Predicting Breast Cancer Using Machine Learning

Classification Project

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October 30, 2019

Motivation

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Source: National Breast Cancer Foundation

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Early detection **survival rate** is **99%**

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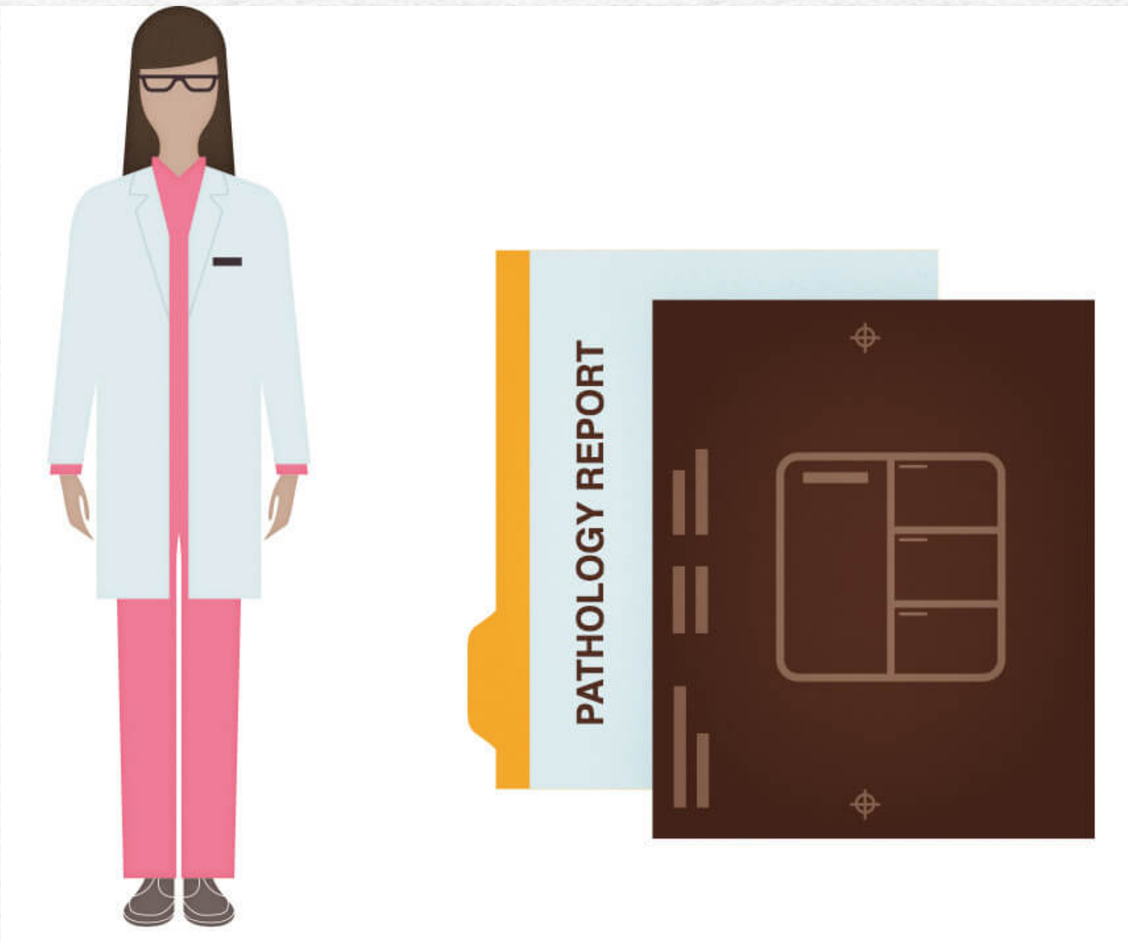
Objective

