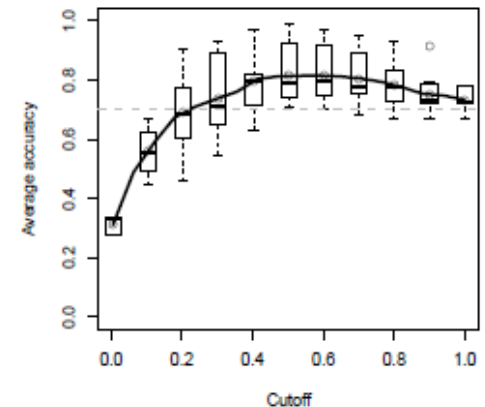
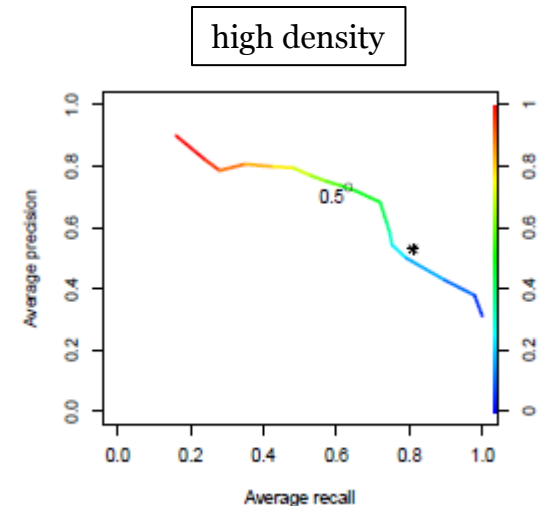
Sens: 0.57 (+/- 0.20)

Spec: 0.92 (+/- 0.07)

F: 0.64 (+/- 0.17)

Radiologist's accuracy = 70 %

Classifier \approx 81 %



Results - Experiments

TEST

- E_6 – Predicting *retro_density*
(model E_4 applied)

SVM's

CCI: 84.5%

Sens: 0.57

Spec: 0.90

F: 0.55

180

SVM's

CCI: 81.3% (+/- 8.2)

Sens: 0.57 (+/- 0.20)

Spec: 0.92 (+/- 0.07)

F: 0.64 (+/- 0.17)

Results - Experiments

Predicting malignancy

180

Results - Experiments

10 x stratified. c. v.

- E_1 – Predicting malignancy with *retro_density*

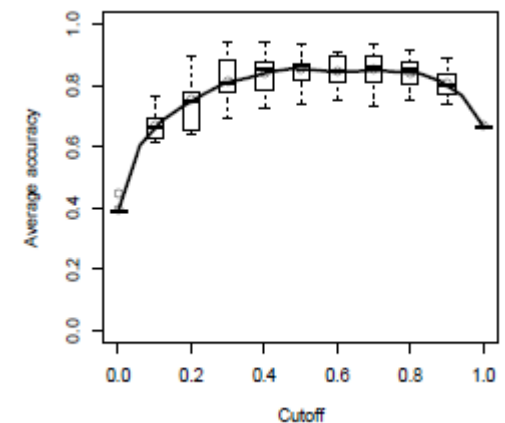
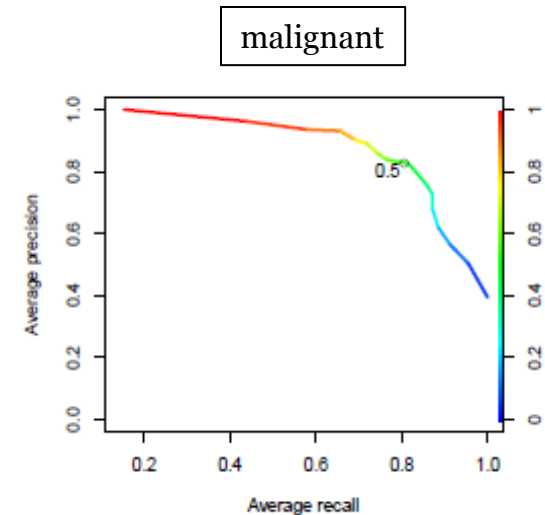
SVM's

CCI: 85.6% (+/-7.3)

Sens: 0.78 (+/- 0.15)

Spec: 0.91 (+/- 0.07)

F: 0.80 (+/- 0.11)



168

Results - Experiments

TEST

180

SVM's

CCI: 85.6% (+/- 7.3)
 Sens: 0.78 (+/- 0.15)
 Spec: 0.91 (+/- 0.07)
 F: 0.80 (+/- 0.11)

- E_8 – Predicting malignancy with *retro_density*
 (model E_1 applied)

SVM's

CCI: 81.0%
 Sens: 0.57
 Spec: 0.90
 F: 0.63

with **real** values
 of **retro_density**

SVM's

CCI: 80.4%
 Sens: 0.57
 Spec: 0.89
 F: 0.62

with **predicted**
 values of
retro_density
 by classifier E_6

MammoClass

- Online tool freely available at:
 - <http://cracs.fc.up.pt/mammoclass/>



MammoClass

Classification of a mammogram based in a reduced set of mammography findings

To obtain a prediction in terms of malignancy for a certain mass is only necessary to provide the values of the findings, annotated through the Breast Imaging Reporting and Data System (BIRADS), in the form bellow. It is also possible to get a prediction of the attribute *mass density* in case this feature is not known.

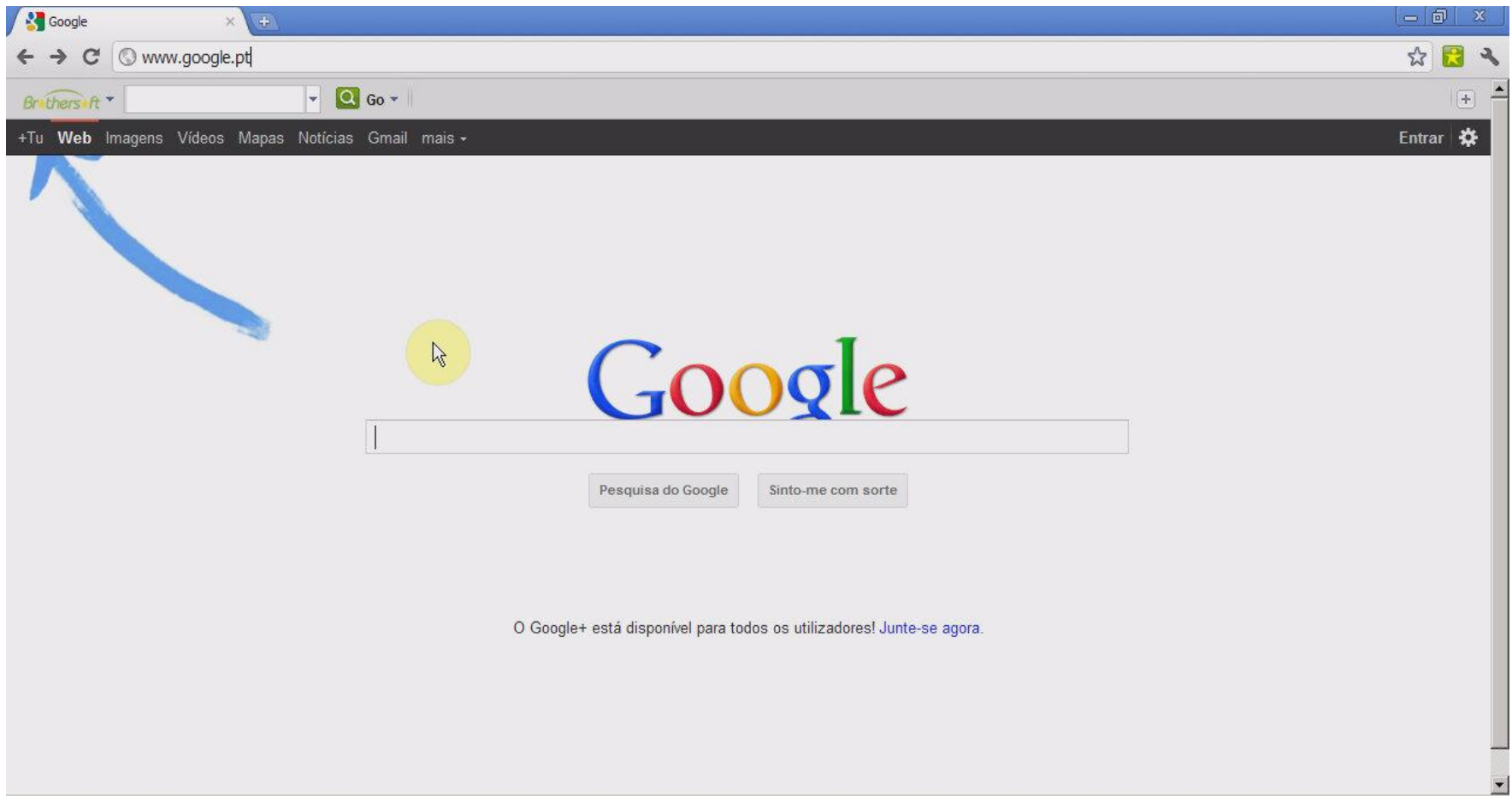
The output will indicate the probability of a certain mass being benign or malignant. In the latter case it is suggested that the patient should perform a biopsy. The probabilities are computed using machine learning models built as described in:

- P.Ferreira, N. A. Fonseca, I. Dutra, R. Woods, and E. Burnside, *Predicting Malignancy from Mammography Findings and Surgical Biopsies*

Enter Data

Patient's age	<input type="text"/>
Mass size	<input type="text"/>
Breast Composition	<input type="text" value="Select a value"/>
Mass shape	<input type="text" value="Select a value"/>
Mass clockface location	<input type="text" value="Select a value"/>
Mass margins (1)	<input type="text" value="Select a value"/>
Mass margins (2)	<input type="text" value="Select a value"/>

MammoClass



MammoClass

Enter Data

Patient's age

Mass size

Breast Composition

Mass shape

Mass clockface location

Mass margins (1)

Mass margins (2)

Mass margins worst

Mass density

Side

Quadrant

Depth

Result

Prediction: mass benign with a probability of 98.8%.

Disclaimer: The predictions are made available in the hope that may be useful, but WITHOUT ANY WARRANTY. The authors of this site and respective institutions are in no way

Conclusions

- a) We built **models** (integrated in *MammoClass*) that **predict malignancy and mass density** based on mammography findings;
- b) Machine learning **classifiers** to **predict mass density** may **aid radiologists** during the prospective mass classification;
- c) One of our classifiers can **predict malignancy even in the absence of mass density**, since we can **fill up** this **attribute** using our **mass density predictor**.

Thank you!



FCT Fundação para a Ciência e a Tecnologia
MINISTÉRIO DA EDUCAÇÃO E CIÊNCIA

<http://cracs.fc.up.pt/mammoclass>

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eburnside@uwhealth.org

Appendices

State of the Art

- R. Woods, et al., “**Validation of Results from Knowledge Discovery: Mass Density as a Predictor of Breast Cancer**”, in J Digit Imaging, pp. 418-419, 2009.
- R. Woods, et al., “**The Mammographic Density of a Mass is a Significant Predictor of Breast Cancer**”, in Radiology, 2010.
- P. Ferreira, et al., “**Studying the relevance of Breast Imaging Features**”, in Proc. of the International Conference on Health Informatics (HEALTHINF), 2011.

- **Conclusions:**

mass density can be an
important attribute when
predicting **malignancy**

State of the Art



UCIRVINE

- 4 datasets
- Main target of study:
 - **Breast Cancer**



State of the Art

- W. H. Wolberg & O. L. Mangasarian, “**Multisurface method of pattern separation for medical diagnosis applied to breast cytology**”, in Proc. of the National Academy of Sciences, 87, pp. 9193-9196, 1990.
- Y. Wu, et al, “**Artificial neural networks in mammography: application to decision making in the diagnosis of breast cancer**”, in Radiology 187:81-87, 1993.
- H. A. Abbass, “**An evolutionary artificial neural networks approach for breast cancer diagnosis**”, in Artificial Intelligence in Medicine 25:265, 2002.
- W. N. Street, et al, “**An Inductive Learning Approach to Prognostic Prediction**”, in ICML, p. 522, 1995.
- T. Ayer, et al, “**Breast cancer risk estimation with artificial neural networks revisited: discrimination and calibration**”, in Cancer 116(14):3310-3321, 2010

Data distribution

- 348

348	<i>retro_density</i>		Total
<i>outcome_num</i>	<i>high</i>	<i>iso</i>	
<i>malignant</i>	59 (70.2%)	59 (22.3%)	118 (33.9%)
<i>benign</i>	25 (29.8%)	205 (77.7%)	230 (66.1%)
Total	84 (24.1%)	264 (75.9%)	

Data distribution

- 180

180	<i>retro_density</i>		Total
<i>outcome_num</i>	<i>high</i>	<i>iso</i>	
<i>malignant</i>	42 (75.0%)	29 (23.4%)	71 (39.4%)
<i>benign</i>	14 (25.0%)	95 (76.6%)	109 (60.6%)
Total	56 (31.1%)	124 (68.9%)	

180	<i>density_num</i>		Total
<i>outcome_num</i>	<i>high</i>	<i>iso</i>	
<i>malignant</i>	51 (63.0%)	20 (20.2%)	71 (39.4%)
<i>benign</i>	30 (37.0%)	79 (79.8%)	109 (60.6%)
Total	81 (45.0%)	99 (55.0%)	

Data distribution

- 168

168	<i>retro_density</i>		Total
<i>outcome_num</i>	<i>high</i>	<i>iso</i>	
<i>malignant</i>	17 (60.7%)	30 (21.4%)	47 (28.0%)
<i>benign</i>	11 (39.3%)	110 (78.6%)	121 (72.0%)
Total	28 (16.7%)	140 (83.3%)	