Fine-needle aspiration biopsy

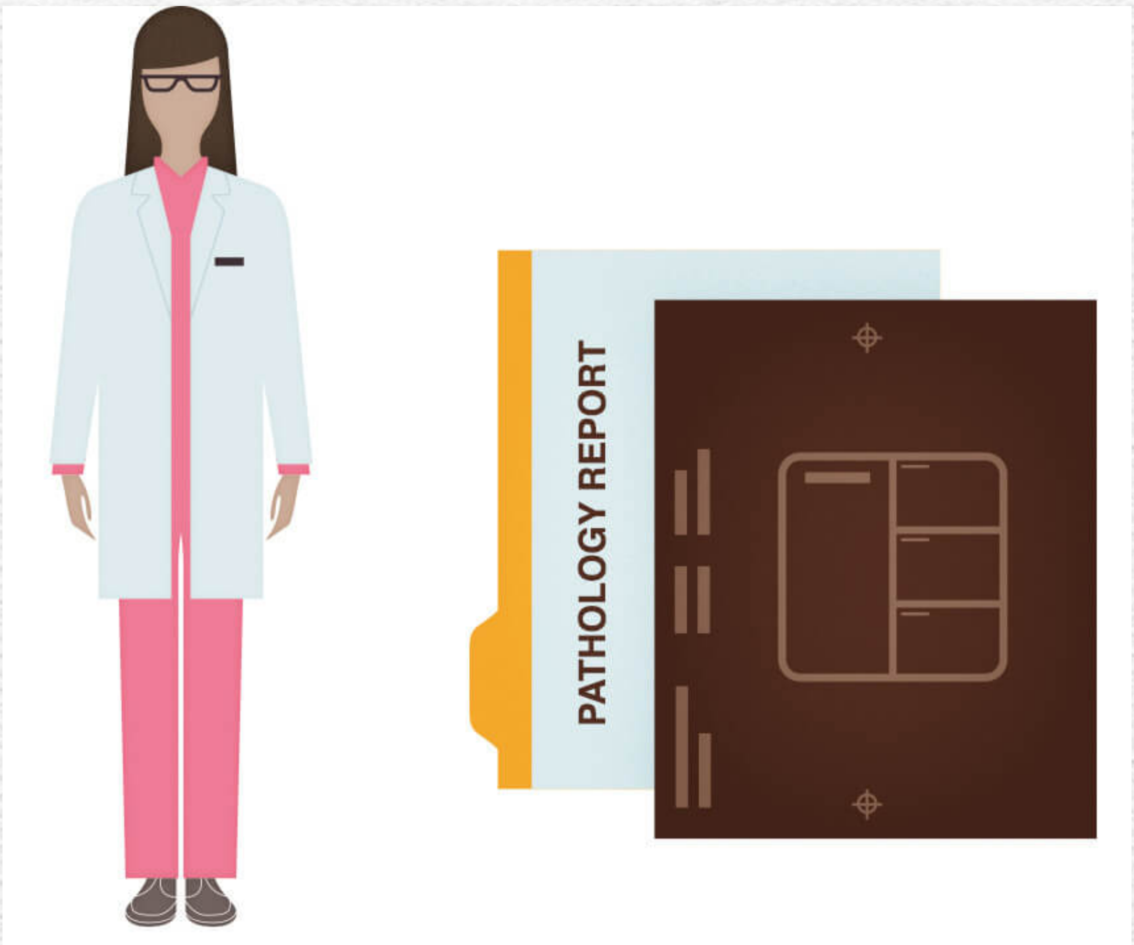


Objective

Fine-needle aspiration biopsy

1~2 weeks

Accuracy ~ 80 %



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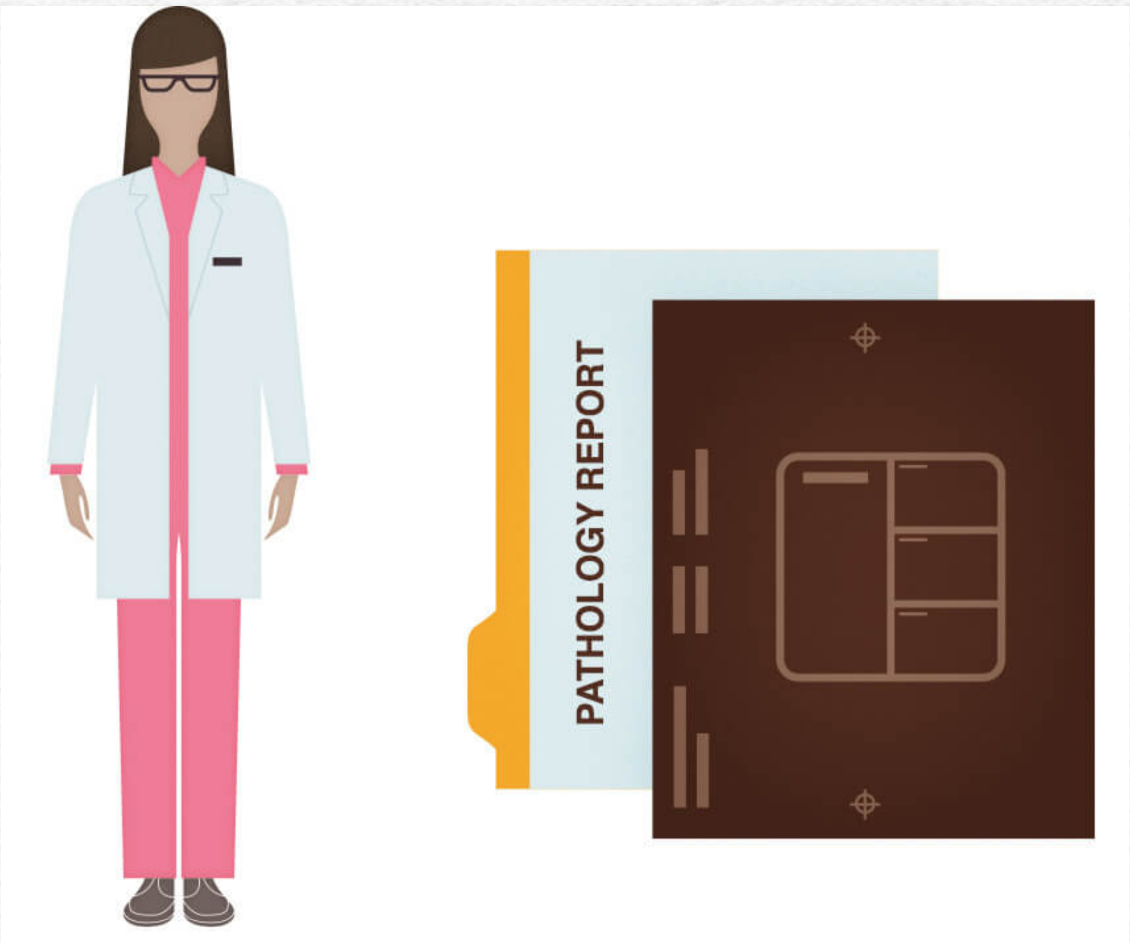

Improve diagnosis accuracy and speed with machine learning

Methodology

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Models

- 9 classification models in SciKit-Learn

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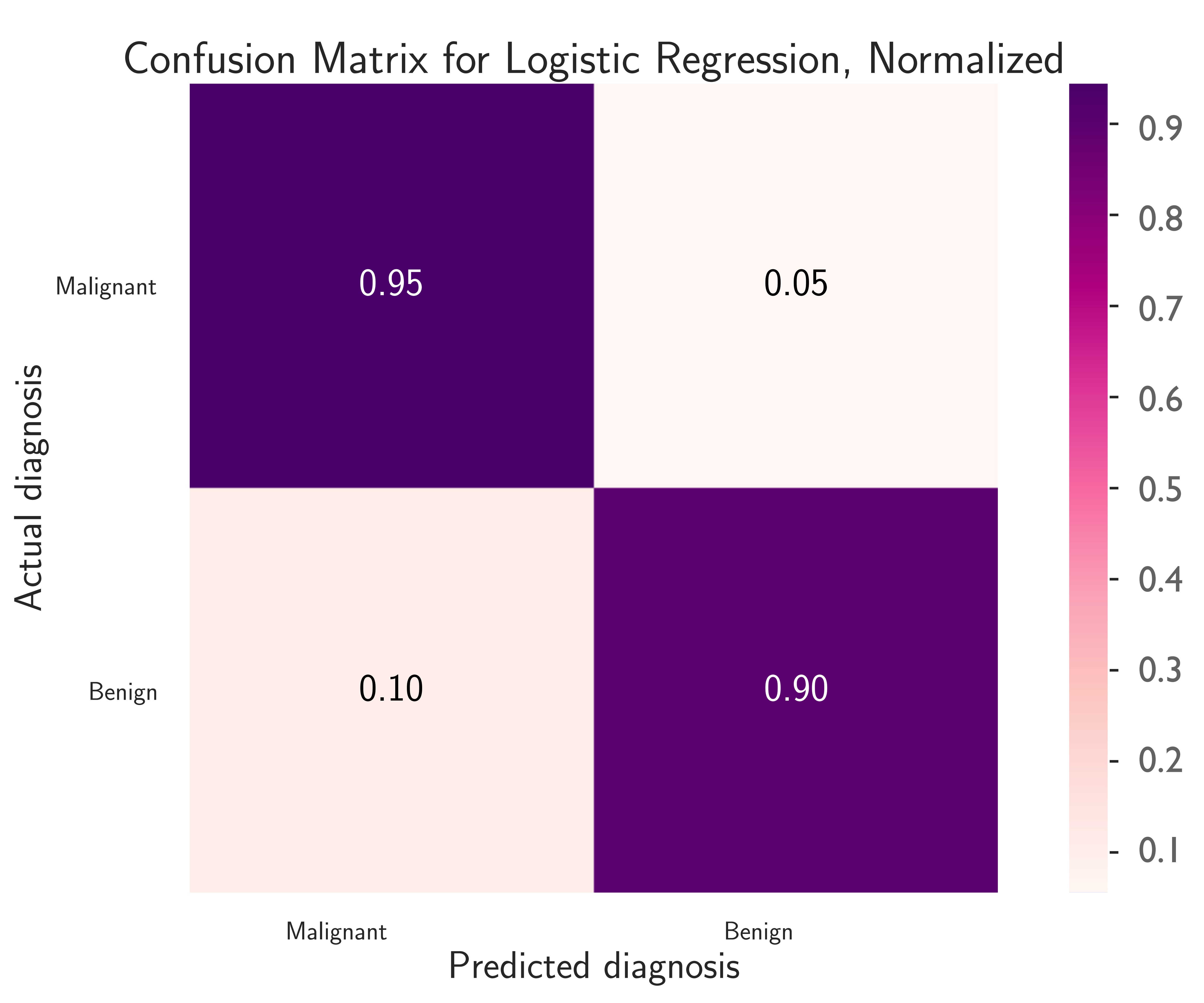
Models

- 9 classification models in SciKit-Learn
  - Top 4: Logistic Regression, Gradient Boosting, Random Forest, SVM

Results



Confusion Matrix for Logistic Regression, Normalized
Actual diagnosis
Malignant
Benign
0.95
0.05
0.10
0.90
Malignant
Benign
Predicted diagnosis
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1

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Future Work

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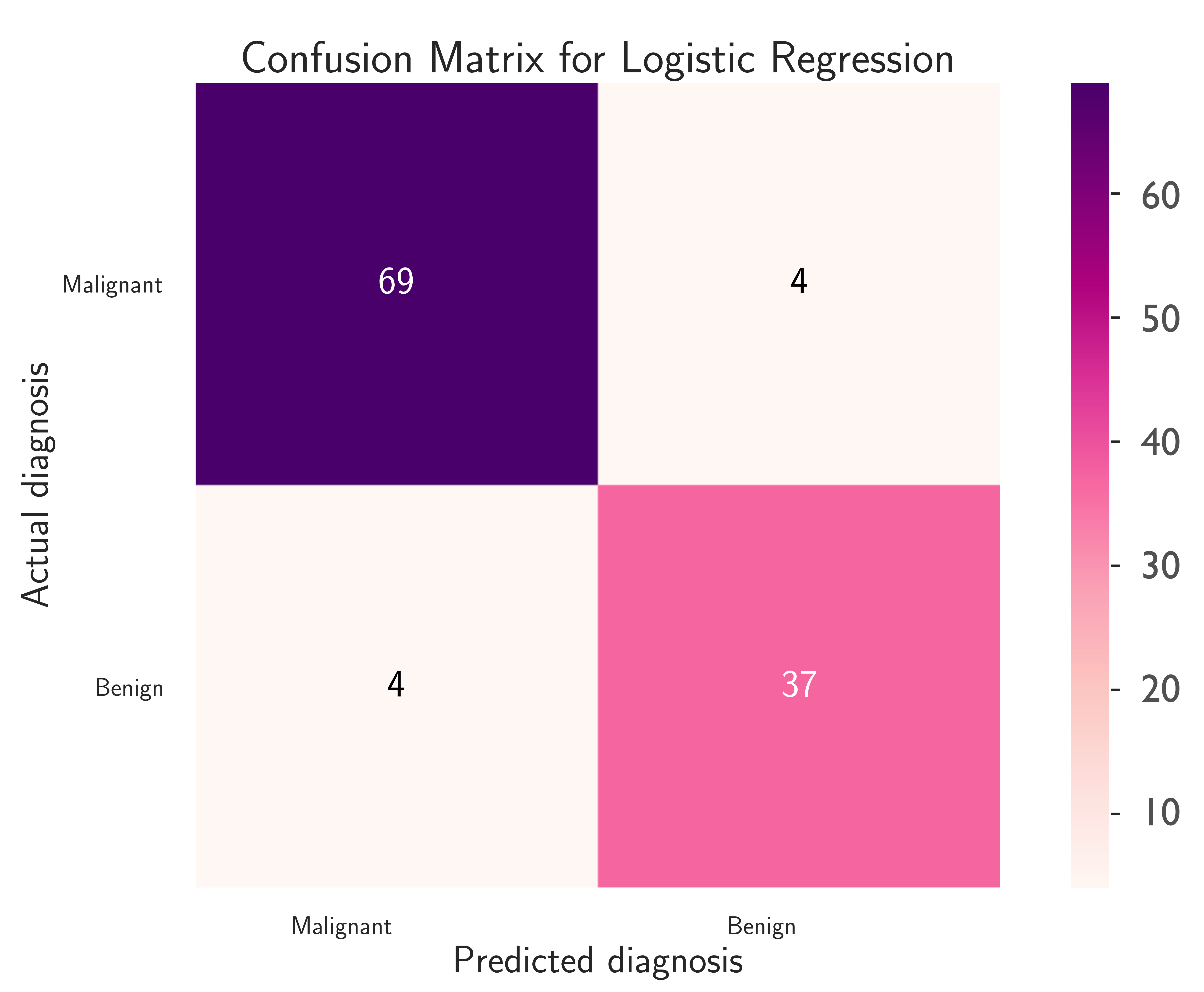
  - 95% prediction accuracy for malignant tumors

Future Work

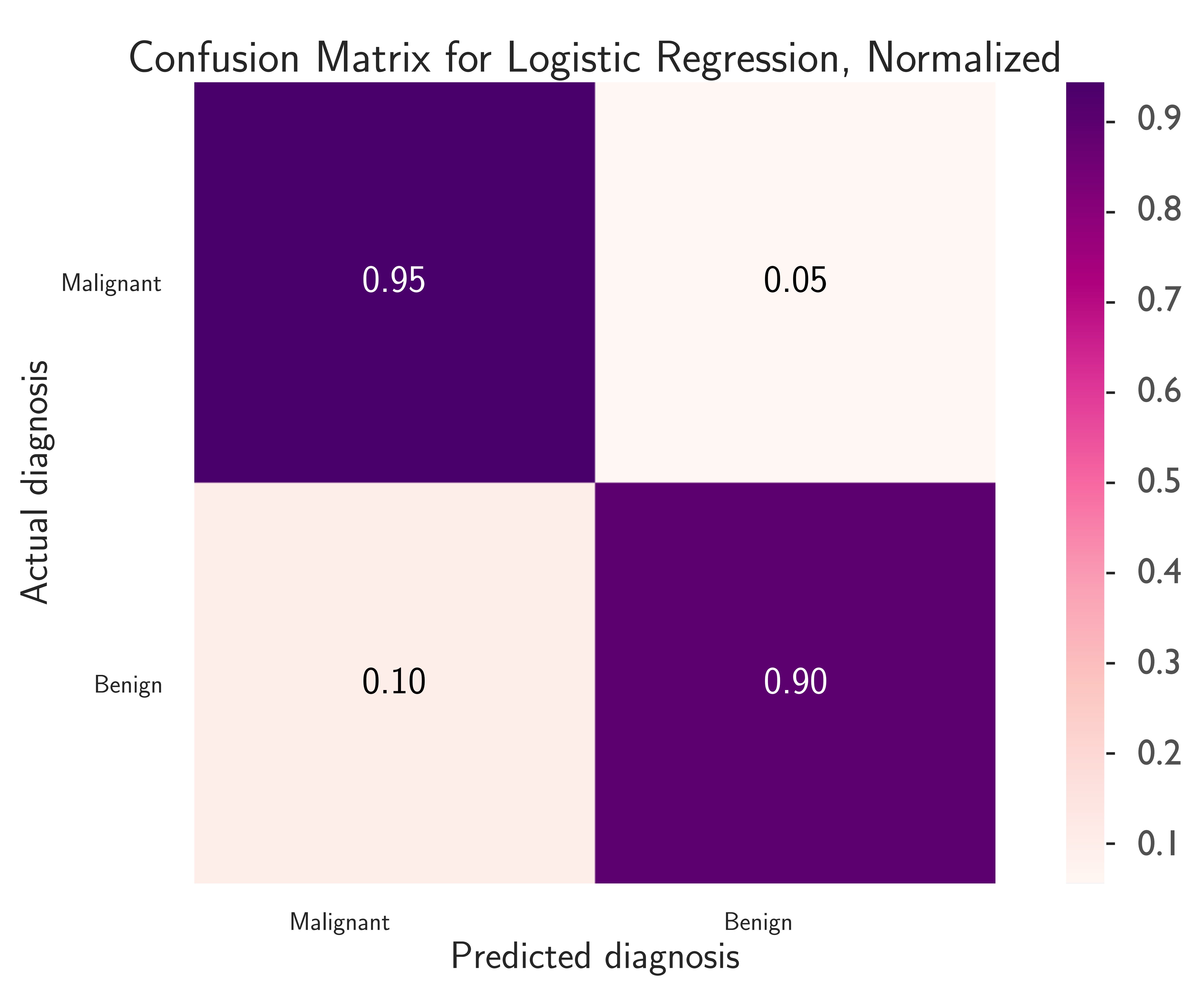
- Image classification — “biopsy to diagnosis”

Appendix



Test set, cross-validation over 5 folds

Appendix

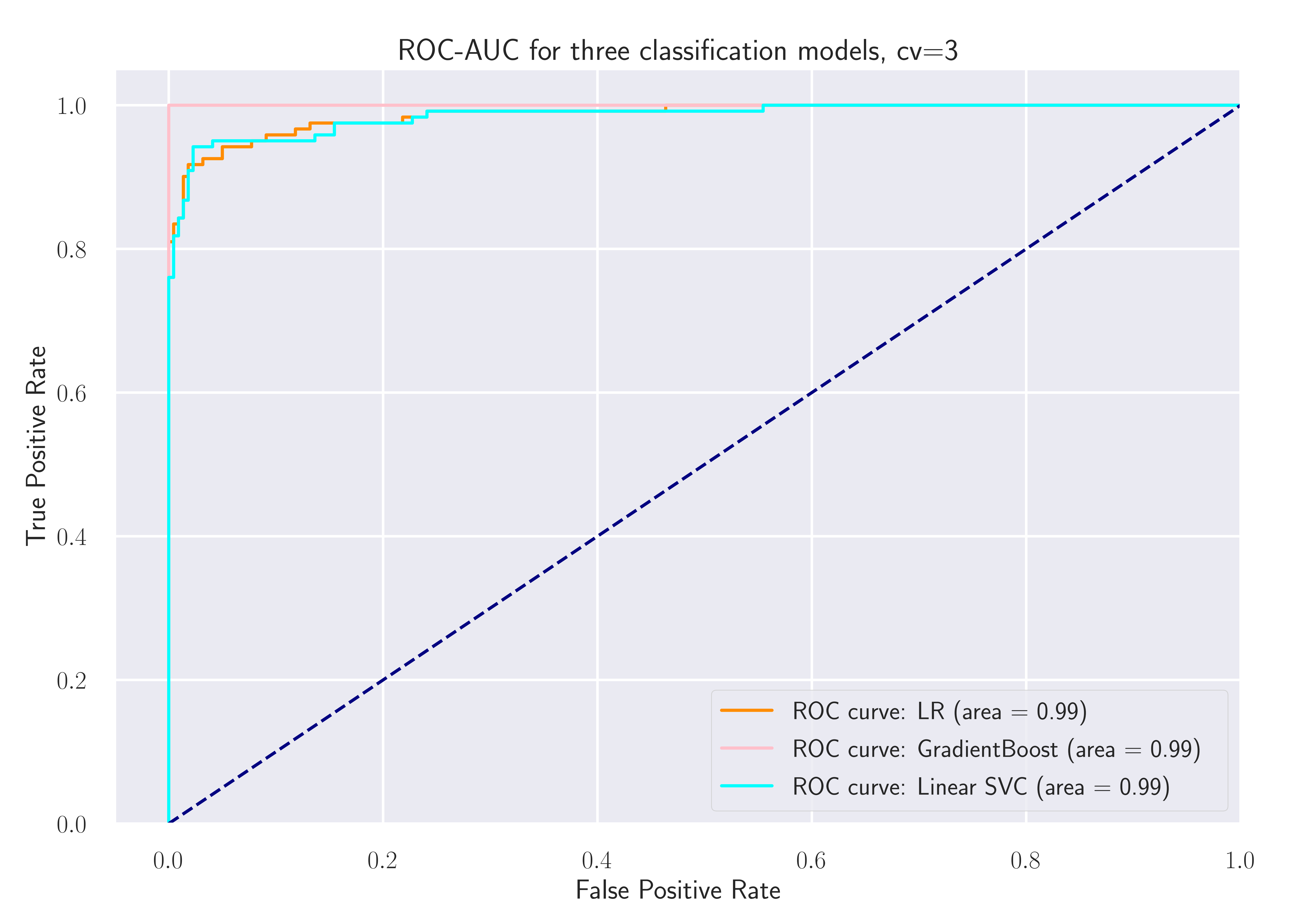


Normalization: divide prediction counts by the sum of each row

Appendix

Using 10 features

LR AUC score validation set 0.9884

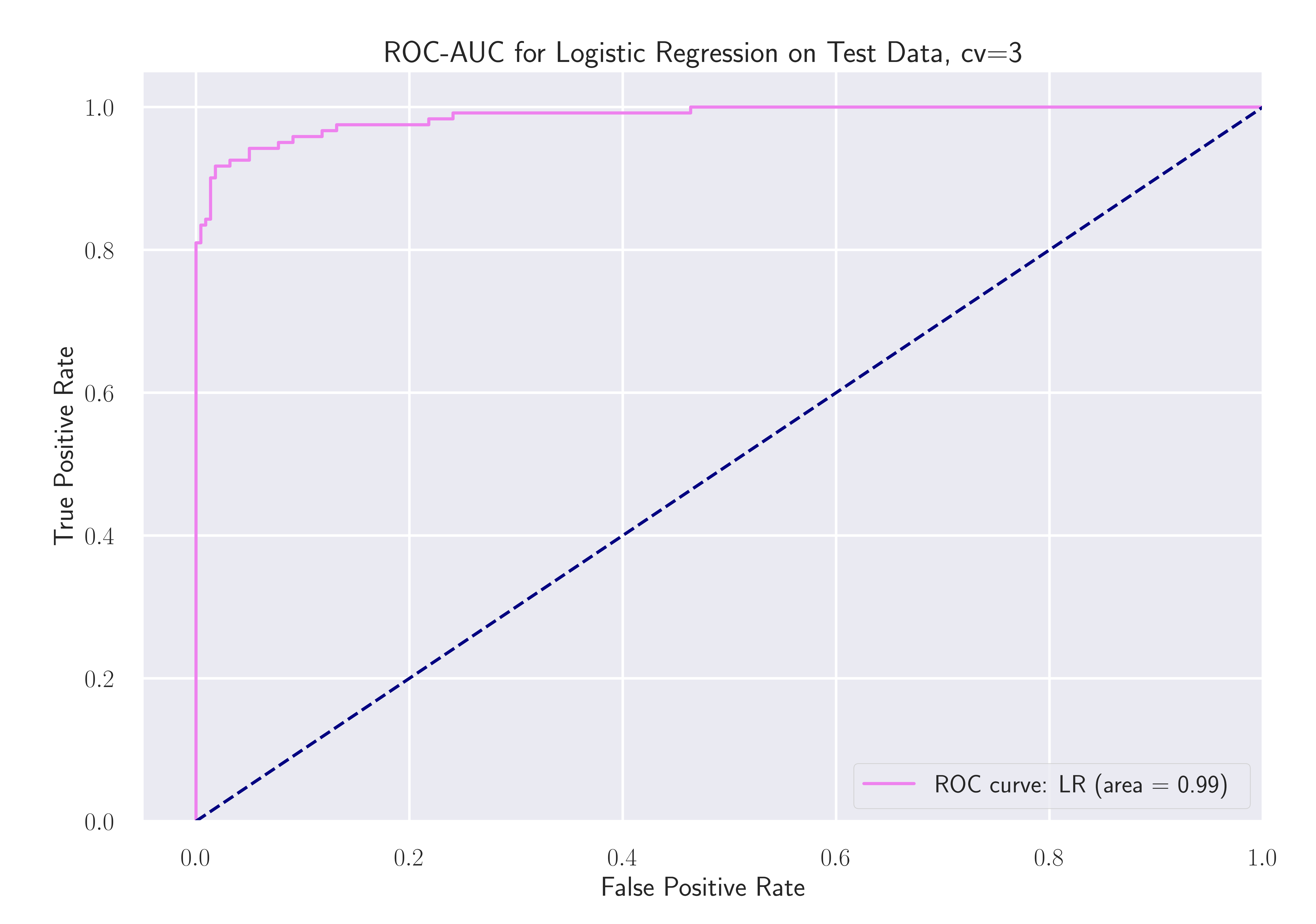


Comparison of the three models with highest roc-auc scores for validation set, with naïve model at 0.5 (dashed line)

Appendix

After feature engineering:
Validation set
0.9909

Test set
0.9870



Area under the curve for Logistic Regression on test data set after feature engineering, with naïve model at 0.5 (dashed line)

Appendix

Model	Metric	Top features	Weights (not normalized, 4 decimals)
LogisticRegression	coefficient	area	3.8253
		concave points	2.7111
		texture	1.6457
SVM - linear SVC	coefficient	area	2.4970
		concave points	1.2092
		texture	1.0927
RandomForest	feature importance	concave points	0.4975
		area	0.3071
		compactness	0.1300

Table showing the most impactful features for predicting diagnosis, for the models with the top roc-auc scores, after feature engineering. **Area** and **concave points** are the two most important features for our prediction.

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AUC score for LR on validation set (10 features): 0.9884
LR on test set (after feature engineering, 5 features): 0.9870

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